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Intellectual property rights, business profitability and competition in the Australian economy

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EXECUTIVE SUMMARY

One of the key purposes of the intellectual property (IP) system is to promote economic development by creating an environment that encourages both innovation and fair competition. Granting exclusive rights, even for a limited time, may however reduce competition by increasing the market power of IP owners. Using Australian data for all businesses between 2002 and 2016, this paper shows that the economic impacts of intellectual property rights (IPRs) on business profitability are positive for profitable firms and they appear to have no negative impact on competition at the industry level.

The number of Australian businesses owning IPRs has been growing

The number of Australian actively trading businesses owning at least one patent, trade mark or design almost doubled in 15 years, from 15 195 in 2001-02 to 28 384 in 2015-16. While this is indicative of increased IP activity in the Australian economy, the overall proportion of Australian businesses that used IPRs also doubled in the 15 year period, from two to four per cent.

Users of IPRs are concentrated in Manufacturing and Wholesale Trade

Manufacturing and Wholesale Trade are the most IPR-intensive industries. Manufacturing alone accounts for eight of the top ten patent-intensive industries, five of the top ten trade mark-intensive industries and eight of the top ten design-intensive industries.

IPRs increase profits for profitable businesses

Ownership of IPRs, specifically patents, trade marks and designs, is strongly and positively associated with business profitability. Specifically, IPR owners earn two and a half times more profit than non-owners on average. Certain IPR portfolios (all three, patents and trade marks, or trade marks and designs), contribute to business profitability more significantly compared to other combinations of IPRs.

This may indicate that technological inventions (as proxied by patents) are more likely to be financially rewarding when they are also commercialised (as proxied by trade marks) and combined with aesthetic designs (proxied by design rights). We found that the number of IPRs that a business owns does not appear to be significantly associated with business profitability, which suggests that the quantity of IPRs owned alone is not a decisive factor in contributing to profitability.

No conclusive evidence that IPRs affect market competition

While IPRs give certain market power for businesses to make a profit, they may also reduce competition in the market due to the granting of exclusive rights. Not all IPRs can create a monopoly or even reduce market competition. The econometric analysis in this study does not find any overall significant impact of IPRs on market competition as measured by concentration at an industry subdivision level. Measures of concentration at the industry level are not always reflective of concentration at the market level, but at the industry level, only the Internet Publishing and Broadcasting industry is both highly concentrated and IPR-intensive.

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1. INTRODUCTION

An effective intellectual property (IP) system seeks to balance the interests of innovators and the public by providing an environment in which creativity and invention can flourish for the benefit of all. The legal system of intellectual property rights (IPRs) aims to promote economic development by creating an innovation friendly and fair competition environment. Granting exclusive rights for a limited period of time may reduce competition in the use of innovations and result in a distortion in the efficient allocation of resources. Few studies have focused on the relationships between IPRs, business profitability and competition. This is particularly true for the Australian context, where the number of comprehensive evidence based studies focusing on the economic impacts of intellectual property at both micro (business level) and macro (market level) scale has been limited. This has been partly attributable to the lack of available data required to do such research. The increasing dependence on technological progress to drive innovation and growth in the modern economy is now attracting more attention to the role of IP.

A lack of basic information on the use of IPRs in Australian businesses and industries has hampered understanding of IPRs' role in business performance. Although IP Australia maintains a comprehensive time series of administrative data for IPRs, economic data on IP has been lacking. For example, what businesses and industries in Australia use or rely more on patents, trade marks and design rights? What are the economic impacts of IPRs on Australian businesses and industries? Do they have a higher profitability than those without IPRs? What are the impacts of IPRs on market competition in Australia? Do the IPRs owned by those IP-intensive businesses reduce competition in those industries?

With these questions in mind, the Office of the Chief Economist at IP Australia integrated its Intellectual Property Longitudinal Research Data (IPLORD) into the Business Longitudinal Analysis Data Environment (BLADE) that is managed by the Australian Bureau of Statistics (ABS), paving the way to conduct a series of research studies on the economic impacts of IPRs in Australia. By using the newly available Australian firm level business and IP data ('micro data') this report provides original evidence and sheds light on how IPRs affect business profitability and market competition in the Australian economy.[1]

[1] This study focuses on patents, trade marks and designs only.

2. DESCRIPTIVE STATISTICS OF IPR OWNERS

2.1 IPR use doubled from 2002 to 2016

From 2001-02 to 2015-16, the total number of actively trading businesses increased from 0.6 to 0.7 million.[2] The number of businesses that owned at least one registrable IPR increased from 15 195 in 2001-02 to 28 384 in 2015-16, accounting for 2.3 and 4.2 per cent of active businesses respectively. The proportion of Australian businesses that have IPRs doubled over the 15 year period.

2.2 IPR owners have more employees and higher profits

To understand how IPRs impact on business performance, much can be learned from a comparison of owners of IPRs with non owners, examining differences in business characteristics such as age as well as performance variables like employment and profit. Table 2.1 shows a comparison of businesses with and without different IPR portfolios.[3] If a business owns at least one registrable IPR in a given year in the dataset, it is classed as an IPR owner, otherwise it is a non owner.

The average number of employees for non owners of IPRs is six, which is much smaller than that for any category of IPR owner. This indicates that larger businesses tend to own IPRs, which could be because it requires resources to create and maintain IPRs, or because young or small businesses that file IPRs grow to be larger and live for longer due to their IPR portfolios. Businesses with all three types of IPRs in force have the largest average number of employees, 736 employees per year, followed by businesses that own both patents and trade marks. Businesses with only registered designs have the smallest average number of employees among all the seven categories of IPR owners, but at 22 employees they are still significantly larger than non owners of IPRs.

Table 2.1 On average, businesses with IPRs are larger and more profitable

	Average number of employees	Average profit	
		per invested capital (%)	per employee ($/year)
Non-owners of IPRs	6	4.8	23 404
IPR owners	105	4.4	48 368
Type of IPRs			
Patents only	76	6.2	61 394
Trade marks only	75	3.2	37 109
Designs only	22	10.2	21 211
Patents and trade marks	416	6.4	101 278
Patents and designs	84	5.6	25 158
Trade marks and designs	281	6.5	27 366
All three types of IPRs	736	7.8	52 068

Source: ABS BLADE (2016-17 frame).

[2] BLADE includes businesses with no financial, production or employment data ('dead businesses'). For this analysis we use actively trading businesses. For the data source, refer to Appendix B.

[3] Full time equivalent (FTE) employees are obtained based on the calculation done by Hansell D., Nguyen, T. and Soriano, F. (2015). *Can we improve on a headcount? Estimating unobserved labour input with individual wage data*, paper presented at the 25th Australian Labour Market Research Conference, Fremantle WA (10 11 November 2014), ABS Canberra. In this report, employees refer to FTE employees.
Invested capital approximately equals a business's total assets minus its current liabilities. For details, see: Damodaran, A. "Return on Capital (ROC), Return on Invested Capital (ROIC), and Return on Equity (ROE): Measurement and Implications" (PDF). New York University Stern School of Business.
See also: https://www.investopedia.com/terms/r/returnoninvestmentcapital.asp or https://en.wikipedia.org/wiki/Return_on_capital. Retrieved 3 September 2019.

The average profit[4] per invested capital is similar for IPR owners and non owners in Australia,[5] but for profit per employee there are significant differences. Businesses with IPRs have more than double the average profit per employee and those who hold patents and trade marks in their portfolio have the highest average profit per employee, $101 278 per year, which is more than four times of that of non owners of IPRs. On average, non owners of IPRs have a profit ratio over invested capital of 4.8 per cent, slightly higher than the 4.4 per cent of IPR owners. This is because the majority of IPR owners are owners of trade marks only, who have a lower profit ratio over invested capital (3.2 per cent) compared with non owners of IPRs. Owners of design rights-only have the highest profit ratio over invested capital on average, at 10.2 per cent; this is likely attributable to such businesses having a relatively smaller need for physical capital, but depending more heavily on human capital, namely the skills of designers. The owners of all three types of IPRs and the remaining categories of IPR owners all have a higher average profit per invested capital than non owners of IPRs.

2.3 Almost half of large businesses, but 3% of SMEs, have IPRs

An overwhelming majority (96.5 per cent) of businesses in Australia do not own any of the three IPRs (Table 2.2). This is most pronounced in the case of small and medium enterprises (SMEs), of which 96.8 per cent do not own any IPRs, whereas the equivalent figure for large businesses is 56.1 per cent.

Large businesses own different IPR types in combination more often than SMEs, adding weight to the likelihood that the cost and complexity of IPR ownership favours large businesses. For example, 11.2 per cent of large IPR owners own a combination of patents and trade marks and 8.4 per cent own all three types of IPRs, while only 3.0 per cent and 1.3 per cent of SME IPR businesses own the same two combinations.

A much greater proportion of IPR owners own trade marks alone compared with patents and designs. Specifically, among all IPR owners, 88.7 per cent of all SME IPR owners and 73.6 per cent of all large IPR owners use trade marks only and have no other rights in their portfolio.

Table 2.2 Large businesses have a higher propensity to own IPRs in combination than SMEs

Type of owners	Large (%)	SME (%)	Overall (%)
Non-owners of IPR	56.1	96.8	96.5
IPR owners	43.9	3.2	3.5
Per cent by type of IPR owner			
Patents only	2.2	2.5	2.5
Trade marks only	73.6	88.7	87.3
Designs only	0.4	1.8	1.7
Patents and trade marks	11.2	3.0	3.7
Patents and designs	0.3	0.3	0.3
Trade marks and designs	4.0	2.4	2.6
All IPRs	8.4	1.3	1.9

Source: ABS BLADE (2016-17 frame).
Note: the overall per cent of ownership refers to the per cent of IPR owners. For example, 2.5 per cent of the 3.2 per cent of SMEs that own IPRs own a patent.

[4] This study analyses both profit per invested capital and profit per employee to measure a business's profitability as they show different aspects of a business's capability to make profit based on its two main factors of production: capital and labour. In the BLADE dataset, profit or loss is reported or can be calculated by the difference between a business's total income and its expenses. Total invested capital can be calculated by subtracting current liabilities from the total assets of a business, FTE employees are obtained based on calculations proposed by the ABS.
[5] All the Australian dollar values in the BLADE datasets have been transformed into real values using the 2015-16 fiscal year as the base year, while the GDP deflators are calculated from https://www.indexmundi.com/facts/australia/indicator/NY.GDP.DEFL.ZS, accessed on 12 June 2019.

