The Economics of Innovation and Intellectual Property Rights

A thesis submitted for the degree of

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This thesis makes contributions to the economics of intellectual property rights (IPR) from different perspectives in three distinct but related empirical studies. First, patent and trademark statistics are used as innovation measures to examine the long-run relationship between innovation and output in countries with long-established IPR systems. The findings show that innovations may not always play a positive role in driving economic growth. Post-World War II evidence for some countries with extensive measured innovations (the US and Germany) shows innovation's non-positive effects on economic growth, despite innovation's positive effects for the previous period. However, innovation retains a positive role in Japan, France and Australia.

Despite the importance of innovation, risk often decreases the incentive to innovate, and can lead to R&D under-investment problems relative to the social optimum. Patents play an essential role in addressing this problem. This role is evaluated in the Australian context by estimating the value of patent rights and calculating the corresponding equivalent subsidy rate (ESR). The average value of patent rights for Australian patents filed during 1980-1992 ranges from AU$9,000 to AU$17,000, lower than the findings of the European and US studies. However, the ESR (3.2-8.4%) is higher than that of large developed economies, indicating that the patent system of Australia has outperformed the systems of other countries.

One shortcoming of using patents as an innovation measure is the small number of patent users, which is less than secrecy users. Consequently, we examine determinants of firms' choices of patenting versus secrecy using Australian data, with a focus on the theory of Henry and Ponce (2011), predicting that firms' preference for secrecy over patents increases with knowledge tradability. In an important improvement over standard empirical practice, a trivariate-probit model is constructed to correct for the endogeneity of the key dummy regressor in a bivariate-probit model. As a robustness check, the potential sample selection bias caused by using only the innovator subsample was corrected. Key findings include that knowledge-trading firms and major R&D investors are more likely to use secrecy than patents, providing evidence for theory and important insights to inform R&D and IPR policy.

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Abstract

This thesis makes contributions to the economics of intellectual property rights (IPR) from different perspectives in three distinct but related empirical studies. First, patent and trademark statistics are used as innovation measures to examine the long-run relationship between innovation and output in countries with long-established IPR systems. The findings show that innovations may not always play a positive role in driving economic growth. Post-World War II evidence for some countries with extensive measured innovations (the US, and Germany) shows innovation's non-positive effects on economic growth, despite innovation's positive effects for the previous period. However, innovation retains a positive role in Japan, France and Australia.

Despite the importance of innovation, risk often decreases the incentive to innovate, and can lead to R&D under-investment problems relative to the social optimum. Patents play an essential role in addressing this problem. This role is evaluated in the Australian context by estimating the value of patent rights and calculating the corresponding equivalent subsidy rate (ESR). The average value of patent rights for Australian patents filed during 1980-1992 ranges from AU$9,000 to AU$17,000, which is lower than the findings of the European and US studies. However, the ESR range of 3.2% to 8.4% is higher than that of large developed economies, indicating that the patent system of Australia has outperformed the systems of other countries.

One shortcoming of using patents as an innovation measure is the small number of patent users, which is less than secrecy users. Consequently, we examine determinants of firms' choices of patenting versus secrecy using Australian data, with a focus on the theory of Henry and Ponce (2011), predicting that firms' preference for secrecy over patents increases with knowledge tradability. In an important improvement over standard empirical practice, a trivariate-probit model is constructed to correct for the endogeneity of the key dummy regressor in a bivariate-probit model. As a robustness check, the potential sample selection bias caused by using only the innovator subsample was corrected. Key findings include that knowledge-trading firms and major R&D investors are more likely to use secrecy than patents, providing evidence for theory and important insights to inform R&D and IPR policy.

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[1] This Chapter draws heavily on Goy and Wang (2013).

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Chapter 1

Introduction

1.1 Motivation and background

Innovation has been regarded as one of the essential driving forces behind economic growth, as demonstrated by endogenous growth theory (see for example Romer (1986)). However, there is a limited amount of empirical evidence supporting this theory, with the main barrier being a lack of adequate measures of innovation. For many centuries, innovation's role in improving living standards and stimulating economic growth has appeared to be self-evident. However, in recent decades many developed countries have observed relative stagnation in the rate of improvement of living standards and economic growth, while their R&D expenditure remained high. As a result, a small but increasing number of economists (particularly in the United States) have become concerned about whether innovation still plays a role in boosting economic growth as it did in the first half of the 20th century. This view is of course subject to further examination. Specifically, some analyses are required to examine innovation's long-run role and how it changes over a period in a number of developed countries.

Innovation is subject to inevitable risks, including market risk, arising from uncertainty about market demand for the new product, and technical risk, arising from the uncertainty about the technical feasibility of innovation outcomes. These risks can reduce innovation incentives and lead to under-investment in R&D relative to the social optimum (see Thomson, 2011). Given innovation's role in driving economic growth and rising living standards, governments are eager to mitigate this problem.

Intellectual property rights (IPR), patents in particular, have played an important role in creating incentives to innovate. From a political perspective, the patent system is useful in assisting the government to address the potential R&D under-investment problem by subsidizing patent owners with certain patent rents, also known as the value of patent rights. It is certainly important for policy makers to be able to judge the effectiveness of the IPR system. One indicator to evaluate the role of the patent system is through the equivalent subsidy rate (ESR) of patent rights, that is, the ratio of aggregate values of patent rights to the corresponding R&D expenditure on underlying inventions. The prerequisite of this approach is the estimation of the value of patent rights using the patent renewal framework. This approach has been employed extensively in studies of major developed countries that all find a reasonably small ESR, which raises questions about the performance of the Australian patent system in encouraging innovators to innovate and in addressing the potential R&D under-investment problem.

As distinct from the macroeconomics approach that assumes perfect IPR, microeconomics is favoured to debate the usefulness of IPR. Firm level data indicate that there has been a surprisingly small share of firms using patents compared to those using secrecy in many countries, in spite of considerable protection provided by the patent system. This brings into question the driver(s) of the choice between patents and secrecy (or, more widely, between formal and informal intellectual property (IP) protections). In a broader view, the current debate surrounding IPR often criticises not only the use of patents, but also their very existence.

Existing studies identify many factors that can determine the uses of patents verses secrecy, such as the significance of innovation, the size and industry category of the innovative firm, and so forth. Some of these theories have been examined in empirical studies using data drawn from the US and major European economies, while other theories still require supporting evidence. This includes the recently developed theory of Henry and Ponce (2011) that the preference for using secrecy verses patents increases as knowledge tradability increases. A study using Australian data may be complementary to those based on the largest economies, providing an interesting perspective because Australia is arguably more representative of the bulk of other countries in terms of levels of innovation and IPR than the US or the UK.

This dissertation is a collection of three distinct but related empirical studies covering both macro and micro perspectives of the economics of innovation and IPR. The thesis first makes uses of IPR statistics as innovation measures to examine innovation's long-run role in driving economic growth, then evaluates the Australian patent system by estimating the value and the ESR of patent rights in Australia, and explores the determinants of firms' preference for patents verses secrecy, with a focus on examining the role of knowledge tradability.

1.2 Overview of chapters

Chapter 2 applies patent and trademark statistics as measures of innovation and uses Fisher and Seater (1993)'s long-run neutrality (LRN) model to examine the long-run relationship between innovation and economic growth in countries with long-established IPR systems. The findings show that the effect of innovation on economic growth varies significantly across the countries studied, and generally changes post-World War

II. The post-World War II evidence for some countries with extensive measured innovation, including the United States, the United Kingdom and Germany, finds non-positive effects on economic growth from innovation. On the other hand, for Japan, France and Australia, a positive role of innovation in driving economic growth has been found in the pre-World War II period, and it is retained in the following period. The long-run output elasticity with respect to innovation among these countries ranges from 0 to 0.65 pre-World War II and -0.60 to 0.82 post-World War II, when innovation is measured by patents; it is a smaller range of 0 to 0.24 and -0.30 to 0.70 for the two periods, respectively, when trademark statistics are used to measure innovation. The qualitative conclusions regarding innovation's roles in driving economic growth across countries tend to hold for two different types of innovation measures.

Chapter 3 estimates the value of patent rights in the Australian context using the patent renewal framework proposed by Pakes and Schankerman (1984), and calculates the corresponding equivalent subsidy rate (ESR) of patent rights. The disaggregate level estimates indicate that the value of patent rights differs across patentee's nationalities and industries, and there is evidence of structural change occurring over time in the industry-level results. At the aggregate level, the average value of patent rights in Australia rises between 1980 and 1992, ranging from approximately AU$9,000 to AU$17,000, much lower than the findings of European and US studies. However, the ESR of patent rights at the aggregate level decreases over time, and ranges from 3.2 to 8.4 per cent, which is higher than the findings of studies of major developed economies. This provides additional evidence that the Australian patent system is probably more effective in providing inventors with incentives to innovate and in helping the government address potential R&D under-investment problems, compared with some of the major developed economies, although the effect has reduced dramatically over the sample period.

Chapter 4 aims to identify the determinants of firms' choices of patenting versus secrecy using Australian data, with a focus on examining the theory of Henry and Ponce (2011). In terms of the methodology, a trivariate probit model was constructed to correct for the endogeneity of the key explanatory dummy variable in the basic bivariate probit model, with dependent variables of patents and secrecy. This approach is new to the patent literature. As is unquestioned common practice in the literature, only the innovator sub-sample was used in the main model. However, as this can potentially lead to sample selection bias, this was corrected for following a robustness check.

One of the key findings of Chapter 4 is that firms engaged in licensing agreements (a proxy for knowledge trading) are more likely to use secrecy than patents, which lends support to Henry and Ponce (2011)'s prediction: When knowledge is tradeable, there is an alternative market-based mechanism to legal IPR protection. Interestingly, in line with the theory of Anton and Yao (2004), the study also finds that the largest R&D investors are more in favour of using secrecy than patents. Other findings are mostly consistent with the existing literature. Large and manufacturing firms are more likely to use patents, while firms obtaining information from internal and non-market sources and those involving process innovations are more inclined to use secrecy. Finally, firms achieving production innovation and those engaging in R&D joint ventures are likely to use both types of IPR protection, and there is no evidence of a clear preference for either.

Chapter 5 provides an overview of the thesis and the main conclusions, and outlines potential future research areas based on various issues that have emerged while undertaking this research.

Chapter 2

The Long-run Effect of Innovation on Economic Growth

2.1 Introduction

New growth theory emphasises the importance of innovation in stimulating economic growth along with other drivers, such as physical and human capital. There is little question that innovation played a remarkable role in driving economic growth for over half a century from the start of the second industrial revolution commencing in the 1870s, and led to a profound improvement in the standard of living in many countries.

However, the strong economic growth stimulated by the innovation that occurred during this period has been difficult to repeat in recent decades. The era of achieving fundamental changes in living standards may be over, and the usefulness of new inventions may have diminished compared with great inventions of the past. For instance, despite high expenditure in medical and pharmaceutical research, the improvement rate in US life expectancy in the second half of the twentieth century was only a third of that achieved in the first half (Gordon, 2012b). The concern that innovation may have stopped driving growth is drawing increasing attention (particularly in the US), but there is a lack of empirical evidence to support this (The Economist, 2013).

Measuring the quantity of innovation activity undertaken at a national level is generally believed to be a difficult task, and there is no perfect innovation measure. Along with support and criticism, research and development (R&D) data and patent statistics are widely used in economic studies as innovation measures. Compared to patents, trademark statistics typically measure minor innovations and capture a wider range of innovation activity across sectors and firms, but very few attempts have been made to use trademarks as a measure of innovation in existing studies.

A patent is a set of exclusive rights granted for an invention to prevent others from making, using, selling, or distributing the patented invention without permission for a limited period of time (i.e. the statutory limit). In exchange the technical information about the invention must be disclosed to the public in the patent application (Greenhalgh and Rogers, 2010). In order to obtain a patent, the inventor must satisfy novelty and non-obviousness requirements.[1] To keep a patent active, an annual renewal process is required after a few years from the filing date until it reaches the statutory limit, and this is subject to a payment of maintenance fee that increases as the patent ages.[2]

The literature using patent data as the innovation measure has consistently found a strong positive role for innovation. For instance, Crosby (2000) employed Fisher and Seater (1993)'s long-run neutrality (LRN) test to examine the long-run effect of innovation on growth in Australia. He found a positive role for innovation as a long-run

[1] Due to the globalization, a large share of patent applications are originated from foreign countries. Therefore, the interpretation of patents data is to some extents affected by international patenting activities. Both international patent laws and trade agreements can influence international patenting incentives, such that patents data can become more rule bounded and less subject to interpretation.

[2] In Australia, the statutory limit was 16 years prior to 1990 when the annual renewal fee was payable from the 2nd anniversary of the patent filing date. Under the Patents Act 1991, the initial payment date of renewal fee and the statutory limit were increased to 3 and 18 years from the filing date, respectively. Since 1999, a patent renewal fee was not required until 5 years after the filing date, and the statutory limit was raised to 20 years accordingly. The patent renewal process is discussed in more detail in Chapter 3.

output driver, although the role is negative in the short run. Also, a more recent Taiwanese study by Yang (2006) followed a similar procedure and found that innovation played a positive role in economic growth in both the short and long run.

These findings, however, tend to disagree with the views of an increasing number of pessimists. In fact, the major share of innovation that is measured by patents filed in Australia originates from the most technologically advanced countries. Since it is highly dependent on foreign technology inflows, Australia (or Taiwan) may not be a good representative for the experience of major technology exporting countries, such as the US. To obtain a broader view of innovation's role, it is necessary to study these major economies that have larger quantities of patents. In addition, by considering the many potential shortcomings of using patent data as innovation measures, using trademarks as an alternative could provide alternative insights.

This study uses patent and trademark statistics as innovation measures and examines the long-run effect of innovation in driving economic growth in six countries with long-established intellectual property rights (IPR) systems, which have the longest time series of IPR statistics: the US, Japan, Germany, the United Kingdom (UK), France and Australia.

The study's findings show that the contribution of innovation to economic growth varies significantly across countries, and generally changes in the post-World War II (WWII) years. For some of the most technologically advanced countries, such as the US and Germany, innovation's role decreased over periods, with a non-positive role for innovation on growth found in the second half of the twentieth century. For Japan, France and Australia, the results showed that innovation retained a positive role and had a significant effect on economic growth, particularly in the post-WWII era.

The study is structured as follows: Section 2.2 discusses the benefits and problems of using different innovation measures, followed by a brief discussion of literature that used patents as an innovation measure. Section 2.3 presents the model used to estimate the long-run relationships between innovation and growth in six countries. Section 2.4 describes the IPR statistics and gross domestic product (GDP) data. Section 2.5 contains the empirical results and Section 2.6 provides a conclusion.

2.2 Background

2.2.1 Measures of innovation

The endogenous growth theory pioneered by Romer (1986) and Lucas (1988) emphasises innovation as a primary driving force of economic growth.[3] However, the empirical implementation of new growth models has been difficult, partly because there is no perfect innovation measure. R&D data, whether R&D expenditure or R&D-related employment, have been most frequently used to measure innovation; see for example Griliches (1990) and Coe and Helpman (1995).[4]

However, R&D data have several shortcomings. Firstly, R&D spending only measures innovation activity input towards new products and processes, rather than successful outputs. The innovator usually faces high uncertainty of innovation outcomes, which means that only a random proportion of R&D expenditure will eventually be transformed into innovations. There is also a possible time lag between R&D activity and the release of new products. The unknown lag structure between R&D and innovation output is believed to be non-linear and varies across firms and sectors. Besides

[3] Other influential works include those by Romer (1990) and Aghion and Howitt (1992).

[4] For an alternative broad class of intangible assets thought to drive innovation, including capitalised R&D expenditures, and their impact on economic growth and productivity, see e.g. Corrado, Hulten and Sichel (2009) and Haskel and Wallis (2013)

its inability to provide accurate innovation levels and timing, R&D data also cover a relatively short period; it is thus difficult to conduct a time-series analysis using R&D data.[5]

Due to its advantages over R&D data, IPR statistics, particularly patents, have drawn attention in the economics literature as an alternative innovation measure. Unlike R&D that measures the innovation input, patent statistics provide innovation output measures. Patents represent successful innovation or innovation outputs, and underlying inventions will have undergone formal tests for 'novelty and non-obviousness'. There is also rich information contained in patent data regarding its inventors, citations and technical fields. Another important benefit of patents (over R&D data) is the data coverage. Patent data are available for many countries and for long periods, in some cases dating back to the late 1800s.

In the earliest work demonstrating the feasibility of using patent data as an innovation indicator, Schmookler (1966) claimed that patent statistics provided an index for the quantity of inventions created in different technology sectors and at different times. By examining patent data and R&D data, he found high correlations between patent statistics, R&D expenditure and the employment involved in R&D. Inspired by Schmookler (1966), researchers have since often used patent statistics as an innovation proxy in studies related to the economics of innovation. Some early studies include those by Pavith (1982), Archibugi (1992), Patel and Pavith (1995) and Griliches (1990), which have all shown the usefulness of patents as innovation indicators.

Although patent statistics have enjoyed broad coverage in the economics literature, there are some potential issues involved in using patents as an innovation measure (Greenhalgh and Rogers (2010), pp 60-61). First, since they are restricted by patent

[5]Time-series analysis, such as that of Fisher and Seater (1993), involves long lags that demand data over a long period.

legislation, only certain types of inventions from a limited number of sectors can be patented. As a result, patent applications are concentrated in the manufacturing and extractive industries.[6] Despite being one of the most innovative sectors, the finance sector rarely uses any patents. This is because the financial service provided by the finance industry is rarely fits into any patent classifications. Second, depending on the type and value of an invention, many firms prefer secrecy over patenting. Since patenting involves revealing an invention's technical details, in cases when the reverse-engineering process is hard to achieve, firms find it more beneficial to use secrecy.[7] Third, because of the cost involved in patent enforcement, it is infeasible for small firms to use patents. Therefore, patent data are less representative of differing firm sizes. Fourth, patents represent inventions, but a share of those inventions may not ever become innovations. Instead of seeking the right to use the invention, some patents are used to prevent others from doing so as a purely anti-competitive strategy. Finally, the strictness of the patent system varies across different countries and over time. Therefore, it is hard to draw precise international or inter-temporal comparisons of innovative activity based on patent statistics. For the first four reasons given, there is likely to be a downward bias when patent data are used as an innovation measure.

The statistics on trademarks can be a complementary innovation measure based both on analytical and empirical grounds. Trademarks are closer to commercialization and with a broader coverage of innovation activities from manufacturing and service sectors. Several surveys showed that trademarks were ranked higher than patents in the importance of various IP protections, and among the highest in the service sector (Levin, Klevorick, Nelson and Winter, 1987; Cohen et al., 1996, 2000). In addition, it has also been pointed out that R&D investment accounts for only half on the expenditures of innovation activities, with production engineering and marketing taking

[6]The largest users of patents include pharmaceutical, aerospace, motor vehicle and electronics companies and the oil and gas extracting industries (Greenhalgh and Rogers, 2010).

[7]The determinants for firms' choices of using patents and secrecy are explored in Chapter 4.

up the other half (Pavith, 1985), which indicates the importance of marketing and its tools in connection with innovation activities.[8] Moreover, with some similar features with patenting patterns among some types of products and sectors, trademarks play a crucial role in the marketing of intermediate inputs and capital goods (Mendonca et al., 2004). Furthermore, trademarks can be a better innovation measure than patents in service sectors, in sectors where patenting data contain unreliable information on innovation activities and low-tech sectors with a large share of small firms.

Much empirical evidence points to a high correlation between innovation activities and the use of trademarks. Schmoch (2003) found that innovation and trademarks were highly correlated in the manufacturing sector. In addition, a report on the use of IPRs by Portuguese firms found that manufacturing sectors with higher technological intensity were significantly more likely to use trademarks (Godinho et. al., 2003). Moreover, the results of the Third Community Innovation Survey (CIS 3) indicate that innovative firms consistently use more trademarks (and patents) than non-innovative firms, which provides additional support to the use of trademarks as an innovation measure (European Commission, 2004).

2.2.2 The role of innovation (measured by patents)

The literature using patents as an innovation measure consistently identified a positive long-run role of innovation in driving economic growth, although there are different views and findings for the short-run role. Schmookler (1966) claimed that there would be a positive long-run relationship between these two variables, whereas in the short-run they were likely to be negatively related. By contrast, Devinney (1994) implicitly showed a short-run positive correlation between patents and GDP growth by examining the associations between changes in these two factors. An Australian study by Crosby (2000) focused on the long-run relationship between innovative activity (mea-

[8]However, not all trademarks are necessarily associated with a new innovative product. It is argued that these trademarks only account for a small share (Mendonca et al., 2004).

sured by patents) and GDP growth, and found evidence of patenting activity's positive effect on labour productivity and economic growth. Crosby's results tend to support the negative short-run relationship, as argued by Schmookler (1966). A more recent study by Yang (2006) analysed Taiwanese patent data using a similar model and found positive effects of innovation on GDP in both the short run and long run. Both the latter studies considered small open economies with a large share of innovations represented by patents owned by foreign entities. For example, over 85 per cent of patent applications in Australia, on average, are owned by technology leaders, including the US, Japan and major European countries, that is, the UK, France and Germany.

However, a small but increasing number of economists, particularly in the US, are not as optimistic about the strength of innovation's current role. A recent study by Gordon (2012a) focussed on concern that there has been a drop in the usefulness of inventions in recent decades compared with the remarkable set of inventions during the second industrial revolution and their extensions. Gordon (2012b) argued that new technologies often fail to improve people's living standard in a cost-effective way.[9] He also found support for his view using the fact that the rate of US life expectancy improvement since the 1950s declined by two thirds compared with that of the earlier half century. On the other hand, economic growth in major developed economies that were challenged by unstable macroeconomic conditions such as two oil price shocks in the 1970s and 1980s and several financial crises in more recent decades, has stagnated since the 1970s. It is thus sensible to question whether there is still a positive association between innovation and economic growth in these countries. In this study, both patent and trademark statistics are used as innovation measures, with Fisher and Seater (1993)'s LRN model used to identify the long-run relationship between innovation and economic growth in six of the major countries of using IPR.

[9] For example, the recently invented protonbeam treatment for prostate cancer is more expensive, but does not promise better results than radiation therapy.

2.3 Methodology

2.3.1 The LRN model

This study's empirical model closely follows the concept of the LRN model proposed by Fisher and Seater (1993) and employed by Crosby (2000), which is based on a system of autoregressive models.[10] By assuming a log-linear system of two variables (in this case the innovation measure and real GDP), the vector autoregressive (VAR) model is formulated as follows:

$$\theta(L)\Delta IP_t = \phi(L)\Delta y_t + \epsilon_t^1, \tag{2.1}$$

$$\gamma(L)\Delta y_t = \eta(L)\Delta IP_t + \epsilon_t^2, \tag{2.2}$$

where L is the lag operator, Δ is the first difference operator, and IP_t and y_t represent the logarithm of the innovation measure (i.e. patent or trademark statistics) and the logarithm of real GDP in year t, respectively. ϵ_t^1 and ϵ_t^2 are error terms, and the vector $(\epsilon_t^1, \epsilon_t^2)'$ is assumed to be independently and identically distributed with zero mean and covariance Σ. The long-run effect of innovations on economic growth is measured using the long-run derivative (LRD) defined by Fisher and Seater (1993) as,

$$LRD_{y,IP} = \lim_{j\to\infty} \frac{\partial y_{t+j}/\partial \epsilon_t^1}{\partial IP_{t+j}/\partial \epsilon_t^1}, \tag{2.3}$$

provided that the denominator $\partial IP_{t+j}/\partial \epsilon_t^1 \neq 0$. This requires that the disturbance for innovation ϵ_t^1 permanently affects the innovation level and the variable used to measure innovations is characterised by $I(1)$. Intuitively, $LRD_{y,IP}$ in Equation (2.3) expresses the permanent effect of innovation disturbances on economic growth relative to that of innovation disturbance on the innovation level, and $LRD_{y,IP}$ represents the long-run

[10] The model was originally designed to test the long-run relationship between economic growth and money supply.

elasticity of economic growth with respect to innovations.

Following Fisher and Seater (1993), it is assumed that: (1) $Cov(\epsilon_t^1, \epsilon_t^2) = 0$ and (2) IP_t is exogenous, $LRD_{y,IP}$ can be the estimated using $\lim_{k\to\infty} \beta_k$ from an ordinary least square (OLS) regression,

$$y_t - y_{t-k-1} = \alpha_k + \beta_k \left(IP_t - IP_{t-k-1}\right) + e_{kt}.^{11} \tag{2.4}$$

That is, $LRD_{y,IP}$ can be approximated by the estimates of β_k for a large enough value of k. The concern of a reduced role of innovation in driving economic growth and the fluctuation of the patent and trademark series (shown in Section 2.4) both suggest that the long-run relationship between innovations and economic growth may contain structural breaks and are significantly influenced by the two world wars. Taking these effects into account, a war dummy, a structural break dummy $D_t(\tau)$, and interaction terms of these two dummies and the term $(IP_t - IP_{t-k-1})$ are included in Equation (2.4), where τ is the date of the structural break.[12] The unknown break date is determined using the Quandt likelihood ratio (QLR) statistic with 15% trimming (see Stock and Watson (2003), pp 468-471).[13]

The validity of Equation (2.4) in estimating the $LRD_{y,IP}$ is based on two conditions. First, the lag length k should be infinite, which is impractical given the limited number of observations in time-series data. As k increases, the degrees of freedom decrease, such that the maximum k should be as large as is feasible given the data length (Crosby, 2000). Fisher and Seater (1993) chose a maximum k of 30 years as the long-run representation, and this choice was followed by Crosby (2000) and Yang

[11] $\lim_{k\to\infty} \beta_k$ is known as the "Bartlett estimator of the frequency-zero regression coefficient"; see Fisher and Seater (1993) for detail.

[12] $D_t(\tau) = 0$ if $t \le \tau$ and $D_t(\tau) = 1$ if $t > \tau$.

[13] The F-statistic for $D_t(\tau)$ and the interaction term was computed for all break dates in the central 70 per cent of the sample. The τ corresponding to the largest F-statistic was the selected break date. Note that similar break dates are found by the QLR statistic using different lag lengths k. For simplicity, the break date found for the maximum k was applied to all other lag lengths.

(2006). A long-run representation of 30 years is also followed in this study.[14]

Second, variables in Equation (2.4) need to contain stochastic trends or to be characterised as $I(1)$ in order for innovation shocks to have permanent effects on economic growth, and this enables the evaluation of the long-run relationship between innovation and economic growth using the $LRD_{y,IP}$.[15] This property can be tested using the augmented Dickey-Fuller (ADF) test, and results are presented in Section 2.4.2.

Finally, for each of the two innovation measures, Equation (2.4) was regressed (with dummy variables and interaction terms) for each k and for each country. The coefficient estimate $\hat{\beta}_{30}$ represents the long-run relationship between innovations and economic growth, and the plots of the $\hat{\beta}_k$ and the corresponding 95 per cent confidence intervals against k provide information on the pattern of innovation's effects on economic growth as the innovation ages.

2.3.2 Missing data

Another problem associated with IPR series is that they often have missing observations.[16] Possible reasons for this missing data are the effects of wars and the incompatibility of standards between national IP offices and the WIPO. In the case that the missing data-generating process does not share the parameters in Equation (2.4), by using only complete observations and simply excluding missing observations from the estimation (known as listwise deletion [LD]) would not cause biases in coefficient estimates in Equation 2.4.[17] The LD approach usually performs better than many

[14] However, β_k was estimated for a larger lag length of up to 40 years, as it may take an even longer period than the assumed maximum lag length before the innovation's role diminishes.

[15] If both variables in Equation (2.4) are stationary, y_t will eventually return to a deterministic trend after a shock, in which case the shock to IP_t has no effect on y_t in the long run (Crosby, 2000).

[16] In particular, as shown in Section 2.4, the WIPO IPR data have missing observations for both patent and trademark statistics for Germany and Australia and for French trademark statistics.

[17] Greene (2012) lists three missing data scenarios: missing completely at random (MCAR), not missing at random (NMAR) and missing at random (MAR). The third scenario sits in between the first two, in which the information about the missing data is achievable based on the available

alternatives, including the dummy variable adjustment approach and various simple data-imputation strategies that usually induce biases (Allison, 2002). However, it tends to lose some efficiencies due to excluded information. An approach that could improve the efficiency without sacrificing the statistical property of unbiasedness is the use of multiple imputation (MI) (see Rubin (1987) and Allison (2002)).

To obtain stable estimates, MI involves repeating the procedure of imputing missing data and estimating Equation (2.4) using imputed data for the missing observations. Particularly, any IPR series with missing observations was linearly regressed on the GDP of the same country, the IPR series in countries without missing data and having a large share of IPR ownership in other countries (effectively the US and UK), and a time trend to obtain the predicted series, $\tilde{IP}_t$ and the standard deviation of the error term $\tilde{\sigma}$ of the regression. Missing observations were replaced by imputed values computed by assigning a random disturbance to the $\tilde{IP}_t$.[18] The Equation (2.4) was then estimated using complete and imputed data to achieve the coefficient estimate $\hat{\beta}_k$ for each k. Due to the randomisation, a different imputed value for the missing observation and thus the coefficient estimate $\hat{\beta}_k$ was obtained each time these steps were performed. To stabilise the estimation result, the imputation and estimation procedures were repeated and the coefficient estimate produced each time were averaged. Fifty imputations ($M = 50$) were carried out for each IPR-country pair that contained missing observations, which is sufficiently large to minimise the sampling error caused by MI.[19]

observations and can be used to improve the model's statistical inference. Considering the context of IPR data, they could best fit the third scenario.

[18]i.e. $IP_t = \tilde{IP}_t + \tilde{\sigma} r_t$, where r_t is a random number between 0 and 1.

[19]Rubin (1987) and van Buuren et al. (1999) claimed that $M = 5$ was sufficiently large by showing that the corresponding asymptotic relative efficiency of the MI procedure was 95 per cent compared with the infinite M. However, some analyses might require a slightly larger M to obtain stable results, depending on the model and data (Kenward and Carpenter, 2007; Horton and Lipsitz, 2001).

