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# Firm Performance and Business Networks

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Research Paper

# Firm Performance and Business Networks


**Methodology Transformation Branch**

Methodology Division



AUSTRALIAN BUREAU OF STATISTICS

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# FIRM PERFORMANCE AND BUSINESS NETWORK

Chien-Hung Chien[1,2], A.H. Welsh[3], and Robert Breunig[4]

[1]Australian Bureau of Statistics (ABS)
[2]ANU Mathematical Science Institute
[3]ANU Research School of Finance, Actuarial Studies & Statistics
[4]ANU Crawford School of Public Policy

## 1 ABSTRACT

We combine three administrative datasets to study the relationship between firm performance and business networks. We explore three types of business networks including research and development (R&D), commercial and shared directors business networks. We find that in general, there are positive associations between firm performance and these three types of business networks.

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**Disclaimer:** the results of these studies are based, in part, on tax data supplied by the Australian Taxation Office (ATO) to the ABS under the Taxation Administration Act 1953, which requires that such data is only used for the purpose of administering the Census and Statistics Act 1905. Legislative requirements to ensure privacy and secrecy of this data have been adhered to. 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. This study uses a strict access control protocol and only a current ABS officer has access to the underlying microdata.

Any findings from this paper are not official statistics and the opinions and conclusions expressed in this paper are those of the authors. The ABS takes no responsibility for any omissions or errors in the information contained here. Views expressed in this paper are those of the authors and do not necessarily represent those of the ABS. Where quoted or used, they should be attributed clearly to the authors.

## Contents

# 2 INTRODUCTION

*"In the new competitive regime, commercial success requires the ability to generate knowledge using resources which are not stored in-house but distributed throughout a vast, and increasingly global, network."*

Gibbons et al. (1994, p.49)

Gibbons et al. (1994) summarise succinctly how firms benefit from participating in business networks (or collaboration) to ensure market success. The Australian Government recognises the benefits to be gained from firms collaboration. It uses a range of initiatives to encourage collaboration to enhance business competitiveness and ultimately achieve economic growth. These include the suite of initiatives under the Australian Research Council's Linkage Program, which provide funding for research collaboration between research institutions and industry organisations. The Department of Industry, Innovation and Science's Entrepreneurs' Programme and Cooperative Research Centres provides funding for industry-led collaborations on new technologies, products, and services to enhance business competitiveness and productivity (DIIS, 2019b,a).

This study contributes to the business literature by exploring the relationship between firm participation in business networks and firm performance. We examine these relationships using three sources - (i) ABS research datasets containing the administrative data from Australian Taxation Office (ATO) and Australia Business Register (ABR), (ii) Intellectual Property (IP) Australia's 2017 Intellectual Property Government Open Data (IPGOD) and (iii) Australian Securities Exchange (ASX) publicly listed company data from MorningStar DatAnalysis Premium. We explore the effect of firms' participation in business networks on firm performance under three different scenarios. We consider a firm to be in a business network if it files a patent or trademark application with at least one other distinct firm or if it shares a director with at least one other distinct firm. We consider firms to be collaborating if they are in a business network.

This paper is organised as follows: Section 3 is the literature review., Section 4 describes the data (summary statistics can be found in Appendix $E$.1 and imputation methods in Appendix $B$.1). Section 5 describes the statistical models. Section 6 contains empirical results and the final section provides a conclusion, discusses limitations and proposes future directions for the research. Appendix $D$ provides further details on our definitions of firm performance and business network measures.

# 3 LITERATURE REVIEW

Firms seek partners with complementary assets to leverage each other's strengths and find competitive advantages to ensure market success. Business networks play a vital role in finding new market opportunities and obtaining the necessary resources to achieve business growth (Lee et al., 2001). Management literature argues that business networks facilitate knowledge spillover between firms and as a result promote innovation (see Brass et al. (2004) for a review). Business networks (or collaboration) play a particularly important role in ensuring the economic success of small firms. Firms in business networks have mutual dependence to ensure each other's success. Business networks can also help better allocate resources and reduce operational risks through cooperative arrangements. This is particularly important in sectors with fast technological advancement and short product life cycle. This is evident by the success of high-tech start-ups in Taiwan, where business networks play an important role in integrating the operation of a large number of specialised small firms in subcontracting and outsourcing industries (Perry et al., 2002, p.2-4).

There are many other types of business networks, see Inkpen and Tsang (2005) for a detailed discussion. We focus on three types of business networks for which we can obtain data - R&D, commercial and shared directors. There are also many measures of firm performance, but we adapt the framework proposed by Gronum et al. (2012) and focus on productivity, sales and innovation. International research shows that firm R&D collaboration is an important source of innovation. Ahuja (2000) and Guan et al. (2015) analyse US patents datasets and Belderbos et al. (2004) study Dutch Community Innovation survey results. These studies find R&D collaboration improves firm performance. Frenz and Ietto-Gillies (2009) analyse UK's and Miotti and Sachwald (2003) study France's Community Innovation Surveys results respectively show that R&D collaboration enables knowledge transfer between firms to share new managerial ideas and technology. Firms look for different competitive advantages in the market through business networks. Wolff and Pett (2000) find that commercial business networks enhance export performance of US small & medium size firms. Firms can also form business networks through shared directors. Hillman and Dalziel (2003) argue that boards of directors can enhance firm performance through effectively monitoring and providing resources. Collins and Clark (2003) also find that directors serve as an important asset to form business networks, particularly for young high-tech firms. Chuluun et al. (2017) study US S&P stock exchange data between 1996 and 2013. They find that shared directors networks have positive effects on innovation.

There are many Australian studies exploring the relationship between collaboration and innovation using survey data. For example, Rogers (2004) analyses ABS Growth and Performance Survey data and finds a positive association between business networks and innovation, particularly for small manufacturing firms. Brunker and Salma (2006) use an ordered categorical probit model to analyse 2003 ABS Business Characteristics Survey results. They find a positive association between collaboration and degree of innovation novelty. Gronum et al. (2012) study the survey results of $1,435$ small & medium size Australian firms in the ABS Business Longitudinal Database (BLD). They find business networks play an important role in enhancing firm performance. Soriano et al. (2018) use a random effect probit model to analyse data in the ABS BLD. They find collaboration between small businesses contributes positively to innovation in the food industry. Divisekera and Nguyen (2018) use logistic regression to analyse ABS BLD also find that collaboration contributes positively to products, process and organisational innovations in the Australian tourism industry

These studies use measures from a combination of administrative data and self-reported survey results on productivity, innovation and collaboration (Gronum et al., 2012). For example, innovation is measured by responses to questions on whether or not respondents have introduced new products and services or new operational or managerial processes. Similarly, collaboration is measured by questions on whether or not respondents enter into collaborative arrangements, e.g. a joint research project or integrated supply chain (ABS, 2018). Firm performance measures such as sales or profits are from administrative data sources. For example, the BLD and Business Longitudinal Analysis Data Environment (BLADE) source information from administrative data sources for business financial results (ABS, 2014).

Musteen et al. (2010) discuss the difficulty of using surveys to collect reliable business network information from small Czech firms because most respondents cannot recollect exactly their business activities. There is also the potential for social desirability bias when we analyse survey results. The bias arises when a respondent chooses to respond in a manner that is perceived to be socially desirable (Grimm, 2010). For example, a respondent is likely to answer 'yes' to questions such as 'are they innovative?' and 'are you more productive than last year?'. We mitigate these potential biases by deriving our measures for business networks (or collaboration) and firm performance only from administrative data sources. However, using administrative data sources for this analysis can still be subject to under coverage bias. This is because not all firm collaborations will lead to joint patent or trademark applications or shared directors. Administrative data, like survey data, is also subject to processing and reporting errors (Chien and Mayer, 2015b).

# 4 DATA

This study uses data from the ABS, IP Australia's 2017 Intellectual Property Government Open Data (IPGOD) and the ASX database on publicly listed companies and their directors from MorningStar DatAnalysis Premium. We use both Australian Business Numbers (ABNs) and Australian Company Numbers (ACNs) to link these datasets. Firm characteristics such as investment, labour and materials used in the production process are from the ABS. We discuss in detail how we define business networks using IPGOD and ASX data below.

## 4.1 ABS research data

The ABS research data includes Business Characteristics Survey, Economic Activity Survey and Survey of Research and Development and ABS Business Register from the ABS. Business Activity Statement, Business Income Tax, Personal Income Tax data and Pay As You Go from the Australian Taxation Office (ATO) and Australia Business Register (ABR) (Hansell and Rafi, 2018) and (Chien and Mayer, 2015b). The data is only accessible in the secure Business Longitudinal Analytical Data Environment for firms (ABS and DIIS, 2017) and the prototype Graphically Linked Information Discovery Environment for workers (Chien and Mayer, 2015a). This section describes the ABS confidentiality protocol and the data processing carried out for this study.

## 4.2 Data confidentiality

The ATO data is provided to the Australian Statistician under the *Taxation Administration Act 1953* and ABR data is supplied to the Australian Statistician under the *New Tax System (Australian Business Number) Act 1999.* These acts require that these data are only used by the ABS for administering the *Census and Statistics Act 1905.* The ABS is obliged to maintain the confidentiality of individuals and businesses in these ATO and ABR datasets, as well as comply with provisions that govern the use and release of this information, including the *Privacy Act 1988* (ABS, 2015).

This study uses a strict access control protocol. Access to the datasets includes audit trails and is limited on a need to know basis. All ABS officers are legally bound to secrecy under the *Census and Statistics Act 1905.* Officers sign an undertaking of fidelity and secrecy to ensure that they are aware of their responsibilities. The ABS policies and guidelines governing the disclosure of information maintain the confidentiality of individuals and organisations. This study presents only aggregate results to ensure that they are not likely to enable identification of a firm.

## 4.3 2017 Intellectual Property Government Open Data

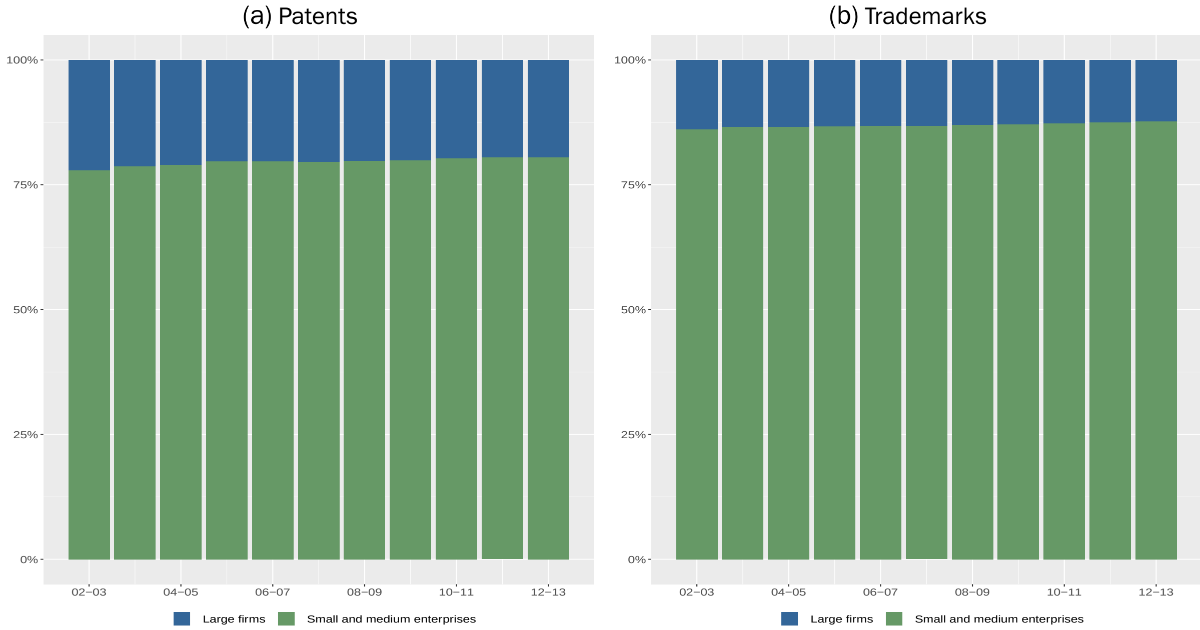
IPGOD includes over 100 years of IP rights records administered by IP Australia comprising patents, trademarks, designs and plant breeders' rights (IP Australia, 2017, Benjamin et al., 2016). Table 1 describes datasets used to study R&D and commercial business networks. We use the joint patent or trademark applicant information to identify business networks. Patent and trademark applications can be filed by one applicant or multiple applicants. Over the sample period, between 2002–03 and 2012–13 there are 129, 306 applicant–patent application combinations with 21, 887 unique patent applications. The data cleaning step removes 23, 530 applications with no ABNs information. In comparison, there are 1, 479, 276 applicant–trademark application combinations with 250, 378 unique trademark applications. The data cleaning step removes 40, 606 applications with no ABNs information. The numbers of edges reduce significantly when we compare raw cleaned IPGOD datasets with the experimental combined ABS—IPGOD datasets.