2.4 IPR owners tend to have a longer business life

To determine the distribution of businesses with or without IPRs and with different types and combinations of IPRs by business age, we further categorise them into five groups: between 1 and 5 years of age, between 6 and 10 years, between 11 and 15 years, between 16 and 20 years, and older than 20 years (Table 2.3). For non-owners of IPRs, their percentage in each age group decreases with an increase in business age, e.g. approximately 40 per cent within 5 years, 30 per cent between 6 and 10 years, 20 per cent between 11 and 15 years, 7 per cent between 16 and 20 years, and 3 per cent over 20 years. This is not surprising as many businesses may not be able to survive in market competition for a variety of reasons. However, for IPR owners, their percentage in each age group is relatively evenly distributed, with 17 per cent within 5 years, 26 per cent between 6 and 10 years, 25 per cent between 11 and 15 years, 16 per cent between 16 and 20 years, and 16 per cent over 20 years old. This suggests that businesses with IPRs tend to have a longer business life than those without IPRs.

For owners of different types of IPRs, owners with all the three types of IPRs have the largest proportion in the category of businesses older than 20 years (53 per cent), followed by those with both patents and trade marks (40 per cent). None of the owners of various types of IPRs exhibits the clear trend of a decreasing proportion in the age distribution seen for non-owners of IPRs. This tends to confirm the hypothesis that IPR ownership, and especially combinations of multiple IPRs, may increase business profitability or give businesses an extra advantage in the competitive market, enabling them to survive for longer.

Table 2.3 Businesses with IPRs tend to have a longer business life than those without

	Distribution of IPR ownership by business age				
	1 to 5 years (%)	6 to 10 years (%)	11 to 15 years (%)	16 to 20 years (%)	Above 20 years (%)
Non-owners of IPR	39.97	29.56	19.86	7.36	3.26
IPR owners	16.83	26.04	25.27	15.80	16.06
% of IPR owners only					
Patents only	9.93	22.37	29.89	18.03	19.78
Trade marks only	17.95	27.08	25.30	15.60	14.07
Designs only	19.87	31.29	29.15	12.93	6.75
Patents and trade marks	5.18	14.94	23.00	16.96	39.92
Patents and designs	11.25	24.95	31.70	15.44	16.67
Trade marks and designs	11.43	19.80	25.62	19.43	23.73
All IPRs	2.99	9.16	17.32	17.17	53.35

2.5 IPRs concentrated in Manufacturing and Wholesale Trade

2.5.1 Overall distribution of IPR owners by industry

Manufacturing and Wholesale Trade are the industries with the most businesses using IPRs in Australia, where industries are based on the Australian and New Zealand Standard Industry Classification (ANZSIC, 2006).[6]

The distribution pattern of businesses with at least one registrable IPR in force across Australian industries has been very similar over the years studied, from 2001-02 to 2015-16. Hence, the rankings of industries with the most businesses that own at least one registrable IPR or those having the highest proportions of IPR owners do not change much over the years. Specifically, the leading industries having the most businesses owning an IPR have consistently been Manufacturing, Wholesale Trade, and Professional, Scientific and Technical Services. The leading industries ranked by their percentage of IPR owning businesses have been concentrated in Wholesale Trade, Manufacturing, and Information, Media and Telecommunications (Table 2.4). This suggests that certain characteristics of an industry play an important role in determining whether a business in that industry tends to use IPRs or not.

[6] For details of ANZSIC 2006, see: http://www.abs.gov.au/ausstats/abs@.nsf/0/EEEBBA8478AF7657CA25711F00146D6A?opendocument.

Table 2.4 IPRs are concentrated in Manufacturing and Wholesale Trade

Industry (ANZSIC division)	Average annual number over 15 years	Average annual % change over 15 years
Agriculture, Forestry and Fishing (A)	460	0.9
Mining (B)	201	6.9
Manufacturing (C)	4 133	9.6
Electricity, Gas, Water and Waste Services (D)	113	5.3
Construction (E)	1 135	1.1
Wholesale Trade (F)	3 940	11.9
Retail Trade (G)	1 834	2.9
Accommodation and Food Services (H)	631	1.4
Transport, Postal and Warehousing (I)	433	1.4
Information Media and Telecommunications (J)	576	9.7
Financial and Insurance Services (K)	1 234	4.7
Rental, Hiring and Real Estate Services (L)	675	2.2
Professional, Scientific and Technical Services (M)	3 799	4.1
Administrative and Support Services (N)	765	2.7
Public Administration and Safety (O)	93	3.3
Education and Training (P)	362	4.7
Health Care and Social Assistance (Q)	525	1.2
Arts and Recreation Services (R)	254	3.4
Other Services (S)	732	1.8

Source: BLADE (2016-17 frame)

2.5.2 IPR-intensive industries

Patent intensive industries are dominated by manufacturing activities, which account for half of the top 25 per cent industries, the top three all coming from the Manufacturing division. The rest of the top patent intensive industries are concentrated in the Wholesale Trade, Mining, and Information Media and Telecommunications industries. Tertiary Education (P81), mainly including universities, and Professional, Scientific and Technical Services (M69) are also relatively patent intensive.

Trade mark intensive industries are also dominated by manufacturing activities, which account for about half of the top 25 per cent industries. The remaining top trade mark intensive industries are concentrated in the Wholesale Trade, Information Media and Telecommunications, and Arts and Recreation Services industries.

Similarly, the list of highly design intensive industries is mainly dominated by Manufacturing and Wholesale Trade activities, while the industry subdivisions that have been identified as highly intensive in all three types of IPRs since 2001-02 are concentrated in the Manufacturing, Wholesale Trade, and Information Media and Telecommunications industries.

Table 2.5 summarises Australia's IPR-intensive industries based on analysis of 87 ANZSIC subdivisions, highlighting industries that are intensive in all three IPRs.

We applied a method for identifying IPR-intensive industries that was similarly employed by the USPTO, the EPO/EUIPO and UKIPO to identify their respective IPR-intensive industries.[7] For example, this paper identifies those industries whose total number of patents over its total employee is above the average of all industries as patent intensive industries in Australia using ANZSIC (2006) industry subdivisions. As the Type of Activity Units (TAUs) of some complex businesses in the BLADE are constructed based on the ANZSIC industry subdivision (2 digit level), this paper has used this industry subdivision level for determining IPR intensities. The same methodology applies to identification of trade mark and design-intensive industries.

[7] For the method used to determine IPR-intensive industries, refer to Appendix C.

Table 2.5 Manufacturing & Wholesale Trade are the main IPR-intensive sectors [8]

			IPR-intensive (IPRs per 1 000 employees)			
	ANZSIC	NACE description*	Patents	TMs	Designs	All
	A02	Aquaculture			9.1	
	B06	Coal Mining	2.4			
	B08	Metal Ore Mining	6.4			
Manufacturing	C11	Food Product Manufacturing		37.1		
Manufacturing	C12	Beverage and Tobacco Product Manufacturing		151.4	1.2	
Manufacturing	C13	Textile, Leather, Clothing and Footwear Manufacturing	1.5	62.8	6.7	Yes
Manufacturing	C15	Pulp, Paper and Converted Paper Product Manufacturing	5.8	37.7	7.4	Yes
Manufacturing	C17	Petroleum and Coal Product Manufacturing	4.6			
Manufacturing	C18	Basic Chemical and Chemical Product Manufacturing	7.2	82.5	1.5	Yes
Manufacturing	C19	Polymer Product and Rubber Product Manufacturing	7.8	72.7	25.8	Yes
Manufacturing	C20	Non-Metallic Mineral Product Manufacturing	4.9	59.5	10.4	Yes
Manufacturing	C21	Primary Metal and Metal Product Manufacturing	12	34.6	13.2	Yes
Manufacturing	C22	Fabricated Metal Product Manufacturing	9	37.7	25.8	Yes
Manufacturing	C23	Transport Equipment Manufacturing	2.6		5.3	
Manufacturing	C24	Machinery and Equipment Manufacturing	12.8	44.5	11.1	Yes
Manufacturing	C25	Furniture and Other Manufacturing	2.6	44.2	9.6	Yes
	D27	Gas Supply	3.1	80.3		
	D28	Water Supply, Sewerage and Drainage Services	1.5			
Wholesale Trade	F33	Basic Material Wholesaling	1.5	38.8	5.6	Yes
Wholesale Trade	F34	Machinery and Equipment Wholesaling	2.3		3.4	
Wholesale Trade	F35	Motor Vehicle and Motor Vehicle Parts Wholesaling			2.9	
Wholesale Trade	F36	Grocery, Liquor and Tobacco Product Wholesaling		49.9		
Wholesale Trade	F37	Other Goods Wholesaling	1.4	143.4	6	Yes
Wholesale Trade	F38	Commission-Based Wholesaling		30.2	1	
	G42	Other Store-Based Retailing			1.2	
	G43	Non-Store Retailing and Retail Commission-Based Buying and/or Selling		76.6		
	J54	Publishing (except Internet and Music Publishing)		47		
	J56	Broadcasting (except Internet)		83.4		
	J57	Internet Publishing and Broadcasting	8.6	105.1	1	Yes
	J60	Library and Other Information Services	1.4			
	M69	Professional, Scientific and Technical Services	3.1		0.9	
	P81	Tertiary Education	6.1			
	R90	Creative and Performing Arts Activities		54.2	1.7	
	R92	Gambling Activities		44.3		

Source: ABS BLADE (2016-17 frame).

Having identified key characteristics of the businesses in the BLADE data, such as their size, age, and distribution by industry, our analysis now seeks to compare the profitability performance between owners and non owners of IPRs, and among owners of different types of IPRs. A central research question is to discover whether IPR-intensive industries are also positively correlated with industries that have relatively higher market concentration. Or in other words, whether owning more IPRs tends to reduce market competition, given IPRs grant their owners exclusive rights protecting them from their competitors for new innovation. In the next two sections, we apply econometric models to estimate the relationship between business profitability and ownership of IPRs as well as the relationship between IPRs on market concentration at an industry sector level as a measure of competition.

[8] Only the top 20 intensive industries are listed for each IP right.

3. IPRS AND BUSINESS PROFITABILITY

This section focuses on examining the link between IPRs and business profitability. Econometric modelling is applied to estimate the relationship between a business's profitability and its ownership and stock of IPRs separately and in combination. Applying econometric techniques to the dataset makes it possible to control for external influences on a business's profitability to the greatest extent possible. Factors such as past profitability performance, business employment and age, industry affiliation and other characteristics can be controlled in order to measure the relatively independent contribution of IPRs to business profitability on average.

3.1 Econometric analysis and selection of variables explained

Econometric analysis involves examining the relationship between a variable, called the dependent variable, whose movements are to be explained by a set of explanatory or independent variables.

This subsection describes the selection of the dependent variable and the explanatory variables, while the econometric modelling and results are discussed in subsection 3.2.

3.1.1 Dependent variable

A central aim of this study is to analyse the relationship between IPRs and business profitability. Therefore, the dependent variable of the models needs to be an indicator of business profitability. This study chooses both profit per invested capital and profit per employee to measure a business's profitability as they may each show different aspects of a business's capability to make profit based on the two major factors of production, capital and labour.