2.4 Data

2.4.1 Data description

This study uses real GDP data as the measure of economic growth and IPR data (the number of patent or trademark applications each year) as the innovation measure for the analysis.[20] The real GDP data shown in Figure 2.1 combines the observations of Organisation for Economic Co-operation and Development (OECD) data and Maddison historical data (see Maddison (2010)). The observations since 1960 (inclusive) are available from the OECD online database and are measured in 2005 US dollars. However, a longer length of GDP data is needed to make use of the whole IPR data series of over 100 years in length. Maddison historical data contains GDP measures dating back to 1820; these earlier observations from Maddison (2010) are spliced together with OECD data using the overlapping observation for 1960.[21]

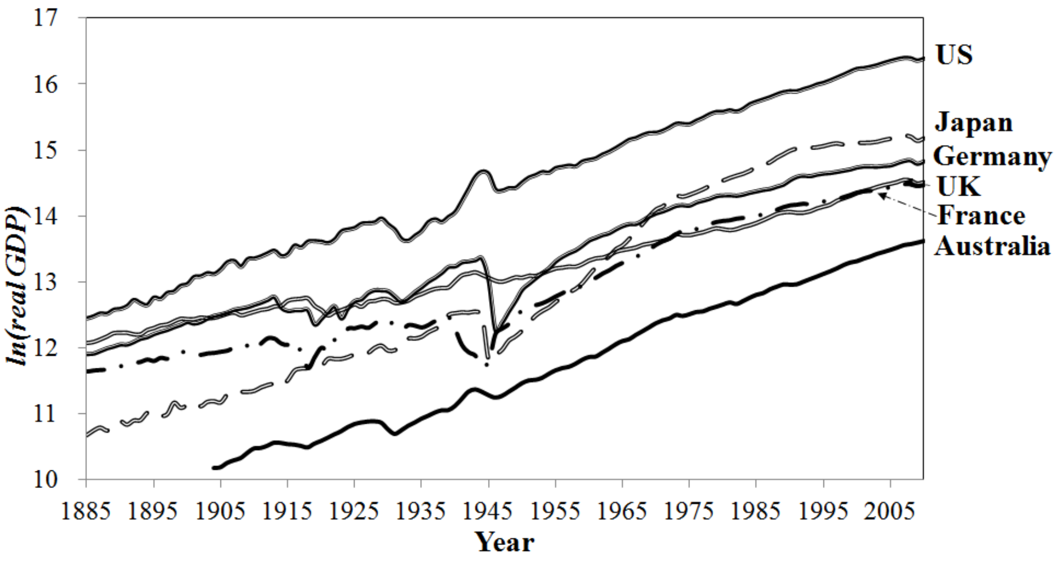


Figure 2.1: GDP (in Logarithms) of Leading Countries using IPR.

GDP series in these countries consistently follow a rather similar and upward linear trend, and growth is relatively more stable as compared with the IPR series shown

[20]IPR applications rather than IPR grants are used because the former reflect the innovative activity in a year, whereas the latter are often restricted by the examination capacity of the IP office that varies over time (Crosby, 2000).

[21]Maddison real GDP data share many similarities with OECD data for the period 1960 to 2008, with a correlation of at least 99 per cent between these two GDP series for each country studied.

below. Unsurprisingly, as can be seen from Figure 2.1, the world wars clearly had a significantly negative effect on economic growth, especially for countries extensively involved in World War II, such as Germany, Japan and France. After experiencing a rapid increase during the post-World War II period, the growth in the real GDP of some of the countries studied slow down over recent decades, slower than the growth of measured innovations during the same period as can be seen from examining figures 2.1, 2.2 and 2.3. This slow down in real GDP growth can be largely attributed to events such as the 'oil shocks' in the 1970's and economic crises.[22]

Figures 2.2 and 2.3 show trends in the number of new patent and trademark applications, respectively, in six major countries of using IPR dating back to the mid 1880s. The missing data are replaced by imputed values produced using the method described in Section 2.3. Imputed data are indicated by plotting using dots. The annual patent and trademark series are available from the World Intellectual Property Organization (WIPO) online database. These statistics are patents or trademarks filed in the national intellectual property (IP) office of each country, except for the patent statistics of France, Germany and the United Kingdom (UK) since 1978, which are combined using the WIPO's patent statistics and the number of patents filed separately in the European Patent Office (EPO).[23] As shown in Figure 2.2, the number of patents in these countries generally increases and fluctuates over time. In particular, the patent statistics in Japan clearly follow a different trend than other countries in this study, being much steeper.

[22]On the other hand, the investment in intangibles (such as economic competencies, computerized information and innovative property) rises dramatically, more than proportionally to the rise of the measured economic growth. Excluding intangible assets can potentially understate economic growth (see Corrado et al. (2009)). That is, the GDP plots in Figure 2.1 will be steeper and probably more comparable to the innovation measures by accounting for intangibles.

[23]Since the EPO was founded in 1978, inventors who used to patent applications only through the regional IP offices, were able to file patents either through regional offices or through the EPO. Some advantages of filing patents in the EPO are avoiding the complications caused by different languages and patent systems across countries, and reducing the effort required to make separate applications to each designated country.

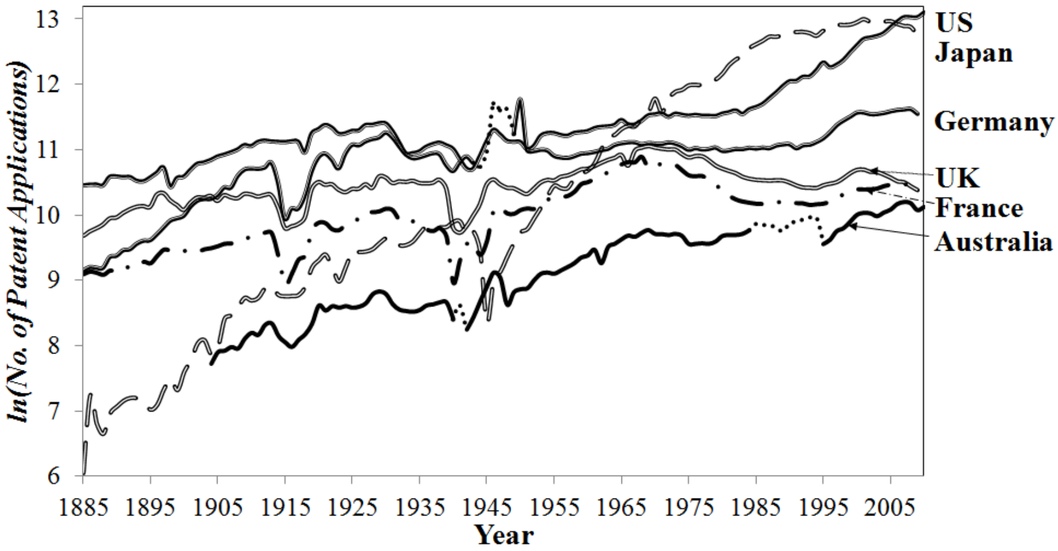


Figure 2.2: Patent Statistics (in Logarithms) of Leading Countries using IPR.

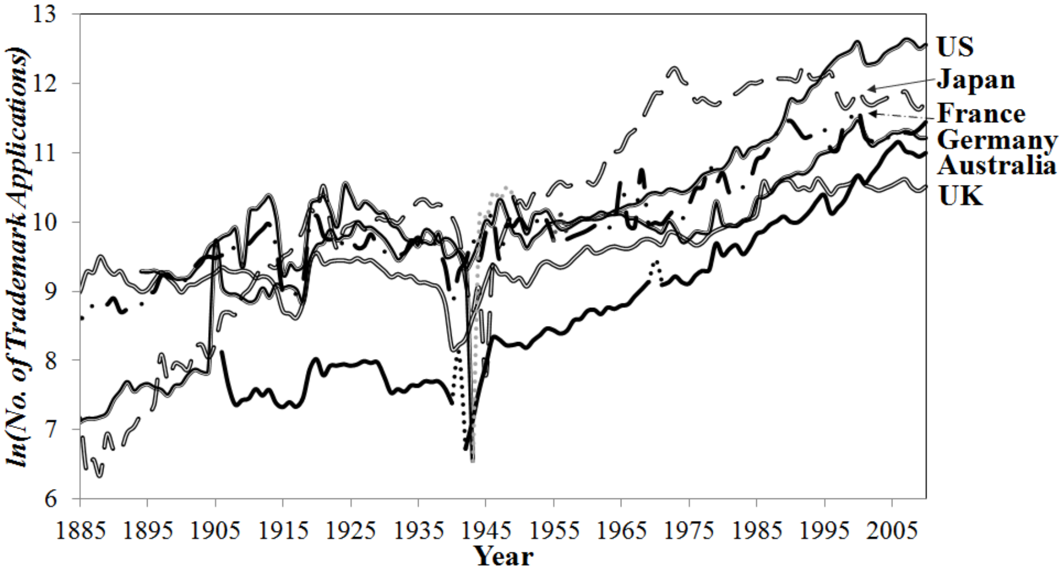


Figure 2.3: Trademark Statistics (in Logarithms) of Leading Countries using IPR.

Both world wars had a significantly negative effect on innovation activities and thus on patent statistics; European countries in particular experienced the most severe declines. By contrast, patent numbers in the US and Australia were less adversely affected by the wars. After experiencing little change during World War I (when Japan was on the side of the Allies), patent numbers in Japan underwent a sharp fall during World War II.

The patenting activity of countries that were seriously affected by World War II instantly recovered and increased rapidly after the war. However, the growth of patent statistics in European countries stagnated from the 1970s. In particular, a decline in patent numbers was observed in the UK and France throughout the 1970s and 1980s, which indicates a possible weakening of innovation activity in these two countries.[24] This view is supported by declining R&D intensities (i.e R&D expenditure as a percentage of GDP) in the UK during this period; and its R&D intensities are low compared with the US (OECD, 2010). On the other hand, this reduction in the patent numbers of European countries could have been caused by institutional change. Since the founding of EPO, an increasing share of new patent applicants was redistributed from national patent offices to the EPO. This tends to reduce the chance of repetitive applications of the same patent and therefore decreases the patent number in many countries, especially European countries.

By contrast, patent numbers in the US rose rapidly in the mid 1980s and have maintained the momentum thereafter. Meanwhile, there are debates about the functionality of the US patent system given this dramatic increase in the patent statistics (Hall, 2005; Jaffe and Lerner, 2004; Boldrin and Levine, 2013). This is supported by the rising R&D intensity figure in the US during recent decades, indicating a large rise in innovation activities (OECD, 2010). Similarly, Germany also saw a significant patent increase in the 1990s, although it slowed down after 2000.

Japan's patenting activities were among the lowest in the late nineteenth century among all countries in this study, at around 5 to 10 per cent of the level of major Western economies. However, patent numbers in Japan experienced a spectacular rise throughout the twentieth century, overtaking that of major European economies after World War II and remaining the largest in the world after outstripping the US in the

[24] These may have put pressure on the patenting activities of small economies closely related to these European countries, such as Australia, which largely rely on the effects of foreign innovations.

1970s. One reason for the high patent numbers in Japan in recent decades is that Japanese patents became less significant than those of other countries after the late 1980s after some changes in the Japanese patent system. There is a view that each US patent is roughly equivalent to three Japanese patents, as the Japanese patent system differs from others by splitting a patent application into multiple stages (Greenhalgh and Rogers, 2010; Sakakibara and Branstetter, 1999).

The trademark series for the six OECD countries studied shown in Figure 2.3 are generally more volatile than those of patents. Trademarks measure innovations differently from patents by representing minor innovations and new varieties of existing products. Therefore, trademark numbers are in a line with the fluctuating level of market activities and respond more instantly and sensitively to economic conditions, rather than the relatively more stable growth of patents.

As shown in Figure 2.3, trends of trademark series differ between the post-World War II period and the prior period, indicating some structural breaks between these two periods. During the period before World War II, trademark series of most countries in this study followed a relatively flat trend, except for that of the US and Japan. Despite these two countries having the largest number of trademarks in the world in recent decades, their trademark numbers in the late 1800s were only a fraction of the major European countries'. After a rapid tenfold rise for a few decades during the early twentieth century, trademark statistics of these two countries reached a similar level to those of major European counterparts between the two world wars.

The number of trademark applications for most countries suffered the sharpest drop during the wars, and the decline was relatively more severe than that of patents. They fell by 50 to 60 per cent for major European economies soon after the outbreak of World War I. However, the effect of World War II seemed to be more catastrophic.

In particular, countries on the losing side of the war saw a dramatic drop of over 90 per cent in the trademarks. The number in Australia was also to some extent affected by wars and dropped slightly, likely because of its significant dependence on European economies. In contrast, the trademark number in the US was less adversely affected by the two wars and maintained steady growth. Trademark statistics of countries experiencing large declines during World War II quickly regained their pre-World War II levels after the war.

The post-World War II growth of trademark numbers in Japan was distinct from the other countries studied. Japanese trademarks grew sharply after World War II and gained the leading position in the early 1950s, whereas only modest growth in trademarks was observed for other countries during the same period. The top position (of Japanese trademark numbers) was retained for over four decades before being surpassed by the US in the mid 1990s. Throughout the 1980s and 1990s, most countries studied showed strong increases in trademark numbers. This was followed by a sudden correction in the year 2000.[25]

2.4.2 Testing for stochastic trends

The ADF test is used to determine the order of integration of the GDP and two IPR variables, and results are reported in Table 2.1.[26] The test-statistic for the first difference of these variables consistently rejects the null hypothesis of unit root at any conventional levels, indicating that they are stationary and are characterised as the integration of order zero (i.e. $I(0)$). As for the levels of these variables, the null hypothesis could not be rejected at even a 10% significant level for almost all cases. The only exception is that of the UK patents, where the null hypothesis was rejected at the 5 per cent level (but not at the 1 per cent level) when the test was performed with more

[25] This was due to a cutback of costs in the 2000s recession after the 'long boom' (Greenhalgh and Rogers, 2010).

[26] They were tested with a constant and no time trend, but including a trend would not change the conclusion.

than one lag. The evidence shows that all variables at their levels contain stochastic trends and are integrations of order one, $I(1)$. As such, the long-run relationship between innovations and economic growth is testable using the LRN test.

Variable	Lags	AUS	DEU	FRA	GBR	JAP	USA
$ln(GDP_t)$	1	0.23	-0.60	-0.09	0.35	-0.15	-0.58
	2	0.21	-0.57	0.04	0.28	-0.30	-0.63
	3	0.14	-0.61	-0.24	0.69	-0.32	-0.58
$\triangle ln(GDP_t)$	1	-5.58***	-9.29***	-7.35***	-7.14***	-7.19***	-8.40***
	2	-4.61***	-7.29***	-4.78***	-6.50***	-5.59***	-6.96***
	3	-5.25***	-5.68***	-4.81***	-6.91***	-4.64***	-6.65***
$ln(Patent_t)$	1	-1.40	-2.67*	-2.17	-2.41	-1.36	0.78
	2	-1.01	-2.44	-1.93	-3.29**	-1.56	0.86
	3	-0.82	-2.49	-1.96	-2.94**	-1.35	1.45
$\triangle ln(Patent_t)$	1	-10.19***	-8.52***	-9.02***	-12.68***	-9.29***	-7.42***
	2	-8.19***	-6.17***	-6.27***	-6.58***	-6.39***	-7.28***
	3	-7.46***	-5.52***	-4.84***	-6.64***	-5.90***	-6.96***
$ln(TM_t)$	1	0.30	0.17	-1.43	-1.36	-1.66	-0.98
	2	0.77	0.29	-1.17	-1.44	-2.19	-0.89
	3	1.43	0.29	-1.16	-0.94	-2.30	-0.86
$\triangle ln(TM_t)$	1	-7.17***	-4.45***	-10.05***	-7.27**	-7.66***	-11.63***
	2	-6.16***	-3.20**	-7.14***	-7.40***	-6.33***	-8.44***
	3	-7.11***	-2.82*	-7.34***	-6.50***	-5.30***	-6.83***

$***$, $**$ and $*$ represent statistically significant at 1%, 5% and 10% levels, respectively.

Table 2.1: ADF Statistics for the GDP and IPR Variables and their First Differences.

2.5 Results

The results using each innovation measure (patents or trademarks) are reported in Tables 2.2 and 2.3, respectively. The plot of coefficient estimates $\hat{\beta}_k$ and the corresponding 95 per cent confidence intervals against k for each IPR-country pair is presented in Figures 2.4 to 2.15.

Shown in column 2 of each table, the break date of structural changes for innovation's long-run role in driving economic growth as determined by QLR statistics varies across countries and innovation measures used. For most IPR-country pairs, this was found to be close to World War II, except for the patents-France and trademarks-Japan

Country	Break date	Before break	After break	Chow test
Australia (LD)	1947	-0.0223	0.2398 ***	30.98
Australia (MI)		-0.0223	0.2077 ***	31.98
France	1972	0.6549 ***	0.6574 ***	89.52
Germany (LD)	1958	-0.0150	-0.5979 ***	44.40
Germany (MI)		-0.1140 *	-0.7399 ***	24.93
Japan	1941	-0.0388	0.8150 ***	340.33
UK	1948	0.1170 **	-0.0825 ***	143.23
USA	1940	0.5870 ***	-0.0456	26.75

$***$, $**$ and $*$ represent statistically significant at 1%, 5% and 10% levels, respectively.

Table 2.2: Long-run Elasticities of Output with respect to Innovations (measured by Patents).

Country	Break date	Before break	After break	Chow test
Australia (LD)	1947	-0.0283	0.1317***	11.03
Australia (MI)		-0.0277	0.1321***	15.19
France (LD)	1947	-0.0631	0.1574*	58.91
France (MI)		-0.0631	0.1686**	59.73
Germany (LD)	1960	-0.0512*	-0.2346***	68.27
Germany (MI)		-0.1642*	-0.2998***	43.21
Japan	1975	0.1483***	0.6991***	86.34
UK	1948	0.0356	0.0921***	118.26
USA	1943	0.2405***	-0.0485**	39.11

$***$, $**$ and $*$ represent statistically significant at 1%, 5% and 10% levels, respectively.

Table 2.3: Long-run Elasticities of Output with respect to Innovations (measured by Trademarks).

cases that occurred during the 1970s, during the period known as the first ‘oil shock’. Given the determined break date, the Chow test-statistic (Chow, 1960), that is simply an F test, for the structural break of the long-run relationship between innovations and economic growth (in column 5) for each IPR-country pair rejects the null hypotheses of no structural changes at the 1% significance level.[27]

Results achieved using both the LD and MI approaches are reported for patent and trademark series with missing data. These two estimation strategies offer similar sign and statistical significance of coefficient estimates, particularly when the number of missing observations is small. However, when the MI was used, the set of coefficient estimates obtained was slightly smaller in absolute value and plots of coefficient estimates $\hat{\beta}_k$ were generally less volatile, as can be seen from Figures 2.4, 2.7, 2.11, 2.13 and 2.14.

The long-run elasticity of output with respect to innovations ranges from 0 to 0.65 in the period before the structural break and -0.74 to 0.82 in the period after when using patents as an innovation measure, and it is in a range of 0 to 0.24 and -0.30 to 0.70 respectively for the two periods when trademarks are used as an innovation measure. These are discussed in sections 2.5.1 and 2.5.2.[28] Each subsection broadly describes the unique features of the results by using the innovation measure before categorising countries studied into two scenarios depending on whether the innovation's role in driving economic growth has decreased. This is followed by providing some explanations for the case of the decreasing and non-positive role of innovation in the post-World War II period in Section 2.5.3, and acknowledging the limitation of the analysis in Section 2.5.4.

[27] Also, the F-statistic testing the joint significance of war dummies and their interactions with $IP_t - IP_{t-k-1}$ is sufficiently large to reject the null hypotheses at the 1% significance level for all cases, which confirms the influential effect of wars on the effects of innovation on economic growth.

[28] These results are obtained using OECD and Maddison data on real GDP in US$ terms to ensure the longest data series possible. It is also interesting to see if the results are robust by using real GDP in constant national currencies. When the same analysis is carried out using Australian data directly from the Australian Bureau of Statistics in real Australian dollar terms from 1960 combined with data from Maddock and McLean (1987) from 1947, the elasticity estimates are generally larger than those reported here and similar to those found by Crosby (2000), but the qualitative conclusions are the same and the estimates are not statistically different at the 5% level.

2.5.1 Innovation measure: patents

More broadly, as shown in Figures 2.4 to 2.9, the plot of $\hat{\beta}_k$ in each country shows a distinct shape for periods before and after the break date. For each country, one of the two periods, the $\hat{\beta}_k$ plot follows either a flat trend or a downward-sloping trajectory, and the $\hat{\beta}_k$ for any k is statistically insignificant at any conventional levels, indicating no evidence of the influence of innovation on economic growth in the short or long-run. By contrast, in the other period when innovations appear to play an effective role in driving economic growth, a trapezoidal or inverted-V shape is observed for the $\hat{\beta}_k$ plot. Specifically, the $\hat{\beta}_k$ is practically and/or statistically insignificant when the k is small. It then rises rapidly as the k increases, and gradually vanishes after reaching a peak or platform stage.

This trapezoidal (inverted-V) shape of the $\hat{\beta}_k$ plot demonstrates the effects of innovations on economic growth as innovations age. Both social benefits and costs are attached to innovations and time lags are often inevitable before the effects of any benefits materialise due to the uncertainties involved. Therefore, costs are likely to dominate benefits in the early stage of innovations (or in the short run), when the innovation's role has not yet been fully revealed. However, the effectiveness of innovations gradually improves over time as market share rises, such that benefits outstrip costs in the long run. The negative effect of monopoly rents on the national economy can be another explanation for the shape. Although it has a tendency to reduce the net social benefit in the short run, this negative effect becomes limited in the long run when the innovation is no longer characterised as new and sophisticated. Restricted by the statutory limit enforced by the patent system, the underlying innovation also has a finite lifespan; the role of innovation thus eventually fades away over an even longer run, which explains the phenomenon that $\hat{\beta}_k$ eventually converges to zero after reaching the maximum.

Decrease in the role of innovation: Germany, the UK and the US

The first scenario includes the US, UK and Germany, some of the world largest economies and major technology exporters. Results show that the role of innovation in these three countries decreased to a large extent during the second period (mainly the post-World War II period), when a non-positive relationship between innovations and economic growth was found. Although, positive and statistically significant coefficient estimates of β_k were obtained in the first period (roughly the pre-World War II period) given a sufficiently large k value, which emphasises the strong role played by innovations during the earlier period.

In particular, innovations made an extraordinary contribution to the US economy during the long period before World War II; in the long run; a 1 per cent increase in innovation measures is associated with a nearly 0.6 per cent increase in real GDP. By comparison, the role of innovation was effective but smaller in the other two countries (i.e. the UK and Germany) in the pre-World War II period, and the lifespan of inventions' effects in these countries seems to be much shorter than that of the US.[29] This explains the negative but statistically insignificant $\hat{\beta}_{30}$ reported for Germany in the pre-World War II period in Table 2.2, where the effect of innovation ceases before k reaches 30 years, the default long-run lag length; a positive $\hat{\beta}_k$ of around 0.3 can be achieved with a slightly smaller k value. Similarly, if a smaller long-run representation of k value was assumed, the output elasticity with respect to innovations $\hat{\beta}_k$ in the UK at its maximum is approximately 0.2 with $k = 24$, twice as large as that reported in Table 2.2, with $k = 30$.

Surprisingly, a similar role of innovation was not found for these three countries in the second (post-World War II) period: the evidence shows a dramatic decrease in

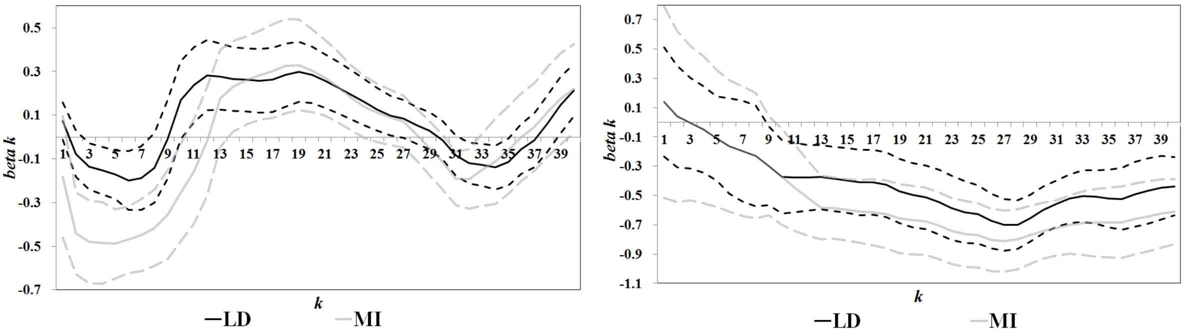
[29] The $\hat{\beta}_k$ peak occurs at a lag length k of around 15-20 and 20-25 for Germany and the UK, respectively.

innovation's role in enhancing economic growth. Specifically, a non-positive coefficient estimate $\hat{\beta}_k$ was consistently found in this period with any k values, and $\hat{\beta}_k$ plots (shown in Figure 2.4b, 2.5b and 2.6b) no longer have a trapezoidal shape as they did for the previous period. Instead, the $\hat{\beta}_k$ remains practically and statistically insignificant, and roughly follows a linear trend as k increases.[30] In the long run, a negative relationship between innovations and economic growth was consistently obtained for the UK and Germany, whereas the $\hat{\beta}_{30}$ of the US shows no evidence of either a positive or a negative effect of innovation in driving output growth.

This result is surprising given that the multifactor productivity (MFP) in the US increases quite rapidly during the late 1990s. There have been different views in existing literature on the role of information technology (IT) on the US productivity surge during this period. Different from the finding above, many earlier studies found a large effect of the use of IT on economic growth and productivity revival (Brynjolfsson and Hitt, 2000); see also Stiroh (2002). The differences are to some extent attributable to different innovation measures. These studies generally used IT investment as the measure of innovation. Despite the many advantages of using patent statistics as discussed in Section 2.2, it is difficult to precisely account for the qualitative changes of innovations, such as the fact that the cost of computers as a major part of input costs dropped dramatically since the mid-1990s.

On the other hand, there is no lack of evidence from a number of studies supporting the findings of this study. For instance, Gordon (2000) argued that the productivity revival occurred mainly in the durable manufacturing sector, the IT sector in particular. At the same time, nondurables did not experience significant MFP growth. In addition, large adjustment costs tend to limit the effect of IT and decrease MFP growth in periods when IT investments are intensive (Kiley, 2000).

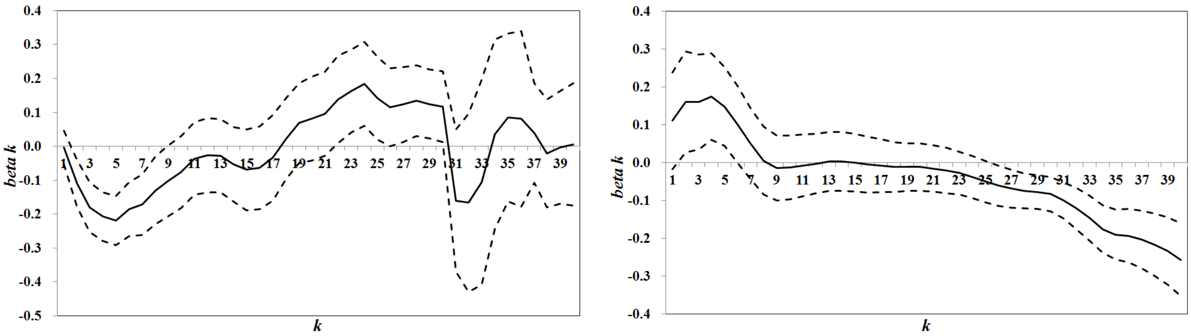
[30] Specifically, a rather flat upward trend was observed for the $\hat{\beta}_k$ plot of the US, and a downward trend for that of the UK and Germany.



(a) Before 1958 (inclusive)

(b) After 1958

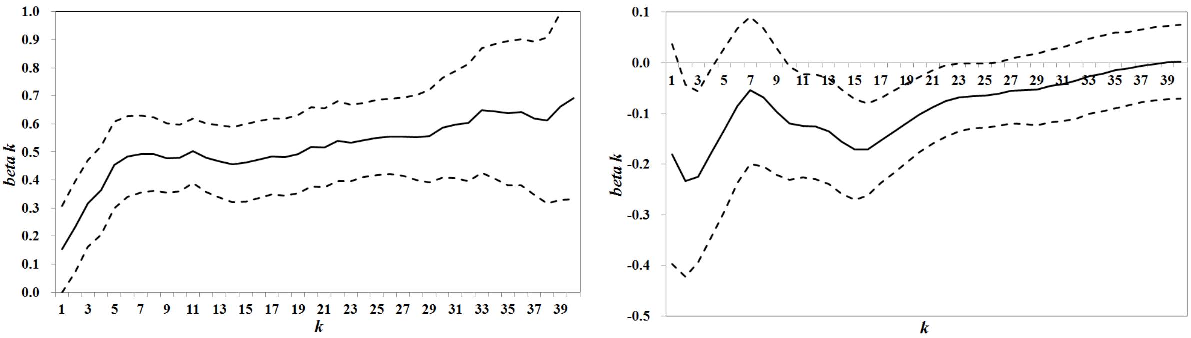
Figure 2.4: The $\hat{\beta}_k$ plot in German when Innovation is measured using Patents.



(a) Before 1948 (inclusive)

(b) After 1948

Figure 2.5: The $\hat{\beta}_k$ plot in the UK when Innovation is measured using Patents.



(a) Before 1940 (inclusive)

(b) After 1940

Figure 2.6: The $\hat{\beta}_k$ plot in the US when Innovation is measured using Patents.

The role of innovation remains: Australia and France, or increases: Japan

For the countries in the second case, including France, Australia and Japan, the role of innovations during the first period remained steady or increased in the second period.[31]

[31] As is shown in column 2 of Table 2.2, the first period is the period before 1947 (inclusive) in the case of Australia or the period before 1972 in the case of France, and the second period is the period after the corresponding break date.