Table 1: Summary of the experimental combined ABS---IPGOD datasets

| **Cleaned IPGOD** | **Patents** | **Trademarks** |
|---|---|---|
| Applications firm observations | 129,306 | 1,479,276 |
| Number of applications | 21,887 | 250,378 |
| Number of distinct ABN | 7,955 | 82,860 |
| Edges | 17,116 | 45,621 |
| **Experimental combined dataset** | **ABS—Patents** | **ABS—Trademarks** |
| Application firm observations | 36,291 | 381,305 |
| Number of distinct ABN | 6,228 | 67,686 |
| Edges | 3,826 | 17,867 |

The five applicant types are international, small or medium-sized enterprises, large firms, private applicant and unknown. We focus only on small and medium-sized enterprises and large firms because these are the only firms we can link to the ABS datasets using ABNs or ACNs. The 100% stacked bar charts in Figure 1 show the proportion of applicant types for patents and trademarks over the sample period before combining datasets. The majority of patent and trademark applicants are from small and medium-sized enterprises.

Figure 1: Proportion of applicant types for patents and trademarks between 2002—03 and 2012—13 before data integration



## 4.4 Purchased publicly listed company data

The data on publicly listed companies and their directors is purchased from MorningStar DatAnalysis Premium. This data service contains detailed reports for all current and formerly listed companies on the ASX. Table 2 describes datasets used to study shared director business networks. There are 1588 listed companies with valid and unique ABNs and $9,198$ directors in the sample reference period between 2002–03 and 2012–13. We use the following data items in our analysis: unique director identification number (DirectorID), ABNs, ACNs, director appointed dates and director resigned dates. The numbers of edges also reduce significantly when we compare raw cleaned ASX dataset with the experimental combined ABS—ASX dataset.

Table 2: Summary of the experimental combined ABS---ASX dataset

| Cleaned ASX data | Directors |
|---|---|
| Directors firm observations | 85,857 |
| Number of directors | 9,198 |
| Number of distinct ABN | 1,588 |
| Edges | 129,088 |
| **Experimental combined dataset** | **ABS—ASX** |
| Application firm observations | 17,068 |
| Number of distinct ABN | 1,247 |
| Edges | 63,990 |

## 4.5 Combining administrative data sources

The study uses a similar linking strategy to ABS (2015) and Chien and Mayer (2015b) to assemble the developmental firm panel using an experimental BLADE. The firm records were deterministically linked using ABNs. This study includes all valid firm data from the following experimental datasets: ABS and Patents, containing more than $6,228$ firms; ABS and Trademarks containing around $67,686$ firms; and ABS and ASX, containing $1,247$ firms. Appendix $B.1$ provides details on the imputation methodology. All subsequent analysis is based on the completed datasets. Tables 8, 9 and 10 in Appendix $E.1$ show the summary statistics for the firm panels after imputing missing data. Tables 3 and 4 show the patterns of years in sample and the number of applications that firms filed in the ABS and Patents and ABS and Trademarks experimental datasets. There are more firms that filed between 1 to 4 applications and there are more in the more than 10 years category than other categories in both experimental datasets.

Table 3: Applications and years in sample --- ABS and Patents

| applications | years in sample | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **>10** | **Total** |
| **1 to 4** | 1.5 | 2.5 | 3.5 | 4.8 | 6.2 | 7.3 | 8.5 | 11.3 | 12.4 | 14.7 | 18.9 | 91.6 |
| **5 to 8** | 0.0 | 0.0 | 0.1 | 0.0 | 0.2 | 0.2 | 0.2 | 0.4 | 0.6 | 1.1 | 2.0 | 4.8 |
| **9 to 10** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.2 | 0.5 | 0.9 |
| **>10** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.2 | 0.2 | 0.3 | 1.9 | 2.8 |
| **Total** | 1.6 | 2.5 | 3.6 | 4.9 | 6.4 | 7.6 | 8.8 | 12.0 | 13.3 | 16.3 | 23.2 | 100.0 |

Table 4: Applications and years in sample --- ABS and Trademarks

| applications | years in sample | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **>10** | **Total** |
| **1 to 4** | 1.4 | 2.7 | 3.8 | 4.9 | 6.2 | 7.2 | 8.8 | 10.8 | 12.0 | 14.7 | 15.7 | 88.2 |
| **5 to 8** | 0.0 | 0.1 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.7 | 1.0 | 1.5 | 2.2 | 7.0 |
| **9 to 10** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.1 | 0.2 | 0.3 | 0.5 | 1.3 |
| **>10** | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.2 | 0.2 | 0.3 | 0.7 | 1.9 | 3.5 |
| **Total** | 1.4 | 2.8 | 3.9 | 5.2 | 6.5 | 7.7 | 9.6 | 11.9 | 13.5 | 17.2 | 20.4 | 100.0 |

Table 5 shows the patterns of years in sample and the number of directors firms had in the ABS and ASX experimental dataset. There are more firms that have 5 to 8 directors and there are more firms in the sample for the more than 10 years categories than other category in the ABS and ASX experimental dataset.

Table 5: Applications and years in sample --- ABS and ASX

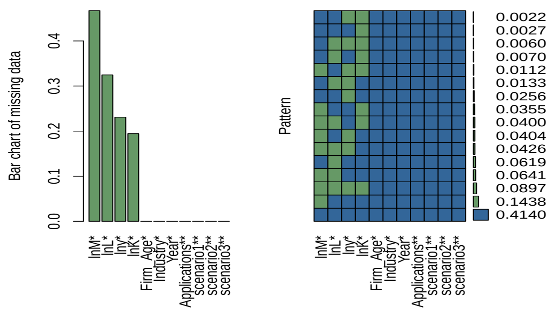
| directors | years in sample | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **>10** | **Total** |
| **1 to 4** | 0.0 | 0.1 | 0.3 | 0.4 | 0.6 | 0.4 | 1.1 | 1.8 | 2.2 | 3.5 | 33.2 | 43.6 |
| **5 to 8** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.5 | 0.8 | 1.2 | 1.6 | 40.5 | 44.6 |
| **9 to 10** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.1 | 6.6 | 6.9 |
| **>10** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 4.9 | 4.9 |
| **Total** | 0.0 | 0.1 | 0.3 | 0.4 | 0.7 | 0.5 | 1.6 | 2.7 | 3.5 | 5.2 | 85.1 | 100.0 |

### 4.6 Missing data

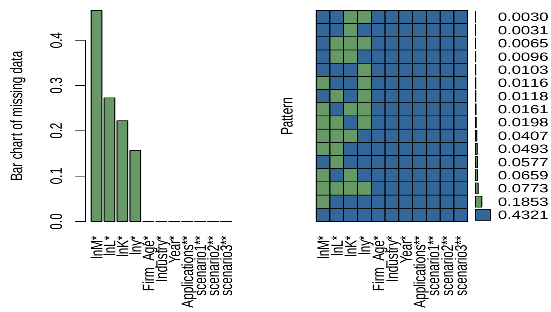
The benefits and challenges in using administrative data for statistical purposes are well documented in Tam and Clarke (2015). Administrative data sources contain deterministic linking keys such as ABNs or ACNs, which enable high quality linked datasets. Missing data, i.e. missing variables from the linked records, can still arise even when quality linking keys are available. Missing data can also be caused by the timing of processing or the scope of firms included in the data sources. Figure 2 shows the patterns of missing data for the combined ABS and ASX and ABS and IPGOD datasets. The blue shows the proportion of a non-missing value and green shows the proportion of missing values. If we use complete cases analysis, we would lose substantial amount of data for the analysis.

Figure 2: Missing data patterns in integrated datasets

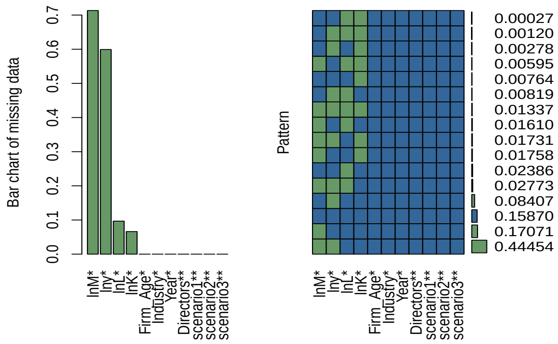
(a) ABS and Patents[1]




(b) ABS and Trademarks[2]




(c) ABS and ASX[3]




Note. In each subfigure, the left panel is a bar chart showing the proportion of missing data for each variable. The right panel shows the six missing data patterns in the data and the proportion of each pattern. These proportions are scaled to increase the readability of the plot (Templ et al., 2012); a green tile indicates missing data, and a blue tile indicates non-missing data. Subscripts are removed to simplify the notation. The variables ln$L$, ln$K$, ln$M$ and ln$Firm_Age$ are the logarithms of labour for firms, capital for firms, materials used for production and firm age, respectively. The variable `Applications' is the trademark or patent registration applications and `Directors' is the number of shared directors. The variable Scenario 1 considers firms to participate in a business network only when they submit a joint patent or trademark application. The variable Scenario 2 considers business network relationships generated by the joint patent and/or trademark applications lasting beyond year $t$. The variable Scenario 3 considers business network relationships generated, by the joint patent and/or trademark applications or firms sharing directors, could have existed before the year $t$ of the application or appointment and lasted beyond year $t$.
1. * ABS data ** Patents data 2. * ABS data ** Trademarks data 3. * ABS data ** ASX data

There are many different approaches to handle missing data ranging from complete cases analysis and mean data imputation, to more complex imputation approaches involving an Expectation Maximisation algorithm. See Graham (2009) for a detailed discussion. There is no single correct approach to handle missing data. We use an approach that minimises information loss when we integrate datasets for our analysis. Appendix $A$ shows the impact on the analysis if we perform complete cases. We use a two step imputation method and assume missing at random (MAR). The consequence of MAR assumption is that missing values can be imputed using models fitted to the observed data (Little and Rubin, 2014). We first use the information from IPGOD to allocate firm different industries before we perform imputation for the integrated datasets. Appendix $B$.1 provides details on the imputation methodology. All subsequent analysis is based on the completed datasets.

## 4.7 Three scenarios for the effects of participating in business networks

This study explores three scenarios for the effect of firm participation in business networks. It is feasible that the business network relationships generated by the joint patent and/or trademark applications or firms sharing directors could have existed before the year $t$ of the joint application or appointment of the shared director and lasted beyond year $t$. Consider the following example.

We observe firm $A$ with four patent applications between 2004 to 2007. Firm $A$ had a joint application with firm $B$ in 2005. The three scenarios we consider include having an effect in 2005 only, having an effect in all years after 2005, i.e. between 2005 and 2007, and having an effect in the whole period, i.e. between 2003 to 2007 (see Table 6).

Table 6: Business network assumptions

| | | Scenario | | |
|---|---|---|---|---|
| year | App | 1. year of application | 2. forward effect | 3. whole period |
| 2004 | 1 | 0 | 0 | 1 |
| 2005 | 1 | 1 | 1 | 1 |
| 2006 | 1 | 0 | 1 | 1 |
| 2007 | 1 | 0 | 1 | 1 |

Note. A 1 in the first column App indicates Firm $A$ filed a patent application. A 1 in the second to final columns indicates Firm $A$ filed a joint patent application with Firm $B$ and 0 indicates otherwise.

# 5 STATISTICAL MODELS

## 5.1 Productivity

This study examines the relationship between firm performance and firm participation in business networks using a modified version of the framework proposed by Gronum et al. (2012). We explore three measures of firm performance (productivity, firm sales and innovation) and three types of business networks (commercial, R&D and shared directors). Appendix $D$ provides further detail on how we define these measures of firm performance and types of business networks.

We use a well documented productivity convergence equation for firm productivity to capture within industry changes in the economy (Bernard and Jones, 1996). We expect more productive firms to grow slower than less productive firms because they face higher diminishing returns (Tsionas, 2000). We adapt the productivity convergence equation of Bahar (2018) to capture within industry changes and specify:

$$\Delta Mfp_{jkt} = \mathbf{X}_{jkt}^{(Mfp)}\boldsymbol{\beta} + \boldsymbol{\epsilon}_{jkt}^{(Mfp)}, \tag{1}$$

where the symbol $\Delta$ represents change so $\Delta Mfp_{jkt} = Mfp_{jkt} - Mfp_{jkt-1}$ is the change in the productivity for firm $j$ in industry $k$ from time $t-1$ to time $t$. We use Wilkinson and Rogers (1973) notation to write the term $\mathbf{X}_{jkt}^{(Mfp)}\boldsymbol{\beta}$ which describes firm productivity convergence characteristics as $Poly(lagMfp, 4) + BusinessNetworks + State + Time$ for each industry. We also fit a model that is simpler than fitting separate models to each industry because the terms $Poly(lagMfp, 4)$ and $BusinessNetworks$ etc. are common across industries. The equation for the simpler model is $Poly(lagMfp, 4){+}BusinessNetworks{+}Industry{+}State{+}Time$. The term $Poly(., 4)$ represents the quadratic, cubic and quartic terms of a variable. The symbol $lag$ means observation at $t-1$. The term $lagMfp$ indicates the initial level of productivity which is the observed firm productivity at $t-1$. They are included to capture non-linearity in the estimation. We include additive fixed effects indicator variables $Industry$ in the equation for all industries. The estimated state fixed effects for firm $j$ in different states at time $t$ is denoted as $State$ with Northern Territory as the reference group. The estimated time fixed effect for firm $j$ in industry $k$ at time $t$ is denoted as $Time$ with 2003 as the reference group. This makes each $\mathbf{X}_{jkt}^{(Mfp)}\boldsymbol{\beta}$ a sum of $p = 21$ terms for each industry and $p = 40$ terms for all industries. The statistical residuals are represented by $\boldsymbol{\epsilon}_{jkt}^{(Mfp)}$. We also include the indicator variable $BusinessNetworks$ in equation (1) to explore how business network affects firm productivity in three scenarios.