In this study, the distribution of the profitability variables and some of the explanatory variables are highly skewed. Logarithmic transformation is a convenient way of transforming a highly skewed variable into one that is more approximately normally distributed after transformation. Therefore, both profitability indicators are further logarithmically transformed to fit the linear regression model. Finally, it is appropriate to make a logarithmic transformation when we want to find out what a given percentage change in a logarithmic explanatory variable will lead to a constant percentage change in the logarithmic dependent variable. A major disadvantage of logarithmic transformation is that any businesses with negative or no profit will be dropped from the econometric estimation.

3.1.2 Explanatory variables

The determinants of business profitability have been a subject of research by various fields of research, but very few studies have explored the impact of IPRs on business profitability. The OHIM Report (2015), a pioneer study, examined whether IPR owners, different types of IPRs, or the stock of IPRs might have a statistically significant impact on a business 's performance in terms of average revenue per employee.

In reality, it is almost impossible to include all the potential determinants of profitability in a model simply due to data availability. There are always unobserved factors that may have an impact on both dependent and independent variables, such as managerial ability, operational efficiency and relationships among colleagues. An estimation strategy is to include one or more lagged dependent variables as explanatory variables which may control for past outcomes and alleviate the omitted variable problem. This method is called dynamic panel estimation.

There is some argument on whether a model should include a lagged dependent variable (Achen 2000; Keele and Kelly 2005; Wilkins 2018). We have included lagged business profitability in our model as the past level of a business's profitability is likely to contribute to its current level of profitability by using its past profit to reinvest in more productive labour and capital. As such, not including the lagged business profitability would lead to an omitted variable problem and the results might be biased and unreliable. While including the lagged dependent variable is methodologically necessary, it also introduces a risk of new endogeneity in the model. However, the potential endogeneity problem may be alleviated by using statistical techniques such as the Generalised Method of Moments (GMM). More details are discussed in Appendices D and E.

Our model then seeks to explain the differences between businesses in their profitability, as represented by profit per invested capital or profit per employee, by a set of explanatory variables, which fall into three main categories:

1) lag(s) of profitability;

2) a set of variables that measure the impact of IPRs, including IPR ownership dummies and IPR stocks; and

3) a set of control variables that measure or control for non-IPR factors, such as age and industry, that affect business profitability (see Appendix E for details).

3.2 Econometric modelling and results

Following the literature, and in view of our data characteristics which feature an unbalanced panel dataset with large cross section groups and relatively short time periods, we use System GMM models to estimate regressions concerning the determinants of profitability. The use of dynamic panel estimators has the following advantages over traditional models, such as OLS regressions, random effects and fixed effects panel models: (i) greater control of endogeneity; (ii) greater control of possible collinearity of the explanatory variables; and (iii) greater effectiveness in controlling the effects caused by the absence of explanatory variables relevant in explaining the dependent variable.[9] The basic linear dynamic model to estimate is expressed as follows:

$$\mathrm{Ln(Profitability)}_{i,t} = \alpha + \beta \mathrm{Ln(Profitability)}_{i,t-l} + \gamma IP_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$$

(Equation 1)

where $\mathrm{Ln(Profitability)}_{i,t}$ denotes the business profitability indicator (natural logarithmic transformation of average profit per invested capital or profit per employee) for business *i* in year *t*, $\mathrm{Ln(Profitability)}_{i,t-l}$ represents lagged profitability (t-l, in which l can be 1, 2, and any number depending on the appropriate lag structure) for business *i* respectively. The term $IP_{i,t}$ includes a set of business IPR features, such as IPR owner or not, IPR ownership of different types of IPRs and their combinations, and stock of different types of IPRs, while the term $X_{i,t}$ contains a set of control variables such as business age, industry and year dummies. The basic model assumes that a business's current profitability is a function of, or mainly determined by, its previous year(s)' profitability, IPR features, and other business , industry and time effects.

Moreover, $\varepsilon_{i,t}$ is the error term of the equation, which can be expressed in two parts, u_i and $v_{i,t}$. The term u_i represents all unobserved time invariant variables, which will be removed during the System GMM estimation. The term $v_{i,t}$ is assumed to be normally distributed with a mean of zero, constant variance, and independent of the other explanatory variables after we have the correct specification of the System GMM model. The constant term α measures a common value of the dependent variable when all the explanatory variables are equal to zero. The coefficients β, γ, and δ are vectors of coefficients of explanatory variables respectively. For example, an estimated coefficient of β measures how much a one per cent change in a previous year's profitability may change the current year's profitability, holding other factors in the regression constant. However, it is important to note that if an explanatory variable is a dummy variable, while its dependent variable is in logarithmic form, the estimated coefficient of the explanatory dummy variable is not the exact percentage change in the dependent variable. To

[9] For details, see Arellano and Bond, 1991 and 1998, and Roodman 2009.

obtain the exact marginal effect in the predicted dependent variable, an additional calculation using properties of exponential and logarithmic functions is necessary.[10]

To determine the relatively independent impact of IPR ownership, different types of IPRs, and stocks of IPRs on business profitability, we further develop three sets of regression models based on Equation 1 and discuss each of them in the following three subsections.

3.2.1 Business profitability and IPR ownership

In the first set of regressions (hereafter Model 1.1), the term IP in Equation 1 is represented by an IPR ownership dummy variable, which equals one if a business owns at least one registrable IPR in a given year between 2001-02 and 2015-16, otherwise it equals zero.

First, it is necessary to determine which explanatory variables are endogenous or exogeneous. By definition, the lagged dependent variables are endogenous, as there is a clear correlation between the error term and the lagged dependent variables. The term IP is likely to be endogenous as a business's IP features, IP ownership or the stock of IPRs, are likely to be influenced by past profitability, and may be correlated with unobserved factors in the error term. For other control variables including age, year and industry dummies, they are treated as exogenous variables since they are unlikely to be influenced by unobserved factors in the residual term.

Second, we need to decide how many lags of the dependent variable should be used. Wintoki, Linck and Netter (2012) argue that if full information from the past that affects the present is not incorporated, the endogeneity problem may still exist. Only the earlier lags are exogeneous to current residuals, so they can be used as instruments. Following Abdallah et al. (2015), we find the appropriate number of lags by adding them one by one until a particular lag of the dependent variable becomes insignificant (or has a suspiciously larger impact than its previous lag as it usually should have a decreasing impact over the years).

To obtain the correct specification of the System GMM estimation, another important rule is to run OLS and fixed effects regressions respectively to set an upper and lower bound for the lagged dependent variable, and to check whether the System GMM estimators fall in this range (Bond 2002). Finally, the Hansen (1982) test and the Arellano Bond test for AR(2) are needed to ascertain whether the instruments are valid without overidentifying issues and that there is no serial correlation after adopting the System GMM.

The final regression results are reported in Table 3.1, with the results on the dependent variable of profit per invested capital on the left side of the table and those of profit per employee on the right side. Their comparison tables with OLS and fixed effects models are reported in the Appendix F Tables F.1 and F.2 respectively. The estimated coefficients of the lagged dependent variables fall in the range between the OLS and fixed effects estimates, and the Hansen test and AR(2) test have been satisfied under each specification of the System GMM.

[10] The mathematical transformation of the marginal effect of a dummy explanatory variable on a logarithmically transformed dependent variable is: $\% \Delta \hat{y} = [\exp(\hat{y}) - 1] * 100$.

Table 3.1 IPR ownership contributes to business average profitability

Dependent variable: Log (profit per invested capital)		System GMM of Model 1.1	Dependent variable: Log (profit per employee)		System GMM of Model 1.1
Explanatory variables		^	**Explanatory variables**		^
IPR owner		1.28*** (2.56)	**IPR owner**		1.24*** (2.46)
Lags of log of profit per invested capital	**Lag1**	.51***	**Lags of log of profit per employee**	**Lag1**	.49***
	Lag2	.13***		**Lag2**	.18***
	Lag3	.04***		**Lag3**	.09***
	Lag4	.02***		**Lag4**	.05***
	Lag5	.01**		**Lag5**	.03***
	Lag6	.006		**Lag6**	.02***
				Lag7	.01***
				Lag8	.004
Age of business		-.05***	**Age of business**		-.02***
Industry dummies		Yes°	**Industry dummies** ~		Yes°
Year dummies		Yes°	**Year dummies** ~		Yes°
Constant		5.48***	**Constant**		1.56***
Number of observations		468 017	**Number of observations**		328 583
Number of instruments/groups		35/138 027	**Number of instruments/groups**		35/96 834
F statistics		2 327.84***	**F statistics**		1 586.99***
Arellano-Bond test for AR(2)		.649	**Arellano-Bond test for AR(2)**		.356
Hansen test of joint validity of instruments		.359	**Hansen test of joint validity of instruments**		.106

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
^ Figures in parentheses are marginal impact after exponential transformation from logarithmic form. For example, exp(1.28)-1=2.56.
° Industry and year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

IPR ownership does contribute significantly to businesses' average profit per invested capital and profit per employee after controlling for their past profitability and certain other business, industry and time characteristics. The estimated coefficient of the IP ownership dummy variable indicates that IPR owners have approximately 2.5 times higher profit than non-owners on average, all else being equal.[11] It should be noted when interpreting these results that only businesses that have been making a profit in the past six years at least have been used in this estimation due to the log transformation of the probability indicator. Any negative or no profit observations are necessarily dropped from the analysis.

The results also show that a one per cent increase in the previous year's average profitability tends to increase the business's profitability in the current year by approximately 0.5 per cent, holding other things constant. The lagged effect decreases over the years and dies on the sixth lag for profit per invested capital, while that on profit per employee fades away after seven lags. The age of a business has a small but negative impact on a business 's profitability, indicating that on average it becomes harder for a business to continue to be profitable, holding other things constant. This suggests that businesses need to invest in innovation to survive in market competition.

[11] The mathematical transformation of the marginal effect of a dummy explanatory variable on a logarithmically transformed dependent variable is: exp(1.28) - 1 = 2.5 and exp(1.24) - 1 = 2.5

3.2.2 Business profitability and types of IPRs

In the second set of regressions (hereafter Model 1.2), the term IP in Equation 1 is represented by seven ownership dummies of different types of IPRs and their combinations to replace the single IPR ownership dummy in Model 1.1. Specifically, we categorise owners of IPRs into seven groups, namely those with only patents, trade marks or designs, or patents and trade marks, patents and designs, trade marks and designs, or all the three types. Similarly to the previous section, we sought to determine the appropriate number of lags of the dependent variable that should be included as the explanatory variables and run both OLS and fixed effects models to obtain the correct System GMM specification.

The final regression results are reported in Table 3.2, with the results of the dependent variable of profit per invested capital on the left side and those of profit per employee on the right side. Their comparison tables with OLS and fixed effects models are reported in Appendix F Tables F.3 and F.4 respectively. The estimated coefficients of the lagged dependent variables fall in the range between the OLS and fixed effects estimates, and the Hansen and AR(2) tests have been satisfied under each specification of the System GMM. For example, the coefficient of 1.19 means that for owners of patents only, their profit is approximately 2.3[12] times higher than non-owners of IPRs on average for profitable businesses.