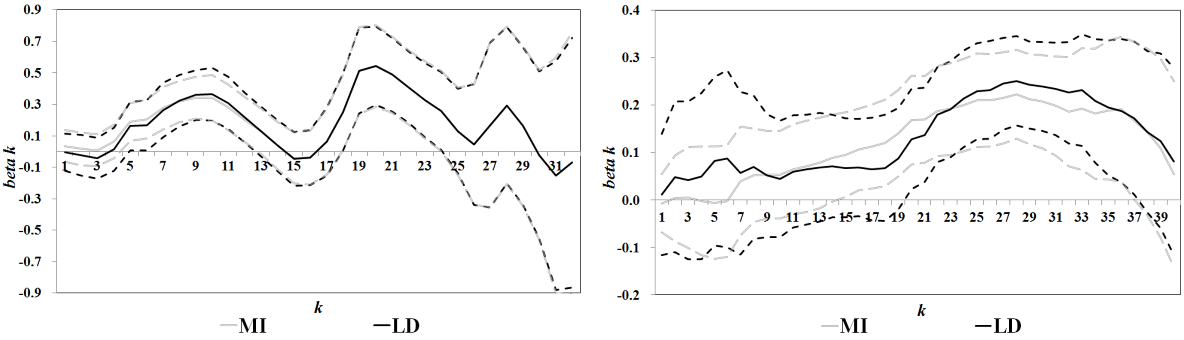
In the case of France, similar trapezoidal-shaped $\hat{\beta}_k$ plots were observed in both periods. However, the $\hat{\beta}_k$ plot in the first period seemed to shift horizontally over time to the right (towards a larger k value). This indicates some potential changes in innovation's role in the second period, although the long-run relationships between innovations and economic growth ($\hat{\beta}_{30}$) in the two periods were reasonably close. Specifically, the $\hat{\beta}_k$ in the first period is positive for some small k values, but it lasts for a relatively short period. A longer lag length is required before the β_k in the second period becomes positive and statistically significant, but it remains so for a much larger k. This shows that it becomes less likely to benefit from innovation in the short run in the recent period than the period before. This is likely to be partly because of the gradually rising monopoly rents and the dramatic increase in innovation costs to accompany the advanced sophistication of new products. On the other hand, this boost in a product's sophistication probably plays a role in enhancing the lifespan of innovations in the second period, which explains the right shift of the $\hat{\beta}_k$ plot.

With regards to the long-run output elasticity with respect to innovations, in France in both periods it was close to two thirds - among the highest across all countries studied. As for Australia, the effect of innovations on economic growth prior to World War II was characterised by a relatively short lifespan; it thus failed to obtain a positive estimate when $\hat{\beta}_{30}$ is assumed to be the long-run effect. In fact, there is strong evidence of positive long-run effects of innovations if a slightly shorter lag length is assumed.[32] The $\hat{\beta}_{30}$ of Australia in the post-World War II period shows that the long-run elasticity of output with respect to innovations is about 0.21.[33]

An extraordinary improvement in the contribution of innovations in the post-World War II period was found for Japan. These results are the reverse of those in the first scenario. The pre-World War II experience of Japan was unlike that of all other coun-

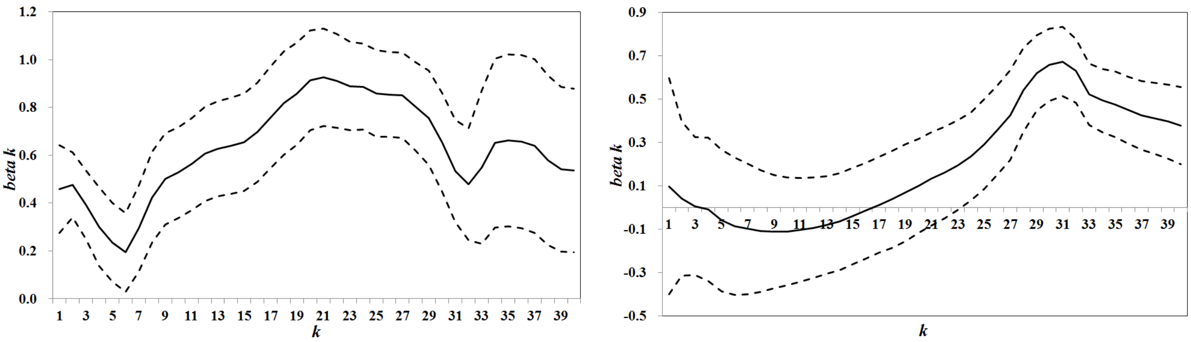
[32] The elasticity of output with respect to innovations is over 0.5 with a k value of 20 years.

[33] A slightly larger estimate of 0.24 was obtained using the alternative LD estimation strategy; see Table 2.2.



(a) Before 1947 (inclusive) (b) After 1947

Figure 2.7: The $\hat{\beta}_k$ plot in Australia when Innovation is measured using Patents.

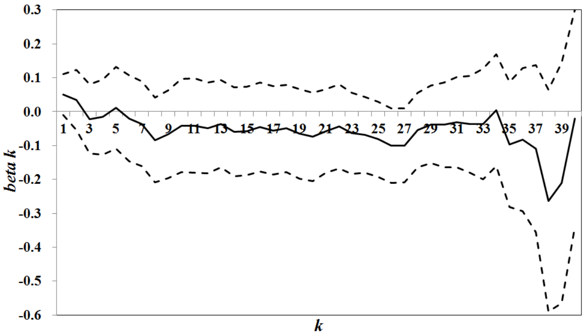


(a) Before 1972 (inclusive) (b) After 1972

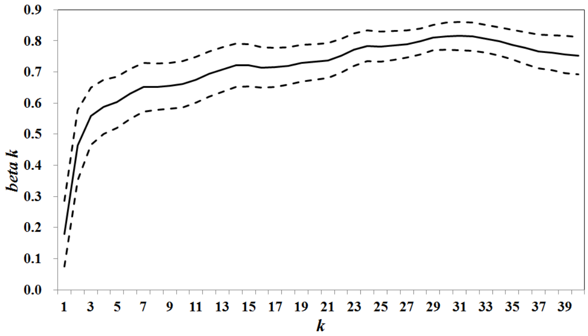
Figure 2.8: The $\hat{\beta}_k$ plot in France when Innovation is measured using Patents.

tries studied; the $\hat{\beta}_k$ remains statistically insignificant for any k values at even the 10% significance level, which shows evidence of the ineffective role of innovation in Japanese economic growth during that period.

Different evidence was found for the post-World War II period compared with those of the earlier period, and it shows some similarities to pre-World War findings of the US. In particular, a positive and statistically significant $\hat{\beta}_k$ was consistently found for any lag length k, indicating innovation's strong effect in driving economic growth in both the short run and long run. For example, a 1 per cent increase in the innovation measure is associated with an approximate 0.82 per cent rise in real GDP in the long run, which is among the highest in the postwar period across all countries studied.



(a) Before 1941 (inclusive)



(b) After 1941

Figure 2.9: The $\hat{\beta}_k$ plot in Japan when Innovation is measured using Patents.

2.5.2 Innovation measure: trademarks

Explained by their rather distinct functions compared with patents, when trademark statistics are used as an innovation measure, the plot of $\hat{\beta}_k$ (shown in Figures 2.10 to 2.15) is characterised by at least two different features. Unlike patents, which are mainly used to protect newly invented ideas, trademarks are used to protect brands and marketing assets and are not attached to any technologies (Sandner and Block, 2011). As a result, a newly registered trademark lacks a consistent history of good quality for sale and contains little economic value. Therefore, a non-positive relationship between trademarks and real GDP is likely to be observed for the relative short run (i.e. when k is small). In addition, trademarks do not have a statutory limit, and their potential economic values increase with age (or in a longer run) as long as trademarks remain active. Thus, as shown in the figures, the $\hat{\beta}_k$ has the tendency to continuously rise as the k value increases.

Decrease in the role of innovation: the US and Germany

Based on the pattern of structural changes for innovation's role, the six countries are grouped into two scenarios, as shown below, in which innovation's role in output growth either decreases or increases during periods after break dates.

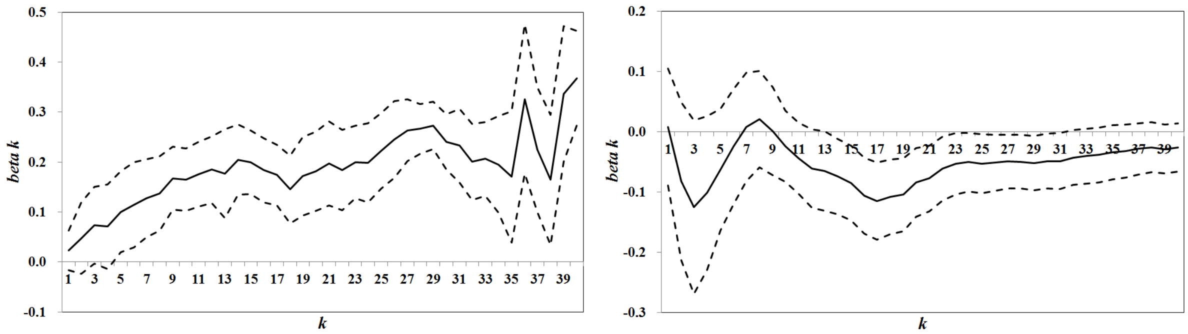
In the first scenario, similar to the first case of patents, two leading economies, the US and Germany, show decreases in the role of innovation in stimulating economic growth in the period after the break date.[34] The results for the US before the break date (shown in Figure 2.10a) shows that innovations (measured by trademarks) played an important role in driving the growth of real GDP. As indicated by $\hat{\beta}_{30}$ (in Table 2.3), a one per cent increase in innovation measures is associated with a 0.24 per cent increase in economic growth in the long-run. After the break, the picture is quite different (Figure 2.10b), with a $\hat{\beta}_{30}$ of -0.05 (Table 2.3). As in most other countries, trademarks in the US show a strong increase in the post-World War II period, particularly during the 'dot-com' boom of the late 1990s. However, economic growth during the same period did not quite align with this measure of innovation, and there was not quite a positive relationship. This indicates a possible decrease in the role of innovations in driving economic growth, consistent with some evidence of overuse of trademarks in the US relative to their use in the pre-World War II period (Greenhalgh and Rogers, 2010).

The findings for Germany also show evidence of decline in the role of innovations in the period after the break date (1960), and there is consistently no evidence of an anticipated positive role of innovations, whether using patents or trademarks as innovation measures; see Figure 2.11. Specifically, the $\hat{\beta}_k$ in the first period is economically and statistically insignificant for any k values, indicating no evidence of any relationships between innovation measures and real GDP in the short or long run. As for the second period, the $\hat{\beta}_k$ remains negative and statistically significant at the 1 per cent level as the k increases, although it has a tendency to move towards zero after k passes 30.

Increase in the role of innovation: Other countries

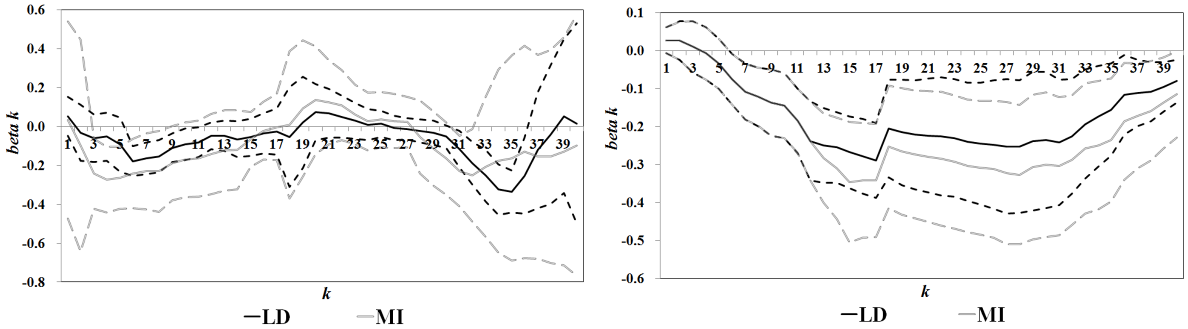
The results for Japan show evidence that the positive role of innovations (measured by trademarks) in boosting the Japanese economy in the period before the break date

[34]The break date is 1943 for the US and 1960 for Germany; see column 2 of Table 2.3.



(a) Before 1943 (inclusive) (b) After 1943

Figure 2.10: The $\hat{\beta}_k$ plot in the US when Innovation is measured using Trademarks.



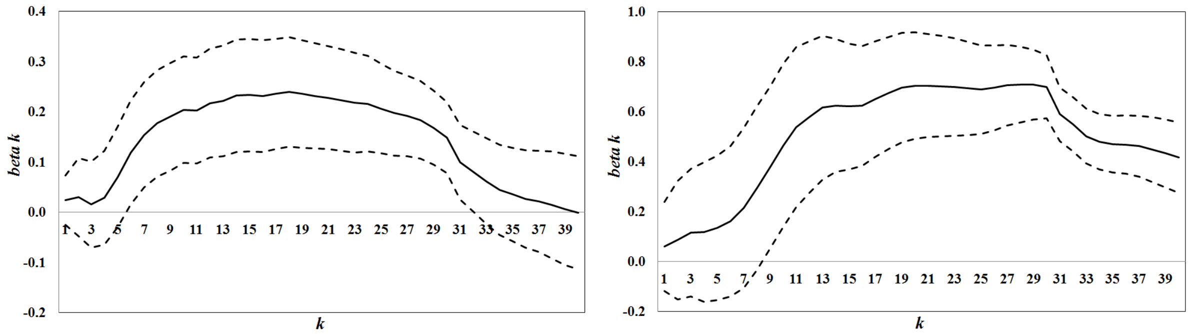
(a) Before 1960 (inclusive) (b) After 1960

Figure 2.11: The $\hat{\beta}_k$ plot in Germany when Innovation is measured using Trademarks.

(1975) becomes even more significant in the period after; see Figure 2.12. In the first period, the long-run elasticity of output with respect to innovations $\hat{\beta}_{30}$ is found to be about 0.15.[35] Unlike the US, there is some evidence of innovation's enhanced role on real GDP growth in the second period, during which a one per cent increase in innovation is associated with an approximately 0.70 per cent real GDP rise in the long run, the highest of all periods or countries studied when the innovation is measured using trademarks. Such a large estimated long-run effect of innovations may seem suspect; however, it is comparable with the results found in Section 2.5.1 using patents as the measure of innovations.

For the remaining three countries (Australia, France and the UK), in the first period the $\hat{\beta}_k$ in these countries remains small (in the absolute value) and statistically

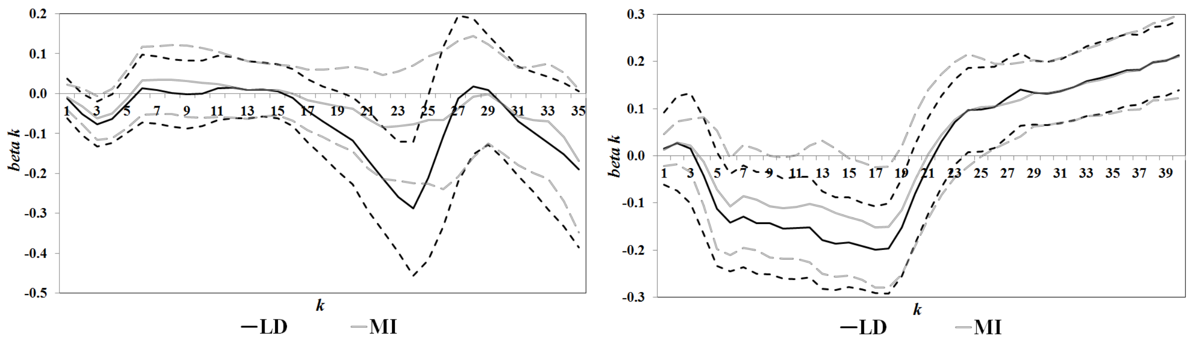
[35] The elasticity is slightly larger if a smaller lag length is used since the peak occurs when $k = 18$.



(a) Before 1975 (inclusive) (b) After 1975

Figure 2.12: The $\hat{\beta}_k$ plot in Japan when Innovation is measured using Trademarks.

insignificant even for large k values, indicating no role has been played by innovations during this period; see figures 2.13, 2.14 and 2.15. In contrast, more promising evidence for the usefulness of innovations was found for the second period: long-run output elasticities with respect to innovations are statistically significant, ranging from 0.09 to 0.17, although there is no evidence of short-run positive effects.

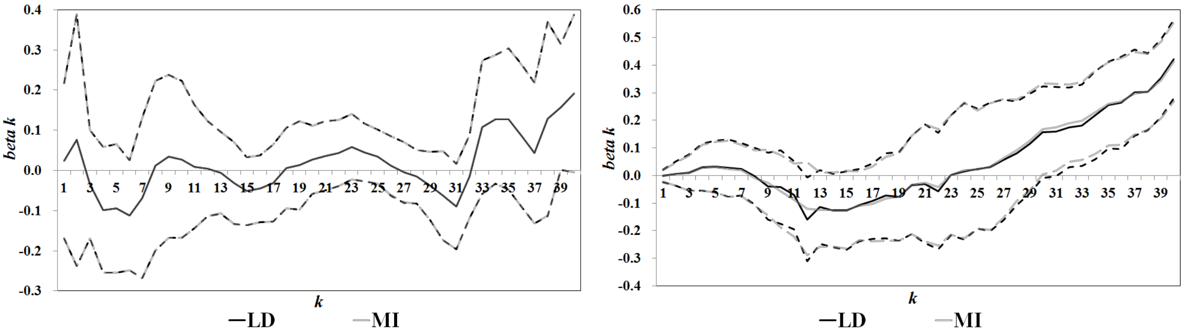


(a) Before 1947 (Inclusive) (b) After 1947

Figure 2.13: The $\hat{\beta}_k$ plot in Australian when Innovation is measured using Trademarks.

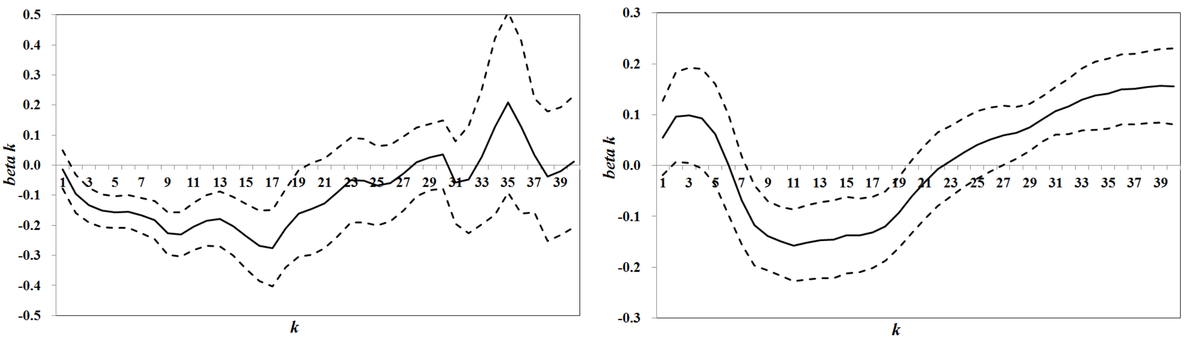
2.5.3 Justifications for the decreased and non-positive innovation's role

Some possible explanations of a reduced and non-positive role of innovation in driving economic growth found for some countries in the more recent period are discussed below. These include but not limited to the following five points. First, a possible explanation is the declining usefulness of inventions in recent decades compared with



(a) Before 1947 (inclusive) (b) After 1947

Figure 2.14: The $\hat{\beta}_k$ plot in France when Innovation is measured using Trademarks.



(a) Before 1948 (inclusive) (b) After 1948

Figure 2.15: The $\hat{\beta}_k$ plot in the UK when Innovation is measured using Trademarks.

those in the past (Gordon, 2012b). Gordon (2012b) argued that most recent inventions are basically diffusions of great inventions of the second industrial revolution occurred in the 2nd half of nineteenth century, and do not fundamentally change our life and improve living standards to the extent that their ancestors did.

Second, the non-positive role of innovation found in the post-WWII period could be due to the timing of the knowledge diffusion of inventions taking place in different industrial revolutions. This is a period when the effect of inventions of the second industrial revolution gradually weakened after being influential for over half a century, while inventions in the third industrial revolution (i.e computers and information technology) starting in the mid 1990s are still quite young. It is likely that their effects on economic growth and living standards have not yet been fully revealed.

Third, the fluctuating macroeconomic condition may be a factor. The oil price shocks in the 1970s, and other economic crisis and their 'macro-consequences' are likely responsible for at least some of the decline of the role of innovation (Griliches, 1988).

Fourth, the combination of globalisation and modern technology could apply downward pressure on the role of innovation in the highest income countries, like the US. Due to globalisation, US labour was forced to compete with foreign inexpensive rivals through both outsourcing and imports (Gordon, 2012a). Developing new technology is expensive and involves inevitable uncertainties. For a technologically advanced country like the US, a large share of innovation activities and expenses occur domestically, while an increasing proportion of their production (and services) have relocated overseas since World War II. As a result of this massive offshoring activity, measured domestic economic growth cannot fully capture the innovation's role.[36]

Finally, innovation is usually associated with both negative monopoly rents and positive social returns. There may be considerably more monopoly rents for countries with larger market sizes and more advanced technology, for example, the US and Germany. For a small economy such as Australia, negative monopoly rents tend to be relatively small. Because of the increased sophistication of new products, these rents are likely to be enhanced and remain influential for a longer duration in the postwar period. The stronger and longer lasting monopoly rents over time could potentially impose downward pressure on the net social benefits of innovation, which could to some extent explain the reduced role of innovation over time obtained for the US and Germany.

[36] In recent years, many multinational firms in these developed economies have sought innovation opportunities offshore in emerging economies to make innovation more cost effective (Manning, Sydow and Windeler, 2012).

2.5.4 Limitation of the analysis

Apart from these explanations above, caution should be taken when comparing long-run elasticities across periods or countries, as evidence of innovation's changing role may be partly influenced by time inconsistencies and international differences in using IPR statistics as innovation measures, which is mainly due to time and country variations in the strictness of IPR systems. The same IPR unit could represent different levels of innovation, which could be associated with different economic values.[37] In the case of patents, there have been debates regarding whether there has been a reduction in patent systems' efficiency in recent decades, given there was a significant rise in the number of patents during the 1990s without a comparable rise in economic growth (see Jaffe and Lerner (2004); Hall (2005)). In addition, this rise reflects the increased quantities of IPR for intermediate products due to the enhanced sophistication of final production and rising demand for different varieties of similar products today; the same number of IPR may represent different innovation levels over time, and therefore their effects on economic growth may have changed. Similarly, distinct patent systems across different countries make innovation levels, and therefore the estimated long-run role of innovation, less comparable.[38]

2.6 Conclusion

This study extends a study by Crosby (2000), that measured innovation using patent statistics and examined the long-run role of innovation in driving economic growth in

[37]Various options were considered for weighting the IPR series to improve cross-country and intertemporal comparability. Unfortunately, the weights typically used in the literature start from the 1960s or later, which is too short a timeframe for this study. For example, the value of patent rights estimated by many studies (see for example Schankerman (1998) for France and Chapter 4 of this thesis for Australia), or the 'index of patent rights' constructed by Park (2002) are only available for period since 1990.

[38]The innovation's outstanding performance in France and Japan probably reflects these countries' more efficient patent systems. Although there has been no evidence directly support this view, Japanese and French patents consistently rank as the most valuable in various studies estimating the values of patent rights, which implicitly provides indications of the higher efficiency or better supportive role of their patent systems (see Schankerman (1998)).

an Australian context, to a wider range of developed countries. In addition to patents, as used by Crosby, it also uses trademarks as an alternative measure of innovation, which is motivated by trademarks' broader coverage in various sectors, across different firm sizes and capturing innovations those are considered to be less significant. Moreover, the potential structural breaks of innovation's long-run role in driving economic growth are rigourously tested. Furthermore, as an improvement to the conventional treatment, the missing data of IPR statistics were resolved using multiple imputation.

The results vary across countries and generally differ between two time periods divided by their country-specific break dates. In line with the concern of a small but increasing number of pessimists, the evidence does not always support a positive role of innovation in stimulating economic growth. When patent statistics are used as innovation measures, for some major developed economies where the majority of the world's innovation activities originate (the US, UK and Germany), the findings indicate that innovation no longer plays a positive role in driving economic growth in the Post-World War II period, as it did in the previous period. In contrast, innovation's role in stimulating economic growth was found to be strong and positive in Japan and Australia in the more recent period, unlike the findings for the earlier period. Further, the results for France show a consistently strong positive long-run relationship between innovation and economic growth in both periods. The long-run elasticity of output with respect to innovation (measured by patents) among these countries ranges between 0 and 0.65 in the period before World War II, and has a wider range between -0.74 and 0.82 in the period after.

When trademark statistics were used as innovation measures, the conclusions remained mostly the same, except for the UK. Similar to the patent case, two of the top economies, the US and Germany, show evidence of innovation's less prominent role, and non-positive associations between innovation and long-run output were found in the post-World War II period. In addition, innovation in Japan shows a long history of having a major role in stimulating economic growth and this remained the case in the second period after the mid 1970s. Finally, for France, Australia and the UK, there is evidence of an improved role for innovation; strong positive long-run elasticities were obtained for the second period after their break dates, although similar positive long-run roles were not found in the earlier periods. The long-run elasticity of output with respect to innovation (measured by trademarks) was found to be between 0 and 0.24, and -0.30 and 0.70 respectively for the two periods, smaller ranges than those obtained in the case of patents.

Some possible explanations for the reduced and non-positive role of innovation for some of the highest income countries in the post-World War II period include declines in the usefulness of modern expensive inventions, insufficient time for the full materialisation of knowledge diffusions by inventions of the third industrial revolution, unstable macroeconomic conditions, hold-up caused by the interaction of globalisation and model technologies, and more extensive negative monopoly rents.

Caution should be used when comparing results across different periods or countries. Since the strictness of each IPR system varies, the same unit of IPR is unlikely to provide a consistent measure of innovation internationally or across time, which makes these results less comparable. To solve this problem, some weighting indices with long series that provide qualitative measures of IPR are needed. However, as such data lack sufficient lengths or are not available at all, this aspects requires further research.

Using a similar approach to that used by Crosby (2000) for Australia and Yang (2006) for Taiwan, but with an additional measure of innovation, this study has found the same conclusions regarding the relationship between innovation and economic growth for Australia, France and Japan. However, differing results are found for the US, UK and Germany. While caveats will necessarily remain for this kind of complex long-run analysis involving multiple countries, through considering a range of countries over a long time period, and with alternative measures of innovation, the results significantly expand the existing sparse empirical literature on the role of innovation in driving growth, an issue of great policy interest and topical relevance.

Chapter 3

Estimating the Value of Patent Rights in Australia

3.1 Introduction

Patenting activity is one of the most commonly used intellectual property (IP) protection strategies by firms to protect their IP rights. Successful applications are granted with exclusive powers over the use of the underlying inventions augmented with additional patent rents, also known as the value of patent rights. The patent system was thus praised as adding "the fuel of interest to the fire of genius, in the discovery and production of new and useful things" by the former US president Abraham Lincoln.

A number of prior studies have attempted to estimate patent values. However, as a result of the different approaches adopted, the definition of patent values among these studies varies, and therefore, clarification of the distinct meaning of the term patent value is necessary. Broadly speaking, the value of a patent mainly consists of two components defined in different perspectives (Hall, 2009). In the welfare perspective, it is the value of the underlying invention that is protected by the patent; and in the incentive perspective, it is defined as the value of patent rights, which is the additional private value added by the patenting activity compared with any profits earned without patent protection.

Among existing empirical studies measuring the patent values, the concept of patent value can be categorised into three main categories according to estimation strategy, which estimates the different types of patent values as stated above. The first is the market value approach, which is based on Tobin's q equation and measures the patent "portfolio" value held by a firm. It applies a regression of the firm market value on the firm's tangible and intangible assets, and including a measure of the patents owned by a firm. It is followed by the patentee survey approach, which obtains the value of a single patent through surveying the information of the estimated patent value from the patent owner or inventor. The common feature of these two approaches is that they both measure the combined value of the underlying invention and the patent rights of that invention. The third approach, which will be employed in this study, is the patent renewal approach. This approach draws on information about the owner's willingness to pay renewal fees for the patent, and estimates only the value of patent rights (as opposed to the value of the underlying invention).

Determining the value of patent rights is a useful economic and policy indicator for many reasons. It captures the value of intangibles that is often difficult to measure and offers indications of the significance of successful inventions. Such that, it is useful to measure the productivity and efficiency of R&D investment. Also, it provides a measure of the additional reward to inventors arising from the patent system and contains important information about the strictness and performance of the current policy. In particular, there have been concerns by governments that the R&D has been under-invested compared to the social optimum. One of the most important policy roles for the patent system is that it provides a means by which the government can address R&D under-investment problems.[1] Thus, an important political implication of determining the value of patent rights in the Australia context is that it allows for the evaluation of the role played by the Australian patent system.

Motivated by these factors, ever since its creation by Pakes and Schankerman (1984), the patent renewal framework has been employed frequently in prior studies to estimate the value of patent rights for many different countries. So far, the value of patent rights for many countries were estimated either at an aggregate level (see Schankerman and Pakes (1986); Bessen (2008); Fikkert and Luthria (1996)) or at disaggregate levels by the patentee's nationality or the technology sector (see Schankerman (1991, 1998); Deng (2007)). In addition, Schankerman (1998) considered the value of patent rights as constituting the reward flowing from patents, and this reward is equivalent to an R&D subsidy. He went on to compute the ratio of aggregate value of patent rights to R&D investment, known as the equivalent subsidy rate (ESR). Most recent studies followed his procedures in evaluating the quality of patent protections for various countries.

Despite the importance of and scholarly focus from other countries on the value of patent rights and its implications, this topic has been under-investigated in Australia.[2] This study attempts to fill this gap by offering some evidences from Australia. In particular, this study aims to investigate the role of the Australian patent system in providing incentives to innovate and in assisting the government to mitigate the R&D under-investment problem.

The contribution of this study can be summarised as follows. First, this study consolidates the original patent renewal data in Australia and the estimated the value

[1] The alternative way the government use to solve this problem is through R&D subsidy (Greenhalgh and Rogers, 2010).

[2] The only other study estimating the patent premium for Australian innovative firms in an innovator survey was that conducted by Jensen et al. (2011). However, they used a different approach.

of patent rights using the patent renewal framework. The result shows evidence of international and inter-industry differences in the value of patent rights. In addition, the approach found evidence of structural changes in patent values across different industries over time, which provides a useful explanation for disagreement raised by Schankerman (1998) and Bessen (2008), whose studies were based on different patent cohorts two decades apart. Moreover, the average value of patent rights at the aggregate level in Australia ranges AU$9,000 to AU$17,000 in cohorts between 1980 and 1992, which is much lower than results in the European and US studies. Furthermore, the aggregate-level equivalent subsidy rate (that is defined as the ratio of aggregate value of patent rights to the corresponding R&D investment) of patent rights, ranges between 3.2 and 8.4 per cent, and it outperforms the European and US counterparts. The Australian patent system actually played a relatively larger role in providing innovation incentives and assisting the government in addressing the R&D under-investment problem. Finally, the industry-level (adjusted) ESR is much higher for pharmaceutical and chemical patents, which shows that these two industries have received more subsidies from the Australian patent system.