## 5.2 Sales

Next, we use a similar approach to explore how firm participation in business networks affects firm sales (i.e., $Sales$). We specify the sales convergence equation as:

$$\Delta \ln Sales_{jkt} = \mathbf{X}_{jkt}^{(Sales)}\boldsymbol{\beta} + \boldsymbol{\epsilon}_{jkt}^{(Sales)}, \tag{2}$$

where the symbol $\Delta$ represents change so that $\Delta \ln Sales_{jkt} = \ln Sales_{jkt} - \ln Sales_{jkt-1}$ is the change in sales for firm $j$ in industry $k$ from time $t-1$ to time $t$. The term $\mathbf{X}_{jkt}^{(Sales)}\boldsymbol{\beta}$ in (2) is specified as $Poly(lagSales, 4) + BusinessNetworks + State + Time$ for each industry and $Poly(lagSales, 4) + BusinessNetworks + Industry + State + Time$ for the simpler model. The term $Poly(., 4)$ represents the quadratic, cubic and quartic terms of a variable. The symbol $lag$ means observation at $t-1$. We use $lagSales$, the observed $Sales$ at $t-1$, to indicate the initial level of sales. The polynomial terms for the initial level of sales are included to capture non-linearity in the estimation. The statistical variability about the regression function is represented by $\boldsymbol{\epsilon}_{jkt}^{(Sales)}$. The dummy indicator variables $Industry$, $State$, $Time$ and $BusinessNetworks$ are the same as above. We use $BusinessNetworks$ to explore how business networks affect firm sales in three scenarios.

### 5.3 Innovation

Finally, we explore how firm participation in business networks affects firm innovation. We pool the data and we do not differentiate between patent or trademark applications for each firm in the analysis. We adapt Hausman et al. (1984) and Guan et al. (2015) to specify the negative binomial equation for measuring innovation as:

$$App_{jkt} \sim \text{Negative Binomial}\left(\lambda_{jkt}\right) \tag{3a}$$

$$log\left(\lambda_{jkt}, \theta\right) = \mathbf{X}_{jkt}^{(App)}\boldsymbol{\beta} \tag{3b}$$

where $App_{jkt}$ is the number of patent and/or trademark applications for firm $j$ in industry $k$ at time $t$. The variable $\lambda_{jkt}$ is the mean and the variable $\theta$ is the overdispersion parameter ($\theta$ equals infinity gives the Poisson case). We express the input variables term $\mathbf{X}_{jkt}^{(App)}\boldsymbol{\beta}$ as $Poly(lagApp, 4) + BusinessNetworks + State + Time$ for each industry and $Poly(lagApp, 4) + BusinessNetworks + Industry + State + Time$ for all industries. The term $Poly(., 4)$ represents the quadratic, cubic and quartic terms of a variable. The symbol $lag$ means observation at $t-1$. We use $lagApp$, the observed $App$ at $t-1$. The term $Poly(lagApp, 4)$ represents the quadratic, cubic and quartic terms of $lagApp$. These lag variables are included to better describe the underlying time series count data generation process (Brandt et al., 2000). The dummy indicator variables $BusinessNetworks$, $Industry$, $State$ and $Time$ are the same as above. We also use $BusinessNetworks$ to explore how business networks affect firm innovation in three scenarios. Appendix $C$ provides details on the estimation methods.

## 6 EMPIRICAL RESULTS

We analyse integrated administrative datasets to describe the relationship between business networks and firm performance. The three measures of firm performance used in this study are productivity, sales and innovations. We also study three types of business networks—R&D consortium, commercial and shared directors—in three different scenarios (see Table 6 above). Our hypothesis is that participation in business networks should, in general, provide positive effects on firm performance after adjusting for $Industry$, $State$ and $Time$ variables.

We show both estimated coefficients using both *Balanced* and *Imputed* datasets. The signs and significance of the estimated coefficients are more similar between productivity and three types of business networks and between innovation and three types of business networks in comparison with between sales and three types of business networks. $(1), (2)$ and $(3)$ are expressed in the logarithmic functional forms. We perform the following calculation $[(exp(\hat{\beta}) - 1) \times 100]$ for interpreting the estimated coefficients as the percentage changes in the predicted dependent variable (Wooldridge, 2006).

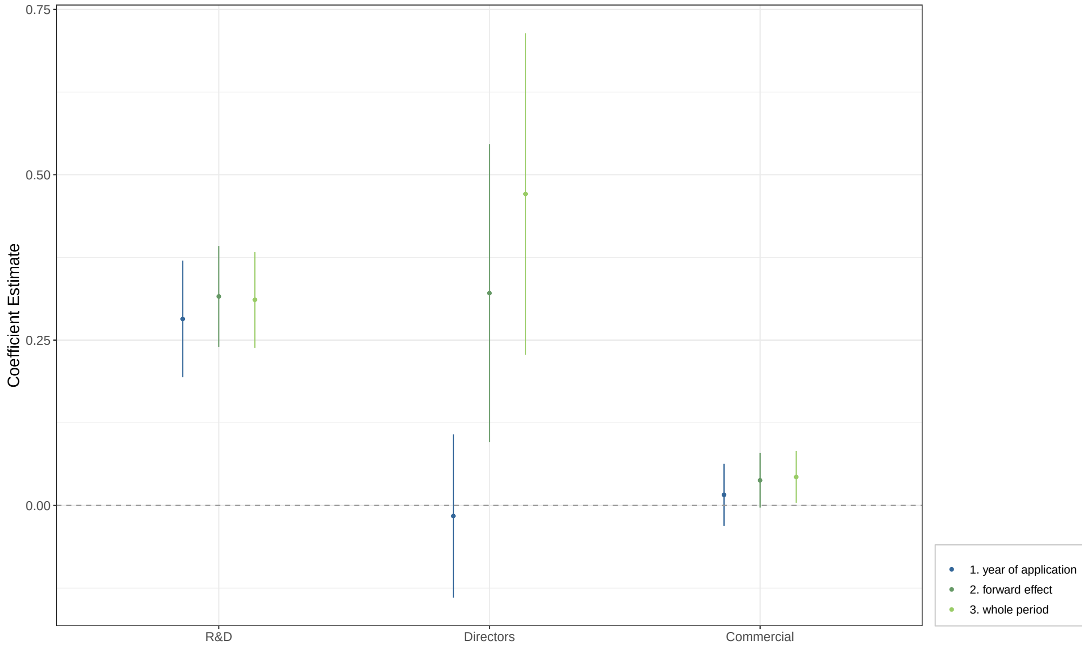
Our results using *Imputed* datasets confirm our hypothesis that there are positive correlations between three measures of firm performance and three types of business networks. This finding is similar to the finding of Gronum et al. (2012) in their analysis of BLD survey results. The amount of information loss is significant when we compare the results using *Balanced* and *Imputed* datasets. For example, the information loss is $\approx 58\%$ for the experimental ABS and Patents, $\approx 55\%$ for the experimental ABS and Trademarks and $\approx 85\%$ for experimental ABS and ASX dataset for productivity.

We also compare the results of the control equations in column (1) and (2) in Tables 11, 12 and 13 in Appendix $E.2$ with Bahar (2018). As expected, firms with higher levels of productivity tend to grow more slowly. However, we find that the quadratic terms are generally negative. The observed differences from Bahar (2018) may be caused by our inclusion of polynomial terms, rather than just the quadratic term, because we have access to a longer time series microdata.

### 6.1 Productivity

Figure 3 shows that the positive impact of shared director business networks and productivity is stronger when we consider firms participate in shared director business networks for a longer period in the *Imputed* datasets. In comparison, the effects are similar for firms that participate in either R&D or commercial business networks. Our findings are consistent with Gronum et al. (2012), who also find that the effect of R&D business networks on firm performance is positive in their analysis of BLD survey results.

Figure 3: Productivity and three business networks --- Imputed dataset




Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(1)$.

Tables 11, 12 and 13 in Appendix $E.2$ show the positive impacts of firm participation in three types of business networks on firm productivity. Columns (3) to (8) show the effect of business networks on productivity in the three scenarios for firms participating in business networks. Columns (3), (5) and (7) show the estimated coefficients using *Balanced* dataset. Columns (4), (6) and (8) show the estimated coefficients using *Imputed* dataset. The magnitudes of the estimated coefficients are different, but we are not expecting them to be the same.

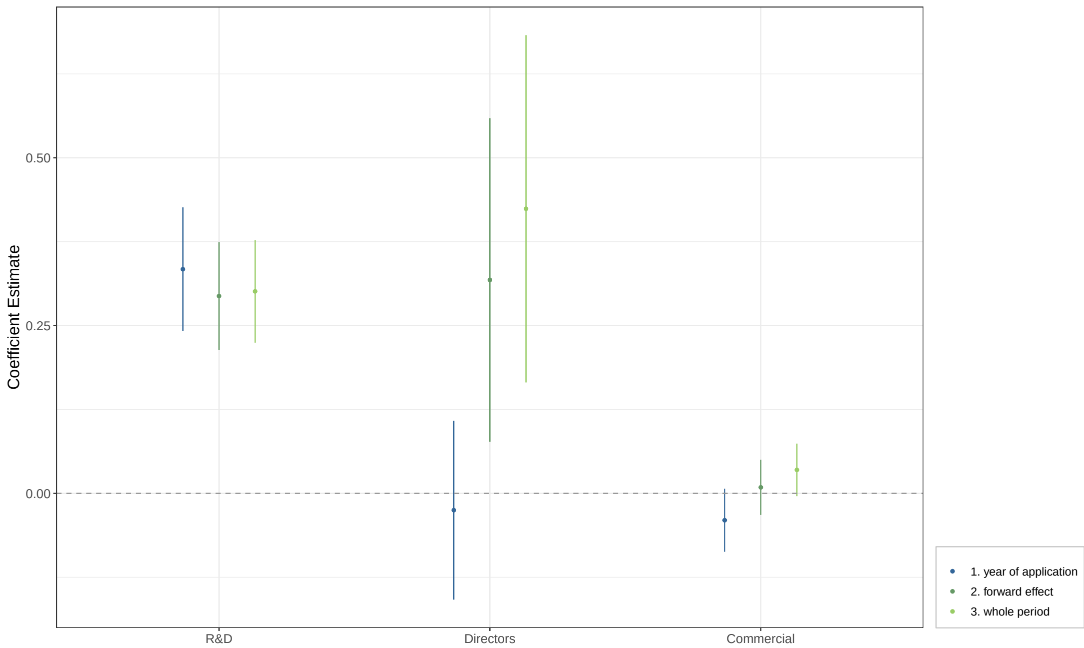
The positive association between productivity and firm participation in R&D business networks increases from ($\approx 32.6\%$) in column (4) to ($\approx 36.5\%$) in column (8) when we consider firms that participate in the R&D business networks for a longer period. We also observe similar results between productivity and firm participation in commercial business networks. The positive association is ($\approx 4.4\%$) when firms participate in the commercial business networks for a longer period.

In comparison, we find a small and insignificant negative association between shared director business networks and productivity in Scenario 1. This is against our hypothesis that firms with shared directors have better firm productivity through effective resource monitoring (Hillman and Dalziel, 2003). Harris and Shimizu (2004) argue that some directors may sit on too many boards and face time constraints and conflicts between board activities. We cannot assess the effectiveness of these directors on firm productivity because we do not have information on how involved these directors are with these firms' day-to-day operations. However, the association between productivity and shared director business networks is positive when we consider firms in shared director business networks for longer periods (see Table 13). Kor and Sundaramurthy (2009) argue from a human capital perspective that outside directors can continue to use their human and social capital to help improve firm performance. Their results show that outside directors' past experience and memberships on different boards contribute positively to firm performance. Our results are similar to their findings; however, as pointed out by Kor and Sundaramurthy (2009), different skill levels and experience of directors matter. Complex data integration to obtain information on director skill levels and experience is outside the scope of this study.