Table 3.2 Different types or combinations of IPRs have a positive impact on business profitability

Dependent variable: Log (profit per invested capital)		System GMM of Model 1.2	Dependent variable: Log (profit per employee)		System GMM of Model 1.2
Explanatory variables		^	Explanatory variables		^
Owners of different types of IPRs	Patents only	1.19 (2.29)***	Owners of different types of IPRs	Patents only	1.19 (2.29)***
	Trade marks only	1.39 (3.01)***		Trade marks only	1.16 (2.19)***
	Designs only	0.43 (0.54)**		Designs only	0.58 (0.79)**
	Patents and trade marks	2.14 (7.50)***		Patents and trade marks	1.76 (4.81)***
	Patents and designs	0.66 (0.93)		Patents and designs	0.99 (1.69)**
	Trade marks and designs	1.77 (4.87)***		Trade marks and designs	1.65 (4.21)***
	Patents, trade marks and designs	2.05 (6.77)***		Patents, trade marks and designs	1.64 (4.16)***
Lags of log of profit per invested capital	Lag1	.52***	Lags of log of profit per employee	Lag1	.49***
	Lag2	.13***		Lag2	.18***
	Lag3	.04***		Lag3	.09***
	Lag4	.02***		Lag4	.05***
	Lag5	.01**		Lag5	.03***
	Lag6	.006*		Lag6	.02***
				Lag7	.01***
				Lag8	.004
Age of business		-.055***	Age of business		-.02***
Industry dummies		Yes°	Industry dummies		Yes°
Year dummies		Yes°	Year dummies		Yes°
Constant		.5***	Constant		1.58***
Number of observations		468 017	Number of observations		328 583
Number of instruments / groups		53/138 027	Number of instruments / groups		47/96 834
F statistics		1780.4***	F statistics		1339.70***
Arellano-Bond test for AR(2)		.623	Arellano-Bond test for AR(2)		.368
Hansen test of joint validity of instruments		.189	Hansen test of joint validity of instruments		.158

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
^ Figures in parentheses are coefficients after exponential transformation from logarithmic form.
° Industry and year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

[12] The mathematical transformation of the marginal effect of a dummy explanatory variable on a logarithmically transformed dependent variable is: exp(1.19) -1 = 2.3

Different types or combinations of IPRs have a different but overall significantly positive impact on business profitability in terms of both profit per invested capital and profit per employee. More specifically, on average, businesses with multiple IPRs have a higher average profitability than those with single types of IPRs, but those with designs only or with both patents and designs have a relatively lower average profitability. Businesses with both patents and trade marks, all three IPRs, and both trade marks and designs are the top three ownership types for highest average profitability.

We also obtained consistent results for lagged dependent variables in Model 1.2: roughly a one per cent increase in the previous year's average profitability tends to increase the business's profitability in the current year by approximately 0.5 per cent, holding other things constant. The lagged effect decreases over the years and fades away after six lags for profit per invested capital, while that on profit per employee expires on the eighth lag. Similar findings of a small but significantly negative impact of business age on profitability are also found in Model 1.2, which reinforces the Model 1.1 finding that on average it becomes harder for a business to continue to be profitable as it gets older, holding other things constant.

3.2.3 Business profitability and stocks of IPRs

In the third set of regressions (hereafter Model 1.3), stocks of the three types of IPRs are used to test their impact on business profitability as the previous two models do not distinguish between IPR owners with respect to the number of IPRs held. For example, a business that holds only one patent is treated in the previous two models the same as a business that holds 100 patents. This section investigates the relationship between a business's profitability and the number of patents, trade marks or designs it owns.

The stock of patents, trade marks or designs respectively is measured for a business based on its total number of valid rights at the end of a fiscal year. As the three types of IPRs have different life cycles, the stocks of patents, trade marks and designs were calculated separately. They were further divided by the number of FTE employees in the business, to account for the heterogeneity of different business sizes in the model and then transformed logarithmically to fit them in the linear regression.

Similar to the first two models, we tested to find the appropriate number of lags of the dependent variable that should be included as explanatory variables by running both OLS and fixed effects models to obtain the correct System GMM specification. The final regression results are reported in Table 3.3, with the results on the dependent variable of profit per invested capital on the left side and those of profit per employee on the right side. Their comparison tables with OLS and fixed effects models are reported in Appendix F Tables F.5 and F.6 respectively. The estimated coefficients of the lagged dependent variables fall in the range between the OLS and fixed effects estimates, and the Hansen and AR(2) tests have been satisfied under each specification of the System GMM.

The results from this model indicate there is no overall significant impact of a business's number of patents, trade marks or designs on its profitability, or at least no strong positive impact is found for a business's number of IPRs on its profitability. This suggests that the quality of IPRs owned by a business may play a more important role in its profitability than the quantity. This model finds a much shorter lagged effect of profitability when we use stocks of IPRs in Equation 1, and the effect fades away after the second lag. The number of observations valid for the estimation of this particular model is reduced significantly because the number of businesses with a valid stock of all three types of IPRs is relatively small. Robustness tests were conducted for individual IP rights—patents, trade marks and designs—by changing the appropriate number of lags for both profitability indicators and the results remain robust.

Table 3.3 There is no overall significant impact of a business's number of IPRs on its profitability

Dependent variable: Log (profit per invested capital)		System GMM of Model 1.3	Dependent variable: Log (profit per employee)		System GMM of Model 1.3
Explanatory variables			**Explanatory variables**		
Stock of three types of IPRs per employee	**Log of patents per employee**	-.30	**Stock of three types of IPRs per employee**	**Log of patents per employee**	-.26
	Log of trade marks per employee	.17		**Log of trade marks per employee**	-.02
	Log of designs per employee	-.21		**Log of designs per employee**	.30
Lags of log of profit per invested capital	**Lag1**	.43***	**Lags of log of profit per employee**	**Lag1**	.53***
	Lag2	.21**		**Lag2**	.19**
Age of business		-.05**	**Age of business**		.01
Industry dummies		Yes°	**Industry dummies**		Yes°
Year dummies		Yes°	**Year dummies**		Yes°
Constant		4.49	**Constant**		-16.33
Number of observations		581	**Number of observations**		605
Number of instruments / groups		60/158	**Number of instruments / groups**		31/165
F statistics		7.75***	**F statistics**		42.06***
Arellano-Bond test for AR(2)		.707	**Arellano-Bond test for AR(2)**		.533
Hansen test of joint validity of instruments		.135	**Hansen test of joint validity of instruments**		.130

Source: ABS BLADE (2016-17 frame).

Notes
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
° Industry and year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

4. IPRS AND MARKET COMPETITION: ECONOMETRIC ANALYSIS

While intellectual property rights may confer a certain market power on businesses for them to make a profit, they may also reduce competition in the market due to their granting of exclusive rights—effectively, a monopoly—to exploit intellectual property, such as patented technologies. However, not all IPRs can cause a monopoly or even reduce market competition significantly. In fact, it is quite rare that an IPR can grant a monopoly power for very long as current technologies develop rapidly and rival technologies can quickly emerge as substitutes, eroding market power for the IPR owner (Bostyn & Petit 1989). Moreover, the protection, scope and term for new inventions that are regulated by intellectual property laws may also limit market power. This study investigates whether IPRs have any statistically significant impact on market competition on average, as measured by the proxy, market concentration.

The Herfindahl Hirschman Index (HHI) is a measure of market concentration that is widely used to determine market competitiveness. It is calculated by squaring the market share of each business competing in a market and then summing the resulting numbers. It can range in value from close to zero to one.[13] A marketplace is generally considered to be competitive if it has a HHI of less than 0.15, while an HHI of 0.15 to 0.25 is considered to be a moderately concentrated marketplace, and an HHI of 0.25 or greater, a highly concentrated marketplace. The closer a market's HHI is to one, the higher the market's concentration (and the lower its competition). If, for example, there were only one business in an industry, that business would have 100 per cent market share, and the HHI would equal one, indicating a monopoly. If there were thousands of businesses competing and each had a relatively equal market share, the HHI would be close to zero, indicating nearly perfect competition.

Using businesses's market share information from BLADE, the HHI was constructed for all industry subdivisions (at 2 digit level) for each year in the 2001-02 to 2015-16 period studied. Table 4.1 lists the industry subdivisions with the highest market concentration, which have an average HHI above 0.25.

Table 4.1 Only Internet Publishing and Broadcasting is both highly market concentrated and intensive in all three types of IPRs

ANZSIC code	NACE description	Average HHI
J58	Telecommunications Services	0.40
J57	Internet Publishing and Broadcasting	0.39
O76	Defence	0.37
I49	Air and Space Transport	0.35
C17	Petroleum and Coal Product Manufacturing	0.34
I51	Postal and Courier Pick-up and Delivery Services	0.32

Source: ABS BLADE (2016-17 frame).

[13] Or it can range from close to zero to 10,000 if the absolute value of the percentage point is adopted in calculation instead of the per cent. Consider, for example, a market that has only one company with a market share of 100%. Using percent, the HHI is 100%*100% = 1, but using percentage point, we get 100*100 = 10 000. Either method is correct, depending on the definition used.

Comparing the highly market concentrated industries with those labelled as IPR-intensive industries in Section 2.8.2, we find that only Internet Publishing and Broadcasting (J57) is both highly market concentrated and intensive in all the three types of IPRs. Telecommunications Services (J58) is at the medium intensive level (above average, but not in the top 20 per cent) in all three types of IPRs, and Petroleum and Coal Product Manufacturing (C17) is highly intensive in patents only, while the remaining industry subdivisions with high market concentration are not IPR-intensive. As such, there may be reasons unrelated to IPRs that cause these industries to be highly market concentrated, such as government control and a high threshold for initial investment to enter a market (e.g. Defence and Air and Space Transport).

Next, we focus on the relationship between IPRs and market competition at the ANZSIC industry subdivision (2 digit) level. A total of 87 industry subdivisions are identified and assigned to each business in the BLADE dataset according to the ANZSIC 2006 industry classification code. Econometric modelling is applied to test whether patent, trade mark and/or design intensive industries are more likely to lead to market concentration, and whether the total amount of patents, trade marks or designs in a market (stocks of the three types of IPRs at an industry subdivision level) may have a significant impact on market concentration.