This study is structured as follows. The different methods of obtaining patent values used in the existing literature are reviewed in Section 3.2 with a focus on the patent renewal approach, followed by a description of the Australian patent renewal data collected for this study in Section 3.3. Section 3.4 presents the specifications of the empirical models. The results are reported in Section 3.5, along with discussion on the implications, and Section 3.6 provides a conclusion.

3.2 Background

This section reviews the three main approaches commonly used in the literature to estimate the patent value. It briefly explains the market value and patentee survey approach, and then referring to the literature applies the patent renewal framework in more detail. The market value approach is based on a regression of firm market value on tangible assets (such as plant, equipment and inventories) and intangible assets (including patent stocks). The coefficient estimates represent the estimated shadow value of each type of asset in the market. There are large amounts of literature studying the impact of the firm's patent stocks on its market valuation, which are concentrated on developed economies, with most firms using R&D and patents intensively being traded in the financial market. These studies consistently show that the patent value (the value of patent rights and of the underlying invention) is highest in the pharmaceutical, chemical, computer and machinery sectors (Bessen, 2006a). In addition, there are a number of studies incorporating patent citations to take control of the quality of patent portfolios (Hall et al., 2005; Czarnitzki et al., 2006; Hall et al., 2007). The findings commonly show that the distribution of patent values is highly skewed towards to more valuable patents, which means most patents are worth little, whereas a minority of them are extremely valuable. Specifically, the patent plays no role in stimulating a firm's market value if the firm's patents receive less than the median number of citations per patent, and for firms in the top five percent of cites per patent distribution, the market value appears to be 1.5 times as high as the rest, ceteris paribus.

The second approach relates to surveys of firms and inventors in valuing a single patent. Examples of inventor surveys include PATVAL surveys for European countries carried out by Harhoff, Scherer and co-authors, and the Australian Inventor Survey 2007 (AIS-07) by Jensen and co-authors. The findings of inventor surveys indicate that the distribution of the patent value is extremely skewed. In particular, the average reported patent value in Europe is around 3 million euros, about ten times higher than the median (Gambardella et al., 2008). (n.d.) developed a framework of innovation and patenting, and incorporated survey data to estimate the patent premium. The results show that the patent premium on average is as high as 50%, although only a limited number of sectors can benefit from it. The recent study by Jensen et al. (2011) drew data from the Australian Inventor Survey and estimated the patent premium was approximately 37%. Despite the usefulness of this information, there are some potential concerns with obtaining patent value using survey data. First, for all survey data, inventors are likely to systematically overvalue their inventions in the self-reported process. Also, it is possible that some surveys suffer from the problem of sample selection, since relatively more successful inventors have higher incentive to respond to the survey. Finally, as an important factor of determining the value of patent values, firms' willingness to enforce their patents are not captured by the surveys (Lanjouw, 1998).

The third and last approach is the patent renewal approach focusing on the value of patent rights (rather than the underlying invention). The earliest interest in patent renewal data by economists can be traced back to Nordhaus (1969) (Lanjouw et al., 1996). The data has become more attractive since Pakes and Schankerman (1984) initiated the patent renewal model, which allows using the renewal data to obtain the value of patent rights. With some constructive improvements, the updated version, Schankerman and Pakes (1986), formed the basis of this area of enquiry. The patent renewal framework assumes that patents in every cohort (defined by the year the application was filed) are endowed with a distribution of initial returns, which are assumed to decay deterministically at an annual rate δ. To keep patents active, the patentees must pay an annual renewal fee that usually increases with the age of the patent, and the renewal fee schedule also undergoes frequent adjustments over time. A patentee maximises the (discounted) net returns to patent protection and pays the renewal fee at age t only if the current return is in excess of the cost. By specifying a functional form for the distribution for the initial returns, Pakes and Schankerman (1984) demonstrates that the parameters of the assumed distribution function and the decay rate can be estimated. These estimates provide sufficient information to characterise the distribution of the value of patent rights and their behaviour over time. Limited by the data, earlier work, including studies by other authors, is restricted to the three major European countries and at aggregate levels.

The early studies in particular highlight the usefulness of conducting similar studies at disaggregate levels. This was not carried out until Schankerman (1991), with the published version being Schankerman (1998). His research applied French disaggregate data by the patentee's nationality and technology sector to the patent renewal framework, and showed evidence of inter-sector and international differences in the value of patent rights. Specifically, he showed patents with Japanese and French ownership are relatively more valuable (in patent rights) than their counterparts. In addition, the results by industry indicate that the value of patent rights for electronic and mechanical patents is higher than that for the other industries. Moreover, Schankerman (1998) argued that the value of patent rights could be considered as the reward inventors receive from patents, which is equivalent to an R&D subsidy - the subsidy required to induce innovators to implement the same R&D investment as that induced by patents. He then calculated the equivalent subsidy rate (ESR), which provides a more meaningful interpretation for the value of patent rights and allows evaluation of the role played by the patent system. Fascinated by the rich implications obtained by Schankerman, researchers showed considerable interest in the similar studies.

More recent evidence for the United States (US) arising from a study conducted by Bessen (2008) reveals that chemical and pharmaceutical patents filed in 1991 are substantially more valuable than their electrical and electronic counterparts, which contradicts the results of Schankerman (1998). In addition, he found that the ESR in the US was around 2.9% and argued that results for earlier studies for European countries should not be higher than 2.6%. The evidence shows the limited role of the patent system in these major economies in subsidising patentees and solving the R&D

under-investment problem. This study attempts to estimate the value of patent rights in Australia following similar procedures as Schankerman (1998), and investigates how the role has been played by the Australian patent system, which is particularly noteworthy because Australia has relatively low R&D investment and high dependence on foreign knowledge inflow (i.e. a large share of foreign ownership for patents).[3]

3.3 Data

3.3.1 Patent renewal rates

Descriptions of patent renewal data are shown in Table 3.1. Patent renewal data are essential for estimating the value of patent rights using the patent renewal framework, and consist of two components: patent renewal rates P_{jt} and patent renewal costs C_jt.[4] The first part is constructed based on the patent count data generated by AusPat from the Australian Patent Office's (APO) official web site.[5] The data cover most of the patents granted in APO filed between 1980 and 1994 and renewed between 1982 and 2011. Patents are categorised according to the filing year (cohort), the patentee's nationality and industry.

The data contain the number of patents granted (by patentees' nationalities or industries) during each of the years subsequent to the cohort date, and the number of patents expired at each age up to the statutory limit for each cohort-age-nationality and cohort-age-industry cell. By dividing the second number by the first one, this gives

[3] As indicated by OECD (2012), the average R&D expenditure as a percentage of gross domestic product(GDP) in Australia is around 1.2% in 1981-1992, significantly lower than those for the UK (2.1%), France(2.2%), Germany(2.5%) and the US(2.6%) during the same period.

[4] A patent can be granted only if it meets all conditions examined by a patent examiner in the patent office. The conditions include novelty, non-obviousness, and suitability for industrial application. After the patent has been granted, the patentee has to pay renewal fees annually to keep the patent alive to its full term.

[5] AusPat is an online patent searching program for all patents filed in APO since 1979.

the proportion of dropouts for cohort j patents aged t. For the same cohort-nationality (cohort-industry) pair, this patent dropout rate at age t is exactly the decrement of the patent renewal rate from the previous age (i.e. $1-P_{jt}$), and the patent renewal rate P_{jt} for each three-dimension cell can be calculated accordingly. The patent renewal rate by patentee nationality or industry is described below, followed by the renewal cost.

Data Characteristic	
Range of cohorts (patent filing year)	1980-1994
Maximum patent age	$20^{\dagger}$
Minimum patent age 1980-1989/1990-1994	3/4
Average No. of patent grants/cohorts	13,594
Number of cohorts	15
Sample size each nation/sector	259
Number of ownership nationalities	6
Coverage over total grants (15 years average)	81%
Number of technology sectors	4
Coverage over total grants	70%
Domestic share patent grants (15 years average)	0.135

†: 25 years for the pharmaceutical substance.

Table 3.1: The Characteristics of the Patent Renewal Data for Australia, 1980-94.

This study focuses on the top six patentees' nationalities in the number of patent grants in APO: the United States (US), Australia, the United Kingdom (UK), Japan, Germany and France, which comprise approximately 81 percent of all patent grants in APO on average over the period 1980-1994. In fact, only a small share (13.5%) of these patents belongs to Australian residents, whereas the majority of them are owned by foreigners. US residents in particular represent over one-third of the share during this period. Figure 3.1 plots the average renewal rate against the patent age, by patentee nationality and over cohorts 1980-1994 . The renewal rate varies across nationalities. In particular, Japanese-owned patents have significantly higher renewal rates at all ages compared with those of other nationalities, followed by the US and European counterparts, with relatively smaller disparities between them. Also, there is a tendency for the convergence of renewal rates across patentees' nationalities, as patents' ages approached the statutory limit. In addition, the lowest renewal rate has been observed for domestically owned patents, especially for early ages.

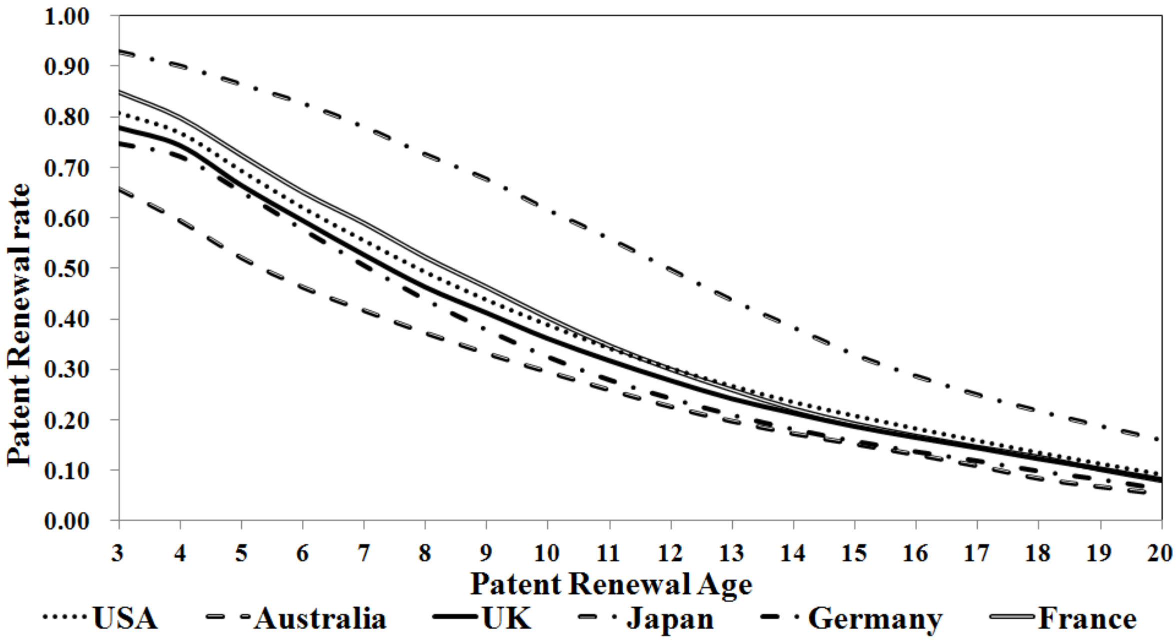


Figure 3.1: Average Patent Renewal Rates by Patentees' Nationalities, 1980-1994.

The main difficulty of collecting industry-level data is the incompatibility of different standards used between the patent and industrial classifications. The patent is assigned by patent examiners of the APO to one of the categories defined by the International Patent Classification (IPC), which classifies patents based on the function of the invention, rather than industrial criteria. To solve this problem, industry-level data were consolidated using the Maastricht Economic Research Institute on Innovation and Technology (MERIT) concordance table between IPC and the International Standard Industrial Classification (ISIC) constructed by Verspagen et al. (1994).[6]

Four of the most heavily patented technology sectors are chemical, pharmaceutical, electronics (excluding computer hardware and software) and electrical machinery.

[6]Verspagen et al. (1994) contains the concordance table between the IPC used by most patent offices including the APO and the ISIC of all economic activities (ISIC-revision 2) of the United Nations. Only the manufacturing sectors of 22 aggregate ISIC sectors are included. This table allows assigning the patent data by APO to a classification by economic sector; See Table A.1 in Appendix A for more details.

Plots of average patent renewal rates against the age in these four industries, over cohorts 1980-1994, are shown in Figure 3.2. As shown in the figure, the average patent renewal rate for electronics patents is among the highest across four industries except for older aged patents. This is followed closely by that of chemical and pharmaceutical patents, and patterns of renewal rates between these two industries are quite similar. In addition, a rather interesting observation is that the renewal rate for pharmaceutical patents aged over sixteen years surpasses that of the other industries. Moreover, there are quite large gaps for average patent renewal rates between electrical machinery patents and those of their counterparts. In general, the inter-industry difference in the pattern of renewal rates is much smaller, compared with the nationality case above, and sometimes the lines in Figure 3.2 cross.

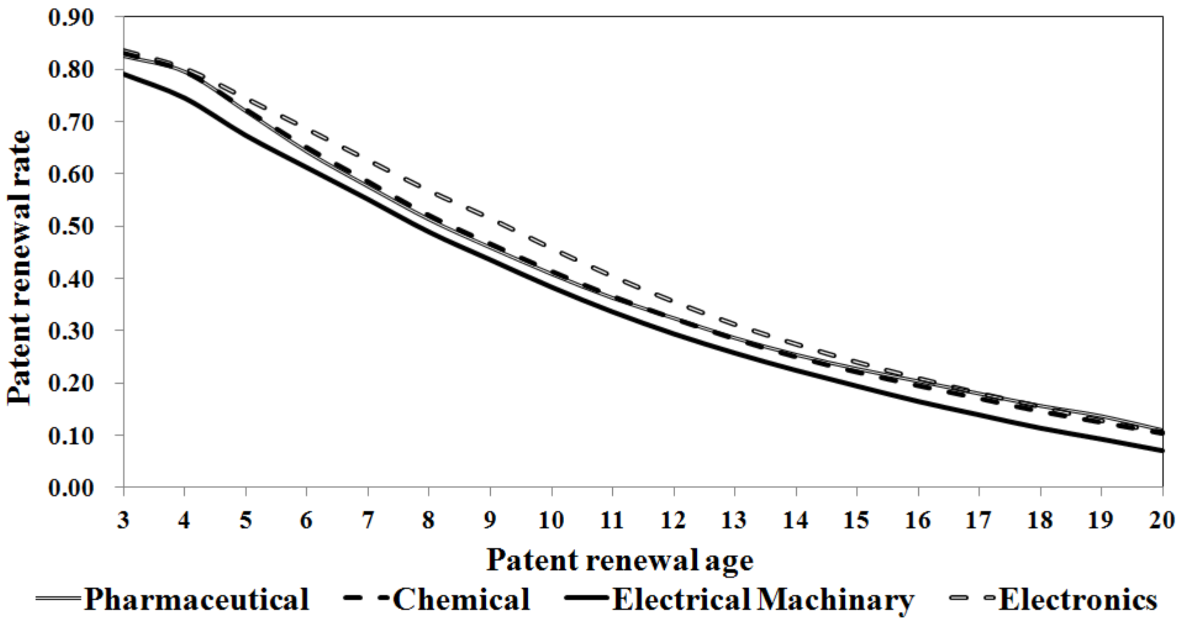


Figure 3.2: Average Patent Renewal Rates by Four Industries, 1980-1994.

3.3.2 Patent renewal costs

The patent renewal fees under different fee schedules are collected from the various versions of the Patent Regulations Amendments under the Patents Acts (1952 and 1990) and IP Legislation (fees) Amendment Regulation under Patent Regulation 1991, which were published in a series of annual Statutory Rules dating back to 1979. The (nominal) renewal fees within the same fee schedule rise monotonically with age, and the schedule has been adjusted sixteen times between 1979 and 2010.[7] However, only the latest schedule is applied to all patents regardless of cohort, nationality or sector. This means that the renewal cost depends both on the age and the year the patent reaches that age (cohort plus age). In terms of dimensionality, the renewal costs C_{jt} are featured with 2 dimensions, and are unique in each cohort-age pair.

To deflate the nominal renewal cost, many existing studies follow the initial work by Schankerman and Pakes (1986) using the gross domestic product (GDP) deflator. However, as argued by Diewert (2002), the GDP deflator is unsuitable as a general index of inflation because the trade components (both imports and exports) in the formation of the GDP deflator are likely to cause fluctuations and inconsistencies, and the Consumer Price Index (CPI) is probably more suitable in this situation. Therefore, the costs are deflated using the CPI and the prices are measured in constant 2009 Australian dollars.

For each cohort, there is a unique set of costs depending on patent age. To present the costs over fifteen cohorts effectively, they are broken down into three consecutive five-year segments, and the graphs of the average of each five-year period are shown in Figure 3.3. The average real patent renewal costs are quite similar among the three periods, but some disparities are observed when the age is large. Further, the average real costs increase over ages ranging approximately between \$80 and \$600. Also, there is roughly a quadratic relationship between the average real renewal costs and the patent renewal age.

[7]Refer to Table A.2 in Appendix A for the detailed information of nominal patent renewal fees for patents filed in APO since 1979.

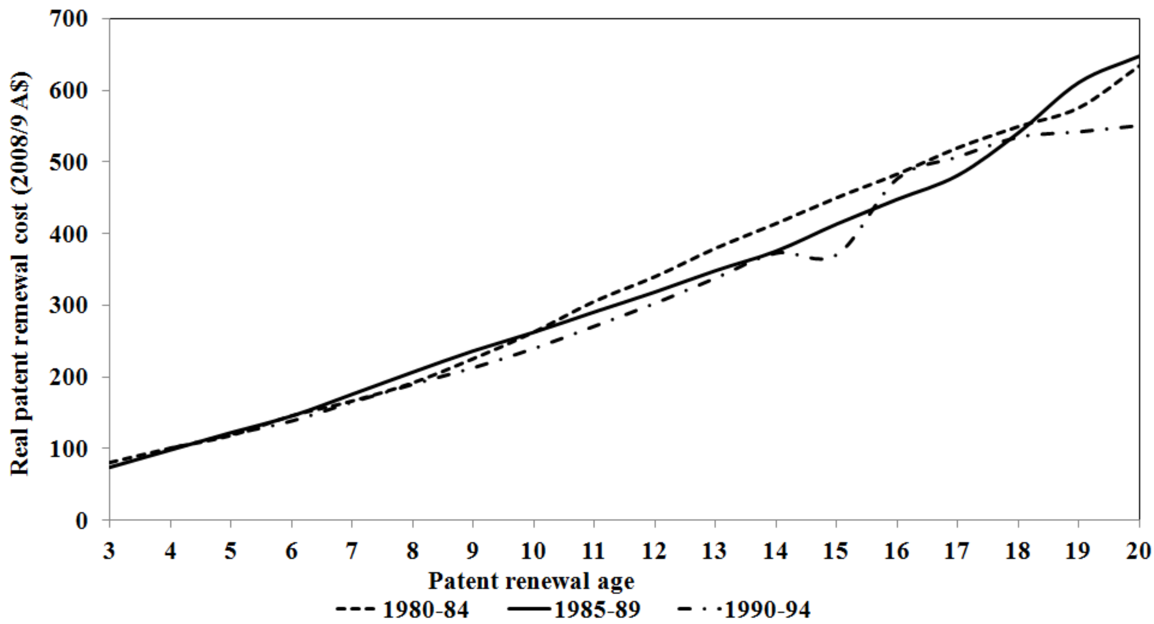


Figure 3.3: Average Patent Renewal Costs in 1980-84, 1985-89 and 1990-94 (2009 AU$).

3.4 Methodology

Two steps are followed to obtain the value of patent rights, including the parameter estimation of the patent renewal model and value simulation based on parameter estimates. The first step involves building up the econometric model, which can incorporate patent renewal data and is able to distinguish the uniqueness of the value of patent rights for patents across different cohorts, patentee nationality or industry. By specifying a distribution function parameterised by θ for the initial return and a decay rule with a decay rate δ, it allows the estimation of the parameter (of the distribution function) along with the decay rate in the patent renewal model. These estimates of the parameter θ and decay rate δ can be employed to simulate the distribution of initial returns of patent rights and the associated value of patent rights. The distinction in the value of patent rights among different cohort-nationality or cohort-industry pairs is then clearly observed. Technical details of the model specifications and limitations of achieving the value of patent rights using this approach are discussed below.

3.4.1 The patent renewal model

The econometric model applied in this study has been developed based on the original patent renewal model proposed by Pakes and Schankerman (1984) and Schankerman and Pakes (1986) and it is analogous to setups in Schankerman (1998). The patent renewal model assumes that the patentee chooses the optimal lifespan for the patent to remain in force, T, to maximise the value of the patent rights, $V(T)$. This is formulated as the expected discounted net annual returns of patent rights (current return minus renewal cost),

$$Max_{T\in\{1,\cdots,\bar{T}\}}V(T) = \sum_{t=1}^{T}\rho^t(R_{jt} - C_{jt}), \tag{3.1}$$

where R_{jt} and C_{jt} respectively denote the real annual return of patent rights and the real renewal cost of a patent in cohort j at age t, ρ is the discount factor, and $\bar{T}$ is the statutory limit of a patent regulated by the patent system. The patent ceases permanently if payment of the annual renewal fee is not made on time.

Assumptions are required on the decay rule of annual returns of patent rights R_{jt} and the distribution of initial returns R_{j0}, to model diverse preferences in choosing the patent's optimal lifespan and the behaviour of profit flows as the patent ages. With consideration for simplification of the modelling process and approaches utilised by earlier studies, two assumptions are imposed here. Specifically, (1) the annual return of patent rights R_{jt} is assumed to diminish over age at a constant decay rate $\delta \in (0, 1)$, and the decay rate is assumed to be common across cohorts (although distinct across nationalities or industries), and (2) the initial return R_{j0} is distributed log-normally.

One concern is that the first assumption of deterministic decay is rather unrealistic. A more sophisticated and flexible alternative is the stochastic decay rule. However, it is technically involved without providing significantly different results; see Pakes (1986). With regards to the lognormal distribution, it has been formally tested by earlier studies including Schankerman and Pakes (1986), and is generally believed to provide the best fit for the distribution of patent values among different distribution functions, and has been employed consistently in the similar studies discussed in Section 3.2.

Under the first assumption (i.e. the constant decay rate), R_{jt} can be written as an equation of the initial return R_{j0} and the decay rate δ:

$$R_{jt} = R_{j0} \prod_{\tau=1}^{t} (1 - \delta_{\tau j}) = R_{j0}(1 - \delta)^t. \tag{3.2}$$

Also, assumption (1) implies R_{jt} is non-increasing in age t. Given that the renewal cost C_{jt} is monotonically increasing in t, it further implies that the sequence $\{R_{jt} - C_{jt}\}_{(t=1)}^{\bar{T}}$ is non-increasing in t. Thus, the unique optimal age $T^* \in \{1, 2, \cdots, \bar{T}\}$ is the age when $R_{jt} - C_{jt}$ switches the sign from positive to negative. In the case that $R_{jt} - C_{jt}$ remains positive even when the age reaches the statutory limit, $T^* = \bar{T}$. Intuitively, there are incentives associated with renewing the patent provided that the current return at least covers the renewal cost. Formally, the renewal criterion for patents in cohort j at age t is given by $R_{jt} \geq C_{jt}$. By substituting Equation (3.2) and taking logarithms, this inequality can be rewritten as,

$$r_{j0} \geq c_{jt} - t \times ln(1 - \delta), \tag{3.3}$$

where the lower case represents the logarithmic form of the associated upper case letter.

Under the second assumption (i.e. R_{j0} is log-normally distributed), r_{j0} follows a normal distribution with mean μ_j and standard deviation σ_j, i.e. $r_{j0} \sim N(\mu_j, \sigma_j^2)$. As such, the standardised version of Equation (3.3) is formulated as,

$$\frac{r_{j0} - \mu_j}{\sigma_j} \geq \frac{c_{jt} - t \times ln(1 - \delta) - \mu_j}{\sigma_j}, \tag{3.4}$$

such that $\frac{r_{j0}-\mu_j}{\sigma_j} \sim N(0,1)$. It could be stated that the proportion of patents in cohort j renewed at age t, P_{jt}, is equal to the probability that the Equation (3.4) is satisfied, or the renewal condition is met. Thus, Equation 3.4 can be expressed in Equation (3.5) as,

$$P_{jt} = Pr[\frac{r_{j0} - \mu_j}{\sigma_j} \geq \frac{c_{jt} - t \times ln(1-\delta) - \mu_j}{\sigma_j}] = 1 - \Phi[\frac{c_{jt} - t \times ln(1-\delta) - \mu_j}{\sigma_j}], \quad (3.5)$$

where $\Phi(\cdot)$ is the standard normal cumulative density function (CDF). Inverting Equation (3.5) gives the basic patent renewal model as,

$$y_{jt} = \Phi^{-1}(1 - P_{jt}) = \frac{c_{jt} - t \times ln(1-\delta) - \mu_j}{\sigma_j}, \quad (3.6)$$

where $y_{jt} = \Phi^{-1}(1 - P_{jt})$ is the inverted standard normal CDF of the proportion of cohort j patents dropped out at age t.

In addition, there are a few more considerations involved in constructing the final estimation model: First, the dimensionality of data needs to be accommodated. The patent renewal rate consolidated for this study has a dimensionality of three (i.e. cohort-age-nationality or cohort-age-industry) that is distinct from either the 2-dimension aggregate-level data (cohort-age) used by Schankerman and Pakes (1986) or the 4-dimension disaggregate data (cohort-age-nationality-industry) by Schankerman (1998).

Second, a large sample size is necessary for the estimation to attain consistent estimators. However, each individual nationality or industry group only consisted of 259 observations (shown in Table 3.1). It is chosen to pool across patentees' nationalities (industries) to obtain a larger sample. One disadvantage of this strategy is that the estimated decay rate is actually an average measure of all nationalities (industries), and fails to differentiate decay rates among these groups. The concern is that the decay rate of returns of patent rights is expected to be different across different patents' industries. However, Schankerman (1998) found that those disparities are in practice small, and the restriction on the decay rate is not thought to be a major issue in estimating the value of patent rights by industry.[8] For the nationality case, it does not lose much generality by holding δ fixed across patentees' nationalities, because these patents are subject to the same (Australian) patent system and market regardless of the patentee's nationality.

The final thought is to maximise the flexibility of the model specification to allow unique distributions for each cohort-nationality or cohort-industry group. The pooling model is incorporated in the cohort and nationality (industry) specific dummies, which allows the identification of evidence of inter-cohort and inter-origin (inter-industry) differences in both parameters μ and σ, that is, a unique distribution function is associated with each cohort-nationality or cohort-industry pair.

Moveover, to account for the patentee's nationality and industry, let n denote the patentee's nationality, $n \in N = \{AU, US, UK, DE, FR, JP\}$, where N consists of six nations: Australia, the US, the UK, Germany, France and Japan; and the set of industries S include electrical machinery (EM), electronics (EL), chemicals (CH) and pharmaceutical (PH), $s \in S = \{EM, EL, CH, PH\}$. The final version of estimation models in the nationality and industry case are formulated respectively as follows,

$$y_{jt}^{n} = \frac{c_{jt} - (\mu_i^{n_{base}} + \sum_{n \neq n_{base}} \beta_n D_n + \sum_{j \neq i} \beta_j D_j) - t \times ln(1-\delta)}{\sigma_i^{n_{base}} + \sum_{n \neq n_{base}} \gamma_n D_n + \sum_{j \neq i} \gamma_j D_j} + u_{jt}^{n}, \tag{3.7}$$

$$y_{jt}^{s} = \frac{c_{jt} - (\mu_i^{s_{base}} + \sum_{s \neq s_{base}} \beta_s D_s + \sum_{j \neq i} \beta_j D_j) - t \times ln(1-\delta)}{\sigma_i^{s_{base}} + \sum_{s \neq s_{base}} \gamma_s D_s + \sum_{j \neq i} \gamma_j D_j} + u_{jt}^{s}, \tag{3.8}$$

where $n_{base} \in N$ ($s_{base} \in S$) is the base nationality (industry); $i \in 1980, \cdots, 1994$ is the base cohort; D_j, D_n, D_s are the cohort, nationality and industry specific dummies;

[8]The higher data dimension allows him to estimate a separate decay rate for each industry.

u^n_{jt} (u^s_{jt}) is the error term.

Finally, two econometric issues to be tackled are the nonlinearity and heteroskedasticity. The econometric models shown in Equations (3.7) and (3.8) are nonlinear in parameters. One way to estimate these models is using the nonlinear least square (NLS) estimation method. NLS estimators of these parameters are consistent with a large sample size (Davidson and MacKinnon, 2004). However, they are not efficient when the error term (u^n_{jt} or (u^s_{jt})) is heteroskedastic.[9] To correct for the heteroskedasticity when the heteroskedastic function is unknown, the feasible generalised least squares (FGLS) estimation method was applied to incorporate with the NLS.[10]

3.4.2 Simulation of patent values

The distribution of initial returns of patent rights R_0 for each cohort-nationality (cohort-industry) pair is obtained by 50,000 random draws from the lognormal distribution parameterised by estimates of the associated parameters μ and σ. Given a generated R_0 value and an estimated decay rate, the value of patent rights for a single patent is computed using

$$V = \sum_{t=1}^{T^*} \rho^t [R_0(1-\delta)^t - C_t], \tag{3.9}$$

where C_t is the real patent renewal cost for a patent at age t; T^* is the optimal patent lifespan; and ρ is the discount factor.[11] Equation (3.9) shows each draw of R_0 is associated with a value of patent rights V, and therefore this simulation process has generated 50,000 V values. By following these procedures, the value distribution of patent rights for each cohort-nationality (cohort-industry) pair is constructed, and the corresponding descriptive statistics can be calculated accordingly.

[9] The White test used to test for the presence of the heteroskedasticity for residuals in the nonlinear models, consistently shows strong evidence of heteroskedasticity.

[10] Refer to Wooldridge (2009), pp 283-284.

[11] A commonly assumed value of 0.9 for parameter ρ is used.