### 6.2 Sales

Figure 4 shows that there are positive associations between firm participation in three types of business networks and firm sale especially when we consider these firms participating in the business networks for a longer period. This finding of positive association between firm participation in business networks and firm sales is consistent with Gronum et al. (2012), who also find that business networks contribute positively to firm sales in their analysis of BLD survey results.

Figure 4: Sales and three business networks --- Imputed dataset




Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting (2).

Tables 14, 15 and 16 in Appendix $E.3$ show the results of firm sales. Columns (3), (5) and (7) show the estimated coefficients using *Balanced* datasets. Columns (4), (6) and (8) show the estimated coefficients using *Imputed* datasets. The magnitudes of the estimated coefficients are different, but we are not expecting them to be the same. We find mixed results in the associations between firms sales and three types of business networks when we compare results between *Balanced* and *Imputed* datasets. As discussed previously, the loss of information is significant if we consider results from *Balanced* datasets.

Similar to the finding of Gronum et al. (2012), we find that the R&D business network effects are positively associated with firm sales. We find that the commercial business networks effect is initially negative ($\approx -3.9\%$) which is against our hypothesis. Bayo-Moriones and de Cerio

(2004) analyse 176 new business ventures in the United States between 1983 and 1988 using multiple regression models and also find negative associations between business networks and firm sales. They argue that it can be difficult to transfer knowledge between partners to improve sales because of the complexity of business operations. However, the association between firm participation in commercial business networks and sales become positive ($\approx$ 3.6%) when we consider firms that participate in commercial business networks for a longer period.

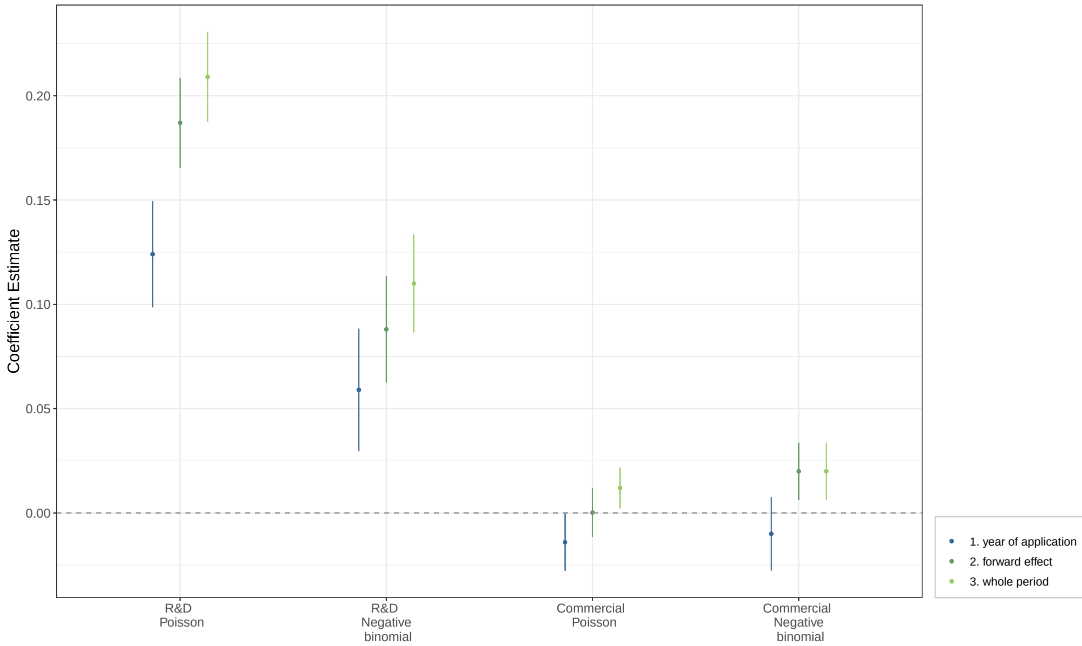
It is also interesting to note that sales and productivity have similar results in shared director business networks. We find that the director effects are initially negative and insignificant, but become positive when firms participate in shared director business networks for a longer period. Collins and Clark (2003) find that incentive pay is an important factor for explaining the relationship between firm sales and shared director business networks; we do not include directors' remuneration packages in this analysis. This information can be used to derive proxies to measure the differences between directors. It would be useful to compare the effects of business networks with and without director incentive pay.

### 6.3 Innovation

Wagner (2007) argues that business networks facilitate innovation, meaning there should be a positive association between innovation and business networks. We measure innovation by counting the number of patents or trademarks each firm owns. Empirical studies using administrative data to explore the effects of business networks on innovation often measure innovation by only counting the number of patent applications (see Ahuja, 2000, Guan et al., 2015). We find similar results when we compare the positive associations between innovation and firms participating in R&D or commercial business networks and productivity and firms participating in R&D or commercial business networks.

Figure 4 shows that there are positive associations between firm participation in three types of business networks and firm innovation when we consider the estimated coefficients using *Imputed* datasets. The positive associations are stronger when we consider firms participate in the R&D and commercial business networks for a longer period. Our results from the Negative Binomial regressions suggest that the positive correlations are stronger when we compare firms that participate in the R&D ($\approx$ 23.2%) and commercial ($\approx$ 1.22%) business networks in Scenario 3. The positive effects of business networks on innovation are slightly stronger when firms participate in business networks for longer periods. This could suggest that firms are more likely to develop more products when they are in commercial and/or R&D business networks for longer periods. Our results are consistent with other studies, which find that business networks and innovation are positively associated. The finding is consistent with Ahuja (2000) who finds a positive correlation between networks and firms' patenting rate using Poisson random effect models. Lahiri and Narayanan (2013) study positive but insignificant network coefficients when they examine the relationship between innovation and alliance portfolio size.

Figure 5: Innovations and three business networks --- Imputed dataset




Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(3)$.

Tables 17 and 18 in Appendix $E.4$ show the results of Negative Binomial regression models in columns (1), (3), (5) and (7) and Poisson regression models in columns (2), (4), (6) and (8). As expected, results are consistent but the business network effects are weaker after we take into account overdispersion.

## 6.4 Industry analysis

There is great variety in our industry results. In general, there are more positive associations between different measures of firm performance and business networks. See Figures 10, 11 and 12 for productivity, Figures 13, 14 and 15 for sales and Figures 16 and 17 for innovation. This variability could be caused by structural differences between industries.

Most industries show consistent results for the three scenarios for the effects of firm participation in business networks. It is interesting to note that the positive association between firm participation in R&D business networks and firm sales in Scenario 1 become negative in Scenario 2 and scenario 3 only in Electricity, Gas, Water and Waste services industry.

# 7 CONCLUSIONS, LIMITATIONS AND FUTURE DIRECTIONS

We use administrative data to explore the relationship between firm performance and business networks. Using administrative data reduces self-response bias; however, there is the possibility of under-coverage because not all collaborations lead to joint patent or trademark applications or shared directors. This under-coverage bias does not affect the analysis because this research does not consider other types of business relationships.

We propose an approach to impute missing data for the three combined datasets we use (details in Appendix $B.1$). The analyses of our *Imputed* datasets suggest that there are generally positive associations between firm performance and R&D, commercial and shared directors business networks. The positive associations between business networks and productivity are slightly stronger and between business networks and sales are slightly weaker when firms participate in these business networks for a longer period. The positive associations are stronger when we compare firms that participate in R&D with firms that participate in commercial business networks. This is not surprising given that there are more opportunities for firms to work closely in R&D activities.

We find that there is a negative association between firm performance and shared director business networks in Scenario 1. In Scenario 1, we do not change the length of time for which firms are in business networks. The association becomes positive when firms participate in shared director business networks for a longer period. However, as discussed, we cannot assess the effectiveness of these directors on facilitating resource allocations because we do not have information on how involved these directors are with these firms' day-to-day operations. We generally find positive associations between firm performance and business networks at the industry level, but there are great variations in the associations between firm performance and business networks.

This preliminary analysis could be extended in several areas. It would be useful to conduct sensitivity analysis using different imputation approaches. We could include additional network measures (e.g., centrality or connectedness) to better capture complex business network effects in our models. It would be useful to extend the work of Lewbel et al. (2019) and estimate the business network effects when we do not know or observe the network directly to better understand how business networks affect firm performance. Finally, this research highlights the opportunities of combining administrative data with survey data for this type of analysis. Survey data contains different types of business network information that is not collected by administrative agencies. Administrative data can also be used to mitigate self-response bias in survey results. It would also be interesting to build on the work of Tranmer et al. (2014) and explore more complex statistical models to better capture the hierarchical and network structures in our data to compare with this analytical results.

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# A COMPLETE CASES ANALYSIS

Figures 6($a$), 7($a$) and 8($a$) show distributions for the changes in multifactor productivity when we use complete cases analysis for the experimental ABS and Patents, ABS and Trademarks and ABS as well as ABS and ASX datasets. These distributions look narrow and most changes in $MFP$ are closed to 0. In comparison, if we use imputed data we see normal distributions for the changes in multifactor productivity. Figures 6($b$), 7($b$) and 8($b$) show that the distributions of the changes in multifactor productivity are closer to what we expect to see.

Figure 6: Histogram of changes in multifactor productivity in experiment ABS and Patents

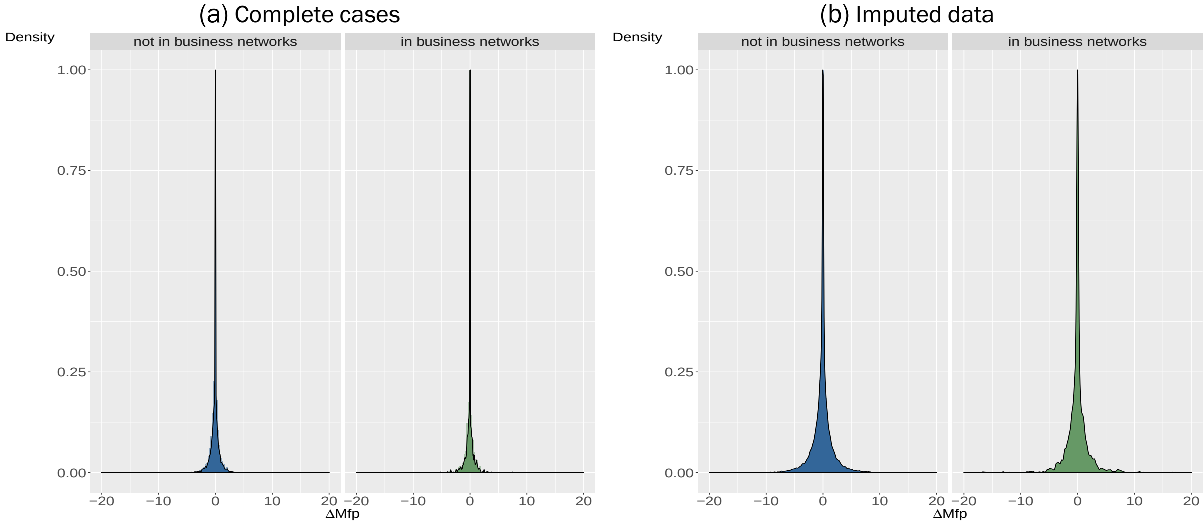



Figure 7: Histogram of changes in multifactor productivity in experiment ABS and Trademarks