4.1 Econometric modelling

To test the above questions, a similar method of using dynamic panel regressions as in Section 3.3 is adopted. The basic model is as follows:

$$\text{Log}(HHI_{s,t}) = \alpha + \beta \text{Log}(HHI_{s,t-l}) + \delta IPR_{s,t} + \eta T_t + \varepsilon_{s,t} \quad \text{(Equation 2)}$$

where $\text{Log}(HHI_{s,t})$ is the natural logarithmic transformation of the Herfindahl Hirschman Index of an industry sector (s) in year (t), while $\text{Log}(HHI_{s,t-l})$ is a set of lagged dependent variables (*t-l*, in which *l* can be 1, 2, or any number, depending on the lag structure). The term $IPR_{s,t}$ is represented by two sets of IPR features in an industry in year(t), depending on (1) whether it is patent, trade mark or design intensive, and (2) its stock of each type of the IPRs per thousand FTE employees at subdivision level. T_t refers to a set of year dummy variables, which captures a year specific effect, while $\varepsilon_{s,t}$ is the error term of the equation. The constant term α measures a common value of the dependent variable when all the explanatory variables are equal to zero. The coefficients β, δ, and η are vectors of coefficients of the explanatory variables respectively.

In contrast to the unbalanced panel data at the business level in Section 4.3, this is a strongly balanced panel dataset with 87 groups of industry subdivisions (N) and 15 time periods (T) from 2001-02 to 2015-16. Both Difference GMM and System GMM are adopted to address the potential econometric issues related to dynamic panel data and to check the results' robustness. Pooled OLS and fixed effects models were also separately applied to set upper and lower bounds to check the results obtained from different GMM estimations (Bond 2002).

4.1.1 Market concentration and IPR intensity

In the first set of regressions (hereafter Model 2.1), the term IPR in Equation 2 is represented by patent, trade mark and design intensive industry dummies respectively. For example, a patent intensive industry dummy equals one if an industry is measured as a patent intensive industry in a given year, as defined in Appendix C (which is in above the average value, based on the ranking of the number of patents per 1 000 employees in an industry), otherwise it equals zero.

Next, following a similar method as in Section 3.3, lagged dependent variables and the proxies for the term IPR are treated as endogenous variables in GMM estimation, while the year dummies are treated as exogenous variables. To find the appropriate number of lags of the dependent variable that should be included as the explanatory variables, we run both OLS and fixed effects models to obtain the upper and lower bounds for GMM estimated lagged dependent variables. The final regression results are reported in Table 5.2, with the results of Difference GMM on the left side and those of System GMM on the right side. Their comparison tables with OLS and fixed effects models are reported in Appendix F Table F.7. The estimated coefficients of the lagged dependent variables fall in the range between the OLS and fixed effects estimates, and the Hansen and AR(2) tests have been satisfied under both Difference GMM and System GMM.

Table 4.2 IPR-intensive industries do not significantly affect the HHI

Explanatory variables		Difference GMM	Explanatory variables		System GMM
IPR-intensive industry dummies	Patent-intensive industry	-.01	IPR-intensive industry dummies	Patent-intensive industry	-.06
	Trademark-intensive industry	-.08		Trademark-intensive industry	-.12
	Design-intensive industry	-.06		Design-intensive industry	-.19
Lags of log of HHI	Lag1	.56***	Lags of log of HHI	Lag1	.60***
	Lag2	.09		Lag2	.10*
Year dummies		Yes°	Year dummies		Yes°
Number of observations		1 044	Number of observations		1 131
Number of instruments / groups		67/87	Number of instruments / groups		69/87
F statistics		17.52	F statistics		29.77
Arellano-Bond test for AR(2)		.325	Arellano-Bond test for AR(2)		.335
Hansen test of joint validity of instruments		.374	Hansen test of joint validity of instruments		.441

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
° Year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table.
The regression results can be provided on request.

The results indicate that on average none of any type of IPR-intensive industries contribute significantly to the industry's market concentration measure - HHI. Both Difference GMM and System GMM produce quite similar and robust results. They also show that a one per cent increase of the previous year's HHI tends to increase the current year's HHI for the industry by approximately 60 per cent, holding other things constant. The lagged effect decreases and fades away after the second lag.

4.1.2 Market concentration and stocks of IPRs

In the second set of regressions (hereafter Model 2.2), stocks of the three types of IPRs are incorporated in the model to test whether they may have any overall impact on market competition. Theoretically speaking, the larger the number of patents in an industry, the less the competition in that industry's market is likely to be, as patents' exclusive rights may give certain market power to their owners, thus reducing competition. However, with the increase of patents in an industry, the patented technologies by rival producers may also provide the market with substitutes between these products, offering alternative choices for both producers and consumers. Similarly, a growing number of trade marks and designs in an industry may indicate the diversity of products in a market, despite their protection by exclusive IPRs.

We used the total number of valid patents, trade marks and designs in an ANZSIC industry subdivision in a given fiscal year as their annual stocks, divided them by the total number of employees in that industry to control for different industry sizes, and further transformed them logarithmically to fit them in the linear regressions.

As in the previous subsection, we tested to find the appropriate number of lags of the dependent variable that should be included as the explanatory variables by running both OLS and fixed effects models to obtain the right Difference and System GMM specification. The final regression results are reported in Table 4.3, with the results of Difference GMM on the left side and those of System GMM on the right side. Their comparison table with OLS and fixed effects models is reported in Appendix F Table F.8. The estimated coefficients of the lagged dependent variables fall in the range between the OLS and fixed effects estimates, and the Hansen and AR(2) tests have been satisfied under both Difference GMM and System GMM.

Table 4.3 Stocks of IPRs in an industry do not affect the industry's market concentration

Explanatory variables		Difference GMM	Explanatory variables		System GMM
Stock intensity of the three different types of IPRs	Log of patents per 1 000 employees	.003	Stock intensity of the three different types of IPRs	Log of patents per 1 000 employees	-.10
	Log of trade marks per 1 000 employees	-.22		Log of trade marks per 1 000 employees	-.04
	Log of designs per 1 000 employees	.03		Log of designs per 1 000 employees	-.03
Lags of log of HHI	Lag1	.59***	Lags of log of HHI	Lag1	.68***
	Lag2	.10		Lag2	.14
Year dummies		Yes °	Year dummies		Yes °
Number of observations		753	Number of observations		829
Number of instruments / groups		67/75	Number of instruments / groups		72/76
F statistics		17.63	F statistics		35.18
Arellano-Bond test for AR(2)		.462	Arellano-Bond test for AR(2)		.541
Hansen test of joint validity of instruments		.543	Hansen test of joint validity of instruments		.397

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
° Year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

The results indicate that on average stocks of patents, trade marks or designs in an industry do not affect the industry's market concentration significantly. Both Difference GMM and System GMM produce a quite similar and robust result.

While industry concentration levels measured by the HHI are a widely accepted proxy for market competition, high levels of market concentration do not necessarily indicate a lack of competition in the market. Highly concentrated markets with low barriers to entry can be competitive. Even if barriers to entry are significant, competition can still be effective in highly concentrated markets with a maverick business or a strong competitive fringe as IPRs can assist innovative businesses to erode the monopoly advantage of incumbents.

In the absence of conflicting evidence from other measures of competition, our findings hold that IPR-intensity and stocks of IPRs are not associated with an increase in market concentration at an overall industry subdivision level.

5. CONCLUSION

This study examines the relationship between IPRs, business profitability and market concentration to provide an evidence base to support future competition and industry policy development. We found that Australian businesses that own any of the three types of IPRs, especially those with multiple types of IPRs, are more likely to perform better in terms of profitability (average profit per invested capital or per employee) than businesses that do not own any IPRs.

However, the number of IPRs that a business owns does not appear to be significantly associated with business profitability. A potential implication is that IP policy should aim not at increasing the number of IPRs alone but should rather focus more on the quality of IPRs, the underlying innovations they are protecting and how businesses exploit IPRs in the marketplace.

IP activity increased over the 15 years from 2001-02 to 2015-16, with the overall proportion of IPR owning businesses doubling in this period.

We did not find any significant impact of IPRs on market concentration at an industry level. This suggests that Australia's IPR system does not currently give rise to strong concerns about its impact in terms of inhibiting market competition significantly at an overall industry level.

APPENDIX A: IP ECONOMICS AND LITERATURE REVIEW

IPRs protect the creation of new knowledge or information which, although intangible in nature, is costly to produce. In fact, it usually takes a considerable amount of human and financial resources to create new knowledge. Knowledge often has the characteristics of a public good: it is non rival and non excludable in consumption. The non rival character of knowledge implies that the amount of knowledge available to any user does not decrease when others use it, while the non excludable character of knowledge refers to the fact that once it is produced, others cannot be stopped from benefiting from it. As a result, everyone can freely use available knowledge unless it is protected by a legal exclusive right. Although knowledge or information sometimes can be excludable by keeping it secret, such as the recipe for Coca Cola, there is a risk that such secrets may be easily discovered through reverse engineering or by other means.

Since newly invented knowledge is non excludable and non rival, the provision of such goods will be below the socially desired level. Therefore, in the absence of incentives granted by the government, entrepreneurs, who expect to ultimately profit from research and development (R&D), may not be willing to take on the risks and costs of such activities since any rewards from doing so may dissipate due to imitation. Hence, economic theory has traditionally argued that perfect competition in the market of knowledge based products does not allow innovators to recover their innovation costs such as R&D investment (Arrow 1962). This is called innovation market failure — summarised in Martin and Scott (2000) and Colombo and Delmastro (2002) — which mainly refers to the phenomenon of underinvestment in innovation from the standpoint of maximising social welfare. The intellectual property system is a social institution intended to alleviate the negative impact of innovation market failure by granting IP owners exclusive rights to make, use and sell their goods and technologies under IP protection, usually for a certain period of time.

For example, a patent for an invention is a property right granted by a government to the patent owner(s) to exclusively make, use and sell that invention, usually for a maximum of 20 years. In exchange, the owner is required to disclose details of the invention to the public, so that other innovators can be inspired to make further technological improvements and introduce follow on innovations. This allows for cumulative growth in knowledge and continuing iterative innovation which leads to progress in the welfare of a community. Thus, acquiring a patent for a particular creation is an example of revealing the invention to the public and making a non rival and often non excludable good excludable. The granting of an exclusive right on a patented invention allows the patentee(s) to charge a higher price or enjoy a lower marginal cost of production while excluding others from exploiting its invention. The exclusive rights given by patents, however, may cause monopolies or certain market power, which are another kind of market failure. Economic theory shows that a monopoly is harmful to social welfare, at least from a static point of view. Although not all patents result in a monopoly, the market power associated with patents can impose social costs. The logic behind the IP system is that the overall benefit—social and private—obtained from the acceleration of the creation of new knowledge and its associated benefits that is generated for the innovator and the public is larger than the cost it imposes. Accordingly, patent law limits the power of patent grants not only in duration and scope, but also by setting requirements on novelty, technical inventiveness, industrial utility and disclosure. Therefore, the core economics of patents, also applied to some other intellectual property rights, such as copyright, designs and plant breeder's rights, is that it is an institution addressing the inherent trade off between encouraging innovation and the consequences of potential monopoly.