3.4.3 Limitations of the patent renewal approach

There are some potential limitations for using this approach to estimate the value of patent rights. First, the assumption of the constant decay rate for the annual returns of patent rights is thought to be unrealistic, and this could lead to a bias in the estimated value of patent rights. Second, patent rights have a very skewed value distribution, probably more skewed than the lognormal distribution used in this study. The thin right tail of the value distribution is where the most interest is. However, this is probably not completely or precisely revealed in the case where a lognormal distribution for the value of patent rights is assumed. Third, patent renewal fees are thought be reasonably low, generally much lower than the value of the underlying invention. Based on only these modest patent renewal costs, the patent renewal approach could potentially underestimate the value of patent rights. Fourth, the value of patent rights is probably endogenous, and is likely to be affected by firms' characteristics. More importantly, it is a function of the costly effort that the patent owner expends in attempting to enforce the patent, which involves detecting infringement and taking the alleged infringers to court to stop the infringing action. The bias in the estimated value of patent rights is unavoidable without controlling for endogeneity that is subject to future research.

3.5 Results

Empirical results for patent renewal models pooling across patentees' nationalities and industries in the base cohort are shown in Tables 3.2 and 3.3 respectively, where [1a] includes all dummy variables defined in Equations (3.7) or (3.8); [1b] keeps only those dummies with statistically significant coefficients and [2] (only for the industry case) includes the cohort-industry interaction terms in addition to (3.8), in order to capture the possible structural changes over time. With concerns regarding relatively inferior data quality for cohorts in the early 1980s, the latest cohort with complete observations of patent renewal data, cohort 1991 is chosen as the base cohort, and Australia (AU) and electrical machinery (EM) industry are used as the base patentee's nationality and industry, respectively. Only estimates (and standard errors) of parameters μ and σ for different nationalities or industries in cohort 1991 are presented in Table 3.2 and 3.3. The complete set of estimates of preferred models in two cases is presented in Tables A.3 and A.4 in Appendix A.

3.5.1 Estimates of patent renewal models

By patentee's nationality

Two sets of coefficient estimates of nationality specific dummies ($\hat{\beta}_n$ or $\hat{\gamma}_n$) are jointly statistically significant (with the p-value approximating zero to 4 decimal places), and are all individually statistically significant at the 1% level. This shows that parameters μ and σ determining the value of patent rights differ dramatically across different patentees' origins.

As for the coefficient estimates of cohort specific dummies $\hat{\beta}_j$ or $\hat{\gamma}_j$, although a fraction of them are not individually statistically significant even at the 10% level, they are jointly significant at the 1% level. $T1 \sim F(14, 1521)$ testing the joint significance of the fourteen cohort specific dummies β_j in the numerator of Equation (3.7) equals 3.97, larger than the critical value of 2.09 at the 1% significance level. Similarly, $T2 \sim F(14, 1514)$ examining the joint significance of coefficient estimates on cohort specific dummies γ_j in the denominator of Equation (3.7) is 5.76, compared with a similar critical value. These statistical results show inter-cohort differences in parameters μ and σ.

Since the parameter μ determines the size (i.e. mean and median) and σ decides the variation (i.e. the variance and the level of skewness) of the initial return of patent rights R_{j0} and thus the value of patent rights, these results imply that the average value of the patents tends to vary across patentees' nationalities and over time. Also, the level of variations and skewness for the value distribution is likely to be unique across nationalities and cohorts.

Parameters	[1a]	[1b]
μ_{AU}	5.404 (0.071)	5.467 (0.074)
μ_{US}	6.074 (0.108)	6.149 (0.110)
μ_{GB}	5.939 (0.111)	6.006 (0.113)
μ_{DE}	5.797 (0.086)	5.860 (0.089)
μ_{FR}	6.160 (0.098)	6.236 (0.101)
μ_{JP}	6.951 (0.135)	7.076 (0.140)
σ_{AU}	2.078 (0.147)	2.149 (0.151)
σ_{US}	1.889 (0.106)	1.975 (0.109)
σ_{GB}	1.918 (0.120)	2.007 (0.124)
σ_{DE}	1.834 (0.137)	1.914 (0.141)
σ_{FR}	1.733 (0.131)	1.816 (0.135)
σ_{JP}	1.609 (0.136)	1.672 (0.142)
δ	0.101 (0.013)	0.110 (0.013)
df	1507	1514
$T1 : F(14, 1521)$	3.97	
$T2 : F(14, 1521)$	5.76	
AIC	-2319.20	-2496.30
BIC	-2100.06	-2314.58

Note: standard errors are reported in brackets.

Table 3.2: Estimates of the Patent Renewal Model for Cohort 1991, by Patentees' Nationalities.

The estimates of parameters μ and σ (shown in Table 3.2) for all nationalities is statistically significant at the 1% level in both models [1a] and [1b].[12] The estimate of the decay rate (measured at an average across nationalities) are 10 and 11 percent in two models, respectively. These are within the range of estimates in similar studies, lying between 5 and 20 percent (See for instance Schankerman and Pakes (1986), Schankerman (1998) and Bessen (2008)). Also, among studies generating the knowl-

[12]All estimates, except those for the base nationality Australia are computed using base parameter estimates $\hat{\mu}^{AU}_{1991}$, $\hat{\sigma}^{AU}_{1991}$ and coefficient estimates on corresponding nationality specific dummies.

edge stock from R&D using the Perpetual Inventory Method (PIM), the depreciation rate is often assumed to be 10-15 percent, which is similar to the decay rate obtained in this study.

The Akaike information criterion (AIC) and Bayesian information criterion (BIC) are used for model selection (see Akaike (1974); Schwarz (1978)).[13] As seen in Table 3.2, results of both criteria are smaller for model [1b], and consistently indicate that [1b] is the preferred model in this case. Consequently, results in model [1b] will be employed in the simulation to obtain the value of patent rights by patentees' nationalities.

By industry

The parameter estimate for different industries shown in Table 3.3 are calculated in the same manner as those in Table 3.2. Model [1b] excludes four cohort specific dummies contained in the numerator of Equation (3.8) and ten of those contained in the denominator of this equation from model [1a], which are statistically insignificant at any conventional significance levels.[14] Despite half of the cohort dummies being excluded, results in model [1b] are reasonably similar to those in model [1a]. Inspired by the possible structural change among industries over time, interaction terms of cohort and industry specific dummies are added to Equation (3.8), and only the statistically significant dummies are retained in model [2].

As shown in Table 3.3, the inter-industry differences in parameters μ and σ are much smaller compared with the nationality case. This is as expected based on the graph of patent renewal rates presented in Section 3.3. The estimated decay rates in the three models are within a narrow range of 11.3 to 11.4 percent, which are similar to the results shown in Table 3.2, although there is a different meaning: the average

[13] Note that the R^2 is not useful when the FGLS is used (see Wooldridge (2009), pp 282-286.

[14] These are twice as many cohorts as are not statistically different from the base cohort (1991) in either parameter μ or σ compared with the previous case.

decay rate across four industries.

$T3 \sim F(14, 1014)$ and $T4 \sim F(14, 1014)$ examine for inter-cohort differences in parameters μ and σ in Equation (3.8), respectively. Both results ($T3$: 5.62 and $T4$: 2.16) are greater than the critical value at the 1% significance level, showing evidence for inter-cohort differences in parameters μ and σ, and in the initial return and value of patent rights at the industry-level.

Unlike the nationality case, two information criteria for the model selection lead to different conclusions. The AIC clearly prefers model [2], with the BIC penalising more heavily the number of parameters is in favour of model [1b], which consists of a smaller number of parameters than model [2]. However, the difference in the BIC between these two models is quite small. Since model [2] provides more flexible model specifications, it is the preferred model in this case.

Parameters	[1a]	[1b]	[2]
μ_{EM}	6.204 (0.147)	6.228 (0.139)	6.268 (0.136)
μ_{EL}	6.545 (0.149)	6.568 (0.142)	6.570 (0.156)
μ_{CH}	6.369 (0.130)	6.392 (0.141)	6.356 (0.142)
μ_{PH}	6.353 (0.145)	6.375 (0.141)	6.350 (0.142)
σ_{EM}	1.848 (0.151)	1.822 (0.136)	1.889 (0.137)
σ_{EL}	1.835 (0.151)	1.808 (0.137)	1.741 (0.129)
σ_{CH}	1.908 (0.159)	1.884 (0.144)	1.958 (0.145)
σ_{PH}	1.969 (0.164)	1.947 (0.151)	2.026 (0.150)
δ	0.113 (0.016)	0.113 (0.015)	0.114 (0.015)
df	1000	1014	980
$T1 : F(14, 1014)$	5.62		
$T2 : F(14, 1014)$	2.16		
AIC	-2190.10	-2226.00	-2385.83
BIC	-2007.21	-2112.31	-2109.01

Note: standard errors are reported in brackets.

Table 3.3: Estimates of the Patent Renewal Model for Cohort 1991, by Industry.

3.5.2 Value of patent rights

By patentee's nationality

The descriptive statistics for the value of patent rights by patentees' nationalities in 1991 cohort are shown in Table 3.4. Also, the weighted average value of patent rights across all six patentees' nationalities (i.e weighted by the patent count of each nationality) between 1980 and 1992 is presented in Figure 3.4, which gives an approximation of the aggregate-level average value of patent rights in Australia.[15]

Percentiles	Australia	USA	UK	Germany	France	Japan
25	111	242	209	189	292	936
50	506	1,193	1,010	835	1,329	3,743
75	3,149	5,783	5,248	4,077	5,843	13,093
95	32,068	47,308	42,291	31,174	38,981	71,804
99	136,670	180,410	165,420	120,060	132,400	231,650
Mean	9,379	12,332	11,224	8,326	9,498	18,466

Table 3.4: Value of Patent Rights (2008/9 A$) in 1991, by Patentees' Nationalities.

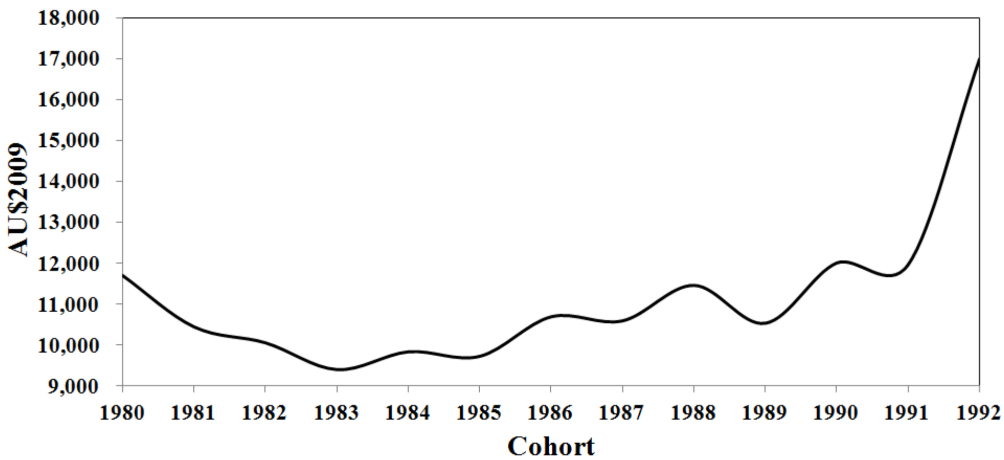


Figure 3.4: The Weighted Average Value of Patent Rights across Patentees' Nationalities (2009 AU$), 1980-1992.

[15]Note that although patent renewal data presented in Section 3.3 cover the period up to the 1994 cohort, the value of patent rights for the latest two cohorts was not estimated, because data for these two cohorts were incomplete at the time of data collection (2011), i.e. the renewal decision for a few patents was yet to be made by their owners, before these patents reached their statutory limit in 2012-2013.

The findings in Table 3.4 can be summarised into three main points. First, patents with domestic ownership are generally less valuable than their foreign counterparts based on both mean and median measures. This result is similar to many other studies using the patent renewal framework, for example, the French study by Schankerman (1998), the US study by Bessen (2008), and Finnish study by Gronqvist (2009). Second, there are large disparities in the value of patent rights among patentees' nationalities. In particular, the average value of patent rights of patents held by Japanese patentees is 50-100% higher than those patents owned by patentees with other nationalities. This is as expected after observing similar conclusions from earlier research, i.e Schankerman (1998) and Bessen (2008) also found a higher value on average for Japanese patents, with a even larger difference in their results than that of this study. Third, a rather unexpected result is that the mean value of patent rights of German owned patents in Australia ranks the lowest among all foreign groups. This result seems in conflict with the fact that Germany is one of the world's most competitive and technologically advanced countries. However, it is consistent with the conclusion given in Schankerman (1998), in which the German-owned patents appear to be one of the lowest in the average value of patent rights among French patents of different origins.[16]

The justification of these findings are discussed below. First, due to the higher risk and uncertainty involved in the foreign market, a new product is normally initiated and examined in the domestic market before being marketed overseas. The underlying inventions of associated foreign patents are most likely to be ones that succeeded in the initial stage and are relatively more profitable and valuable than their domestic rivals in the country of origin, whereas Australian-owned patents without the "selection effect" are a mixture of high and low values. As shown in Table 3.4, the foreign to Australian ownership ratio of the median value of patent rights ranges between 2

[16]The value of rights of German-owned patents in another country is not necessarily a good representation of that of all German patents. Therefore, this result does not indicate the value of patent rights of German patents in general is lower. In fact, Schankerman and Pakes (1986) found that the aggregate-level value of patent rights in Germany was higher than that of the UK and France.

and 7 times that of the top one percentile, indicating that the relatively lower average value of patent rights of Australian-owned patents is to a large extent attributable to the larger share of relatively low-value patents.

In addition, these differences may also arise as a result of diverse trade patterns between countries, which are determined by the level of compatibility between domestic consumer preferences and foreign industrial and export composition. In particular, Australia has been characterised as a small economy with a limited consumption capacity for some of the most sophisticated German inventions. As a result, the underlying invention of German patents in Australia likely under-represents the average level of all German inventions, and so is the value of patent rights, whereas Japanese inventions seem to be more successful in grasping Australian market demand.

Moreover, preferences of patenting activities in securing achievements in technological advances against competitors probably play a role in enhancing the value of patent rights. Surveys consistently show that Japanese firms are relatively more eager for patents than firms from other developed countries (Hall, 2009).[17] Also, the value of patent rights is likely to be related to the international coverage of this patent, i.e it is higher if the patent is granted in a larger number of countries. Japanese multinational enterprises (MNEs) were arguably the most competitive in the world throughout the 1980s, with exceptionally large market shares and extensive patent usages over many countries worldwide. This also to some extent explains the relatively higher value of patent rights for Japanese-owned patents.

Finally, the value of patent rights for foreign-owned patents is possibly overvalued due to the assumption of a constant decay rate over time that is probably unrealistic for foreign-owned patents. In fact, the different decay is often expected in the duration

[17]See Table A.5 in Appendix A for more details.

the product enters the foreign market, compared with the period when it remains in the domestic market. Such that the depreciation rate of profit flow for the foreign patentees may be not constant, nor the decay rate of the return of patent rights (Bessen, 2008).[18] Specifically, the value of patent rights for the foreign owned patents in this study can be potentially over-estimated, without accounting for this change in the decay rate. It is possible to increase the model's flexibility by allowing different decay rates for the return of patent rights for foreign-owned patents before their underlying inventions enter the Australian market, which depends on the market structure of the holding country. However, this requires different data and that is beyond the scope of this study.

Besides the magnitude of the value of patent rights, comment can be made regarding the distribution. Results in this study coincide with conclusions reached by other studies, either estimating the value of patent rights using the patent renewal approach or extracting the patent value through surveying patent owners, that the distribution of the value of patent rights is highly skewed. This can be observed where the mean value of patent rights for each patentee's nationality ranges between approximately 5-18 times the median value. More to the point, the level of skewness for the distribution of the value of patent rights differs substantially among patent owners' nationalities, and it is highest for domestically owned patents and lowest for Japanese counterparts. However, for patents with patent rights valued in the top one percent, there is a much smaller difference in the value of patent rights between Australian and foreign-owned patents, and among five foreign nationalities of ownership.

It is also interesting to look at the the aggregate-level average value of patent rights in Australia over time.[19] As shown in Figure 3.4, the aggregate-level average value of

[18] Bessen (2008) claims that this is probably one of the reasons that the estimated average value of patent rights of Japanese-owned patents is significantly higher than that of the US ones in his study.

[19] This is calculated as the weighted average of the mean value of patent rights across six patentee's nationalities.

patent rights remained stable during the 1980s at a range of AU$9,000 to AU$12,000. This was followed by a sharp rise in the early 1990s, with a peak of nearly AU$17,000 in 1992.[20] One possible explanation for such a surge in patent values is the change in the patent renewal pattern. Under the Patents Act 1991, both the minimum (i.e. the initial anniversary when the patent renewal process is required) and the maximum (i.e. the statutory limit) renewal age of a patent were extended, and renewal fees at various anniversaries from the filing date were increased accordingly. As a result, all patents filed from 1991 onwards can potentially survive for a relatively longer duration, with higher renewal costs. Under the patent renewal framework, a longer survival age and a higher renewal cost of a patent are both associated with a higher estimated patent value.

Study	Cohort	Country	Industry	Mean Pat. Val.
Schankerman and Pakes (1986)	1970	UK	Aggregate	14,578
		France	Aggregate	15,191
		Germany	Aggregate	43,645
Schankerman (1998)	1970	France	Pharm.	9,843
			Chemical	11,341
			Mechanical	34,508
			Electronics	45,273
Bessen (2008)	1991	USA	Aggregate	111,623
			Chem.	710,001
			Pharm.	171,959
			Elec/Electron.	97,759
			Mechanical	122,855
This study	1991	Australia	Aggregate	10,760
			Electrical	10,558
			Electronics	10,589
			Chemical	13,559
			Pharm.	16,035
	1980-1992		Aggregate	10,058
			Electrical	9,422
			Electronics	13,618
			Chemical	12,667
			Pharm.	14,721

Table 3.5: The Average Value of Patent Rights by Other Studies (2009 US$).

[20] A study of the extended period is needed to determine whether this large increase was permanent. However, this requires patent renewal rates data after 2012 for cohort 1993 onwards, due to the lag between the patent filing date and the expiring date up to the statutory limit of 20 years.

To gain further insight into the size of the value of patent rights in Australia, it is informative to make international comparisons with similar studies. Results at the aggregate (and industry) level from selected studies are shown in Table 3.5.[21] It is observed that the average value of patent rights at the aggregate level in Australia is below two-thirds that of European studies, and is around ten per cent of that in the US study. This is not surprising since it has been proven empirically that the value of patent rights is largely determined by the market size (Schankerman and Pakes, 1986), and the Australian GDP is much smaller than those of major European economies, or about five per cent of that of the US.[22]

By industry

Results by industries in the 1991 cohort are shown in Table 3.6. The four industries can be roughly divided into two groups in terms of the mean value of patent rights: pharmaceutical and chemical patents on average receive approximately AU$ 15,000 to AU$18,000 of patent rents from the Australian patent system. These are more than those of electronics and electrical machinery patents valued at less than AU$ 12,000. Also, these inter-industry differences in the average value of patent rights are somewhat smaller than those differences among patentees' nationalities found in the previous Section.

Although the value of patent rights on average for electronic patents is only two-thirds that of the pharmaceutical counterpart, its medium level measure is about 15 percent higher than the latter. This signifies that the value distribution of patent rights for electronic patents is the least skewed among the four industries. In contrast, the

[21] Only the result at the aggregate level is discussed here; the industry-level result will be discussed in the next Section.

[22] According to Schankerman and Pakes (1986), the mean value of patent rights is statistically and positively related to the logarithm of GDP. Intuitively, the value of patent rights is highly correlated to the value of the underlying invention (Hall et al., 2005). In addition, due to a larger quantity demand, products are generally more profitable in a larger market, that is the larger the market size, the higher the market value of an invention. Therefore, a larger GDP is associated with a higher average value of patent rights.

Percentiles	Electrical Machinery	Electronics	Chemistry	Pharmacy
25	285	449	294	301
50	1,366	1,997	1,483	1,646
75	6,250	7,849	7,123	8,096
95	44,225	48,878	53,795	66,770
99	165,480	161,060	203,690	273,220
Mean	11,731	11,765	15,066	17,817

Table 3.6: The Value of Patent Rights (2008/9 A$) in 1991, by Industry.

value of patent rights for pharmaceutical patents has the highest measure of skewness. Also, the value of patent rights for electronics patents distributed at the top one percentile of their value distribution is the lowest among the four industries, and is less than sixty percent of the pharmaceutical counterpart. This indicates that the relatively lower mean value of patent rights for electronics patents is mainly driven by the relatively less valuable leading patents in this industry.

In fact, the result for the 1991 cohort is not necessarily representative of other cohorts. There have been structural changes in the value of patent rights over the sample period, as illustrated in Figure 3.5. The value of patent rights for electronics patents was not always lower than that of the pharmaceutical or chemical counterpart. At the mean level, it was up to 80 percent higher than that of the other industries prior to the mid-1980s, which then experienced a rapid downturn thereafter, while the results for pharmaceutical and chemical patents followed opposite trends during this period. The pharmaceutical patent in particular took up the lead (in the average value of patent rights) from the electronics counterpart roughly in the mid-1980s, and has retained the top position since then. The average value of patent rights for electrical machinery patents remained the lowest in the sample period, which aligns with the observation of the patent renewal rate plot in Section 3.3.

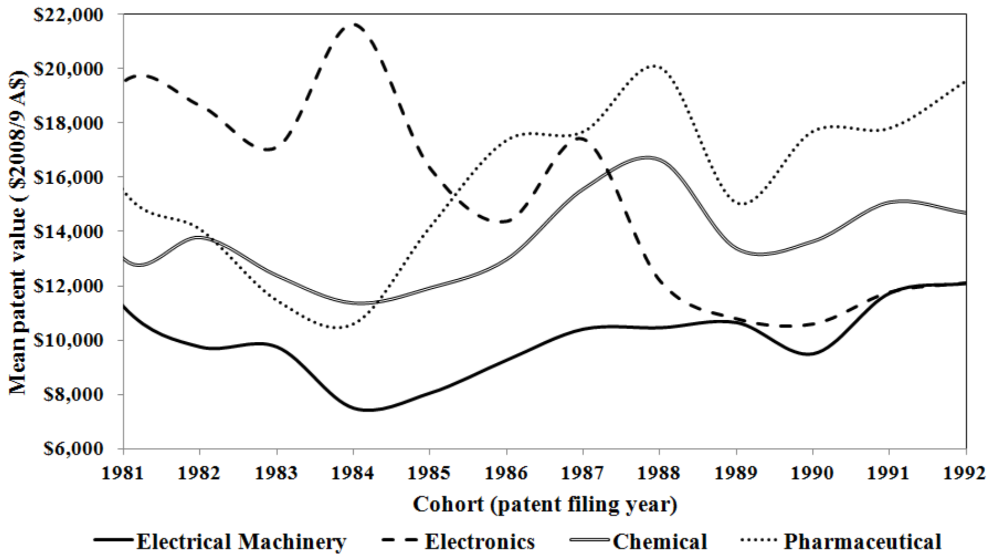


Figure 3.5: The Average Value of Patent Rights by Industries, 1980-1992.

Many factors contribute to the differences in the value of patent rights across industries and their structural changes over time. Two of the important ones are thought to be the inter-industry difference in inventors' preferences of using patents over other means of IP protection, and in political support from the (Australian) patent system.[23]

The average value of patent rights for each industry is likely to be reflected by the incentives of the patenting activity in that industry, depending on the simplicity of identifying infringements and the effectiveness of legal enforcement.[24] The patent was probably a more effective means of IP protection for the electronics industry prior to the early 1980s (than after the mid-1980s), when there was a relative lack of competition and an electronic product consisted of only a few patented ideas. The electronics industry experienced significant evolutionary growth and technological progress in the following decades, which led to not only an increase in the intra-industry competition, but also in the substitutability and complexity of electronic goods. Nowadays, most electronics products are drawn on a large number of patented ideas owned by different

[23]Other factors probably play lesser roles, including the inter-industry difference in domestic market protection, market size and trade structure.

[24]Refer to Table A.6 in Appendix A for the survey by Hall (2009) containing the firms' preference of using different IP protections across industries in major developed countries.

entities. As a result, the role of an individual patent has been reduced, and more importantly, the complex interdependent relationships among electronics firms have forced them to consider other more efficient means of securing their returns. In contrast, it is still possible now for a pharmaceutical or chemical product to be built on a small number of patents or even a single patent owned by one entity, and the use of patents in these two industries is more efficient than for the electronics counterpart because the process of identifying and prosecuting patent infringement is relatively simpler (if needed).

Another factor that may be responsible for the inter-industry difference in the value of patent rights, particularly the higher average value of patent rights for pharmaceutical patents, is that pharmaceutical substances were subjected to a statutory limit term five years longer than other categories since the mid-1980s. As a result of this exclusive political assistance, the value of patent rights for pharmaceutical patents on average became the highest among all industries after that time. Although the advantage of a longer statutory limit over other substances plays no role for patents that expired well before reaching the maximum age, it allows pharmaceutical patents already aged 20 years (i.e top in the value of patent rights) to enjoy an even longer life and more returns.[25] This explains the phenomenon that the value of patent rights for pharmaceutical patents is higher in the mean, but lower in the median (compared with that of electronics patents) as being mainly attributable to the relatively higher value fo top valued pharmaceutical patents .

Results of other studies at the industry-level using a similar approach are listed in Table 3.5. This table reveals considerable disparities in inter-industry ranking orders of the average value of patent rights among these studies. For example, results in a French study by Schankerman (1998) for patents filed in 1970 found that the average

[25] Due to the setup of the patent renewal framework, a longer patent's life is always associated with a higher estimated value of patent rights.

value of patent rights for electronics patents ranked the top, while that of chemical and pharmaceutical counterparts in the same cohort were much lower. Conversely, the US study by Bessen (2008) for patents filed in 1991 reached a different conclusion, i.e. the value of patent rights for chemical and pharmaceutical patents (in cohort 1991) in the US is significantly higher than that of electronics patents. A possible explanation can be structural changes among industries over time, as there is a time lag of over two decades between the patent cohorts they studied. It is reasonable to believe that Australia experienced similar situations as these countries during the same period, because a major share of Australian patents were owned by patentees of these countries, and Australia shared many institutional similarities. Therefore, evidence of structural changes in the industry-level value of patent rights in Australia during the 1980s reveals in this study is somewhat helpful for explaining the divergence of findings in the other two studies. Specifically, Schankerman (1998)'s result for (French) patents filed in 1970 is similar to the finding of the early 1980s in this study, whereas Bessen (2008)'s result is comparable with that of the same cohort here. Thus, this study links the two earlier studies by showing that their different conclusions are not necessarily in conflict, but rather are a function of the structural change that has been identified.

3.5.3 Equivalent subsidy rate of patent rights

The value of patent rights alone without taking into account the corresponding underlying innovation cost fails to provide a good measure for the importance of patents' roles in subsidising R&D investments. A more meaningful measure is the "equivalent subsidy rate" (ESR) as suggested by Schankerman (1998). Besides the exclusive institutional rights, the patent system also offers the inventors complementary patent rents as rewards, which is equivalent to a R&D cash subsidy.[26] The ESR is simply the ratio of the aggregate value of patent rights to the corresponding R&D expenditure

[26]The cash subsidy required to induce firms to make the same investment in R&D as they are induced by patents.

(Schankerman, 1998).

The annual national R&D expenditure during 1980-1991 is directly available from the Australian Bureau of Statistics (ABS). However, industry-level data during this sample period are only available once every 2-3 years, and are classified according to Australian Standard Industrial Classification (ASIC), which is distinct from the ISIC followed in this study. Fortunately, classification concordances are available from ABS's online database to unify different industrial standards.[27] Since national R&D data mainly cover domestic firms, only patents with domestic ownership are considered in the computation of the aggregate-level ESR.[28]

Another issue to be considered is that not all R&D investors use patents. The ESR will be largely understated without excluding those R&D investments not associating with any patenting activities. According to the Innovation in Australian Business survey (IAB) 2003 conducted by ABS, the R&D expenditure of patent users accounted for approximately 16.0% of R&D investment for all registered Australian firms in 2001-2003.[29] This share rate has been used as a weight for adjusting the ESR.

The plot of the aggregate-level adjusted ESR in the sample period 1980-1992 is shown in Figure 3.6 and the ESR, adjusted ESR and those data used for computing ESR in selected cohorts are shown in Table 3.7. The adjusted ESR at the aggregate level ranges between 3.2% and 8.4%. This implies that the Australian patent system subsidised patentees with an amount equivalent to 3.2-8.4% of their R&D investment

[27]A concordance between ISIC and ASIC was not found. Instead, ABS has concordances between these two classifications and the Australian and New Zealand Standard Industrial Classification (ANZSIC). This makes it possible to combine the uses of the ISIC-ANZSIC and the ANZSIC-ASIC concordances.

[28]The aggregate value of patent rights across domestic patentees is calculated by multiplying the estimated average value of patent rights for domestic patents by the number of domestic patent grants. However, the aggregate value of patent rights at the industry-level is less straightforward, because the industry-level average value of patent rights consists of both domestically and internationally owned patents. This is solved by weighting them using the ratio of the average value of patent rights of domestically owned patents to that of all patents in each cohort.

[29]Unfortunately, no survey was conducted during the sample period of this study. It is assumed that the pattern of using patents for R&D investors remained stable throughout the 1980s and 1990s.