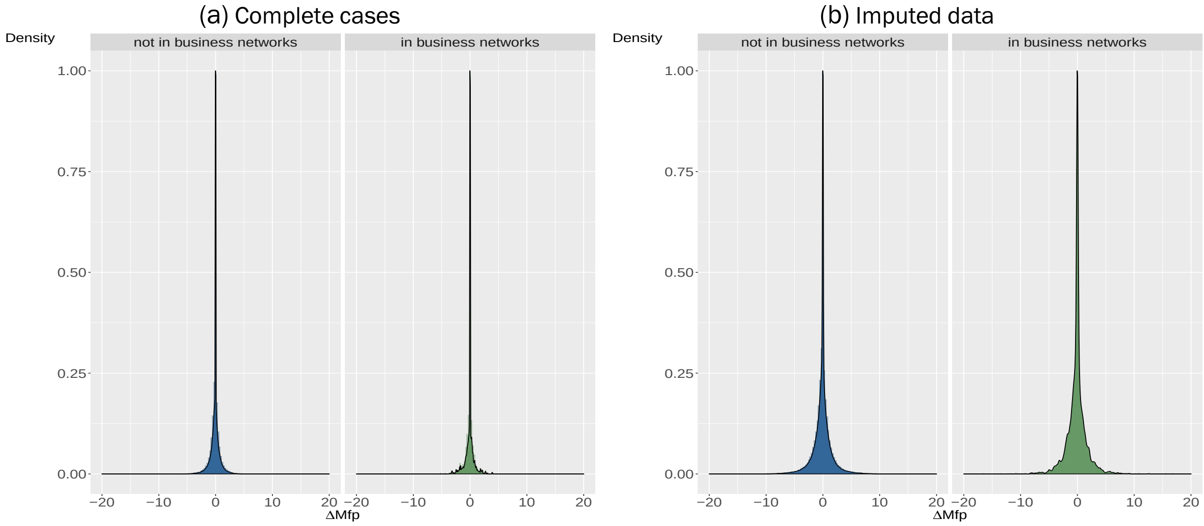
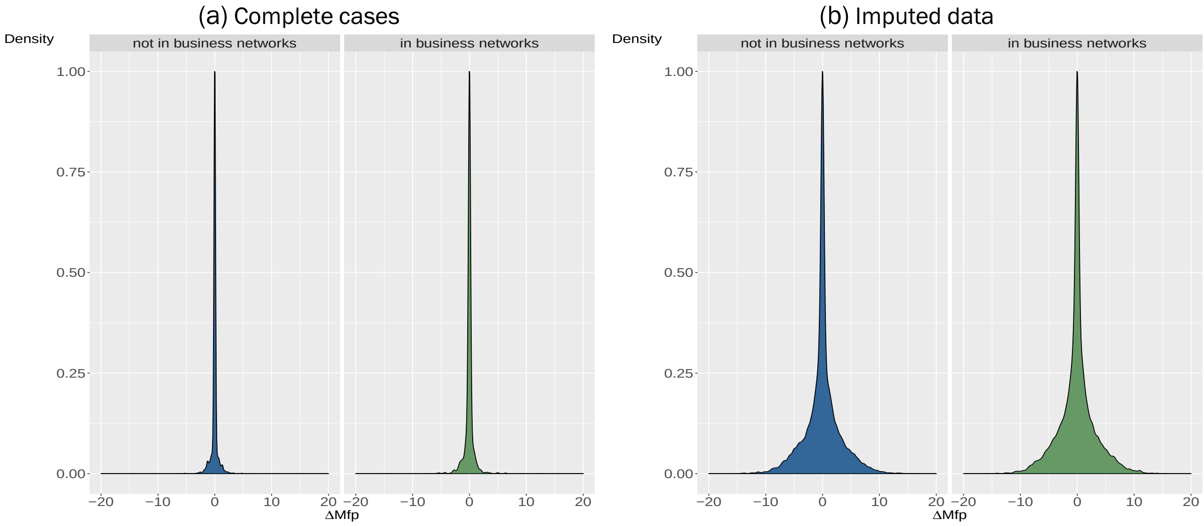


Figure 8: Histogram of changes in multifactor productivity in experiment ABS and ASX



# B MISSING DATA IMPUTATION

## B.1 Imputation methods for categorical data

We first use the information from IPGOD to allocate firm $j$ belonging to an unknown industry $U$ into different industries. The font—$\boldsymbol{\mathcal{X}}$—represents observed dataset in the notation. The formula to allocate firms into different industries is

$$\begin{aligned}
Pr(j=k \mid \boldsymbol{\mathcal{X}}_{jkt}) &= \frac{exp\,(\boldsymbol{\mathcal{X}}_{jkt}^{\top}\mathbf{a}_k)}{1+\sum_{k=1}^{K-1} exp\,(\boldsymbol{\mathcal{X}}_{jkt}^{\top}\mathbf{a}_k)}, k=1,\cdots,K-1 \\
\vdots \quad &= \quad \vdots \\
Pr(j=K \mid \boldsymbol{\mathcal{X}}_{jkt}) &= \frac{1}{1+\sum_{k=1}^{K-1} exp\,(\boldsymbol{\mathcal{X}}_{jkt}^{\top}\mathbf{a}_k)}.
\end{aligned} \tag{4}$$

The one terms in the denominator and in the numerator of the $Pr(j=K|\boldsymbol{\mathcal{X}}_{jkt})$ ensure probabilities over the response categories sums to 1 (Czepiel, 2002, Agresti, 2007). It is convenient to write the term $\boldsymbol{\mathcal{X}}_{jkt}^{\top}\mathbf{a}_k$ in Wilkinson and Rogers (1973) notation as $Products + BusinessNetwork + Time + State$. Here $Products$ is the number of products firm $j$ register at time $t$. The indicator $BusinessNetwork = 1$ for scenario 3 if firm $j$ is in a business network and 0 otherwise. The variable $Time$ is represented by 10 time indicator variables, one for each year with 2002–03 as baseline. The variable $State$ is represented by 8 indicator variables, one for each state with Northern Territory as a reference group. This makes each $\boldsymbol{\mathcal{X}}_{jkt}^{\top}\mathbf{a}_k$ a sum of 18 terms. The formula is applied to the complete cases to obtain the industry coefficients $\mathbf{a}_k$ with $k=1,\cdots,17$ industries. We combine these estimated coefficients with firm characteristics data $\boldsymbol{\mathcal{X}}_{jkt}$ for firms with the missing industry. We allocate firm $j$ to an industry with the highest predictive probability.

We apply the same approach to impute firms with missing data in the combined ABS and ASX dataset. The only difference is replacing $Products$ with $Directors$, number of directors, in formula (4) to allocate firm $j$ to an industry with the highest predictive probability before imputation. Again, we select the dataset that maximises the likelihood for equation (9) in Appendix ($D$) from the 10 datasets in each industry. We keep the unknown industry category $U$ after imputation because we only use the imputed industry categories to improve the results of multiple imputation. Our sensitivity analysis, compares models with and without imputed industry categories, shows consistent results.

## B.2 Imputation methods for continuous data

Next, we assume MAR and impute missing values in the combined ABS and IPGOD datasets by imputed industry. We use sequential regression in SAS `proc mi` procedure for the imputation. We adapt a similar notation to Reiter (2005). The experimental dataset consists of $[\boldsymbol{y}, \boldsymbol{\mathcal{X}}]$, where $\boldsymbol{y}$ is an $N \times 1$ vector that includes the dependent variable, and $\boldsymbol{\mathcal{X}}$ is an $N \times 15$ matrix that includes all the independent variables from (9). This gives 15 unknown regression parameters in (9). We impute missing variables ln$y$, ln$K$ and ln$M$. The observed dataset consists of two $N \times 16$ matrices, $\boldsymbol{\mathcal{D}} = [\boldsymbol{y}, \boldsymbol{\mathcal{X}}]$, where $\boldsymbol{\mathcal{X}}$ includes all the independent variables from (9); and the response indicator matrix $\boldsymbol{\mathcal{R}}$ which we use to partition $\boldsymbol{\mathcal{D}}$ into the observed $\boldsymbol{\mathcal{D}}^{obs}$ and the missing $\boldsymbol{\mathcal{D}}^{mis}$. We use $\boldsymbol{\mathcal{X}}$, $\boldsymbol{\mathcal{X}}^{(K)}$ and $\boldsymbol{\mathcal{X}}^{(M)}$ to denote the design matrix for imputing missing data in $\ln y$, $\ln K$ and $\ln M$, respectively.

We impute the missing values in $\ln y$, $\ln K$ and $\ln M$ separately, using sequential regression (SR). The SR method uses appropriate regression models for different variable types. For example, continuous variables are imputed using a normal model and binary variables using a logit model. The SR method generates a continuous vector $\boldsymbol{y}^{seq}$ from the parameters directly estimated from the fitted regression following Raghunathan et al. (2001). The SR formula for generating missing data for $\boldsymbol{y}$ is:

$$\boldsymbol{y} = \boldsymbol{\mathcal{X}}\boldsymbol{\beta}. \tag{5}$$

We apply (5) three times, with $\boldsymbol{y}$ denoting each of the three variables $\ln y$, $\ln K$ and $\ln M$. We use $\boldsymbol{\mathcal{X}}$, $\boldsymbol{\mathcal{X}}^{(K)}$ and $\boldsymbol{\mathcal{X}}^{(M)}$ to denote the design matrix for creating missing data in $\ln y$, $\ln K$ and $\ln M$, respectively. If the missing data variable is $\ln y$, then $\boldsymbol{\mathcal{X}}$ includes all the independent variables from (9). In comparison, if the missing data variable is $\ln K$, then $\boldsymbol{\mathcal{X}}^{(K)}$ includes all the independent variables and $\ln y$ but excludes $\ln K$. Similarly, if the missing data variable is $\ln M$, then $\boldsymbol{\mathcal{X}}^{(M)}$ includes all the independent variables and $\ln y$ but excludes $\ln M$. Algorithm 1 describes the basic concept of the algorithm (Drechsler, 2011).

**Algorithm 1** Sequential regression algorithm

1: **procedure**
2: **Step 1**: **draw** a new value $\theta = (\sigma^2, \boldsymbol{\beta})$ from $Pr(\theta \mid \boldsymbol{y}_{obs})$
3: **draw** variance from $\sigma^2 | \boldsymbol{\mathcal{X}}_{obs} \sim (\boldsymbol{y}_{obs} - \boldsymbol{\mathcal{X}}_{obs}\widehat{\boldsymbol{\beta}})'(\boldsymbol{y}_{obs} - \boldsymbol{\mathcal{X}}_{obs}\widehat{\boldsymbol{\beta}})\chi^{-2}_{n-k}$, where $n$ is the total number of observations and $k$ is the number of parameters
4: **draw** coefficients from $\boldsymbol{\beta} \mid \sigma^2, \boldsymbol{\mathcal{X}}_{obs} \sim \mathcal{N}(\widehat{\boldsymbol{\beta}}, (\boldsymbol{\mathcal{X}}'_{obs}\boldsymbol{\mathcal{X}}_{obs})^{-1}\sigma^2)$
5: **Step 2**: **draw** an imputed value $\boldsymbol{y}^{seq}$ from $Pr(\boldsymbol{y}^{seq} \mid \boldsymbol{y}_{obs}, \theta)$
6: **draw** from fitted regression $\boldsymbol{y}^{seq} \mid \boldsymbol{\beta}, \sigma^2, \boldsymbol{\mathcal{X}}_{obs} \sim \mathcal{N}(\boldsymbol{\mathcal{X}}_{obs}\boldsymbol{\beta}, \sigma^2)$
7: **repeat** Step 1 and Step 2 to impute each variable sequentially

We create 10 imputed datasets in each imputed industry and we select the best imputed dataset which maximises the likelihood for equation (9) in Appendix ($D$) from the 10 datasets in each industry (Schomaker and Heumann, 2014, Chien et al., 2018).

# C ESTIMATION METHODS

## C.1 The Poisson regression model

A count of the number of patent and/or trademark applications can be specified as the model as $y$ given $\mathbf{X}$ is Poisson distributed with density

$$P(Y = y \mid \mathbf{X}) = \frac{e^{-\lambda}\lambda^{y}}{y!}, \quad y = 0, 1, 2, \cdots, \text{ and the mean parameter} \tag{6}$$

$$E(y \mid \mathbf{X}) = \lambda = exp(\mathbf{X}\boldsymbol{\beta}) \tag{7}$$

where $y$ represents the observed events, $\mathbf{X}$ denotes the independent variables and $e$ is Euler's number ($e = 2.71828\cdots$). The key feature of Poisson regression model is that the condition mean equals its variance i.e., $E(y|\mathbf{X}) = Var(y|\mathbf{X})$ (Cameron and Trivedi, 1998, Hilbe, 2011). Table 7 shows that this assumption may not hold in the sample data. This is because the variances are not the same as means and they are larger than means for the firms do not participate in business networks.

Table 7: Overdispersion in the integrated datasets

| | Firms do not participate in business networks | Firms participate in business networks |
|---|---|---|
| **ABS — IP Australia (patents)** | | |
| Mean (St. Dev.) | 2.04 (6.19) | 3.05 (3.80) |
| **ABS — IP Australia (trademarks)** | | |
| Mean (St. Dev.) | 2.53 (4.42) | 3.10 (5.55) |

## C.2 The negative Binomial model

The negative binomial model relaxes the assumption of the conditional mean equals variance (Hausman et al., 1984, Greene, 2008). This allows inclusion of a statistical term $\theta$ to allow the distribution of the conditional mean to vary according to the term (Fleming, 2001, Zwilling, 2013).

We use the R `glm.nb` function from the `MASS` package. Venables and Ripley (2002) explain the negative binomial probability function is specified as

$$P(Y = y \mid \mathbf{X}, \theta, \lambda) = \frac{\Gamma(\theta + y)}{\Gamma(\theta) y!} \frac{\lambda^{y}\theta^{\theta}}{(\lambda + \theta)^{(\theta + y)}} \tag{8}$$

where $\Gamma(.)$ is the gamma function with $\theta$ overdispersion parameter. The mean is $E(y \mid \mathbf{X}) = \lambda$ and the variance is $Var(y \mid \mathbf{X}) = \lambda + \lambda^{2}/\theta$ (Hilbe, 2011). This parameterisation is flexible and allows for using different versions of gamma distribution under different assumptions to address overdispersion (Fleming, 2001).