Trade marks are different in nature from patents: they protect brand names and logos used in goods and services in order to alleviate a different type of market failure associated with knowledge—information asymmetry. A trade mark serves as a way of identifying a unique product or service. It plays an important role in bridging the information gap between producers and consumers, as there are unobservable differences in quality across goods and services. A unique trade mark helps consumers to identify their desired products or services by associating it with quality, reputation and any other attributes that are bundled together and described as a business's goodwill (Carter 1990). Trade marks allow buyers and sellers to create concise identifiers for specific goods and services, thereby facilitating market transactions and encouraging further investment to improve quality. Without trade mark protection, others may counterfeit products by exploiting brands that are not their own, often deceiving consumers with products of lower quality and causing losses to the original brand owners not only in revenue but also in business goodwill.

IP and competition policies are often treated as being in conflict. IPRs create a certain market power, or potentially a monopoly, which may limit competition. By contrast, competition policy seeks to promote competition to ensure consumers can enjoy the benefits from competition such as lower prices and a range of products to choose from. Nonetheless, these two strands of policy share the same ultimate objectives; encouraging innovation, promoting technological progress, and advancing economic growth. In fact, they are both necessary for realising these societal goals, by each playing their different roles. The key is how to balance the inherent tensions between them. One of the main goals of this research is to determine whether there are any significant impacts of IPRs on business profitability and market competition.

The real world relationship between IPRs, business profitability, competition and overall economic growth is more complicated. A large body of literature has addressed the economic impacts of IPRs, but little of it provides sound evidence that is clear and useful to policy makers (de Beer 2016). de Beer (2016) is one of the most up to date literature reviews related to evidence based investigations of the economic impacts of IPRs. It classifies the literature into four major types and explains their key findings and potential issues.

The first type is the IP economics literature focusing on data for advocacy, which de Beer found is mainly produced and used by special interest lobby groups and often lacks transparent, verifiable and peer reviewed data, methodologies and results. Second is the literature on valuations of aggregate economic contributions of IP related industries and businesses, which has become popular among IP offices, but has some methodological deficiencies and lacks attention to policy implications for answering questions about the economic impacts of IP.[14] The third type of IP economic literature describes a number of studies focusing on creating innovation indices and rankings which have been increasingly used to compare and assess different countries' innovation performance and progress over time (WIPO 2012-2018 and Schwab and Sala i Martin, 2016). These studies rely on most available and easily comparable data, such as the number of patents, trade marks, and R&D investment, but they often neglect the hidden variation in the quality of their proposed innovation indicators and lack comprehensive analysis of the statistical deficiencies in their rankings. The fourth and last type of IP economics literature is the vast amount of the extensive and scholarly theoretical and empirical research and modelling. As his review notes, while these studies seek to address specific research questions, they frequently encounter limitations in their theoretical assumptions and the availability and quality of data, as well as research methods. Considerable scope remains for evidence based research on the economic impacts of IP to explore.

This study follows the literature on valuations of economic impacts of IP related businesses and industries conducted by the US and EU IP offices and seeks to explore some new areas untouched by these pioneering studies, such as the relationship between IPRs and business profitability and market competition. It also attempts to overcome some of the methodological difficulties in econometric estimation and provide policy implications accordingly.

The studies done by the US and EU IP offices in 2012, 2013 and 2016 mainly focused on identifying "IP-intensive industries" and their contributions to the whole economy in terms of employment and GDP. Their common method is to calculate the relative ratio of the total number of each type of IPR over the total number of employees at an industry level and then identify those that are above average as IP-intensive industries. As de Beer (2016) points out, this methodology shows some industries use the IP system more than other industries in relative numbers per employee but provides little information on the economic impacts of IPRs in those industries. It raises a question as to whether it is appropriate to use these "IP-intensive" industries' economic contribution to indicate how important IPRs are in the economy. However, due to the availability of data and the intrinsically complex nature of IPRs in measuring their values, the methodology adopted by the US and EU IP offices might be the best available way of identifying the contribution of IPRs to the economy, as it is impossible to estimate the individual value of every IPR and its contribution to the economy.

[14] Economics and Statistics Administration (ESA) and the United States Patent and Trademark Office (USPTO), 2012 and 2016; European Patent Office (EPO) and the European Union Intellectual Property Office (EUIPO), 2013, 2016, and 2019. Please refer to the reference at the end of the report for their web links.

The Office for Harmonization in the Internal Market (OHIM) attempted to quantify the economic impacts of IPRs on business performance in Europe (OHIM 2015). One of its key findings was that businesses that own IPRs generate more revenue per employee than those that do not. The result is based on a set of fixed effects and random effects econometric estimations, but it lacks a thorough treatment of the potential endogeneity problems in the models. The fixed effects model is useful for removing time invariant unobserved effects, but the model may still suffer OVB and other problems. Our study follows the OHIM report (2015) methodology but with a different focus on the economic impacts of IPRs on business profitability and market competition, as well as attempting to overcome certain econometric difficulties by using more advanced econometric techniques, such as generalised method of moments (GMM) estimation.

APPENDIX B: DATA

This report draws from the Business Longitudinal Analysis Data Environment (BLADE), which is a collection of business level data sourced from the Australian Taxation Office (ATO) and other government agencies, that is managed by the ABS. At the core of BLADE are the ATO's Business Activity Statement (BAS), Pay As You Go (PAYG), and Business Income Tax (BIT) data. BLADE is a statistical resource that contains information on Australian businesses based on fiscal years from 2001-02 onwards.[15]

Business Activity Statements are submitted to the ATO by businesses to report their Goods and Services Tax (GST) obligations. The data items available include total sales, other GST free sales, non capital purchases, capital purchases, export sales, wages and salaries. Employing businesses are responsible for collecting the personal income tax obligations of their employees and providing employees with an annual payment summary at the end of each fiscal year. They report this information to the ATO through a PAYG statement or Single Touch Payroll system. Business Income Taxation (BIT) forms are submitted to the ATO by businesses to report taxable income or loss. There are four main types of businesses that report annual income tax; these are companies, trusts and beneficiaries, partnerships and partners, and sole traders. Across the four different types of BIT forms the majority of items reported are similar, such as income, expenses, profit or loss, sales, total and current assets, and total and current liabilities. However, the level of detail required can be quite different.

In addition to the above datasets, a series of surveys conducted by the ABS in various years, such as the Business Characteristics Survey, the Economic Activity Survey, and the Survey of Research and Experimental Development, Businesses, are also available as supplements to the BLADE core.[16] This research uses the core ATO data and the IPLORD dataset, as the survey data were not available at the commencement of this project.

IPLORD is the annual snapshot of the stocks and flows of registrable intellectual property (IP) rights for Australian and international applicants since 1997-98 onwards. IPLORD was built from the Intellectual Property Government Open Data (IPGOD), which captures the life cycle of all patents, trade marks, designs and plant breeder's rights administered by IP Australia.[17] IPLORD systematically transforms all the application information in IPGOD into derived variables to track each applicant's IP activity over time.[18] In the 2018 release, IPLORD contains 68 data items including key details about an applicant as well as its IP activity and profile over time, with further disaggregation by technology fields in patents and Nice classes in trade marks. There are two versions of IPLORD. The public version is available on data.gov.au, the Australian Government's open data platform. The BLADE version of IPLORD is a subset of this, but excludes private and international applicants that do not have an Australian business number (ABN). Linking the financial and IP information about businesses, the BLADE IPLORD dataset provides an evidence base of high granularity for IP related economic analysis with the potential to yield valuable insights into the impact of IP on Australian businesses.

In the BLADE, the basic unit of observation is what the ABS terms the Type of Activity Unit (TAU). The majority of TAUs have a one to one relationship with businesses who have a unique ABN. However, for large and diverse businesses with complex structures, the TAU is structured to represent a grouping of one or more businesses within the Enterprise Group (EG) that cover all the operations within an industry sub division and for which a basic set of financial, production and employment data can be reported.

In the BLADE version of IPLORD, an average of 3.9 per cent of the total annual observations are duplicates, which may be caused by two sources. The first comes from the input of dataset duplicates caused by the same ABNs having multiple observations in the IPLORD dataset for a given year; these will appear in the final BLADE version of IPLORD as multiple observations. The second type of duplicate is caused by a matching process. Some businesses in IPLORD match to more than one TAU identifier during data integration and these will remain as duplicates in the BLADE version of IPLORD. Duplicates in IPLORD were treated and dropped prior to integration with the core business datasets in BLADE. The detailed integration methodology can be obtained upon request.

[15] When this research started, the available data were from 2001-02 to 2015-16 fiscal year.
[16] See ABS Cat. No. 8171.0 for full details, https://www.abs.gov.au/AUSSTATS/abs@.nsf/mf/8171.0.
[17] https://www.ipaustralia.gov.au/about us/data and research/ip government open data.
[18] https://www.ipaustralia.gov.au/about us/news and community/blog/ip australia data products ipgod 2018 and iplord.

APPENDIX C: METHOD FOR DETERMINING IPR-INTENSIVE INDUSTRIES

This study follows the method adopted by the USPTO, the EPO/EUIPO and UKIPO to identify their respective IP-intensive industries.[19] For example, patent intensity at an industry level is measured in two steps. First, the total number of patents registered at an IP office for each industry was calculated, based on applicants' industry affiliation. This is termed the absolute intensity at industry level. Second, for each industry, the total number of patents was divided by the number of persons employed in that industry. The result is called the relative intensity of that industry. Finally, the overall employment weighted average of relative patent intensities was calculated for all the industries that have patents. Those industries whose relative patent intensities were above the average value were considered to be patent intensive. A similar method can be applied to derive trade mark and design intensive industries.

This method of identifying IP-intensive industries may have a few limitations. First, by definition, about half of the industries may be identified as IP-intensive given their relative IP intensities will be above the average value, depending on the distribution of their relative design intensities. Second, only IPRs issued to domestic companies are included, while those issued to individuals and foreign companies are excluded. The UKIPO has attempted to improve this method by introducing an additional "cut off" point to try to capture those industries appearing in the steepest part of the distribution that it considers to be "high" IP usage. More specifically, for example, the UKIPO calculated a new average of the above average industries' design relative intensities and identified those whose design relative intensity was above the new average as "high" design intensive industries. This method relieves some of the shortcomings of the above average method for identifying IP-intensive industries, since a large number of industries may have zero or very few IP registrations, which drags down the average value and makes it less meaningful as a yardstick.

Nonetheless, the above method based on company applicants' industry affiliation has an advantage in enabling the easy linking of industry data such as employment at an industry level and providing a good means of international comparison with the findings of the USPTO, EUIPO/EPO and UKIPO reports.

[19] Please see: https://www.uspto.gov/sites/default/files/news/.../IP_Report_March_2012.pdf, to https://euipo.europa.eu/tunnel web/secure/webdav/guest/document_library/observatory/documents/IPContributionStudy/IPR intensive%20industries_en.pdf and https://euipo.europa.eu/tunnel web/secure/webdav/guest/document_library/observatory/documents/IPContributionStudy/performance_in_the_European_Union/performance_in_the_European_Union_full.pdf; and https://www.gov.uk/government/publications/use of intellectual property rights across uk industries.