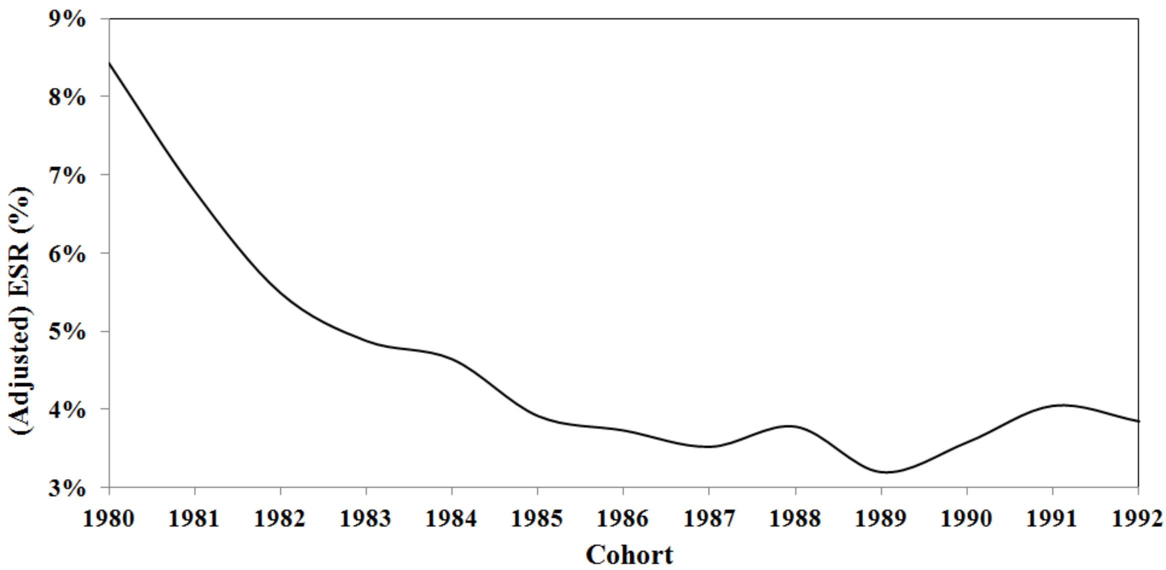


Figure 3.6: The Trend of Aggregate Level Adjusted ESR, 1980-1992.

during the 1980s and early 1990s. In addition, as shown in Figure 3.6, the adjusted ESR dropped dramatically from over 8% to less than half of that during the first half of the 1980s, and remained relatively stable at around 4% thereafter. The patent system played quite a important role in subsidising innovators and helping the government with its R&D under-investment issue. However, the role is reasonably small compared with the estimated return to R&D in the similar period.[30]

Results at the industry-level show that the adjusted ESR was always the highest for the pharmaceutical and chemical patents, followed by electrical machinery, and adjusted ESR for electronics patents remained the lowest (shown in Table 3.7). Taking the most recent cohort 1990/1 as an example, the adjusted ESR varies among different industries. The highest adjusted ESR of over 12% is found for pharmaceutical and chemical patents, which are approximately three times as large as the aggregate-level measure in that cohort. The lowest ESR has been observed for the electronics industry at less than 2 per cent, less than half that for electrical machinery, and only a fraction of that for pharmaceutical and chemical patents, which implies that patentees in the pharmaceutical and chemical industries receive significantly higher subsidies on aver-

[30]Based on studies with similar sample periods surveyed by IC(Industry Commission) (1995), the private return to R&D ranges 13-30%.

Cohort	Industry	Agg. patval (M AU$09)	R&D(M AU$09)	ESR	Adjusted ESR
1981/82	EM	0.80	131.0	0.61%	3.85%
	EL	0.55	186.8	0.29%	1.83%
	CH	1.47	134.7	1.09%	6.83%
	PH	0.63	40.6	1.56%	9.79%
	Aggregate	9.73	1110.2	0.88%	5.49%
1984/85	EM	0.87	215.6	0.40%	2.53%
	EL	0.66	259.6	0.26%	1.60%
	CH	1.66	174.2	0.95%	5.97%
	PH	0.94	85.5	1.10%	6.89%
	Aggregate	10.72	1716.0	0.62%	3.91%
1986/87	EM	1.40	312.3	0.45%	2.81%
	EL	1.09	348.0	0.31%	1.96%
	CH	3.13	236.5	1.32%	8.29%
	PH	1.74	122.5	1.42%	8.88%
	Aggregate	14.91	2655.6	0.56%	3.52%
1988/89	EM	1.47	300	0.49%	3.07%
	EL	0.88	350.6	0.25%	1.57%
	CH	3.08	229.7	1.34%	8.40%
	PH	2.18	184.8	1.18%	7.38%
	Aggregate	16.10	3158.2	0.51%	3.20%
1990/91	EM	1.73	252.1	0.69%	4.30%
	EL	1.03	392.6	0.26%	1.65%
	CH	5.05	248.7	2.03%	12.72%
	PH	3.51	176.7	1.99%	12.45%
	Aggregate	21.07	3264.4	0.65%	4.05%

Table 3.7: The Industry and Aggregate-level ESR in 1982, 1985, 1987, 1989 and 1991.

age from the patent system than the others.

By comparing the results across different cohorts available, there have been various levels of improvements in the ESR observed in all industries, except for electronics, which remained stable over the entire sample period. Specifically, the lowest adjusted ESR for pharmaceutical and chemical patents is found to be 6% and 7% respectively in the 1985 cohort, which nearly double their peaks occurred in cohort 1991. Similarly, the adjusted ESR for electrical machinery patents rose from 2.5% to 4.3% during the same period. Despite the fact that the average value of patent rights for electrical machinery patents has always been lower than the electronics counterpart in every cohort, the adjusted ESR for the former ranges up to twice that of the latter. This is because of the relatively more extensive R&D investment in the electronics industry.

These findings for the ESR are consistent with a group of innovation surveys summarised by Hall (2009). One question studies the preference for using patents across different industries. The patent is most preferred by the pharmaceutical industry in most of the nations, followed by the chemical industry.[31] Electrical machinery also occasionally appears in the list.[32] And the electronics does not show up in the table, which means there has always been a better choice for electronics firms regardless of the nationality, which is consistent with a low ESR.

Study	Cohort	Nation	Industry	ESR	Recal. ESR
Schankerman and Pakes (1986)	1970	UK	Aggregate	26.4%	1.6%
		France	Aggregate	21.7%	1.1%
		Germany	Aggregate	15.2%	2.6%
Lanjouw (1998)	1975	Germany	Computers	10.4%	0.4%
	1967-80		Pharmacy	6.8%	0.5%
Schankerman (1998)	1970	France	Pharmaceutical	4.1%	0.2%
			Chemical	7.2%	0.2%
			Mechanical	29.9%	0.7%
			Electronics(excl. JAP)	35.4%	1.0%
Bessen (2008)	1991	USA	Aggregate	2.9-5.3%	N/A

Source: Bessen (2006b, 2008).

Table 3.8: The Computed ESR by Other Studies.

Several earlier studies (Schankerman and Pakes, 1986; Schankerman, 1998; Lanjouw, 1998) calculated the ESR by dividing the aggregate value of patent rights from all origins by the aggregate R&D expenditures, both measured at the aggregate national level (shown in Table 3.8). They obtained the ESR for patent cohorts back to 1970 ranging between 4 and 35 per cent, and with an average of around 18 per cent, which are generally larger than those in this study. However, these ratios tend to be overestimated, because the R&D activity is not well measured for many patentees, such that the national level R&D would misrepresent the innovative effort by all patentees. In particular, for the proportion of patent grants with foreign ownership, those R&D

[31]See Table A.6 in Appendix A.

[32]It is partially integrated in other groups in these surveys, including transport equipment and special machines.

expenditures are not captured by the national R&D data. Bessen (2006b) recalculated these ESR and concluded that the ESR for European countries in these studies should actually be in the range of 0.2 to 2.6 per cent. He calculated the ESR in the US to be approximately 2.9 per cent, which is higher than those for the European countries after the adjustment. Despite that the estimated value of patent rights in Australia is much lower than the European and US counterparts, the ESR is actually higher. This is partly explained by the considerably lower R&D investment in Australia. Also, it suggests the Australia patent system plays a relatively larger role in subsidising patentees and helping the Australian government to address the R&D under-investment problem, compared with those of the world's top developed economies.

As the only other Australian study estimating the patent premium, the recent work by Jensen et al. (2011) develops a completely different method using the Australian Inventor Survey data. Their study attempts to distinguish the value of patent rights (patent premium) and the value of underlying inventions given the self-reported monetary value of the patent by inventors. They estimate that the patent premium for Australian patents is around 37 per cent, which is much larger than the ESR obtained in this study. However, their estimate is not directly comparable to the results of this study because of the different approaches.

3.6 Conclusion

This study consolidates the patent renewal data and estimates the value of patent rights in Australia using the patent renewal framework pioneered by Pakes and Schankerman (1984). Also, the (adjusted) ESR of patent rights is computed, which could be used to evaluate the Australian patent system's role of encouraging innovation and helping the government address the R&D under-investment problem.

There are several useful findings in this study: First, the patents owned by the domestic patentees are generally less valuable than the foreign counterparts. Specifically, the patents with Japanese ownership outperform the other foreign patents. These findings are consistent with the similar French and US studies.

Second, this study finds evidence of structural change in the pattern of the value of patent rights among industries over the sample period, which suggests a useful explanation for the distinct conclusions made between the existing studies on the ranking orders of the value of patent rights across industries.

Third, the average value of patent rights in Australia at the aggregate level falls in a range of 9,000-17,000 dollars (2009 AU$), which is much smaller than the findings of the major European and the US studies. This result is as expected by taking into account Australia's much smaller market size.

Fourth, the (adjusted) ESR for the domestically owned patents in Australia ranges between 3.2 and 8.4 per cent, which is actually larger compared with results for the major European countries and the US. The Australian patent system probably plays a relatively better role than the major economies in subsidising patented innovations and helping the Australian government with the R&D under-investment problem.

Finally, the Australian patent system tends to subsidise patentees in different industries unequally. The (adjusted) ESR is much higher for pharmaceutical and chemical patents than for that for electronics and electrical machinery counterparts. This helps explain the reason behind the survey's results that pharmaceutical and chemical industries rank the top in the preference of using patents among all industries.

There are some possible improvements that could be made in addition to those suggested in this study. These include exploring more flexible model specifications, such as relaxing the constant decay assumption for the annual return to patent rights and seeking a more suitable or flexible value distribution function in capturing the extreme skewness of the value of patent rights. Further, another direction of further research is controlling for the endogeneity of the value of patent rights. The estimation model can include the firms' characteristics as determinants of the value of patent rights, and incorporate the potential cost of patent infringement. However, this require linkage between patent renewal data and firm level data that is the subject of future research.

Chapter 4

The Role of Knowledge Tradability on Firms' Preferences of Using Patents verses Secrecy[1]

4.1 Introduction

Intellectual property rights (IPR), particularly patents, play an important role to secure firms' return to innovation and offer incentives to innovate. However, there is a surprisingly low proportion of firms using patents compared to firms using secrecy in many countries. This brings into question the driving force behind the choice of patenting verses secrecy (or between the formal and informal intellectual property (IP) protections). More broadly, the current debate surrounding IPR does not only question the use of patents, but also its very existence, which has been particularly well encapsulated by the following quote from Gallini and Scotchmer (2002): "Are there natural market forces that protect inventors so that formal protections or other incentives are not necessary?".

[1]This Chapter draws heavily on Goy and Wang (2013).

In a recent study, Henry and Ponce (2011) constructed a theoretical model to address the question posed by Gallini and Scotchmer (2002) and found that allowing for the possibility of knowledge being traded may mitigate the need for patent protection. Their study does not claim that IPR protection is welfare weakening and that it should be eliminated but that there is a market-based mechanism, which can provide the innovator with similar innovation incentives as patent protection. In a nutshell, they show that when knowledge is tradeable, competitors wait before entering the market in the hope that the price of knowledge will decrease and thereby provide the innovator with a temporary monopoly for a random period of time.

An important implication of their model is that the more tradeable knowledge is, holding the patent term life constant, the more likely firms are to rely on secrecy rather than patents. The authors argue that this provides a novel explanation for the fact that, based on business surveys, firms use secrecy significantly more than patenting to protect their innovations.

The focus of this study is to empirically test this implication by Henry and Ponce (2011). Specifically, we investigate the impact of the use of licensing contracts on a firm's choice of IP protection strategy (patent or secrecy). Furthermore, our empirical model enables us to check a number of other results, which have been previously highlighted in the literature as determinants for the use of patents versus secrecy.

To undertake this analysis, we use the results of the Innovation in Australian Business survey (IAB) conducted by the Australian Bureau of Statistics (ABS) and covering the period from 2001 to 2003. This dataset contains information about the use of IP protection methods by the firms surveyed. It shows that about 2.5 per cent of all registered businesses and 4.5 per cent of innovative firms in Australia use patents to protect their innovation. This share of patent users is comparable with other countries.

For instance, based on UK and European Patent Office data on patent holdings, Hall, Helmers, Rogers and Sena (2013) report that 1.7 per cent of all registered firms in the UK patent and around 4 per cent of firms engaged in R&D have applied for a UK or European patent. By contrast, the share of secrecy users based on the IAB is 16.7 per cent for all firms and 29.5 per cent for innovators.[2] This, again, is consistent with survey evidence from the US and Europe, which consistently shows that firms rate secrecy higher than patent as an IP protection instrument (see Cohen et al. (2000) for the US and Arundel (2001) for Europe).

The IAB also provides data on whether or not a firm is engaged in licensing agreements. We interpret this variable as a proxy for being involved in knowledge trading. This enables us to empirically study the relationship between the use of patents and secrecy as IP protection instruments on the one hand and the use of licensing (i.e. trading knowledge) on the other.

Of course, the variables of interest are subject to firms' endogenous choices. A firm's decision to protect its inventions through patents or secrecy and to sign a licensing agreement are far from random. First, in theory, only innovators face this type of decisions. For this reason, we restrict the sample we use to firms, which report having introduced an innovation between 2001 and 2003. Second, the use of IP protection mechanisms, in particular patents and secrecy, appear to be correlated with each other. Firms have a propensity to either use some kind of protection, formal or informal, or to use no protection at all (see Hall et al. (2013)). Following Pajak (2010), we use a bivariate probit model to address the likely dependence between the choices of using patents and secrecy. Third, we suspect that the licensing variable is endoge-

[2] Since 2006-2007, using business survey data, the ABS has regularly published aggregated data on the use of IP methods which report similar findings. Based on these statistics, on average 2 to 3 per cent of all businesses in Australia use patents to protect their innovation while between 12 and 16 per cent use secrecy. Unfortunately, these data are only available at the aggregate level, so firm level data were not available to construct panel or even time series data for our analysis.

nous to the choice of using an IP instrument, in particular patent, since firms with similar characteristics and motives should patent and license by definition. According to Knapp and Seaks (1998), based on Maddala (1983), the potential endogeneity of a dummy variable in a probit model can be corrected using a recursive structure in which the primary equation explains the variable of interest (i.e. Patent or Secrecy) and the second reduced form equation explains the endogenous binary variable (i.e. Licensing). Further, Maddala (1983) showed that estimates of this model can be found by a bivariate probit regression. Building on this approach, we construct a trivariate probit model in which patent, secrecy and licensing are our three dependent variables.

Our estimation results show that licensing is positively associated with IP protection of any kind - patent or secrecy - but also with a relatively strong preference for secrecy over patents. This agrees with Henry and Ponce (2011)'s theoretical prediction that the more knowledge is tradeable, the more firms use secrecy over patent because they benefit from a non legal period of temporary monopoly. In addition, our empirical model also indicates that the largest investors in R&D are more likely to use secrecy than patent. Moreover, we also find that patent users are more likely to employ a large personnel, to generate a large turnover, to introduce new products and to be in manufacturing industries. By contrast, secrecy users tend to be smaller firms in non-manufacturing industries and are more likely to create new processes as well as new products. Furthermore, firms that obtain their information from internal and non-market sources and those participating in process innovation are more inclined to use secrecy. Finally, firms that share their knowledge through R&D joint venture and those achieving product innovation are more likely to use both patents and secrecy with a similar preference.

In terms of the methodology, we acknowledge that by selecting innovators as our sample we may have potentially introduced a sample selection bias in our estimation results. To check whether there is a sample selection problem, we applied the corrective method for sample selection to a probit model (Van de Ven and van Praag, 1981). This model enables to estimate the likelihood of using patent or secrecy, taking into account the selection mechanism behind the innovation outcome. This robustness check shows that a bias exists; however, once correcting for it, our main results continue to hold qualitatively.

In summary, the contribution of this study is three-fold. To our knowledge, this study is the first to examine the impact of licensing on the choice of patenting versus secrecy, and more specifically to test the new theory of Henry and Ponce (2011). Second, we are unaware of any studies in the patent literature that corrects for the endogeneity of a dummy variable in a (bivariate) probit model. It is also relatively common practice in the literature to use a sub-sample of innovators to study the determinants of patenting and secrecy (see Hall et al. (2013), Pajak (2010) and Arundel (2001)). However, we have not encountered any studies correcting for the potential sample selection bias arising from this approach. Third, it is also the first time that the choice of patents versus secrecy has been studied empirically using Australian data from the IAB survey.

This study is organised as follows. Section 4.2 briefly summarises the existing literature and the theoretical model of Henry and Ponce (2011). Section 4.3 presents our empirical modelling approach. Section 4.4 describes the dataset and the variables selected for the analysis. Section 4.5 discusses the results. Section 4.6 checks for sample selection bias and Section 4.7 concludes.

4.2 Background

This study relates to the very extensive literature on a firm's choices between formal and informal IPR protection methods. Here, we provide a summary of this literature before exposing in more detail the model of Henry and Ponce (2011). For a comprehensive review, refer to the extensive survey by Hall, Helmers, Rogers and Sena (2012).

The empirical evidence based on surveys from many countries shows that on average, patents are not the most important mechanism of IP appropriation while secrecy and lead time are. The seminal studies in this area are those from Levin, Kelvorick, Nelson and Winter (1987) and Cohen et al. (2000), which report that US managers rank patents below secrecy as an appropriation method for both product and process innovations, except in a few industries which specialize in "discrete" products such as pharmaceuticals and chemicals. Similar research conducted, for instance, by Arundel (2001) in Europe confirms these findings. Furthermore, recent studies based on patent and census data find that very few firms own a patent. For instance, Hall et al. (2013) find that only 1.7% of all registered firms in the UK patented between 1998 and 2006. Balasubramanian and Sivadasan (2011) report similar findings for the US where only 5.5 % of the manufacturing firms own a patent.

The existing theoretical literature has identified and analyzed a wide range of factors that could explain the decision to use patents or secrecy. Much of the theory relies on the premise that there is a clear trade-off between the disclosure requirement imposed by a patenting system and the non-disclosure permitted by secrecy and therefore assumes that patents and secrecy are mutually exclusive. In the early literature, such as Friedman and Posner (1991), the choice is explained by the benefits and costs of using patents relative to relying on secrecy. These benefits and costs are mainly a function of the nature of the innovation that qualifies for protection and of strategic considerations based on the firm's competitive environment.

A key issue is whether the invention is easy to reverse engineer. If it is the case, then patent protection may be preferred because secrecy cannot prevent imitation.

This latter theoretical argument can explain why empirical studies find that the use of patents is usually more likely to be associated with product, in particular 'discrete' product innovation, than with process innovation, and inversely for secrecy.

While the early literature rests on the assumption that a patent ensures protection with certainty, this is not always the case.[3] Based on this observation, some theoretical models rely on a probabilistic view of patent rights (Lemley and Shapiro, 2005).[4] Introducing this assumption, it has been shown in particular that the size of an innovation may be an important determinant of the choice between patents and secrecy. For instance, Anton and Yao (2004) propose a model of duopoly competition with asymmetric information - the inventor has the best knowledge of the value of the invention while its rival learns about it either through disclosure from a patent or once it is on the market - and imperfect IP protection. In this setting, the innovator invests in R&D to reduce the cost of a process. The innovator then chooses the amount of disclosure as well as whether to protect the innovation with a patent or trade secret. The model predicts that under these assumptions the amount of information disclosed by a firm may be decreasing in the value of its innovation, mesured in terms of the cost reduction assocaited with the innovation. In particular, only small and medium innovations may be patented while large inventions are mainly protected through secrecy. The intuition is that in a weak IPR protection environment, the value of the disclosure (e.g through obtaining a patent and/or a licensing agreement) is offset by the increased imitation. This theory has been tested by Pajak (2010). Using data from the French version of the European Community Innovation Survey (CIS), Pajak (2010) analyzes the choice between patents and secrecy with a bivariate probit model. He finds in particular that, in the intermediate goods industry, firms reporting innovations new to firms (which he uses as a proxy for small innovations) are more likely to use patents while firms report-

[3]The most obvious sources of uncertainty are the outcome of the patent application process and litigation for infringement of a patent right.

[4]Note that a distinct implication is that, in the presence of uncertain property rights, the benefits of patenting are reduced compared with secrecy.

ing innovations new to the market (which he uses as a proxy for large innovations) are more likely to use secrecy. Note however that this result appears to be in contradiction by the findings, of Hall et al. (2013).

Another important issue is the state of competition. For instance, when there are both strong product competition and the risk of simultaneous invention, Kultti et al. (2007) show that patenting is the only choice in equilibrium. If the firm chooses secrecy, there is a risk that the competitor will win the patent and since the patentee always earns higher profits, the incentive to patent dominates the incentive to use secrecy. On the other hand, Zaby (2010), using an asymmetric duopoly model where one firm has a relatively large technological lead over its competitor but that competitor has the capability of making a closely related invention, shows that the leader may prefer to use secrecy rather than patent. In this particular environment, while a patent provides protection for the invention, it also requires the disclosure of this same invention, which may result in the innovator losing the lead. In Heger and Zaby (2010), the authors verify their theory empirically using the Mannheim Innovation Panel (MIP) i.e. the German contribution to the European Community Innovation Survey (CIS) for 2005. They find that the patenting behaviour of a firm is negatively influenced by the technological lead of the innovator as predicted by the theory. Nevertheless, the result is not statistically significant. This can be explained by the fact that their initial analysis does not separate the effect of products that are easy to reverse engineer. Introducing an interaction term between the technological lead and the ease of reverse engineering, they claim that a firm's propensity to patent increases in its technological lead in industries in which reverse engineering is easy, which, they allege, confirms their theory.

Finally, both the theoretical and empirical literature indicate that the decision to patent may be guided by other strategic motives such as earning licensing revenue, accumulating bargaining chips in negotiations (e.g cross-licensing negotiations) and building a defensive strategy to prevent lawsuits. In general, large firms are the most sensitive to these strategic issues. Further, as discussed by Arundel (2001), smaller firms, particularly in new technology sectors, may also use patents for strategic ends to signal their expertise, to capitalize intangible assets and to attract investment. However, small firms tend to be financially constrained and more sensitive to the various costs of the patent system, in particular the cost of a patent application and the cost of protecting their patents from infringement. This is in fact the most likely explanation that Arundel (2001) offers for the key empirical finding that patenting propensity rises with firm size (or equivalently that secrecy propensity decreases with firm size), other things being equal.

4.2.1 Henry and Ponce (2011)'s model and predictions

The economic justification for IPR protection is based on the non-rival nature of knowledge. That is, innovation can be easily copied, so that inventors cannot appropriate the rewards from their IP and would have no incentive to innovate if left to market forces only. One direct implication of this theory is that unless knowledge is protected by a patent, it is impossible for the creator of this knowledge to sell it without being immediately expropriated.

Henry and Ponce (2011) challenge this premise by constructing a dynamic model in which an inventor has developed an innovation that is not legally protected and potential imitators have the choice between buying the invention from the innovator or imitating the innovation at a cost. In equilibrium, the imitators choose to buy the knowledge rather than copying it and the inventor optimally chooses to sell knowledge through contracts that allow subsequent reselling by the buyers. Consequently, the first imitator competes with the inventor in the market for knowledge to sell it to other imitators, which has the potential to drive the price of knowledge to zero. However, Henry and Ponce (2011) show that the imitator has an incentive to delay its entry to the market in the hope that other firms will buy the knowledge before him and drive its price down. As a result, the innovator enjoys a temporary monopoly without the recourse to formal IP protection. Furthermore, Henry and Ponce (2011) show that their model implies that the more tradeable knowledge is, the higher will be the expected innovator's return from secrecy relatively to patenting. Their framework can be presented as follows.

When knowledge is not tradeable, the payoff of the inventor under secrecy is given by π_{n+1}, which is the equilibrium discounted profit when n imitators have entered the market and the innovation is immediately imitated at time $t = 0$. This is the equilibrium according to the conventional theory justifying the need for legal IPR protection.

When knowledge is tradeable, the expected payoff of the inventor under secrecy based on Henry and Ponce (2011)'s model becomes:

$$V_{is} = \underbrace{\mu(k,c)\pi_1}_{Monopoly\, profit\, for\, random\, time} + \underbrace{(1-\mu(k,c))(\pi_{n+1}+k-c)}_{Profit\, when\, all\, imitators\, in\, market}, \tag{4.1}$$

where π_1 denotes the profit if no imitators enter the market (i.e. the monopoly profit), and $\mu(k,c)$, the 'natural' expected duration of monopoly due to the delayed entry of imitators as a function of k, the price of knowledge in equilibrium and c, the cost of transferring knowledge incurred by the seller.

The expected pay off of the inventor if legal protection is chosen is given by:

$$V_{ip} = \underbrace{\nu(T)\pi_1}_{Monopoly\, profit\, for\, duration\, T} + \underbrace{(1-\nu(T))(\pi_{n+1}-P)}_{Profit\, when\, all\, imitators\, in\, market}, \tag{4.2}$$

where $\nu(T)$, the expected duration of monopoly due to patent protection is a function of T, the finite length of the patent, and P denotes the cost of patenting.

Comparing π_{n+1} and V_{ip}, Henry and Ponce (2011) point out that when knowledge is not tradeable, secrecy is preferred to patenting only if the length of patent does not cover its costs. Comparing V_{is} and V_{ip}, they also note that when knowledge is tradeable, whether secrecy or patenting is chosen, the payoffs follow a similar pattern; the innovator enjoys monopoly profits for some time until all the imitators enter the market. More importantly, in this case, the patent needs to be much longer, since under secrecy the inventor enjoys monopoly profit for a random period of time. In other words, because firms can now reap the profits from the delayed entry of imitators, the length of patent protection has to increase to outweigh the additional opportunity cost of choosing patents versus secrecy.

Henry and Ponce (2011) also point to empirical evidence of their theory. Based on a number of studies using data from the 1980s and 1990s, they observe that the use of secrecy grew between 1983 and 1994, while the number of licensing deals that they assume to be positively correlated with knowledge trading, also increased in the 1990s (see Levin, Kelvorick, Nelson and Winter (1987), Cohen et al. (2000) and Arundel (2001)).

The theory of Henry and Ponce (2011) turns on its head the traditional belief that natural market forces reduce a firm's incentive to innovate and that government intervention such as legal IP protection is required to ensure a certain level of innovation. Further, their model provides an explanation for the well established preference of innovators for secrecy versus patents. The more fluid the contracting environment is, the more firms should rationally choose secrecy over patenting. However, this conclusion challenges another belief, that firms find patenting useful when constructing knowledge contracts. In fact, licensing, which is the predominant form of knowledge contract is supposed to be by definition an authorisation to use IPR. The focus of this study is to investigate empirically whether this is the case: do innovators who are involved in knowledge contracts i.e. licensing, prefer patents or secrecy?

4.3 Empirical model

4.3.1 Modelling the choice of IPR protection method: A bivariate probit model

Our first task is to model a firm's choice between patents and secrecy. We start by considering an innovator who chooses between patenting denoted by P and secrecy denoted by S in order to maximize its profit function: $\pi(P, S, Z, \theta)$, where Z is a vector of observable factors that influence profits and θ represents a vector of factors that are known by the innovator but are not measured by the available data. The solution to the profit maximization problem includes reduced forms for the choice of patenting and secrecy such that:

$$P = P(X, \theta) \tag{4.3}$$

$$S = S(X, \theta), \tag{4.4}$$

where X denotes a vector of exogenous factors that affect the choice of patenting or secrecy and the profit function. Note that although many of the theoretical models assume that patents and secrecy are mutually exclusive, in reality, they are not. For instance, a firm can use secrecy to protect an invention during the development phase and then rely on patents when the product is on the market. Multiproduct firms can also use secrecy for some of their innovations and patents for others. This suggests that the choices of patenting or secrecy may not be independent and that there are probably common unobservables (i.e. included in θ) to explain both choices.

This simple theoretical framework can be translated into the following econometric model. Consider a firm i and two latent variables y^*_{pi} and y^*_{si}, where p stands for patenting and s stands for secrecy. The empirical specification of the Equations (4.3) and (4.4) is given by:

$$y^*_{ji} = x'_{ji}\beta_j + \varepsilon_{ji},\ j = p, s \tag{4.5}$$

where the realization of the latent variable y^*_{ji} is defined by $y_{ji} = 1$ if $y^*_{ji} > 0$ and $y_{ji} = 0$ otherwise. x_{ji} are vectors of control variables explaining the use of patenting or secrecy and the error terms ε_{pi} and ε_{si} are assumed to be bivariate normal with: $var(\varepsilon_{ji}) = 1$ and $cov(\varepsilon_{pi}, \varepsilon_{si}) = \rho_{sp}$.

Under these assumptions, Equation (4.5) specifies a bivariate probit model. Note that this type of model collapses to two separate probit models if $\rho = 0$ but allows for correlation between the unobserved determinants of using patents and secrecy if $\rho \neq 0$.

4.3.2 Introducing a proxy for knowledge trading : A trivariate probit model

Since our objective is to measure the impact of knowledge trading on the choice of patenting versus secrecy, we would like to include a proxy for knowledge trading in our model. Following Henry and Ponce (2011), we assume that the volume of trade in knowledge and licensing activities undertaken by firms are positively correlated. Thus we introduce a dummy variable representing a firm's licensing choice denoted by $Licensing_i$ on the right-hand side of Equation (4.5), so that our model becomes:

$$y^*_{ji} = x^{'}_{ji}\beta_j + \gamma_j Licensing_i + \varepsilon_{ji},\ j = p, s \tag{4.6}$$

As noted by Maddala (1983), all the variables on the right-hand side have to be exogenous for such a model to give consistent estimates of the parameters in the equations. However, given the close association between the IP protection and trading knowledge, we suspect that the choices of IP protection methods and entering into a licensing agreement are determined by a number of common variables. In particular, it is likely that some unobserved factors such as the strategic motives of the firm's management, or the characteristics of the innovation technology, influence both choices simultaneously, in which case the exogeneity condition for our main regressor of interest, the variable *Licensing*, would be violated. Fortunately, Maddala (1983) provides a relatively simple procedure to obtain consistent estimates if *Licensing* is an endogenous variable.

Consider a latent variable $Licensing_i^*$ defined as follows:

$$Licensing_i^* = w_i^{'}\alpha + u_i, \tag{4.7}$$

where $Licensing_i = 1$ if $Licensing_i^* > 0$ and $Licensing_i = 0$ otherwise, u_i is $N(0,1)$ and w_i are vectors of variables affecting the decision to license.

Note that each of the probit models given by (4.6) forms a two equation recursive probit model with this second reduced equation (4.7). Maddala (1983) observes that if the errors ε_{ji} and u_i are not correlated (i.e. $Licensing_i$ is exogenous), the equations of this system can be estimated separately using a simple probit model. On the other hand, if ϵ_{ji} and u_i are correlated (i.e. $Licensing_i$ is endogenous), the separate probit method does not give consistent estimates. Furthermore, Maddala (1983) shows that consistent estimates of such a recursive probit model can be found by bivariate probit (see Knapp and Seaks (1998) for further details and an example).