# D FIRM PERFORMANCE AND BUSINESS NETWORK MEASURES

## D.1 Firm productivity

This study will use the productivity measure from Chien et al. (2019). Following Zellner et al. (1966), Breunig and Wong (2008), Nguyen and Hansell (2014), Mare et al. (2017), the statistical model for the firm production function is specified as

$$\ln y_{jkt} = \beta_k + \beta_1 \ln L_{jkt} + \beta_2 \ln K_{jkt} + \beta_3 \ln M_{jkt} + \beta_4 Firm\_Age_{jkt} + \tau_{kt} + \varepsilon_{jkt}, \tag{9}$$

where the formula for firm value added $\ln y_{jkt}$ is

$$log \left[ \frac{\text{(total sales - the repurchase of stocks)}}{\text{gross value added implicit price deflators by industry}} \right]$$

for firm $j$ in industry $k$ at time $t$ (ABS, 2018). We use the method proposed by Abowd et al. (2002) to derive the logarithm of estimated firm average labour components, $\ln L_{jkt}$ for firm $j$ in industry $k$ at time $t$. The formula for the logarithm of capital cost per employee $\ln K_{jkt}$ is

$$log \left[ \frac{\text{(equipment depreciation + business rental expenses + capital investment deductions)}}{\text{consumption of fixed capital deflators by industry}} \right].$$

We calculate the per employee logarithm of material inputs $\ln M_{jkt}$ as

$$log \left[ \frac{\text{materials used in the production process}}{\text{Producer Price Index for intermediate goods}} \right]$$

for firm $j$ in industry $k$ at time $t$. The logarithm of age for firm $j$ in industry $k$ at time $t$ is $Firm\_Age_{jkt}$. The estimated time fixed effect for firm $j$ in industry $k$ at time $t$ is denoted as $\tau_{jkt}$. The term $\varepsilon_{jkt}$ are assumed to satisfy $\varepsilon_{jkt} \overset{iid}{\sim} \mathcal{N}(0, \sigma_k^2)$ to estimate unbiased coefficients for the Cobb Douglas production function.

We follow Mare et al. (2017) and define productivity measure as $Mfp_{jkt} = \hat{\tau}_{kt} + \hat{\varepsilon}_{jkt}$, where $\hat{\beta}_k$ represents technology used in the production process for industry $k$. The residual terms $\hat{\varepsilon}_{jkt}$ are the estimated multi-factor productivity for firm $j$ in industry $k$ at time $t$.

## D.2 Innovation

We measure innovation by counting the number of patent and/or trademark applications a firm has between 2003 and 2013. A majority of firms in IPGOD has only one product. We also note that there are 112 firms with ABNs classified in the International and Unknown categories. This may be due to misclassification. We have excluded these firms in our analysis.

## D.3 Firm sales

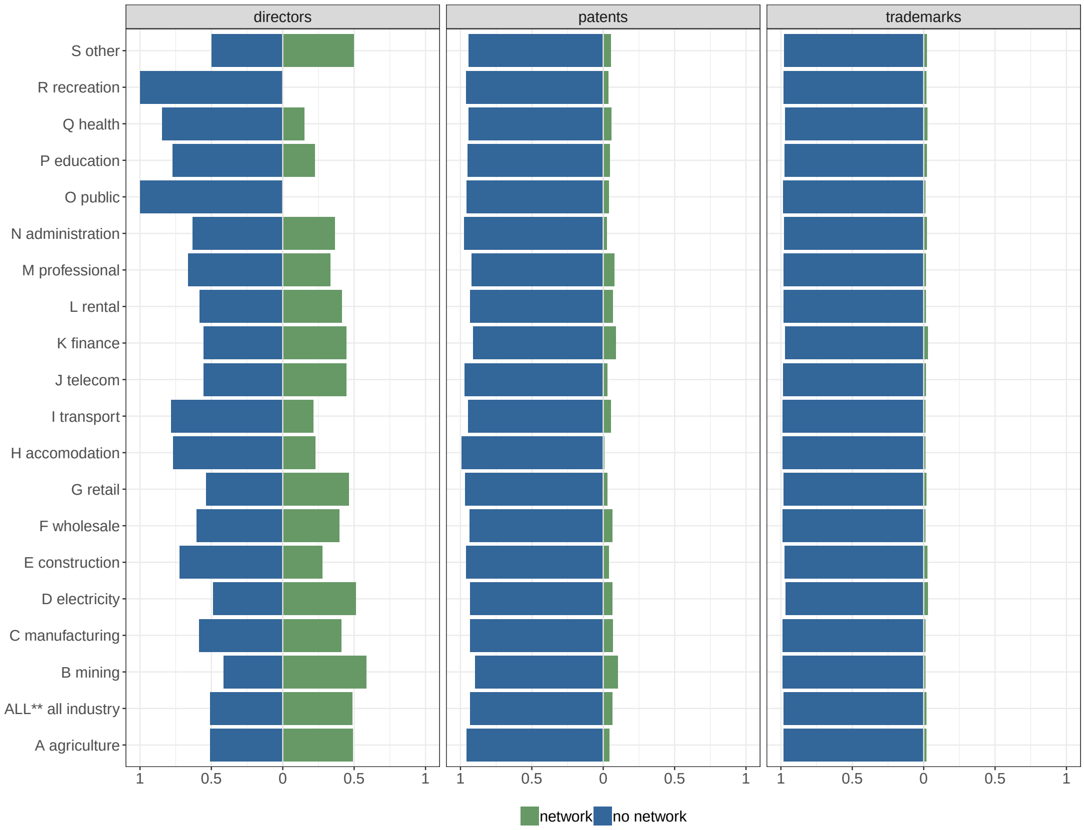
The formula for firm value added $Sales$ is

$$log \left[ \frac{\text{(total sales - the repurchase of stocks)}}{\text{gross value added implicit price deflators by industry}} \right]$$

## D.4 Business networks

Figure (9) shows the proportion of firms in business networks by industry for three types of business networks - commercial, R&D and shared directors business networks. It is also interesting to note that there is a higher proportion of firms in shared director business networks than in R&D or commercial business networks.

Figure 9: Proportion of network and no network firms by industry




Note. ALL$*{*}$ represents all industries.

In the analysis of shared directors business networks in the finance, transport, public and recreation industries, all firms are either in business networks or not in business networks. So we are unable to compare firm performance between those in a shared directors business network and not those in a shared directors business network. Therefore we exclude these industries in the analysis (54 observations).

### D.4.1 Commercial or R&D business networks

We observe if a firm files a patent or trademark application by itself or with another firm(s) in IPGOD. Therefore, we define a firm as being in a business network in year $t$ when it shares a patent and/or a trademark application with at least one other firm. One drawback in our analysis is that there are other kinds of business networks that do not generate patents and trademarks that remain in our sample. We create a network indicator that equals 1 if a firm has a patent and/or trademark application with at least one other firm in year $t$. The indicator takes value 0 if a firm files an application by itself. We explore different scenarios and assumptions for the business networks to study their effects on firm productivity. This is because, depending on its type, a patent right can last between 8 and 25 years. Similarly, a trademark right can be renewed every ten years (IP Australia, 2018a,b). The duration covers the reference period of the data. For example, if a firm registers a trademark protection with another firm at the beginning of the sample period e.g. 2003 and a trademark protection lasts for 10 years so we can consider this firm is in the business networks until 2013.

#### D.4.2 Shared directors business networks

We create an indicator variable if a firm shares a director with at least one other firm during the sample period. If a director's appointed date is before $01-01-2003$, we use $01-01-2003$ as the appointed date. We exclude directors who resigned before $01-01-2003$. The duration of the shared director network is derived by taking into account the director's earliest appointed and latest resigned dates. For example, if director 001 worked in firm $A$ between 2003 and 2004 and firm $B$ between 2004 and 2005 then firm $A$ and $B$ are connected in the director network between 2003 to 2005.

# E TABLES & FIGURES

## E.1 Summary statistics

Table 8: ABS and Patents dataset

| Statistic | N | $P_{1^{st}}$ | $P_{50^{th}}$ | $P_{99^{th}}$ | St. Dev. |
|---|---|---|---|---|---|
| **Balanced data** | | | | | |
| $\Delta Mfp$ | 12,703 | -3.136 | -0.06603 | 2.568 | 0.9495 |
| $lagMfp$ | 12,703 | -5.769 | 0.4932 | 4.475 | 1.818 |
| $lagMfp^2$ | 12,703 | 0.0002103 | 0.8445 | 42.96 | 14.2 |
| $lagMfp^3$ | 12,703 | -192 | 0.1199 | 89.61 | 251.4 |
| $lagMfp^4$ | 12,703 | 4.421e-08 | 0.7132 | 1,846 | 5,467 |
| $\Delta Sales$ | 23,472 | -3.297 | 0 | 2.808 | 0.9867 |
| $lagSales$ | 23,472 | 2.463 | 12.3 | 17.12 | 3.025 |
| $lagSales^2$ | 23,472 | 9.229 | 151.2 | 293.5 | 66.3 |
| $lagSales^3$ | 23,472 | 14.94 | 1,859 | 5,020 | 1,389 |
| $lagSales^4$ | 23,472 | 85.18 | 22,876 | 86,138 | 31,227 |
| **Imputed data** | | | | | |
| $\Delta Mfp$ | 30,063 | -6.38 | -0.0787 | 6.35 | 2.095 |
| $lagMfp$ | 30,063 | -7.281 | 0.5523 | 6.396 | 2.485 |
| $lagMfp^2$ | 30,063 | 0.0006179 | 1.687 | 69.96 | 19.76 |
| $lagMfp^3$ | 30,063 | -385.9 | 0.1685 | 261.7 | 332.9 |
| $lagMfp^4$ | 30,063 | 3.818e-07 | 2.845 | 4,895 | 6,719 |
| $\Delta Sales$ | 30,063 | -6.888 | 0 | 6.931 | 2.139 |
| $lagSales$ | 30,063 | 2.499 | 12.03 | 17.61 | 3.114 |
| $lagSales^2$ | 30,063 | 9.229 | 144.8 | 310.4 | 68.52 |
| $lagSales^3$ | 30,063 | 15.61 | 1,742 | 5,457 | 1,403 |
| $lagSales^4$ | 30,063 | 85.18 | 20,969 | 96,329 | 30,496 |
| **No missing data** | | | | | |
| $App$ | 30,063 | 1 | 1 | 14 | 6.613 |
| $lagApp$ | 30,063 | 1 | 1 | 14 | 6.195 |
| $lagApp^2$ | 30,063 | 1 | 1 | 196 | 1,929 |
| $lagApp^3$ | 30,063 | 1 | 1 | 2,744 | 669,661 |
| $lagApp^4$ | 30,063 | 1 | 1 | 38,416 | 235,560,721 |

$\Delta$ represents change and $lag$ represents observation at $t-1$.

Table 9: ABS and Trademarks dataset

| Statistic | N | $P_{1^{st}}$ | $P_{50^{th}}$ | $P_{99^{th}}$ | St. Dev. |
|---|---|---|---|---|---|
| **Balanced data** | | | | | |
| $\Delta Mfp$ | 139,659 | -3.304 | -0.06806 | 2.774 | 1.023 |
| $lagMfp$ | 139,659 | -6.378 | 0.5514 | 4.605 | 2.076 |
| $lagMfp^2$ | 139,659 | 0.0003551 | 0.9467 | 60.08 | 32.21 |
| $lagMfp^3$ | 139,659 | -259.5 | 0.1676 | 97.68 | 1,507 |
| $lagMfp^4$ | 139,659 | 1.261e-07 | 0.8963 | 3,609 | 95,460 |
| $\Delta Sales$ | 268,908 | -3.463 | 0 | 3.033 | 1.072 |
| $lagSales$ | 268,908 | 2.804 | 12.04 | 16.98 | 2.959 |
| $lagSales^2$ | 268,908 | 12.68 | 145.1 | 289.2 | 74.94 |
| $lagSales^3$ | 268,908 | 22.05 | 1,746 | 4,892 | 3,506 |
| $lagSales^4$ | 268,908 | 160.9 | 21,050 | 83,663 | 282,079 |
| **Imputed data** | | | | | |
| $\Delta Mfp$ | 313,619 | -5.985 | -0.09136 | 5.695 | 1.876 |
| $lagMfp$ | 313,619 | -7.174 | 0.6158 | 5.995 | 2.512 |
| $lagMfp^2$ | 313,619 | 0.0005716 | 1.595 | 72.09 | 44.73 |
| $lagMfp^3$ | 313,619 | -369.3 | 0.2335 | 215.5 | 3,155 |
| $lagMfp^4$ | 313,619 | 3.268e-07 | 2.544 | 5,198 | 291,573 |
| $\Delta Sales$ | 313,619 | -6.253 | 0 | 6.294 | 1.857 |
| $lagSales$ | 313,619 | 2.934 | 11.92 | 17.31 | 3.014 |
| $lagSales^2$ | 313,619 | 12.17 | 142.2 | 301 | 74.79 |
| $lagSales^3$ | 313,619 | 25.25 | 1,694 | 5,188 | 3,288 |
| $lagSales^4$ | 313,619 | 148.1 | 20,215 | 90,575 | 261,375 |
| **No missing data** | | | | | |
| $App$ | 313,619 | 1 | 1 | 20 | 4.737 |
| $lagApp$ | 313,619 | 1 | 1 | 18 | 4.341 |
| $lagApp^2$ | 313,619 | 1 | 1 | 324 | 477.6 |
| $lagApp^3$ | 313,619 | 1 | 1 | 5,832 | 111,096 |
| $lagApp^4$ | 313,619 | 1 | 1 | 104,976 | 31,026,259 |

$\Delta$ represents change and $lag$ represents observation at $t-1$.