APPENDIX D: EXPLANATION ON MODEL SELECTION

The OHIM (2015) report adopted fixed and random effects models to deal with the potential endogeneity problem that may be caused by omitted variables. The fixed effects model can deal with the omitted variable bias (OVB) caused by time invariant or group invariant omitted variables, but not that caused by potential omitted variables that may change over time and have an impact on the dependent variable and which are also correlated with explanatory variables. A random effects model assumes there are no fixed effects, which means that unobserved time invariant or group invariant variables are not correlated with explanatory variables. Hence, omitting such variables does not induce bias as they effectively become part of the random error term. However, a random effects model may still suffer from OVB if the potential omitted variables are time variant and have a significant impact on the dependent variable. Due to the limitation of available data, there are always some unobserved business characteristics that may have an impact on business profitability, such as a business 's organisational structure, its operational efficiency and management quality. Some of them may be time invariant during the period of this study but some may change over time.

Fixed and random effects models are not without flaws. Typically, the assumption that some important omitted variables are time invariant is implausible, and the models may still suffer from an OVB. An alternative estimation strategy is to include one or more lagged dependent variables as explanatory variables which may control for past outcomes and alleviate the omitted variable problem (dynamic panel estimation). A major advantage of panel data is that repeated observations make it possible to analyse individual dynamics. In fact, many empirical relationships are dynamic in nature: businesses are not always able to respond immediately to changes in their environment because of their pre existing business patterns. Such dynamic relations are typically modelled by adding lagged dependent variables to the panel model specification.

However, introducing one or more lagged dependent variables as explanatory variables will cause a new endogeneity problem. The basic argument is straightforward. Let y_{it} be the value of the dependent variable for individual *i* at time *t*. Here is a simple model that includes a lagged value of the dependent variable, as well as a set of predictor variables represented by the vector x_{it}:

$$y_{it} = b_0 + b_1 y_{i(t-1)} + b_2 x_{it} + u_i + e_{it}$$

The term u_i represents the combined effect on y of all unobserved variables that do not change over time, which is also called the fixed effect. If u_i is normally distributed with a mean of zero, constant variance, and independent of the other variables on the right hand side of the equation, which can be treated as a part of e_{it} that is assumed to be a random error term, we can obtain unbiased estimates for the coefficients of the explanatory variables. However, because the model applies to all time points, u_i has a direct effect on $y_{i(t-1)}$. But if u_i affects $y_{i(t-1)}$, it cannot also be statistically independent of $y_{i(t-1)}$. The violation of this assumption can bias both the coefficient for the lagged dependent variable (usually overestimating it) and the coefficients for other variables (usually underestimating them).

Nickell (1981) has shown that the standard fixed effects (FE) estimator for dynamic panel estimation is inconsistent when the number of cross section units N goes to infinity while the number of time periods T is fixed, as our dataset is. Only when T goes to infinity, can this problem be alleviated. Given that the asymptotic bias may be quite sizeable in many cases that are relevant to applied research, various alternative estimators have been proposed. Particularly popular are a variety of generalized method of moments (GMM) estimators, most notably the Difference GMM (Arellano and Bond 1991) and the System GMM (Arellano and Bover 1995; Blundell and Bond 1998) estimators. These GMM estimators are, under appropriate assumptions, asymptotically unbiased (when N tends to infinity and T is finite). They are more appropriate than fixed effects and random effects models for regressions concerning the determinants of profitability by controlling for unobserved heterogeneity (i.e. the effect of variables that are not observable in the data but which might have an impact on the dependent variable of interest). Because our dataset is an unbalanced panel dataset with a very large number of groups and relatively small and fixed time periods (T <= 15 with an average of 6), the best available method to handle such data is probably System GMM, which is more effective in dealing with unbalanced panel data than Difference GMM.

The Difference GMM approach deals with this inherent endogeneity by transforming the data to remove the fixed effects. The standard approach applies the first difference transformation, which removes the fixed effect at the cost of introducing a correlation between regressor $\Delta y_{i,t-1}$ and error Δv_{it} , both of which have a term dated (t − 1). The one disadvantage of the first difference transformation is that it magnifies gaps in unbalanced panels. If the value of $y_{i,t\ 1}$ is missing, then both Δy_{it} and $\Delta y_{i,t-1}$ will be missing in the transformed data. This motivates an alternative transformation: the forward orthogonal deviations (FOD) transformation, proposed by Arellano and Bover (1995) and used in System GMM. In contrast to the within transformation, which subtracts the average of all observations' values from the current value, and the first difference transformation, that subtracts the previous value from the current value, the FOD transformation subtracts the average of all available future observations from the current value. While the first difference transformation drops the first observation on each individual in the panel, the FOD transformation drops the last observation for each individual. It is computable for all periods except the last period, even in the presence of gaps in the panel.[20]

Therefore, System GMM corrects endogeneity by introducing more instruments than Difference GMM to dramatically improve efficiency and transforming the instruments to make them uncorrelated (exogenous) with the fixed effects by using the orthogonal deviations. Moreover, Bond (2002) has developed a set of rules to choose from Difference GMM and System GMM as follows: (i) The dynamic model should be initially estimated by pooled ordinary least squares (OLS) regression and the fixed effects approach. (ii) The pooled OLS estimate for the lagged dependent variable should be considered an upper bound estimate, while the corresponding fixed effects estimate should be considered a lower bound estimate. (iii) If the Difference GMM estimate obtained is close to or below the fixed effects estimate, this suggests that the former estimate is downward biased because of weak instrumentation and a System GMM estimator should be preferred instead.

GMM controls for endogeneity of the lagged dependent variable in a dynamic panel model where there is correlation between the explanatory variable and the error term in a model, OVB, and unobserved panel heterogeneity and serial correlation. However, the fact that the GMM uses an instrumental variables technique to avoid dynamic panel data bias often leads to poor small sample properties, which may cause an overidentifying problem. There are mainly two GMM diagnostics for determining the validity of GMM estimates. The first is about instruments validity regarding overidentifying restrictions. Tests devised by Hansen (1982) and Sargan (1985) are used to test the null hypotheses of overall validity of the instruments used regarding overidentifying restrictions. The Sargan test is only appropriate under Difference GMM estimation with the assumption of homoscedasticity and no serial correlation (in levels) of the idiosyncratic error term. For System GMM, the decision should be based on the Hansen test that uses an optimal weighting matrix (Roodman 2009). Failure to reject the null hypothesis in the Hansen test gives support to the choice of the instruments, but caution is necessary in the case of a high Hansen p value (above 0.4), which may cause doubt about its validity as it might be "too good to be true" (Roodman, 2009). The second test is about the autocorrelation (or serial correlation) of the error term. Arellano Bond tests for AR(1) and AR(2) verifies the null hypothesis that the differenced error term is first and second order serially correlated. Success in rejecting the null hypothesis of no first order serial correlation but failure to reject the null hypothesis of no second order serial correlation implies that the original error term is serially uncorrelated and the moment conditions are correctly specified. We also adopted two step System GMM using robust standard errors as it is generally believed to be more robust to one step System GMM and more efficient in dealing with heteroscedasticity and autocorrelation (Roodman, 2009). Nonetheless, we performed both one step and two step System GMM for the purpose of comparison, but only robust results of the two step System GMM are reported since their results are consistent.

[20] Roodman D. 2009, How to do xtabond2: An introduction to difference and System GMM in Stata, *The Stata Journal*, Vol. 9, Number 1, pp. 86 136.

APPENDIX E: EXPLANATORY VARIABLES AND DESCRIPTIVE STATISTICS

Explanatory variables

The differences between businesses in their profitability, as represented by profit per invested capital or profit per employee, are sought to be explained by a set of explanatory variables, which fall into three main categories:

1) Lag(s) of profitability: the previous year(s)'s profitability of a business may have an impact on its current profitability as the business can utilise its previous profitability to make further investment in both capital and labour.

2) A set of variables that measure the impact of IPRs, including IPR ownership dummies and IPR stocks.
   a) Binary or dummy variables that indicate whether a business owns at least one IPR or whether it owns a particular type of IPR, such as a patent, trade mark and design or combinations of them.
   b) Quantity of a particular type of IPR owned by a business.

More specifically, with regard to measures of IPR ownership, a set of dummy variables which indicates whether or not a business owns a specific combination of IPRs in a given year and which divides the sample into eight corresponding groups:

- **IPR owner**: takes the value 1 if a business owns at least one registrable IPR in a given year, and 0 otherwise.
- **Patents only**: takes the value 1 if a business owns patents but no other type of IPR, and 0 otherwise.
- **Trade marks only**: takes the value 1 if a business owns trade marks but no other type of IPR, and 0 otherwise.
- **Designs only**: takes the value 1 if a business owns design rights but no other type of IPR, and 0 otherwise.
- **Patents and trade marks**: takes the value 1 if a business owns at least one patent and one trade mark but not design, and 0 otherwise.
- **Patents and designs**: takes the value 1 if a business owns at least one patent and one design but not trade mark, and 0 otherwise.
- **Trade marks and designs**: takes the value 1 if a business owns at least one trade mark and one design but not patent, and 0 otherwise.
- **Patents, trade marks and designs**: takes the value 1 if a business owns all three types of IPR, and 0 otherwise.

Stock measures of a particular form of IPR were also used.

- **Patent stock per employee**: number of Australian standard patents in force owned by a business per employee in a given year.
- **Trade mark stock per employee**: number of Australian trade marks owned by a business per employee in a given year.
- **Design stock per employee**: number of Australian design rights owned by a business per employee in a given year.

3) In addition, a set of control variables that measure or control for non IPR factors affecting business profitability need to be included when analysing the relationship between business profitability and IPR ownership. These include:

- **Age**: indicates the age of a business in a given year, which is equal to the survey year minus the starting year.
- **Year dummies**: a set of dummy variables which equals 1 for a given fiscal year and 0 for all other years. It allows control for year specific fixed effects, i.e. shocks whose impact is restricted to a given year period and which are not controlled by other explanatory variables. As there are a total of 15 fiscal years, only 14 such year dummies are included in the model.
- **Industry dummies**: there are 18 industry dummies out of the total 19 ANZSIC industry divisions with Agriculture, Forestry and Fishing set as the base industry for comparison.

Descriptive statistics of main variables

The dataset used for the regression analysis consists of approximately 1.3 million businesses.[21] The basic descriptive statistics for the main variables are shown in Table E.1. For example, the dataset used for the regression analysis of profitability using profit per invested capital consists of 1 225 929 businesses with a total 5 137 392 observations over an average span of 4.56 years. The mean value of the logarithm of profit per invested capital is -0.74, which is equivalent to saying the average profit per invested capital is 0.48.