To address the possible endogeneity of the licensing variable, we apply Maddala (1983)'s approach to our initial bivariate probit model. We construct a trivariate probit model using the two equations specified by (4.6) and Equation (4.7). A simple formation of this trivariate probit model is given by:

$$\begin{aligned} y^*_{pi} &= \beta_{p0} + \gamma_p Licensing_i + \beta_{p1} x_i + \varepsilon_{pi}, & (4.8) \\ y^*_{si} &= \beta_{s0} + \gamma_s Licensing_i + \beta_{s1} x_i + \varepsilon_{si}, & (4.9) \\ Licensing^*_i &= \alpha_0 + \alpha_1 w_i + u_i. & (4.10) \end{aligned}$$

The errors $(\varepsilon_{pi}, \varepsilon_{si}, u_i)$ are trivariate normal such that:
$var(\varepsilon_{pi}) = 1$, $var(\varepsilon_{si}) = 1$, $var(u_i) = 1$ and $cov(\varepsilon_{pi}, \varepsilon_{si}) = \rho_{sp}$, $cov(\varepsilon_{pi}, u_i) = \rho_{lp}$, $cov(\varepsilon_{si}, u_i) = \rho_{ls}$.

Note that this kind of model can be identified solely on functional forms due to the non-linearity of the probit model; however it may be fragile. It is recommended that at least one variable should appear in w_i but not in x_i which, in our case, amounts to choosing an instrumental variable for $Licensing_i$ (Wilde, 2000). The selection of an appropriate instrument and other control variables for the model is discussed in the section below.

4.4 Data

4.4.1 Sample

The data set used in our analysis comes from a business survey conducted by the Australian Bureau of Statistics (ABS) entitled 'Innovation in Australian Business' (IAB) in 2004 and covering the period 2001-2003. This survey is concerned with the incidence of innovation in Australian business and draws on the Oslo Manual, Guidelines for Collecting and Interpreting Innovation Data.

The survey uses a stratified sample of 4,463 firms with more than five employees operating in Australia. One of the main advantages of the survey is the availability of information on innovation output, i.e. firms are asked whether they introduced any new or significantly improved products or processes during the period covered by the survey. The 2,053 firms reporting to be innovative in this manner constitute our core sample. A breakdown of the sample by firm size and industry sector as given by the Australian and New Zealand Standard Industrial Classification (ANZSIC) is provided in Table B.1 in Appendix B. The population shares have been produced using sampling weights to take into account the stratified nature of the sample.

Using the innovators as our main sample enables us to focus our analysis on the group of firms facing the same decision to protect their IP, conditional on a range of observed characteristics. However by selecting this sub-sample we are aware that we may face a sample selection problem. This is addressed in Section 4.6.

4.4.2 Key variables of interest and descriptive statistics

The IAB survey collects detailed information on the general characteristics of firms and their innovative activities and behaviours. Most variables are binary variables. In particular, firms are asked whether they use any of six IP protection methods - three formal methods including patents (Patent), registration of design (Registration) and copyright or trademarks (Copyright), and three informal methods including secrecy (Secrecy), complexity of product design (Complexity) and making frequent and rapid changes to the goods or services (Changes).

Due to the binary character of the data on protection methods, we interpret the frequency of use of a method in the sample as evidence of the firms' propensity to use this method. Table 4.1 gives the frequency with which each IP protection method is used according to whether the innovation is a product or a process. We note that secrecy is ranked as the top method of protection, while patenting is the fourth out of the six methods. This ranking does not appear to change by type of innovation. Further, the secrecy to patents users ratio of the process innovators (3.24) is larger than that of the product innovators (2.69), which implicitly suggests that process innovators are probably relatively more likely to use secrecy than patents compared to product innovators, and vice versa.

IP type	Product Innovation	Process Innovation
Secrecy	40.64%	37.64%
Copyright	29.64%	25.23%
Complexity	20.76%	14.42%
Patent	15.08%	11.61%
Changes	11.09%	8.36%
Registration	10.83%	8.72%
Total Number	1127	1387

Table 4.1: Ranking of IP Methods by Product and Process Innovators

To shed some light on the characteristics of the firms using patents and secrecy, Table 4.2 reports the frequencies of patenting and secrecy by firm size and in different industries. We also calculate the patent-to-secrecy ratio defined as $\frac{Patent}{patent+Secrecy}$, where patent and secrecy are the frequencies of use of the protection instruments in the sample.

Table 4.2 shows that the frequencies of both patenting and secrecy increase with firm size. The patent-to-secrecy ratio also suggests that secrecy is used more frequently by firms of all sizes (i.e. ratio is less than half) but that the use of patenting tends to increase as firms grow (i.e. the patent-to-secrecy ratio increases with the number of employees).

Firms in all industries also appear to prefer secrecy to patents (i.e the share of secrecy users is larger than the share of patent users, and the patent to secrecy ratio is less than 0.5 for all industries). However, the patent-to-secrecy ratio indicates that patenting is relatively more frequent in manufacturing, mining and communication services.

	(Sample) Patent share of innovators	(Sample) Secrecy share of innovators	$\frac{Patent}{Patent+Secrecy}$
Firm size			
5-19 persons	3.89%	28.32%	0.1208
20-99 persons	11.32%	32.35%	0.2593
≥100 persons	17.68%	45.54%	0.2796
ANZSIC industry			
Mining	14.58%	41.67%	0.2593
Manufacturing	16.22%	31.80%	0.3378
Electricity	6.67%	46.67%	0.1250
Construction	0.97%	32.04%	0.0294
Wholesale	9.15%	41.18%	0.1818
Retail	3.42%	25.64%	0.1176
Accommodation	1.41%	22.54%	0.0588
Transport	3.67%	31.19%	0.1053
Communication	11.76%	47.06%	0.2000
Finance	2.73%	48.18%	0.0536
Property	7.21%	42.79%	0.1441
Cultural services	6.86%	36.27%	0.1591
All firms	10.57%	34.92%	0.2323

Note: ANZSIC is the current industrial classification standard used in Australia and New Zealand.

Table 4.2: Patent and Secrecy Shares for Innovators by Firm Sizes and Industries

The IAB survey also contains one question, in a yes-or-no format, that asks whether the firm was actively engaged in any form of collaboration, including licensing agreements, to develop its innovation. We use this variable as our proxy to measure a firm's involvement in knowledge contracting. In a similar fashion to the protection method, we interpret the percentage of yes to that question as indicative of the firm's propensity to be involved in licensing i.e. knowledge contracting.

These measures of the use of patents or secrecy and of knowledge contracting are naturally not perfect. In particular, the dummy variables are given at the firm level, not at the innovation level. For instance, we do not know how many times a firm has used a protection method or licensing and even if its use of IP protection or licensing relates to an innovation made during 2001-2003, only whether or not it has used it during the period. For multiproduct firms with multiple protection methods, it is therefore not possible to exactly match one innovation with one method of protection and one licensing contract. Furthermore, we cannot tell from the data whether a firm is selling or buying a license (although based on the survey data, less than 25% of the innovators engaged in licensing in 2001-2003 appear to have purchased any sort of IP, e.g., patents, licences or other during that period). Because of these caveats, our analysis focuses on the general relationship between the use of patents or secrecy and the engagement in knowledge trading at the firm level.

	Patent	Secrecy	Registration	Copyright	Complexity	Changes
Patent						
Secrecy	0.1436					
Registration	0.4142	0.0500				
Copyright	0.3173	0.1814	0.3057			
Complexity	0.1972	0.2083	0.1548	0.1646		
Changes	0.1409	0.1437	0.1278	0.1311	0.2844	
Licensing	0.0841	0.1648	0.0920	0.1386	0.0779	0.1470

Table 4.3: Pairwise Correlations between the use of different IP Methods and Licensing

Table 4.3 presents the pairwise correlations between the different IP protection instruments and licensing. The table reveals that all the various IP protection methods are positively correlated with one another. As expected, secrecy and patenting present a correlation of 0.14, which confirms that using a bivariate probit model is justified (i.e. the dependence between secrecy and patenting threatens the validity of two separate probit models).

Interestingly, we note that the correlations between the Licensing variable and formal IPR protection methods seem to be relatively weak. This suggests that firms do not interpret licensing in the legal sense of the term - an agreement to use IP rights - but probably more in its knowledge trading sense. The Licensing variable also appears to be more positively correlated to Secrecy (0.16) than to Patent (0.08). These pairwise relationships needs to be investigated further, controlling for other explanatory variables.

4.4.3 Selection of control variables and instrument

We select a number of control variables in addition to our two dependent variables - Patent and Secrecy - and our main independent variable of interest - Licensing. Table 4.4 provides a brief description of all the variables to be used in the estimation.

Variable	Variable description	Mean ($n = 2053$)
Patent	1 if firm uses patent; 0 otherwise	0.11
Secrecy	1 if firm uses secrecy; 0 otherwise	0.35
Licensing	1 if firm engages any licensing agreements; 0 otherwise	0.13
RDtop	1 if the R&D expd ranks top 5% of the sample; 0 otherwise	0.05
RD	1 if firm incurs any R&D expenditure; 0 otherwise	0.81
Product innovation	1 if firm introduces new goods and services; 0 otherwise	0.55
Process innovation	1 if firm implements new operational process; 0 otherwise	0.68
Large	1 if No. of employees: ≥ 100; 0 otherwise	0.31
Medium	1 if No. of employees: $20 - 99$; 0 otherwise	0.33
Income over $5M	1 if firm's gross income is 5 million or more; 0 otherwise	0.52
JointRD	1 if firm engages any joint R&D; 0 otherwise	0.10
SOI internal	1 if firm's source(s) of ideas is from internal; 0 otherwise	0.90
SOI institutional	1 if firm's source(s) of ideas is from University, Government or non-profit organization; 0 otherwise	0.23
BDEX	1 if firm's purpose of innovation is to increase export	0.45
Industry Dummies	Categorized according to the ANZSIC classification	

Table 4.4: Variable Descriptions and Means

Based on the literature and in particular on Arundel (2001), we have identified four groups of other factors influencing the choice of patents versus secrecy: 1) the firm's own innovation strategies; 2) firm size; 3) the different types of information sources used to innovate; and 4) the firm's sector of activity.

Two measures of innovation strategies are included in the models. First, an important characteristic of a firm's innovation strategy is whether the firm creates new products or new processes. As showed by Table 4.1, this strategy seems to have an influence on the choice between patenting and secrecy. We therefore include two dummy variables to indicate the type of innovation (product or process innovation) introduced by the firm. Second, the amount of R&D expenditures is likely to positively influence the size of an innovation which, based for instance on Anton and Yao (2004), should also affect the choice of patenting versus secrecy. In particular, we construct a dummy for the top five percentile of firms engaged in R&D (RDtop) to analyze whether firms that are the most likely to develop large innovations tend to prefer patenting or secrecy.

Table 4.2 clearly shows that as the number of employees increases, the patent-to-secrecy ratio tends to increase, indicating that there may be a strong relationship between the size of a firm and its preferred method of IPR protection. To control for the firm size, our models contain two variables, Large and Medium, which refer to the number of employees. Further, we include a dummy variable for a firm's income that is over \$5 million Australian dollars (Income over \$ 5M) as an additional control for size but also as an indicator of a firm's financial resources - the lack of sufficient financial reserves to use the patent system and protect patents from infringement is often cited as a reason to explain the low proportion of patenting firms in the population of registered companies.[5]

[5]This choice of income dummy variable is motivated by two reasons. First, the IAB survey divides the firm's income into four ranges, i.e. 1) below \$100,000; 2) \$100,000 up to less than \$1 million; 3) \$1 million up to less than \$5 million; and 4) \$5 million or above. Approximately 52 per cent of the sample is in the last group. Second, by also including dummy variables for groups 2) and/or 3), respectively, in the main model defined in Section 4.3, their coefficient estimates are individually statistically insignificant at the 10% level.

As noted by Arundel (2001), firms using external sources that require extensive sharing of information may be more inclined to use patents. This is the case when joint research and development takes place, for instance. On the other hand, firms using primarily internal or institutional sources of information by opposition to market sources could place greater importance on secrecy. The IAB contains data on both the cooperative R&D undertaken (JointRD) and the sources of information used by firms to develop their innovation (SOI internal and SOI institutional). Three dummy variables are included in the models using this information.

Finally, empirical studies of the relative importance of patents and secrecy for firms have shown that there are large differences in the effectiveness of patents by sector of activity, with patents being most useful in sectors where products are expensive to develop but relatively cheap to copy, such as chemicals or mechanical equipment (see for instance Levin, Kelvorick, Nelson and Winter (1987), Cohen et al. (2000) and more recently Arora et al. (2008)). Our own descriptive statistics shown in Table 4.2 confirm that patenting is most used in manufacturing. Therefore, we include industry sector dummies in our regression models. We note, however, that the industry grouping provided by the IAB is relatively unhelpful for our purpose. Specifically, it does not break up the manufacturing sector into finer sub-sectors. It also does not enable the grouping of the sectors according to technological content or opportunities, which according to Arundel (2001) and Hanel (2008) is important for understanding why there are differences in the level of use of patents by sector.

In addition to these control variables, we have also tried to identify a valid instrument for the Licensing variable. We found that firms which are driven by establishing new markets or exporting to develop new products or processes are more likely to be engaged in licensing agreements. On the other hand, this variable does not have a significant partial effect on our two dependent variables, Patent and Secrecy. The fact that the exporting variable has a statistically significant effect on licensing appears to be reasonably intuitive since licensing is often used in association with exporting overseas either to affiliates or non-affiliates. Furthermore, we can think of a number of reasons why exporting is exogenous to the Patent and Secrecy variables, ceteris paribus. First, the question in the IAB survey implies that the decision to export pre-dates the decision to innovate and hence to use some kind of IP protection (i.e. exporting is one of the choices in a multiple choice question asking "what reasons drive the business to innovate?"). Second, the sector of activity the firm is in usually pre-determines whether a firm can export or not. For instance, Hall et al. (2013) find that the exporting firms are significantly more likely to use patents, but only when sector dummies are excluded from the regression. The relationship becomes insignificant as soon as the sector dummies are included. Third, firms usually apply for patents in the US or in Europe, so that their innovations are protected in markets overseas as well as locally. Therefore, in most cases, exporting does not require additional protection. For all these reasons, we believe the variable "exporting as a business driver" (BDEX) can serve as a valid instrument in the Licensing equation of our trivariate probit model.

4.5 Estimation Results

4.5.1 The trivariate probit model; the preferred model

Estimation results for our bivariate and trivariate probit models are reported in Table 4.5. The estimate for ρ_{sp} in the first model indicates strong positive correlation between the unobservables explaining Patent and Secrecy. Using the Likelihood Ratio (LR) test to examine for the null hypothesis that $\rho_{sp} = 0$, the χ^2 test-statistic is 14.05 with an associated p-value of 0.0002. Hence, the hypothesis of zero correlation is rejected and the bivariate probit model is the preferred model instead of two univariate probit models.

Note that one possible explanation for the positive correlation between the residuals of the Patent and Secrecy equations is that firms seem to have a "taste for protection".[6] As noted by Hall et al. (2013) for instance, firms that use one IP mechanism are more likely to use another one, and they have a propensity to use or not use IP, possibly due to their (lack of) familiarity with the system. The relatively strong positive pairwise correlation between the different IP protection instruments in Table 4.3 tends to support this claim.

Furthermore, although the estimate of ρ_{lp} in the second model suggests a negative but statistically insignificant correlation between the residuals of the Patent and Licensing equations, the estimate of ρ_{ls} indicates a negative and statistically significant correlation between the residuals of the Secrecy and Licensing equations. Testing for the absence of correlation between the residuals of the three equations, we find that the χ^2 test-statistic of the LR test is 11.80 with an associated p-value of 0.0081, which again strongly rejects the null hypothesis. This implies that the bivariate probit model without correction for the endogeneity produces a biased coefficient estimate for the Licensing variable, and it justifies the choice of the trivariate probit model as our preferred model.

The negative sign for ρ_{lp} and ρ_{ls} suggests that unobserved factors that increase the likelihood of using IP protection decrease the likelihood of engaging in licensing agreements, and vice versa. One can think of a number of such factors. For instance, if a firm's strategic motive for licensing is primarily collaboration, it may be less worried about protecting its IP. Similarly, if the management of a firm is risk averse, the firm

[6] This can be captured by including variables measuring the use of other IP protection methods in the regressions. Although the IAB contains such variables, we did not include them because of the additional endogeneity threat that it creates for the bivariate probit model. Note that however the univariate probit models for patent and secrecy including the "use of other IP methods" as a regressor does not change our results qualitatively.

Independent Variables	Model 1 (Biprobit)		Model 2 (Triprobit)		
	Patent	Secrecy	Patent	Secrecy	Licensing
Licensing	0.063	0.335***	0.132	0.781***	
	(0.122)	(0.093)	(0.214)	(0.219)	
RDtop	0.195	0.376***	0.186	0.343**	0.268*
	(0.160)	(0.141)	(0.161)	(0.142)	(0.163)
RD	0.217	0.111	0.214	0.094	0.303**
	(0.146)	(0.085)	(0.146)	(0.085)	(0.134)
Product innovation	0.458***	0.222***	0.457***	0.197***	0.214**
	(0.096)	(0.064)	(0.097)	(0.064)	(0.087)
Process innovation	0.038	0.126*	0.037	0.106	0.174**
	(0.094)	(0.065)	(0.094)	(0.066)	(0.089)
Large	0.667***	0.165	0.664***	0.155***	0.205*
	(0.155)	(0.104)	(0.155)	(0.104)	(0.138)
Medium	0.419***	0.016	0.419***	0.012	0.119
	(0.130)	(0.083)	(0.130)	(0.083)	(0.112)
Income over \$5M	0.291**	0.126	0.293**	0.127	-0.072
	(0.120)	(0.084)	(0.120)	(0.084)	(0.113)
JointRD	0.366***	0.332***	0.338**	0.167	1.196***
	(0.121)	(0.103)	(0.137)	(0.128)	(0.104)
SOI internal	0.021	0.285***	0.029	0.287***	-0.131
	(0.152)	(0.106)	(0.153)	(0.106)	(0.138)
SOI institutional	0.148	0.251***	0.150	0.230***	0.172*
	(0.096)	(0.071)	(0.097)	(0.071)	(0.089)
Manufacturing	0.552**	-0.109	0.560***	-0.060	-0.471***
	(0.216)	(0.140)	(0.217)	(0.141)	(0.166)
Mining	0.487	0.145	0.493	0.191	-0.484
	(0.317)	(0.229)	(0.317)	(0.229)	(0.322)
IV: BDEX					0.313***
					(0.081)
Other industry dummies	Yes		Yes		
Sample size	2053		2053		
ρ_{sp} (Patent & Secrecy)	0.200***		0.131***		
	(0.055)		(0.045)		
ρ_{lp} (Patent & Licensing)			-0.038		
			(0.098)		
ρ_{ls} (Secrecy & Licensing)			-0.243 ***		
			(0.111)		
LR test: $\rho_{sp} = 0$	14.05***				
LR test: $\rho_{sp} = \rho_{lp} = \rho_{ls} = 0$			11.80***		

Note: Numbers reported in parentheses are standard errors;
***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4.5: Results for Bivariate and Trivariate Probit Models

may shy away from licensing but use a lot of IP protection, especially secrecy.[7]

Finally, we note that the coefficient estimate for the instrumental variable BDEX in the Licensing equation is statistically significant at the 1% level. This indicates that BDEX is a relevant variable.

4.5.2 Firms engaged in licensing contracts are more likely to use secrecy than patents

We compare our coefficient estimates in the bivariate and trivariate models for our main variable of interest, Licensing. We find that the signs and the statistical significance of the coefficients are the same in both models: positive but statistically insignificant at the 10% level for the Patent equation and positive and statistically significant at the 1% level for the Secrecy equation. However, coefficients increase in the trivariate model compared to the bivariate model as a result of the negative bias resulting from the endogeneity of the Licensing variable in the bivariate model.

To gain further insights into the magnitude of these effects, the average partial effects (APE) of the Licensing variable on the probability of the use of patents and secrecy have been computed in Table 4.6. While firms engaged in licensing agreements have an increased probability of 2.1% of using patents, based on the trivariate model, they have an increased probability of 28.8% of using secrecy. In other words, firms using licensing are almost fourteen times more likely to use secrecy than patents.[8]

[7]This explanation may be particularly relevant for Australia where there are many small firms that are relatively more protected from competition and as a result more conservative in their way of doing business than, for instance, in the US.

[8]Even using the results of the bivariate model, we find that firms engaged in licensing agreements have an increased probability of 1% of using patents and 12% of using secrecy, so that they are 12 times more likely to use secrecy than patents.

The first implication of these results is that firms engaged in licensing are more likely to use an IP protection method - patents or secrecy. This finding is consistent with the traditional view that knowledge is non rival, so that by entering into licensing agreements, firms could easily have their innovations expropriated; hence they will seek to protect their IP.

Independent Variables	Model 1 (Biprobit)		Model 2 (Triprobit)	
	Patent	Secrecy	Patent	Secrecy
Licensing	0.010*** (0.001)	0.120*** (0.001)	0.021*** (0.004)	0.288*** (0.007)
RDtop	0.032*** (0.005)	0.135*** (0.004)	0.030*** (0.005)	0.121*** (0.004)
Product innovation	0.066*** (0.007)	0.076*** (0.005)	0.065*** (0.007)	0.065*** (0.002)
Process innovation	0.006*** (0.001)	0.043*** (0.001)	0.005*** (0.001)	0.035*** (0.001)
JointRD	0.063*** (0.007)	0.119*** (0.006)	0.058*** (0.007)	0.058*** (0.002)

Note: Numbers reported in parentheses are standard errors;
***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4.6: The Average Partial Effect for Key Variables

More counterintuitive is the fact that licensing firms appear to use secrecy more than patents. Intuitively, we expect that firms sharing their IP with rivals will tend to use patents more than secrecy, especially when knowledge sharing is done through licensing, whose legal definition is an agreement to use IP rights. This result first confirms what we suspected from the pairwise correlation analysis (see Table 4.3): that is, firms do not just interpret licensing from a legal perspective, but more broadly in a knowledge trading perspective. Further, it suggests that companies do not find patents useful and prefer secrecy when they trade knowledge. Hence, our result provides support for the theory of Henry and Ponce (2011), which predicts that the more knowledge is tradeable, the more firms prefer to use secrecy over patents because knowledge trading provides some temporary non-legal protection, which makes patenting superfluous.

This result is so striking that we investigated whether it holds for formal versus informal IP protection. We estimated the same bivariate and trivariate probit models using Formal Protection (including patents, copyrights and trademarks, registration of design and other formal methods) and Informal Protection (including secrecy, complexity of product design, making frequent and rapid changes to goods and services and other informal methods) as our two dependent variables. The estimation results are presented in Table B.2 in Appendix B and show that firms involved in licensing are significantly more likely to use both formal and informal protection.

The computation of the APE in Table 4.7 below reveals that the increased probability of using informal protection is higher than it is for formal protection, but to a lesser extent than previously. This change in the magnitude of the effects can be explained by the fact that licensing firms appear to use other formal methods of IP protection such as copyright and trademarks more than patents (see as evidence in Table 4.3 the higher pairwise correlation between copyright and licensing than between patent and licensing). Exploring the reasons for this finding is an avenue for further research and requires new data that contain richer qualitative information for different types of IP protection.

	Model 3 (Biprobit)		Model 4 (Triprobit)	
	Formal IP	Informal IP	Formal IP	Informal IP
Licensing	0.113***	0.122***	0.218***	0.319***
	(0.003)	(0.004)	(0.011)	(0.010)

Note: Numbers reported in parentheses are standard errors;
***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4.7: The Average Partial Effect of the Licensing Variable on the using Formal and Informal Methods of Protection

Interestingly, even this latter result can be reconciled with the theory of Henry and Ponce (2011), who predict that the random duration of the temporary monopoly obtained by firms using secrecy increases in the imitation cost of the innovation. We note that copyright, trademark and registration of design provide longer protection for the innovator than patents, and that these formal IP methods are used to protect tangible representations of ideas, which are relatively easy to copy.[9] Hence, based on the theory, it is not surprising that the use of formal protection versus informal protection increases compared to the use of patents versus secrecy when knowledge is traded - on the one hand, the duration of legal protection of other formal protection is longer than for patents, and on the other hand, the length of the temporary monopoly stemming from informal protection is shorter. As a result, the benefit from using informal protection decreases, relative to using formal protection.

Overall, our main result and its possible theoretical explanation appear to hold quantitatively when we replace the Patent and Secrecy dependent variables with the model broadly defined Formal and Informal protection variables.

4.5.3 The largest R&D investors are more likely to use secrecy than patents

Our second key result is that the coefficient for RDtop is statistically insignificant although positive for Patent in both the bivariate and trivariate probit models. However, it is positive and statistically significant at least at the 5% level for Secrecy using both models. The computed APE of RDtop on Patent and Secrecy confirms this result. Based on the trivariate probit model, the additional likelihood of using patents for firms being the top five percent in R&D expenditures to use patent is 3%, while it is 12% in the case of secrecy, which implies that top R&D active firms are four times

[9] A creation under copyright is protected for the lifetime of its creator, and trademark and registration of design can be renewed indefinitely.

more likely to use secrecy than patents.[10]

If we believe that large R&D expenditures are positively correlated with large value innovations as assumed for instance by the model from Anton and Yao (2004), this result provides support to the theoretical prediction of this paper that is: Firms with large sized innovations choose secrecy rather than patents due to the legal uncertainty associated with IP rights.

We note, however, that the evidence in the empirical literature is divided over this prediction. For instance, Pajak (2010), which focuses on testing Anton and Yao (2004)'s theory using a bivariate probit model, finds that small firms in the intermediate goods industry use patents to protect their smaller innovations and secrecy for the larger ones. The author uses two different measures of innovation size: a firm's share of innovative sales and the self-reported magnitude of the innovation i.e. an innovation reported by the firm as "new for the market" is considered to be of a large magnitude by comparison with an innovation "new for the firm". On the other hand, Hall et al. (2013) who also uses "innovation new to the market" as an independent variable measuring the novelty of an innovation in an univariate probit model for patents, draw the opposite conclusion. The firms reporting "innovation new to the market" tend to use patents more than the firms reporting "innovation new to the firm". However, the authors do not estimate the model for secrecy, so it is not possible to compare the relative effects of innovation size on the use of patents versus the use of secrecy. Since our measure of innovation size differs from those used in the above studies, our results are not directly comparable.

[10]Using the results of the bivariate model, we find that firms in the top 5 percentile of R&D expenditures have an increased probability of 11.9% of using patents and 13.6% of using secrecy, so they are still more likely to use secrecy than patents but only by a relatively small margin.

4.5.4 Other determinants

We now briefly comment on other results, which are mostly consistent with the existing literature, in particular with Hall et al. (2013) and Arundel (2001). Excluding the Licensing and RDtop variables discussed above, the sign of the estimated coefficients and their statistical significance in Table 4.5 largely conform to our expectations.

According to these estimates, we find that the effect of Product innovation is positive and statistically significant at the 1% level, while the effect of Process innovation is positive but statistically insignificant at the 10% level on both Patent and Secrecy using the trivariate model.[11]. To further investigate the magnitude of these effects, we calculate the APE of Product and Process innovation on the probability of using patent and secrecy. The results presented in Table 4.6 confirm that product innovators are more likely to use some protection and as likely to use patents as secrecy, but also indicate that firms developing new processes are about seven times more likely to use secrecy than patents.

We also find that the likelihood of using patents increases with the size of a firm (measured by the number of employees) and with its income range. Larger firms are also more likely to use secrecy, which is consistent with the fact that larger firms are more likely to be multiproduct and to use several methods of protection including patents and secrecy. However, the likelihood of using secrecy between small and medium firms is statistically insignificant at any of the standard significance levels. Also, the Income over $5M variable has no statistically significant effect on secrecy at any conventional levels. This suggests that, ceteris paribus, secrecy rather than patenting tends to be used by relatively smaller firms. Furthermore, the positive effect of Income over $5M on using patents, which is statistically significant at the 5 per cent level, tends to support the claim that the cost of the patent system is a barrier for firms with limited

[11] However, the effect of Process innovation is significant at the 10% level in the bivariate model

financial resources.

Consistent with Arundel (2001), firms sourcing their information internally or from non market institutions are more likely to use secrecy. However, distinct from the finding of Arundel, the APE of JointRD variable (Table 4.6) indicates that firms involved in joint R&D are more likely to use both types of protection method, and there is evidence of a large difference in the preference.[12]

Finally, in line with all the empirical literature on patents, we find that patent users are more likely to be in manufacturing industries. In contrast, using secrecy and being in manufacturing industries is negatively related, but this is not a statistically significant result.

4.6 Robustness check

This section addresses the sample selection issue arising from using the group of innovators as our sample for our previous analysis. The problem is that the innovator subsample may not be consistent with exogenous sample selection if the decision to use patents or secrecy is related to the antecedent decision to innovate. As shown by Heckman (1979), in the case that y^*_{ji} is observable, the coefficients estimates in Equation (4.5) from a non-random innovator subsample are biased. This implies that the two binary decisions of innovating and choosing a method of protection need to be jointly studied.

To correct for this problem, we follow Van de Ven and van Praag (1981) and use a probit model with sample selection for patent and secrecy separately. We consider our latent variable of interest y^*_{ji} and a latent variable representing innovation activity

[12] Arundel (2001) found that that firms involved in joint R&D are more likely to use patents.

denoted by y^*_{Ii} forming the following system of equations:

$$\begin{aligned} y^*_{ji} &= x^{'}_{ji}\beta_j + \varepsilon_{ji},\ y_{ji} = 1\, if\ y^*_{ji} > 0,\ 0\, otherwise && (4.11) \\ y^*_{Ii} &= x^{'}_{Ii}\beta_I + u_{Ii},\ y_{Ii} = 1\, if\ y^*_{Ii} > 0,\ 0\, otherwise, && (4.12) \end{aligned}$$

where the errors are bivariate normal with $var(\varepsilon_{ji}) = 1$, $var(u_{Ii}) = 1$ and $cov(\varepsilon_{ji}, u_{Ii}) = \rho_j$ and $j = p, s$. Importantly, y_{ji} is observed only when $y_{Ii} = 1$. Thus there are three unconditional probabilities to take into account when computing the likelihood function:

$$\begin{aligned} P_{11} &= Prob(y_{ji} = 1, y_{Ii} = 1) \\ P_{01} &= Prob(y_{ji} = 0, y_{Ii} = 1) \\ P_{00} &= Prob(y_{ji} = 0, y_{Ii} = 0) \end{aligned}$$

Note that the outcome $P_{10} = Prob(y_{ji} = 1, y_{Ii} = 0)$, which would be included in the standard bivariate probit model is not taken into account in this model.[13]

To implement this model, we need to identify factors which affect the decision to innovate, but not the choice of using patents or secrecy, which can be used as instruments in the model. As noted previously in Section 4.4, the IAB provides data on what drives a firm to innovate. In particular, three positive innovation driver variables have a significant effect on the innovation variable. These are "improve productivity" (BDRP), "increase revenue" (BDIR) and "be at the cutting edge of the industry" (BDCE). We interpret these variables as indicators of the firm's commitment to become a successful

[13]Note that in reality about 25% of patent and secrecy users report no innovation between 2001-2003 in the IAB survey i.e. $P_{10} \neq 0$. This is easily explained by the fact that responding firms can report the use of IP protection relating to innovations introduced before 2001. However, as a result of its specification, our bivariate probit model with sample selection merges outcomes P_{10} and P_{00}. The test of pooling states proposed by Cramer and Ridder (1991) was used to examine whether combining these two outcomes leads to significantly different estimation results compared with the case in which they are in separate states. The test statistic is too small to reject the null hypothesis at any conventional level, indicating that our approach is acceptable in practice.

innovator and a technology leader, which should influence the innovation outcome. All the other regressors (except for Product and Process innovation) used in our primary models to explain patents (and secrecy) are included in both Equations (4.11) and (4.12), because they all have the potential to influence the decision to innovate.

Table 4.8 reports the estimates of the two bivariate probit models with selection for patent and secrecy. The total sample after omitting the relevant missing values is 4,319 and the innovator sub-sample is 2,053. The ρ_j estimates for the two models indicate similar and strong negative correlations between the residuals, and they are both statistically different from zero at the 1% level, which suggests some sample selection for both the patent and secrecy models.[14]

The evidence shows that the self-selection does lead to some results being sensitive to the choice of sample. Specifically, the coefficient estimates for most variables decreases after controlling for the sample selection, however, they tend to retain the expected signs or level of significance, and the main conclusions made based on the results of our main models still hold. In particular, there is no statistically (or economically) significant effect of Licensing on Patent (although its sign is negative) while this effect is statistically significant at the 5% level on Secrecy. After controlling for the sample selection of the innovator subsample, the firms engaging licensing agreement are more likely (and only) to use secrecy. Further, the APE of RDtop (Table 4.9) shows that the firms with the top 5 percentile R&D expenditures prefer to use secrecy to patents, although they tend to use more of both methods.[15]

[14] In the case of patenting, the χ^2 test-statistic of the LR test is 3.74 with an associated p-value of 0.053, and it is 14.60 with a p-value of 0.0001 in the secrecy case.

[15] Note that, combined with the strong negative correlation between the Innovation and Patent or Secrecy equations, this would suggest that the firms using IP protections are at the two ends of the spectrum in terms of their innovative capabilities: at one end, a relatively large proportion of IP users have probably very small innovations while at the other end, a few of them develop the largest innovations in the market.

	Patent Model		Secrecy Model	
	Patent	Innovator	Secrecy	Innovator
Licensing	-0.083	0.759***	0.203**	0.778***
	(0.130)	(0.157)	(0.094)	(0.155)
RDtop	0.142	0.301*	0.165	0.244
	(0.122)	(0.171)	(0.105)	(0.171)
RD	-0.638**	1.874***	-0.663***	1.874***
	(0.320)	(0.055)	(0.165)	(0.055)
Product innovation	0.404***		0.193***	
	(0.093)		(0.059)	
Process innovation	0.024		0.106*	
	(0.085)		(0.059)	
Large	0.505***	0.212**	0.089	0.201**
	(0.161)	(0.095)	(0.101)	(0.094)
Medium	0.340***	0.085	-0.021	0.073
	(0.125)	(0.068)	(0.078)	(0.068)
Income Over $5M	0.249**	0.003	0.100	0.011
	(0.113)	(0.073)	(0.079)	(0.073)
JointRD	0.301**	0.204	0.279***	0.205
	(0.119)	(0.147)	(0.101)	(0.146)
SOI internal	-0.183	0.381***	0.088	0.398***
	(0.160)	(0.069)	(0.107)	(0.068)
SOI institutional	0.122	0.041	0.217***	0.046
	(0.092)	(0.075)	(0.068)	(0.074)
IV: BDCE		0.178***		0.193***
		(0.057)		(0.055)
IV: BDIR		0.332***		0.323***
		(0.062)		(0.060)
IV: BDRP		0.337***		0.334***
		(0.060)		(0.059)
Industry dummies	Yes		Yes	
Sample size	4319		4319	
ρ_j	-0.641***		-0.648***	
	(0.176)		(0.107)	
LR test of ρ_j	3.74*		14.60***	

Note: Numbers reported in parentheses are standard errors;
***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4.8: Bivariate Probit Models with Sample Selection for Patent and Secrecy

Interestingly, we note that the coefficient for R&D (RD) is positive and statistically significant at the 1% level for the dependent variable Innovation, but it becomes negative and statistically significant for both the Patent and Secrecy variables. This implies that once it is taken into account that firms investing in R&D are significantly

	Patent Model	Secrecy Model
Licensing	-0.018***	0.077***
	(0.002)	(0.001)
RDtop	0.033***	0.063***
	(0.003)	(0.001)
JointRD	0.073***	0.106***
	(0.006)	(0.001)

Note: Numbers reported in parentheses are standard errors;
***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4.9: The Average Partial Effect for Key Variables in Biprobit Models with Selection.

more likely to innovate, R&D is not a good predictor of choice of IP protection except for large R&D investors.

Another counterintuitive result is that collaborating in an R&D joint venture is not a strong determinant of being an innovator, but it appears that firms engaged in this kind of cooperation are more likely to use both patents and secrecy. As shown in Table 4.9, there is a reasonably small distinction in the APE of between these two models, similar to our main results in Section 4.5. Overall, this additional analysis correcting for sample selection confirms qualitatively our main results and also brings new insights. Of course, these models do not address the dependence between the Patent and Secrecy variables and the endogeneity issue presented by the Licensing variable, and thus can only complement but not replace our previous analysis.

4.7 Conclusion

This study explored firms' IPR protection strategies in relation to their involvement in knowledge trading proxied by their use of licensing agreements. The traditional belief is that patents are useful for constructing licensing contracts and therefore it is expected that firms using licensing will prefer patenting to secrecy. The recent model by Henry and Ponce (2011) predicts the opposite, the more knowledge is tradeable, the more firms use secrecy rather than patents because firms can reap the benefits from the non-legal temporary monopoly, arising from the tradeability of knowledge. Our results provide the first rigorous empirical support for this theory. Specifically, using an Australian data set, we find that firms which are engaged in licensing agreements are significantly more likely to use secrecy than patents.

In addition, our results show that the largest investors in R&D are more likely to use secrecy than patent, which is supported for instance by the theory of Anton and Yao (2004). Other results are mostly consistent with the existing literature. In particular, large or manufacturing firms are more likely to use patents, while firms obtaining information from internal and non-market sources are more inclined to use secrecy. Finally, process innovators are more likely to use secrecy, while product innovators and firms involved in R&D joint-ventures are more likely to use both protections without a clear difference in the preference.

This paper makes some additional contribution to the literature by using two novel econometric approaches to study the choice between patents versus secrecy. We developed a trivariate probit model to correct for the endogeneity of a dummy variable in a bivariate probit model. We also applied a corrective method for sample selection to a probit model.

Furthermore, most studies, to this date, use data from large economies with atypical levels of innovation relying on very strong high-tech industries, such as the USA, Japan or the large European economies. Using a data set from Australia arguably presents the advantage to be more representative of the bulk of developed countries in terms of innovative capacity and output, so that perhaps we can learn more about the general international situation with regards to firms' IPR protection choices from the Australian context than from very large innovating countries. However we also acknowledge the limitations of this data set and we see at least two avenues for further research.

Firstly, using data at the innovation level that enables matching of an IPR protection method with a specific innovation and licensing contract would greatly enhance the analysis. Such data appears difficult to obtain, however. Alternatively, using firm-level data but analyzing separately the group of firms using both patents and secrecy from the users of only patents or secrecy may provide some further insights. Firms using both forms of protection are more likely to be multiproduct firms, while patent-only users, for instance, are more likely to have a single innovation and to make IP protection and licensing choices relating to that particular innovation.[16]

Secondly, conducting the same analysis for different countries may also shed some new insights on these results. Australia is small open economy with a very large proportion of small firms (having less than twenty employees) and a relatively small manufacturing sector.[17] For these reasons, it is possible that the use of secrecy to protect IP, especially by small innovators, would be more prominent in Australia than in other larger developed economies, which would have the potential to skew our results in favour of secrecy over patent use.[18]

[16] Some kind of multinomial choice model would need to be specified to perform this type of analysis.

[17] Based on the IAB, the share of manufacturing firms out of the total population of Australian firms represents about 14%, while based on Hall et al. (2013), about 31% of all UK firms are in manufacturing.

[18] Unfortunately, we have not found statistics on the use of secrecy that are comparable to the statistics that we have computed for Australia based on the IAB for other countries.

Chapter 5

Conclusions and Recommendations for Future Research

5.1 Conclusions

Innovation has been emphasised by economists as an important driver of economic growth. However, in the recent decades there have been some signs of a reduction in the role of innovation, although there is a lack of extensive empirical evidence due to the difficulty of measuring innovation. Chapter 2 used two different IPR statistics as innovation measures in six major countries using IPR, and explored the long-run effect of innovation in driving economic growth in these countries. The results are diverse among these countries, and do not always support a positive role for innovation. For instance, for the US, Germany and UK, the post-World War II evidence indicates non-positive effects on economic growth, in line with concerns of a small but increasing number of pessimists, although such effects were reasonably strong in the pre-World War II period. Conversely, the findings show that innovation continued its role in stimulating economic growth in Japan, France and Australia in the more recent period. When innovation is measured by patent statistics, the long-run elasticity of output with respect to innovation among these countries was found to be between 0 and 0.65 in the period before World War II and between -0.74 and 0.82 in the period after. With the same analysis carried out using trademark statistics, smaller ranges of 0 to 0.24 and -0.30 to 0.70 were obtained respectively for the two periods.

R&D investment is often lower than the socially optimum level, because it has been discouraged by the risks associated with innovative activities, which has caused concern for policy makers. The IPR system is generally thought to play an essential role in assisting the government address this problem. Chapter 3 evaluated the role of the patent system in the Australian context for the first time, by constructing a novel data set and estimating the value of patent rights using the patent renewal method and computing the equivalent subsidy rate accordingly. The results indicate that the value of patent rights differs across the patentee's country of origin and across industries, and the industrial-level findings also show some structural changes across industries over the sample period from 1980 to 1992. At the aggregate level, the estimated value of patent rights on average in Australia increases over the sample period, ranging from AU$9,000-AU$17,000, which is much lower than the findings of studies of the US and the major European countries. In addition, the (adjusted) ESR of patent rights for domestically owned patents tends to fall over the sample period and ranges between 3.2 and 8.4 per cent. These numbers are actually larger than those for the European and US studies, indicating the Australian patent system is more effective than those of the major economies in promoting innovating incentives through subsidising patented innovations.

Chapter 4 investigated primarily how firms' engagement in licensing agreements - an indicator of knowledge tradability - affects their decisions in selecting IPR protection strategies. The results present the first rigorous empirical evidence for the theory of Henry and Ponce (2011), which implies that higher knowledge tradability of firms is associated with a higher preference for using secrecy over patents, because they can take advantage of the non-legal temporary monopoly occurring with knowledge trading. In addition, this study finds that secrecy is more likely to be selected by the largest R&D investors than patents, which is supported by the theory of Anton and Yao (2004). Moreover, there are further findings agreeing with the existing literature. For instance, firms large in size and categorised as belonging to the manufacturing industry are more likely to use patents, whereas firms acquiring information internally or from non-market institutions, and those conducting process innovation, are more in favour of using secrecy. Finally, innovators carrying out product innovation and R&D joint ventures tend to use both patents and secrecy, although there is no evidence of an obvious preference between these two IPR protections.

In terms of the econometric methodology, Chapter 4 contributes to the literature by applying two novel approaches to study firms' choice between patents versus secrecy. Specifically, a trivariate-probit model was developed to correct for the endogeneity of a dummy variable in a bivariate-probit model. Also, this study adopted a corrective approach for the sample selection bias in a probit model.

Finally, as a useful complement to studies in the existing empirical literature using data drawn from the US or the major European economies - countries with extraordinary levels of innovation depending on exceptionally powerful high-tech industries relative to most countries, the findings of a study using Australian data are likely to be more representative of the bulk of developed countries with a comparable level of innovative capacities and outputs; that is, more internationally general evidence of firms' IPR protection can be found from the Australian context.

5.2 Recommendations for future research

One major shortcoming of using IPR statistics as innovation measures in Chapter 2 was that each unit of IPR is likely to be associated with a different quantity of innovations across countries and over time. This is primarily due to the distinct level of strictness among international IPR systems, and the IPR policy usually changes over time. Ideally, these international and time inconsistencies should be accounted for by applying suitable weighting. However, such weighting figures with sufficiently long length are difficult to obtain, and are the subject of future research.

The quality of the estimated value of patent rights using the patent renewal model in Chapter 3 relies on two rather strong assumptions - constant decay and a lognormal distribution. The estimation results, especially for those patents with the highest values, can possibly be improved by imposing more flexible model specifications. These include a non constant stochastic decay rule and an alternative distribution function in characterising the extremely skewed distribution of patent values. Exploration of these alternatives forms a direction of future research. Also, the possible endogeneity of the value of patent rights could be investigated further by including variables determining the value of patent rights, such as firms' characteristics and the cost of patent infringement. This will require significant additional and time-consuming work consolidating patent renewal data and firm level data.

Similarly, limited by the data, there are at least two directions for further research for Chapter 4. First, the analysis that is limited by the firm-level data used in this study, is expected to be improved using data at the innovation level that allows pairing of an IPR protection method with a specific innovation and licensing agreement; however, such data is difficult to obtain. On the other hand, considering the fact that firms using both patents and secrecy are more likely to have multi-products, while those using only one form of protection are more likely to have only a single innovation related to their IP protection and licensing choices, modelling separately the group of firms using both forms of protection and those using only patents or secrecy may contribute some further insights. Second, it is useful to apply the same analysis using data from different countries. Due to the large share of small firms and relatively small manufacturing sector in Australia, secrecy is found to be used more, especially by small innovators, in Australia than in larger developed economies. This can potentially cause the results to skew towards a preference for using secrecy over patents.

In summary, while the thesis has advanced understanding of the economics of innovation and intellectual property rights, there remain multiple avenues of further investigation. These form a significant on-going research agenda which will be assisted by increasing availability of data in years ahead.

Appendix A

Appendix for Chapter 3

A.1 IPC - ISIC concordance table for four industries studied

A.2 Nominal patent renewal fees for patents filed in APO since 1979

Industry	ISIC	IPC
Electric mach., ex. electronics	3830 (except 3832)	A45D, A47J, A47L, A61H, B03C, B23Q, B60Q, B64F, F02P, F21H, F21K, F21L, F21M, F21P, F21Q, F21S, F21V, F27B, G08B, G08G, H01B, H01F, H01G, H01H, H01J, H01K, H01M, H01R, H01S, H01T, H02B, H02G, H02H, H02J, H02K, H02M, H02N, H02P, H05H
Electronics	3832	G08C, G09B, H01C, H01L, H01P, H01Q, H03B, H03C, H03D, H03F, H03G, H03H, H03J, H03K, H03L, H04A, H04B, H04G, H04H, H04J, H04K, H04L, H04M, H04N, H04Q, H04R, H04S, H05K
Chemistry, except pharmacy	3510+3520 (except 3522)	A01M, A01N, A61K, A61L, A62D, B09B, B27K, B29B, B29C, B29D, B29F, B29G, B29K, B29L, B41M, B44D, C01B, C01C, C01D, C01F, C01G, C02F, C05B, C05C, C05D, C05F, C05G, C06B, C06C, C06D, C06F, C07B, C07C, C07D, C07F, C07G, C08B, C08C, C08F, C08G, C08H, C08J, C08K, C08L, C09B, C09C, C09D, C09F, C09G, C09H, C09J, C09K, C10H, C10J, C10K, C10N, C11B, C11C, C11D, C12D, C12K, C12R, C14C, E04D, F41H
Pharmacy	3522	A61J, A61K, C07B, C07C, C07D, C07F, C07G, C07H, C07J, C07K, C12N, C12P, C12S

Source: Verspagen et al. (1994).

Table A.1: MERIT Concordance Table (Partial): IPC - ISIC (rev. 2).

ComlawID Year	1979	1980	1981	1982	1983	1984	1986	1988	1989	1991	1992	1993	1998	1998	2002	2007	2010
ComlawID No.	93	320	243	232	206	254	259	100	93	71	148	113	264	319	173	355	181
Commencing Date	28/6	01/11	01/10	01/10	03/10	01/10	01/10	01/7	01/7	30/4	01/7	01/7	01/11	01/1(99)	01/9	01/3	01/8
2nd Anniversary	20	25	40	50	50	60	60	70	75								
3rd Anniversary	30	35	50	60	60	75	80	90	100	110	115	115					
4th Anniversary	40	45	60	70	70	90	95	110	120	135	140	140					
5th Anniversary	50	55	70	80	85	110	115	130	140	160	165	165	165	165	180	250	250
6th Anniversary	60	65	80	90	100	125	135	155	170	190	195	200	200	200	200	250	250
7th Anniversary	70	75	90	100	115	145	160	180	195	220	225	235	235	235	250	250	250
8th Anniversary	80	85	100	110	130	170	185	210	230	255	265	270	270	270	300	250	250
9th Anniversary	90	95	110	120	145	195	215	240	260	290	300	305	305	305	350	250	250
10th Anniversary	100	105	120	130	160	215	245	275	300	330	340	345	345	345	400	400	450
11th Anniversary	110	115	130	140	180	240	275	310	335	370	380	385	385	385	450	400	450
12th Anniversary	120	125	140	150	200	265	305	345	375	410	420	430	430	430	500	400	450
13th Anniversary	130	135	150	160	220	290	335	380	410	450	465	475	475	475	550	400	450
14th Anniversary	140	145	160	170	240	325	370	420	455	500	515	525	525	525	600	400	450
15th Anniversary	150	155	170	180	260	360	410	465	505	550	565	575	575	575	650	900	1020
16th Anniversary										600	620	630	630	630	700	900	1020
17th Anniversary										650	670	680	680	680	800	900	1020
18th Anniversary										700	720	730	730	730	900	900	1020
19th Anniversary										750	775	790	790	790	1000	900	1020
20th Anniversary														790	1200	2000	2000
onwards														790	1200	2000	2000

Source: Patent Regulations(various versions); Regulations under Patents Act 1952, 1990 and IP Legislation (fees) Amendment Regulation under Patent Regulation 1991.

Table A.2: The (Nominal) Patent Renewal Fees (AUD$) for Patents filed in APO since 1979.

A.3 Complete estimates of the preferred model by patentees' nationality

Parameters	Estimates	Parameters	Estimates
μ_{1991}^{AU}	5.467 (0.074)	σ_{1991}^{AU}	2.149 (0.151)
β_{JP}	1.609 (0.115)	γ_{JP}	-0.477 (0.051)
β_{FR}	0.770 (0.062)	γ_{FR}	-0.333 (0.042)
β_{UK}	0.540 (0.050)	γ_{UK}	-0.141 (0.039)
β_{DE}	0.394 (0.043)	γ_{DE}	-0.235 (0.039)
β_{US}	0.683 (0.057)	γ_{US}	-0.174 (0.038)
β_{1982}	0.091 (0.037)	γ_{1981}	-0.061 (0.030)
β_{1983}	0.153 (0.027)	γ_{1982}	-0.138 (0.039)
β_{1984}	0.140 (0.029)	γ_{1983}	-0.199 (0.032)
β_{1985}	0.131 (0.031)	γ_{1984}	-0.160 (0.037)
β_{1986}	0.117 (0.028)	γ_{1985}	-0.163 (0.036)
β_{1987}	0.097 (0.029)	γ_{1986}	-0.120 (0.033)
β_{1988}	0.194 (0.033)	γ_{1987}	-0.109 (0.034)
β_{1989}	0.069 (0.036)	γ_{1988}	-0.118 (0.035)
β_{1993}	0.130 (0.046)	γ_{1989}	-0.098 (0.041)
β_{1994}	0.178 (0.036)	γ_{1992}	0.160 (0.035)
		γ_{1993}	0.165 (0.062)
δ	0.110 (0.013)		
R^2	1.000		
n	1548		

Note: standard errors are reported in brackets.

Table A.3: Complete Estimates of the Preferred Model by Patentees' Nationality.

A.4 Complete estimates of the preferred model by industry

A.5 The Rank of means of IP protections

A.6 The industries preferring patents in descending order of preference

Parameters	Estimates	Parameters	Estimates
μ_{1991}^{EM}	6.268 (0.136)	σ_{1991}^{EM}	1.889 (0.137)
β_{CH}	0.088 (0.023)	σ_{CH}	0.069 (0.026)
β_{PH}	0.082 (0.025)	σ_{PH}	0.137 (0.035)
β_{EL}	0.303 (0.027)	σ_{EL}	-0.148 (0.029)
β_{1980}	-0.211 (0.056)	σ_{1980}	0.222 (0.069)
β_{1982}	-0.127 (0.026)	σ_{1983}	-0.104 (0.025)
β_{1983}	0.056 (0.019)	σ_{1984}	-0.172 (0.060)
β_{1984}	-0.085 (0.027)	σ_{1985}	-0.101 (0.037)
β_{1985}	-0.125 (0.029)	σ_{1986}	-0.075 (0.035)
β_{1986}	-0.061 (0.023)		
β_{1987}	-0.082 (0.026)		
β_{1988}	-0.142 (0.027)		
β_{1989}	-0.078 (0.019)		
β_{1990}	-0.185 (0.026)		
β_{1992}	0.032 (0.019)		
β_{1993}	0.064 (0.027)		
β_{1994}	0.161 (0.030)		
Interaction terms: industry and cohort dummies			
$\beta_{CH,81}$	-0.088 (0.032)		
$\beta_{CH,82}$	0.123 (0.030)		
$\beta_{CH,84}$	0.161 (0.041)		
$\beta_{CH,85}$	0.177 (0.037)		
$\beta_{CH,86}$	0.133 (0.034)		
$\beta_{CH,87}$	0.149 (0.042)		
$\beta_{CH,88}$	0.240 (0.039)		
$\beta_{CH,90}$	0.134 (0.035)		
$\beta_{CH,93}$	0.087 (0.049)		
$\beta_{PH,81}$	-0.066 (0.033)		
$\beta_{PH,83}$	-0.177 (0.036)		
$\beta_{PH,85}$	0.135 (0.048)		
$\beta_{PH,86}$	0.204 (0.046)		
$\beta_{PH,87}$	0.110 (0.051)		
$\beta_{PH,88}$	0.294 (0.053)		
$\beta_{PH,90}$	0.228 (0.043)		
$\beta_{PH,92}$	0.102 (0.036)		
$\beta_{PH,93}$	0.152 (0.048)		
$\beta_{EL,82}$	0.084 (0.039)	$\sigma_{EL,81}$	0.241 (0.041)
$\beta_{EL,87}$	0.229 (0.037)	$\sigma_{EL,82}$	0.228 (0.054)
$\beta_{EL,88}$	0.192 (0.034)	$\sigma_{EL,83}$	0.253 (0.042)
$\beta_{EL,90}$	0.080 (0.029)	$\sigma_{EL,84}$	0.536 (0.081)
		$\sigma_{EL,85}$	0.318 (0.045)
		$\sigma_{EL,86}$	0.198 (0.038)
		$\sigma_{EL,87}$	0.113 (0.036)
δ	0.114 (0.015)		
R^2	1.000		
n	1036		

Note: standard errors are reported in brackets.

Table A.4: Complete Estimates of the Preferred Model by Industry.

Survey	Year	Country	1	2	3	4
Yale	1982	US	SS	LT	**PA**	SE
Carnegie-Mellon	1993	US	LT	secrecy	SS	**PA**
Japan C-M	1993	Japan	LT	**PA**	SS	SE
SESSI/INSEE EFA	1993	France	LT	**PA**	SE	CP
StatCan Innovation	1999	Canada	CF	TM	**PA**	SE
CIS 3 2000	2000	EU12	LT	SE	TM	CP

Note: CF: confidentiality; CP: complexity; LT: lead time; PA: patents; SE: secrecy; SS: sales & service; TM: trademarks.
Source: Table 1, Hall (2009).

Table A.5: The Rank of Means of IP protection.

Survey	Year	Country	1	2	3	4
Yale	1982	US	**PH**	PL	**CH**	ST
Carnegie-Mellon	1993	US	**PH**	ME	SM	PC/CH
SESSI/INSEE EFA	1993	France	**PH**	IS	TR	**CH**
CIS 3 2000	2000	EU12	TR	IS		**CH/PH**

Note: CH: chemical; IS: instruments; ME: medical instruments; PH: pharmaceutical; PL: plastic; SM: special machine; ST: steel; TR: transport equipment.
Source: Table 2, Hall (2009)Transport equip.

Table A.6: The industries preferring patents in descending order of preference.

Appendix B

Appendix for Chapter 4

B.1 Break down of population, innovators, patent and secrecy users by firm size and industry sector

	All firms	Innovator share of all firms		Patent share of all firms		Patent share of innovators		Secrecy share of all firms		Secrecy share of innovators	
		Sample	popul.	Sample	popul.	Sample	popul.	Sample	popul.	Sample	popul.
Firm size											
5-19 persons	2168	34.36%	29.32%	2.35%	1.23%	3.89%	2.20%	16.10%	14.38%	28.32%	25.70%
20-99 persons	1343	50.63%	44.80%	7.25%	5.29%	11.32%	7.18%	22.56%	21.98%	32.35%	34.88%
$\geq$ 100 persons	952	65.97%	61.39%	15.65%	12.85%	17.68%	15.45%	37.61%	33.31%	45.54%	43.92%
ANZSIC industry											
Mining	136	35.29%	29.48%	6.62%	5.27%	14.58%	12.08%	28.68%	26.33%	41.67%	41.93%
Manufacturing	1873	50.03%	44.60%	10.57%	7.43%	16.22%	12.16%	22.00%	17.92%	31.80%	28.07%
Electricity	58	51.72%	50.10%	8.62%	8.75%	6.67%	6.37%	32.76%	31.18%	46.67%	44.60%
Construction	255	40.39%	30.79%	1.18%	0.63%	0.97%	1.32%	15.69%	9.24%	32.04%	20.95%
Wholesale	302	50.66%	41.68%	8.61%	5.97%	9.15%	4.91%	25.50%	20.57%	41.18%	36.22%
Retail	295	39.66%	31.42%	1.69%	0.56%	3.42%	0.20%	15.59%	13.88%	25.64%	23.67%
Accommodation	217	32.72%	23.24%	1.38%	0.33%	1.41%	0.29%	12.44%	10.77%	22.54%	25.21%
Transport	246	44.31%	33.28%	2.03%	0.66%	3.67%	1.79%	20.73%	16.52%	31.19%	26.38%
Communication	101	50.50%	49.02%	6.93%	6.57%	11.76%	11.88%	27.72%	24.97%	47.06%	44.93%
Finance	197	55.84%	44.12%	3.55%	2.25%	2.73%	3.60%	36.04%	31.21%	48.18%	45.07%
Property	546	40.66%	29.99%	4.03%	2.00%	7.21%	4.85%	26.37%	19.44%	42.79%	34.11%
Cultural	237	43.04%	36.54%	4.64%	1.20%	6.86%	2.43%	23.63%	19.45%	36.27%	29.19%
All firms	4463	46.00%	33.78%	6.74%	2.52%	10.57%	4.49%	22.63%	16.69%	34.92%	29.50%

Table B.1: Industry Sector and Firm Size Break Down.

B.2 Bivariate and Trivariate probit models for Formal versus Informal IP protection methods

	Model 3 (Biprobit)		Model 4 (Triprobit)		
	Formal IP	Informal IP	Formal IP	Informal IP	Licensing
Licensing	0.339***	0.334***	0.634***	0.889***	
	(0.094)	(0.095)	(0.216)	(0.199)	
RDtop	0.156	0.332**	0.138	0.310	0.262
	(0.142)	(0.146)	(0.142)	(0.145)	(0.163)
RD	0.123	0.182**	0.111	0.156*	0.308**
	(0.090)	(0.082)	(0.090)	(0.082)	(0.134)
Product innovation	0.375***	0.360***	0.361***	0.329***	0.199**
	(0.066)	(0.062)	(0.067)	(0.063)	(0.086)
Process innovation	0.080	0.110*	0.070	0.078	0.185**
	(0.067)	(0.063)	(0.068)	(0.064)	(0.089)
Large	0.462***	0.268***	0.455***	0.151	0.203
	(0.107)	(0.100)	(0.107)	(0.101)	(0.138)
Medium	0.086	0.096	0.086	0.093	0.118
	(0.087)	(0.080)	(0.087)	(0.080)	(0.111)
Income over $5M	0.325***	0.118	0.321***	0.113	-0.070
	(0.087)	(0.082)	(0.087)	(0.081)	(0.112)
JointRD	0.237**	0.469***	0.127	0.260**	1.201***
	(0.105)	(0.108)	(0.127)	(0.129)	(0.104)
SOI internal	0.299***	0.338***	0.302***	0.335***	-0.132
	(0.111)	(0.102)	(0.111)	(0.101)	(0.137)
SOI institutional	0.085	0.224***	0.074	0.192***	0.164*
	(0.073)	(0.071)	(0.074)	(0.071)	(0.089)
Manufacturing	-0.267*	0.165	-0.237*	0.227*	-0.486***
	(0.140)	(0.140)	(0.141)	(0.139)	(0.166)
Mining	-0.754***	0.388*	-0.731***	0.442**	-0.524
	(0.252)	(0.228)	(0.253)	(0.226)	(0.326)
IV: BDEX					0.325***
					(0.081)
Other industry dummy	Yes		Yes		
Sample size	2053		2053		
ρ_{if} (Formal IP, Informal IP)	0.320***		0.290***		
	(0.036)		(0.036)		
ρ_{lf} (Formal IP, Licensing)			-0.162		
			(0.107)		
ρ_{li} (Informal IP, Licensing)			-0.302***		
			(0.100)		
LR test: $\rho_{21} = 0$	68.93***				
LR test: $\rho_{21} = \rho_{31} = \rho_{32} = 0$			67.91***		

Note: Numbers reported in the bracket are standard errors;
***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table B.2: Biprobit and Triprobit model for formal versus informal IP

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