Table E.1 Descriptive statistics of main variables

Variable		Mean	Std. dev.	Min	Max	Observations
Log of profit per invested capital	Overall	-.74	2.69	-24.79	22.83	N = 5 137 392
	Between		2.31	-24.79	16.88	n = 1 125 929
	Within		1.53	-17.56	22.00	T-bar = 4.56
Log of profit per employee	Overall	10.04	1.84	-8.27	23.81	N = 6 057 532
	Between		1.72	-3.93	22.56	n = 1 303 789
	Within		1.02	-2.59	22.62	T-bar = 4.65
IPR owner	Overall	0.03	0.18	0.00	1.00	N = 9 225 972
Owner of patents only	Overall	0.001	0.03	0.00	1.00	N = 9 225 972
Owner of trade marks only	Overall	0.03	0.17	0.00	1.00	N = 9 225 972
Owner of designs only	Overall	0.001	0.02	0.00	1.00	N = 9 225 972
Owner of patents and trade marks	Overall	0.001	0.04	0.00	1.00	N = 9 225 972
Owner of patents and designs	Overall	0.0001	0.01	0.00	1.00	N = 9 225 972
Owner of designs and trade marks	Overall	0.001	0.03	0.00	1.00	N = 9 225 972
Owner of patents, trade marks and designs	Overall	0.001	0.03	0.00	1.00	N = 9 225 972

[21] Only businesses which appeared in at least two financial years during the period from 2001-02 to 2015-16 were kept in the dataset.

Table E.1 Descriptive statistics of main variables

Variable		Mean	Std. dev.	Min	Max	Observations
Log of patents per employee	Overall	-2.71	2.16	-10.39	9.70	N = 27 080
	Between		2.15	-10.06	9.70	n = 4 319
	Within		.63	-7.77	7.05	T-bar = 6.27
Log of trade marks per employee	Overall	-1.49	1.75	-11.31	10.92	N = 307 199
	Between		2.15	-10.06	9.70	n = 50 021
	Within		.61	-7.22	9.17	T-bar = 6.14
Log of designs per employee	Overall	-3.13	2.20	-10.39	3.23	N = 2 516
	Between		2.22	-10.18	2.85	n = 586
	Within		.45	-5.82	1.46	T-bar = 4.29
Age	Overall	8.33	5.71	1	37	N = 9 225 972
	Between		4.55	1.5	35.5	n = 1 460 321
	Within		3.18	-12.75	33.41	T-bar = 6.32

Source: ABS BLADE (2016-17 frame).

Note: The number of observations n is the number of businesses for which there is data. *T-bar* is the average number of years with observations per business . The number of observations N is the product of *n* and *T-bar*. Descriptive statistics are displayed for the overall sample and also decomposed into between (across businesses) and within (over time) components.

Analysis of the correlation matrix between the eight different types of IPR owners reveals that the majority of IPR owners are those who own trade marks only, with a highly positive correlation index of 0.9323 in Table E.2. This suggests that it is not advisable to include both an IPR owner dummy variable and a dummy for trade mark owner only in the same regression as they may affect each other's respective impacts on the dependent variable.

Table E.2: Correlation matrix for owners of different types of IPRs

	Any IPR	Patent only	Trade mark only	Design only	Patent and trade mark	Patent and design	Trade mark and design	All three IPRs
Any IPR	1.0000							
Patent only	.1552	1.0000						
Trade mark only	.9323	-.0052	1.0000					
Design only	.1274	-.0007	-.0043	1.0000				
Patent and trade mark	.1893	-.0011	-.0064	-.0009	1.0000			
Patent and design	.0542	-.0003	-.0018	-.0002	-.0004	1.0000		
Trade mark and design	.1581	-.0009	-.0053	-.0007	-.0011	-.0003	1.0000	
All three IPRs	.1360	-.0008	-.0046	-.0006	-.0009	-.0003	-.0008	1.0000

Source: BLADE (2016-17 frame).

APPENDIX F: TABLES

Table F.1

Dependent variable: Log (profit per invested capital)		System GMM	OLS	Fixed Effects
Explanatory variables				
IPR owner		1.28***	-.07***	-.04*
Lags of log of profit per invested capital	Lag1	.51***	.58***	.15***
	Lag2	.13***	.16***	-.02***
	Lag3	.04***	.06***	-.05***
	Lag4	.02***	.04***	-.04***
	Lag5	.01**	.03***	-.04***
	Lag6	.006	.03***	-.04***
Age of business		-.05***	-.01***	-.03
Sector dummies		Yes°	Yes°	Omitted
Year dummies		Yes°	Yes°	Yes°
Constant		.26***	.06***	-.16

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
° Industry and year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

Table F.2

Dependent variable: Log (profit per employee)		System GMM	OLS	Fixed Effects
Explanatory variables				
IPR owner ~		1.24***	-.02***	-.09***
Lags of log of profit per invested capital	Lag1	.49***	.49***	-.001
	Lag2	.18***	.18***	-.08***
	Lag3	.09***	.09***	-.08***
	Lag4	.05***	.06***	-.07***
	Lag5	.03***	.04***	-.06***
	Lag6	.02***	.02***	-.04***
	Lag7	.01***	.03***	-.03***
	Lag8	.004	.03***	-.03***
Age of business		-.02***	-.002***	-.04
Sector dummies		Yes°	Yes°	Omitted
Year dummies		Yes°	Yes°	Yes°
Constant		1.56***	.76***	15.25***

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
° Industry and year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

Table F.3

Dependent variable: Log (profit per invested capital)		System GMM of Model 1.2	OLS of Model 1.2	Fixed Effects of Model 1.2
Explanatory variables				
Owners of different types of IPRs	Patents only	1.19***	-.07**	-.11
	Trade marks only	1.39***	-.07***	-.04
	Designs only	0.43**	-.15**	-.14
	Patents and trade marks	2.14***	.06**	.10
	Patents and designs	0.66	-.19**	-.03
	Trade marks and designs	1.77***	-.06**	-.05
	Patents, trade marks and designs	2.05***	-.03	.08
Lags of log of profit per invested capital	Lag1	.52***	.58***	.15***
	Lag2	.13***	.16***	-.02***
	Lag3	.04***	.06***	-.05***
	Lag4	.02***	.04***	-.04***
	Lag5	.01**	.03***	-.04***
	Lag6	.006*	.03***	-.04***
Age of business		-.02***	-.01***	-.03
Sector dummies		Yes°	Yes°	Omitted
Year dummies		Yes°	Yes°	Yes°
Constant		.29***	.06***	-.15

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
° Industry and year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

Table F.4

Dependent variable: Log (profit per employee)		System GMM of Model 1.2	OLS of Model 1.2	Fixed Effects of Model 1.2
Explanatory variables				
Owners of different types of IPRs	Patents only	1.19***	-.01	-.001
	Trade marks only	1.16***	-.02***	-.10***
	Designs only	.43**	.06	.01
	Patents and trade marks	1.76***	.03	.002
	Patents and designs	1.65***	.15	-.25
	Trade marks and designs	.99**	-.04	-.09
	Patents, trade marks and designs	1.64***	.01	.07
Lags of log of profit per employee	Lag1	.49***	.49***	-.001
	Lag2	.18***	.18***	-.08***
	Lag3	.09***	.09***	-.08***
	Lag4	.05***	.06***	-.07***
	Lag5	.03***	.04***	-.06***
	Lag6	.02***	.02***	-.04***
	Lag7	.01***	.03***	-.03***
	Lag8	.004	.03***	-.03***
Age of business		-.02***	-.002***	-.04
Sector dummies		Yes°	Yes°	Omitted
Year dummies		Yes°	Yes°	Yes°
Constant		1.58***	.76***	15.25***

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
° Industry and year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

Table F.5

Dependent variable: Log (profit per invested capital)		GMM	OLS	Fixed Effects
Explanatory variables				
Stock of the three different types of IPRs per employee	Log of patents per employee	-.30	-.01	-.16
	Log of trade marks per employee	.17	.005	.05
	Log of designs per employee	-.21	.04	-.11
Lags of log of profit per invested capital	Lag1	.43***	.49***	.09
	Lag2	.21**	.24***	.01
Age of business		-.05**	-.02**	-.05***
Sector dummies		Yes°	Yes°	Omitted
Year dummies		Yes°	Yes°	Yes°
Constant		4.49	-.34*	-1.46**

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
° Industry and year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

Table F.6

Dependent variable: Log (profit per employee)		GMM	OLS	Fixed Effects
Explanatory variables				
Stock of three types of IPRs per employee	Log of patents per employee	-.26	.02	-.03
	Log of trade marks per employee	-.02	.001	-.06
	Log of designs per employee	.30	.03	-.01
Lags of log of profit per employee	Lag1	.53***	.54***	.03
	Lag2	.19**	.24***	-.07
Age of business		.01	-.001	-.05***
Sector dummies		Yes°	Yes°	Omitted
Year dummies		Yes°	Yes°	Yes°
Constant		-16.33	1.99*	12.04**

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.
° Industry and year dummy variables were included in the analysis as control variables. In order to maintain readability, these are not included in the table. The regression results can be provided on request.

Table F.7

Explanatory variables		Difference GMM	System GMM	OLS	Fixed effects
IPR-intensive industry dummies	Patent-intensive industry dummy	-.01	-.06	-.01	-.06
	Trademark-intensive industry dummy	-.08	-.12	.02	.03
	Design-intensive industry dummy	-.06	-.19	-.09***	-.08
Lags of log of HHI	Lag1	.56***	.60***	.74***	.51***
	Lag2	.09	.10*	.20**	.05

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.

Table F.8

Explanatory variables		Difference GMM	System GMM	OLS	Fixed effects
Stock intensity of the three different types of IPRs	Log of patents per 1000 employees	.003	-.10	.01	-.10***
	Log of trade marks per 1000 employee	-.22	-.04	.01	-.05
	Log of designs per 1000 employee	.03	-.03	-.03**	-.001
Lags of log of HHI	Lag1	.59***	.68***	.75***	.48***
	Lag2	.10	.14	.19*	.016

Source: ABS BLADE (2016-17 frame).

Notes:
* = significant at the 10 per cent level; ** = significant at the 5 per cent level; *** = significant at the 1 per cent level.

Disclaimer

The results of these studies are based, in part, on Australian Business Registrar (ABR) data supplied by the Registrar to the ABS under *A New Tax System (Australian Business Number) Act 1999* and tax data supplied by the Australian Taxation Office (ATO) to the ABS under the *Taxation Administration Act 1953*. These require that such data is only used for the purpose of carrying out functions of the ABS. No individual information collected under the *Census and Statistics Act 1905* is provided back to the Registrar or ATO for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes and is not related to the ability of the data to support the ABR or ATO's core operational requirements. Legislative requirements to ensure privacy and secrecy of this data have been followed. Only people authorised under the *Australian Bureau of Statistics Act 1975* have been allowed to view data about any particular business in conducting these analyses. In accordance with the *Census and Statistics Act 1905*, results have been confidentialised to ensure that they are not likely to enable identification of a particular person or organisation.

APPENDIX G: REFERENCES

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