Table 10: ABS and ASX dataset

| Statistic | N | $P_{1^{st}}$ | $P_{50^{th}}$ | $P_{99^{th}}$ | St. Dev. |
|---|---|---|---|---|---|
| **Balanced data** | | | | | |
| $\Delta Mfp$ | 1,392 | -4.365 | -0.08931 | 3.93 | 1.458 |
| $lagMfp$ | 1,392 | -8.818 | 0.5554 | 7.235 | 2.942 |
| $lagMfp^2$ | 1,392 | 0.0001292 | 2.337 | 96.15 | 24.77 |
| $lagMfp^3$ | 1,392 | -685.8 | 0.1713 | 379.3 | 400.4 |
| $lagMfp^4$ | 1,392 | 1.675e-08 | 5.46 | 9,245 | 7,254 |
| $\Delta Sales$ | 1,392 | -2.613 | 0 | 2.838 | 0.9552 |
| $lagSales$ | 1,392 | 0.9569 | 13.4 | 19.91 | 3.265 |
| $lagSales^2$ | 1,392 | 5.465 | 179.5 | 396.4 | 78.52 |
| $lagSales^3$ | 1,392 | 0.9032 | 2,405 | 7,892 | 1,851 |
| $lagSales^4$ | 1,392 | 30.16 | 32,226 | 157,142 | 46,779 |
| **Imputed data** | | | | | |
| $\Delta Mfp$ | 9,229 | -9.865 | -0.07197 | 9.589 | 3.541 |
| $lagMfp$ | 9,229 | -8.914 | 0.5615 | 8.391 | 3.33 |
| $lagMfp^2$ | 9,229 | 0.001205 | 3.745 | 101.3 | 24.79 |
| $lagMfp^3$ | 9,229 | -708.3 | 0.1771 | 590.9 | 374.1 |
| $lagMfp^4$ | 9,229 | 1.452e-06 | 14.03 | 10,258 | 6,453 |
| $\Delta Sales$ | 9,239 | -10.13 | 0 | 10.11 | 3.653 |
| $lagSales$ | 9,239 | 1.836 | 12.62 | 20.59 | 3.797 |
| $lagSales^2$ | 9,239 | 6.736 | 159.2 | 423.9 | 92.29 |
| $lagSales^3$ | 9,239 | 6.201 | 2,009 | 8,728 | 2,256 |
| $lagSales^4$ | 9,239 | 45.37 | 25,360 | 179,712 | 63,793 |

$\Delta$ represents change and $lag$ represents observation at $t-1$.

## E.2 Productivity and business networks

Table 11: Productivity and R&D business networks

| | *Dependent variable: $\Delta Mfp$* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Balanced control | Imputed control | Balanced scenario1 | Imputed scenario1 | Balanced scenario2 | Imputed scenario2 | Balanced scenario3 | Imputed scenario3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| R&D business networks | | | $0.074^{**}$ | $0.282^{***}$ | | | | |
| | | | (0.033) | (0.045) | | | | |
| R&D business networks | | | | | $0.089^{***}$ | $0.316^{***}$ | | |
| | | | | | (0.029) | (0.039) | | |
| R&D business networks | | | | | | | $0.099^{***}$ | $0.311^{***}$ |
| | | | | | | | (0.028) | (0.037) |
| $lagMfp$ | $-0.078^{***}$ | $-0.379^{***}$ | $-0.079^{***}$ | $-0.381^{***}$ | $-0.079^{***}$ | $-0.383^{***}$ | $-0.080^{***}$ | $-0.383^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| $lagMfp^2$ | $-0.010^{***}$ | $-0.016^{***}$ | $-0.010^{***}$ | $-0.016^{***}$ | $-0.010^{***}$ | $-0.016^{***}$ | $-0.010^{***}$ | $-0.016^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $lagMfp^3$ | $0.0003^{***}$ | $0.001^{***}$ | $0.0003^{***}$ | $0.001^{***}$ | $0.0003^{***}$ | $0.001^{***}$ | $0.0003^{***}$ | $0.001^{***}$ |
| | (0.00004) | (0.00004) | (0.00004) | (0.00004) | (0.00004) | (0.00004) | (0.00004) | (0.00004) |
| $lagMfp^4$ | 0.00000 | $0.00004^{***}$ | 0.00000 | $0.00004^{***}$ | 0.00000 | $0.00004^{***}$ | 0.00000 | $0.00004^{***}$ |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Observations | 12,703 | 30,063 | 12,703 | 30,063 | 12,703 | 30,063 | 12,703 | 30,063 |
| $R^2$ | 0.039 | 0.149 | 0.039 | 0.151 | 0.040 | 0.151 | 0.040 | 0.151 |
| Adjusted $R^2$ | 0.036 | 0.148 | 0.036 | 0.149 | 0.037 | 0.150 | 0.037 | 0.150 |
| *Note:* | | | | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 12: Productivity and Commercial business networks

| | *Dependent variable: $\Delta Mfp$* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Balanced control | Imputed control | Balanced scenario1 | Imputed scenario1 | Balanced scenario2 | Imputed scenario2 | Balanced scenario3 | Imputed scenario3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Commercial business networks | | | 0.0005 | 0.016 | | | | |
| | | | (0.022) | (0.024) | | | | |
| Commercial business networks | | | | | 0.012 | $0.038^{*}$ | | |
| | | | | | (0.019) | (0.021) | | |
| Commercial business networks | | | | | | | 0.019 | $0.043^{**}$ |
| | | | | | | | (0.018) | (0.020) |
| $lagMfp$ | $-0.047^{***}$ | $-0.250^{***}$ | $-0.047^{***}$ | $-0.250^{***}$ | $-0.047^{***}$ | $-0.250^{***}$ | $-0.047^{***}$ | $-0.250^{***}$ |
| | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) |
| $lagMfp^2$ | $-0.004^{***}$ | $-0.007^{***}$ | $-0.004^{***}$ | $-0.007^{***}$ | $-0.004^{***}$ | $-0.007^{***}$ | $-0.004^{***}$ | $-0.007^{***}$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| $lagMfp^3$ | $0.0002^{***}$ | $0.0002^{***}$ | $0.0002^{***}$ | $0.0002^{***}$ | $0.0002^{***}$ | $0.0002^{***}$ | $0.0002^{***}$ | $0.0002^{***}$ |
| | (0.00001) | (0.00000) | (0.00001) | (0.00000) | (0.00001) | (0.00000) | (0.00001) | (0.00000) |
| $lagMfp^4$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Observations | 139,659 | 313,619 | 139,659 | 313,619 | 139,659 | 313,619 | 139,659 | 313,619 |
| $R^2$ | 0.017 | 0.097 | 0.017 | 0.097 | 0.017 | 0.097 | 0.017 | 0.097 |
| Adjusted $R^2$ | 0.017 | 0.097 | 0.017 | 0.097 | 0.017 | 0.097 | 0.017 | 0.097 |
| *Note:* | | | | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 13: Productivity and Directors business networks

| | Dependent variable: $\Delta Mfp$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Balanced control | Imputed control | Balanced scenario1 | Imputed scenario1 | Balanced scenario2 | Imputed scenario2 | Balanced scenario3 | Imputed scenario3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Directors business networks | | | 0.023 | $-0.016$ | | | | |
| | | | (0.075) | (0.063) | | | | |
| Directors business networks | | | | | $-0.085$ | $0.321^{***}$ | | |
| | | | | | (0.105) | (0.115) | | |
| Directors business networks | | | | | | | $-0.095$ | $0.471^{***}$ |
| | | | | | | | (0.110) | (0.124) |
| $lagMfp$ | $-0.104^{***}$ | $-0.684^{***}$ | $-0.104^{***}$ | $-0.684^{***}$ | $-0.105^{***}$ | $-0.686^{***}$ | $-0.104^{***}$ | $-0.687^{***}$ |
| | (0.016) | (0.012) | (0.016) | (0.012) | (0.016) | (0.012) | (0.016) | (0.012) |
| $lagMfp^2$ | $-0.017^{***}$ | $-0.027^{***}$ | $-0.017^{***}$ | $-0.027^{***}$ | $-0.017^{***}$ | $-0.027^{***}$ | $-0.017^{***}$ | $-0.027^{***}$ |
| | (0.003) | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) |
| $lagMfp^3$ | $-0.001^{***}$ | $0.002^{***}$ | $-0.001^{***}$ | $0.002^{***}$ | $-0.001^{***}$ | $0.002^{***}$ | $-0.001^{***}$ | $0.002^{***}$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| $lagMfp^4$ | $0.0001^{***}$ | $0.0001^{***}$ | $0.0001^{***}$ | $0.0001^{***}$ | $0.0001^{***}$ | $0.0001^{***}$ | $0.0001^{***}$ | $0.0001^{***}$ |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) | (0.00001) |
| Observations | 1,392 | 9,229 | 1,392 | 9,229 | 1,392 | 9,229 | 1,392 | 9,229 |
| $R^2$ | 0.206 | 0.310 | 0.206 | 0.310 | 0.206 | 0.311 | 0.206 | 0.312 |
| Adjusted $R^2$ | 0.187 | 0.308 | 0.186 | 0.308 | 0.187 | 0.308 | 0.187 | 0.309 |
| *Note:* | | | | | | | | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ |

## E.3 Sales and business networks

Table 14: Sales and R&D business networks

| | Dependent variable: $\Delta Sales$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Balanced control | Imputed control | Balanced scenario1 | Imputed scenario1 | Balanced scenario2 | Imputed scenario2 | Balanced scenario3 | Imputed scenario3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| R&D business networks | | | 0.017 | $0.334^{***}$ | | | | |
| | | | (0.025) | (0.047) | | | | |
| R&D business networks | | | | | 0.015 | $0.294^{***}$ | | |
| | | | | | (0.022) | (0.041) | | |
| R&D business networks | | | | | | | 0.024 | $0.301^{***}$ |
| | | | | | | | (0.021) | (0.039) |
| $lagSales$ | $0.127^{***}$ | $0.042^{***}$ | $0.127^{***}$ | $0.044^{***}$ | $0.128^{***}$ | $0.045^{***}$ | $0.128^{***}$ | $0.046^{***}$ |
| | (0.007) | (0.014) | (0.007) | (0.014) | (0.007) | (0.014) | (0.007) | (0.014) |
| $lagSales^2$ | $-0.005^{***}$ | $-0.017^{***}$ | $-0.005^{***}$ | $-0.017^{***}$ | $-0.005^{***}$ | $-0.017^{***}$ | $-0.005^{***}$ | $-0.017^{***}$ |
| | (0.0005) | (0.001) | (0.0005) | (0.001) | (0.0005) | (0.001) | (0.0005) | (0.001) |
| $lagSales^3$ | $-0.0002^{***}$ | 0.0001 | $-0.0002^{***}$ | 0.0001 | $-0.0002^{***}$ | 0.0001 | $-0.0002^{***}$ | 0.0001 |
| | (0.00004) | (0.0001) | (0.00004) | (0.0001) | (0.00004) | (0.0001) | (0.00004) | (0.0001) |
| $lagSales^4$ | $0.00001^{***}$ | $0.00001^{***}$ | $0.00001^{***}$ | $0.00001^{***}$ | $0.00001^{***}$ | $0.00001^{***}$ | $0.00001^{***}$ | $0.00001^{***}$ |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Observations | 23,472 | 30,063 | 23,472 | 30,063 | 23,472 | 30,063 | 23,472 | 30,063 |
| $R^2$ | 0.022 | 0.090 | 0.022 | 0.092 | 0.022 | 0.092 | 0.022 | 0.092 |
| Adjusted $R^2$ | 0.020 | 0.089 | 0.020 | 0.091 | 0.020 | 0.091 | 0.020 | 0.091 |
| *Note:* | | | | | | | | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ |

## Table 15: Sales and commercial business networks

| | *Dependent variable: ΔSales* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Balanced control | Imputed control | Balanced scenario1 | Imputed scenario1 | Balanced scenario2 | Imputed scenario2 | Balanced scenario3 | Imputed scenario3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Commercial business networks | | | $-0.040^{***}$ | $-0.040^{*}$ | | | | |
| | | | (0.015) | (0.024) | | | | |
| Commercial business networks | | | | | $-0.027^{**}$ | 0.009 | | |
| | | | | | (0.013) | (0.021) | | |
| Commercial business networks | | | | | | | $-0.010$ | $0.035^{*}$ |
| | | | | | | | (0.013) | (0.020) |
| *lagSales* | $0.069^{***}$ | $-0.013^{***}$ | $0.069^{***}$ | $-0.013^{***}$ | $0.069^{***}$ | $-0.013^{***}$ | $0.069^{***}$ | $-0.013^{***}$ |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) |
| $lagSales^2$ | $-0.004^{***}$ | $-0.008^{***}$ | $-0.004^{***}$ | $-0.008^{***}$ | $-0.004^{***}$ | $-0.008^{***}$ | $-0.004^{***}$ | $-0.008^{***}$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| $lagSales^3$ | $0.00002^{***}$ | $0.0001^{***}$ | $0.00002^{***}$ | $0.0001^{***}$ | $0.00002^{***}$ | $0.0001^{***}$ | $0.00002^{***}$ | $0.0001^{***}$ |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| $lagSales^4$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ | $0.00000^{***}$ |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Observations | 268,908 | 313,619 | 268,908 | 313,619 | 268,908 | 313,619 | 268,908 | 313,619 |
| $R^2$ | 0.018 | 0.060 | 0.018 | 0.060 | 0.018 | 0.060 | 0.018 | 0.060 |
| Adjusted $R^2$ | 0.018 | 0.060 | 0.018 | 0.060 | 0.018 | 0.060 | 0.018 | 0.060 |
| *Note:* | | | | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

## Table 16: Sales and directors business networks

| | *Dependent variable: ΔSales* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Balanced control | Imputed control | Balanced scenario1 | Imputed scenario1 | Balanced scenario2 | Imputed scenario2 | Balanced scenario3 | Imputed scenario3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Directors business networks | | | 0.010 | $-0.025$ | | | | |
| | | | (0.053) | (0.068) | | | | |
| Directors business networks | | | | | 0.065 | $0.318^{***}$ | | |
| | | | | | (0.075) | (0.123) | | |
| Directors business networks | | | | | | | 0.058 | $0.424^{***}$ |
| | | | | | | | (0.079) | (0.132) |
| *lagSales* | 0.049 | $-0.027$ | 0.050 | $-0.027$ | 0.050 | $-0.026$ | 0.049 | $-0.026$ |
| | (0.054) | (0.031) | (0.054) | (0.031) | (0.054) | (0.031) | (0.054) | (0.031) |
| $lagSales^2$ | 0.002 | $-0.045^{***}$ | 0.002 | $-0.045^{***}$ | 0.002 | $-0.046^{***}$ | 0.002 | $-0.046^{***}$ |
| | (0.009) | (0.004) | (0.009) | (0.004) | (0.009) | (0.004) | (0.009) | (0.004) |
| $lagSales^3$ | $-0.001$ | $0.001^{***}$ | $-0.001$ | $0.001^{***}$ | $-0.001$ | $0.001^{***}$ | $-0.001$ | $0.001^{***}$ |
| | (0.001) | (0.0002) | (0.001) | (0.0002) | (0.001) | (0.0002) | (0.001) | (0.0002) |
| $lagSales^4$ | 0.00002 | $-0.00000$ | 0.00002 | $-0.00000$ | 0.00002 | $-0.00000$ | 0.00002 | $-0.00000$ |
| | (0.00001) | (0.00000) | (0.00001) | (0.00000) | (0.00001) | (0.00000) | (0.00001) | (0.00000) |
| Observations | 1,392 | 9,239 | 1,392 | 9,239 | 1,392 | 9,239 | 1,392 | 9,239 |
| $R^2$ | 0.061 | 0.259 | 0.061 | 0.259 | 0.061 | 0.260 | 0.061 | 0.260 |
| Adjusted $R^2$ | 0.039 | 0.257 | 0.038 | 0.256 | 0.039 | 0.257 | 0.038 | 0.257 |
| *Note:* | | | | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

## E.4 Innovation and business networks

Table 17: Innovations and R&D business networks

| | *Dependent variable: App* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Negative Binomial control | Poisson control | Negative Binomial scenario1 | Poisson scenario1 | Negative Binomial scenario2 | Poisson scenario2 | Negative Binomial scenario3 | Poisson scenario3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| R&D business networks | | | $0.059^{***}$ | $0.124^{***}$ | | | | |
| | | | (0.015) | (0.013) | | | | |
| R&D business networks | | | | | $0.088^{***}$ | $0.187^{***}$ | | |
| | | | | | (0.013) | (0.011) | | |
| R&D business networks | | | | | | | $0.113^{***}$ | $0.209^{***}$ |
| | | | | | | | (0.012) | (0.011) |
| *lagApp* | $0.235^{***}$ | $0.181^{***}$ | $0.241^{***}$ | $0.180^{***}$ | $0.231^{***}$ | $0.176^{***}$ | $0.230^{***}$ | $0.176^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $lagApp^2$ | $-0.003^{***}$ | $-0.002^{***}$ | $-0.004^{***}$ | $-0.002^{***}$ | $-0.003^{***}$ | $-0.002^{***}$ | $-0.003^{***}$ | $-0.002^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $lagApp^3$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $lagApp^3$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\hat{\theta}$ | | | 22.39 | | 22.67 | | 21.79 | |
| Observations | 30,063 | 30,063 | 30,063 | 30,063 | 30,063 | 30,063 | 30,063 | 30,063 |
| Log Likelihood | -42,614 | -43,476 | -42653 | -43432 | -42564 | -43,335 | -42,560 | -43,288 |
| Akaike Inf. Crit. | 85,310 | 87,032 | 85,390 | 86,947 | 85,212 | 86,751 | 85,203 | 86,659 |
| *Note:* | | | | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 18: Innovations and commercial business networks

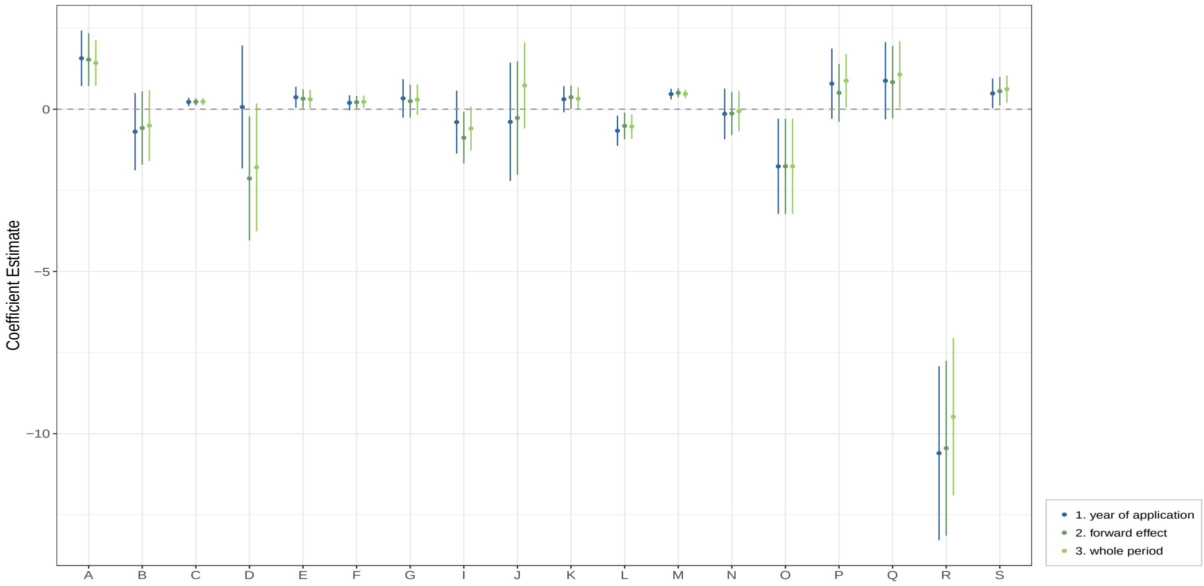
| | *Dependent variable: App* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Negative Binomial control | Poisson control | Negative Binomial scenario1 | Poisson scenario1 | Negative Binomial scenario2 | Poisson scenario2 | Negative Binomial scenario3 | Poisson scenario3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| R&D business networks | | | $-0.010$ | $-0.014$ | | | | |
| | | | (0.009) | (0.007) | | | | |
| R&D business networks | | | | | $0.020^{**}$ | $-0.000$ | | |
| | | | | | (0.007) | (0.006) | | |
| R&D business networks | | | | | | | $0.025^{***}$ | $0.012^{*}$ |
| | | | | | | | (0.007) | (0.005) |
| *lagApp* | $0.241^{***}$ | $0.188^{***}$ | $0.241^{***}$ | $0.188^{***}$ | $0.240^{***}$ | $0.188^{***}$ | $0.241^{***}$ | $0.188^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $lagApp^2$ | $-0.004^{***}$ | $-0.003^{***}$ | $-0.004^{***}$ | $-0.003^{***}$ | $-0.004^{***}$ | $-0.003^{***}$ | $-0.004^{***}$ | $-0.003^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $lagApp^3$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ | $0.000^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $lagApp^3$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ | $-0.000^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\hat{\theta}$ | | | 21.72 | | 21.63 | | 21.7 | |
| Observations | 313,619 | 313,619 | 313,619 | 313,619 | 313,619 | 313,619 | 313,619 | 313,619 |
| Log Likelihood | -472,852 | -488,788 | -472,851 | -488,786 | -472,828 | -488,788 | -472,838 | -488,785 |
| Akaike Inf. Crit. | 945,788 | 977,657 | 945,788 | 977,655 | 945,742 | 977,659 | 945,761 | 977,654 |
| *Note:* | | | | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 19: Australian and New Zealand Standard Industrial Classification (ANZSIC), 2006

| **Industry Codes** | **Titles** |
|---|---|
| A | Agriculture, Forestry and Fishing |
| B | Mining |
| C | Manufacturing |
| D | Electricity, Gas, Water and Waste Services |
| E | Construction |
| F | Wholesale Trade |
| G | Retail Trade |
| H | Accommodation and Food Services |
| I | Transport, Postal and Warehousing |
| J | Information Media and Telecommunications |
| K | Financial and Insurance Services |
| L | Rental, Hiring and Real Estate Services |
| M | Professional, Scientific and Technical Services |
| N | Administrative and Support Services |
| O | Public Administration and Safety |
| P | Education and Training |
| Q | Health Care and Social Assistance |
| R | Arts and Recreation Services |
| S | Other Services |

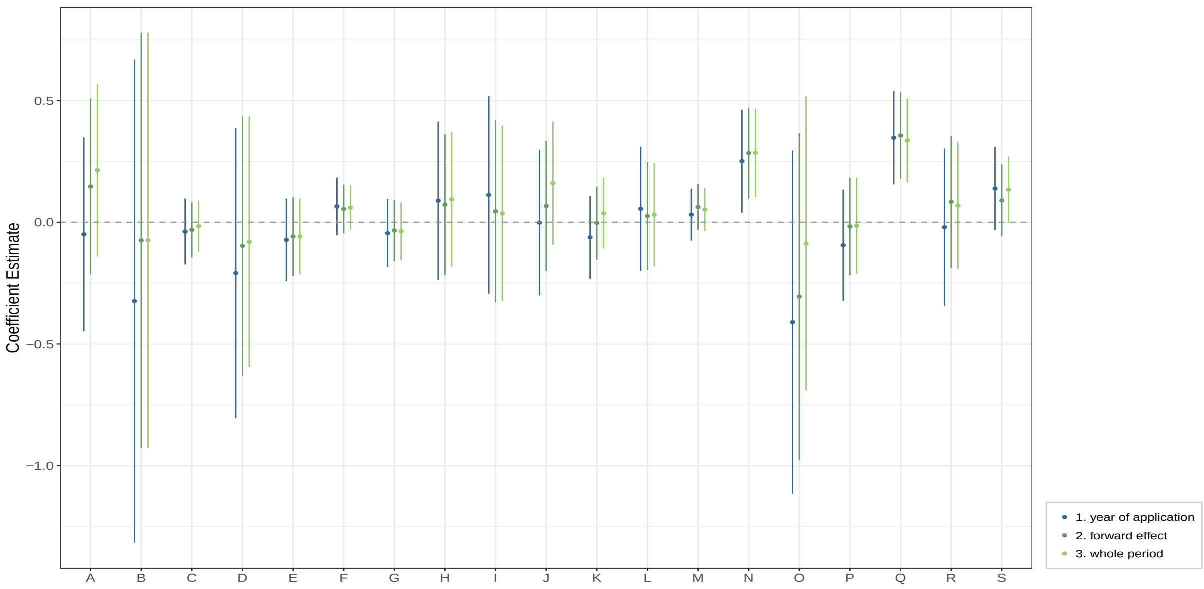
## E.5 Productivity and business networks by industry

Figure 10: Productivity and R&D business networks by industry



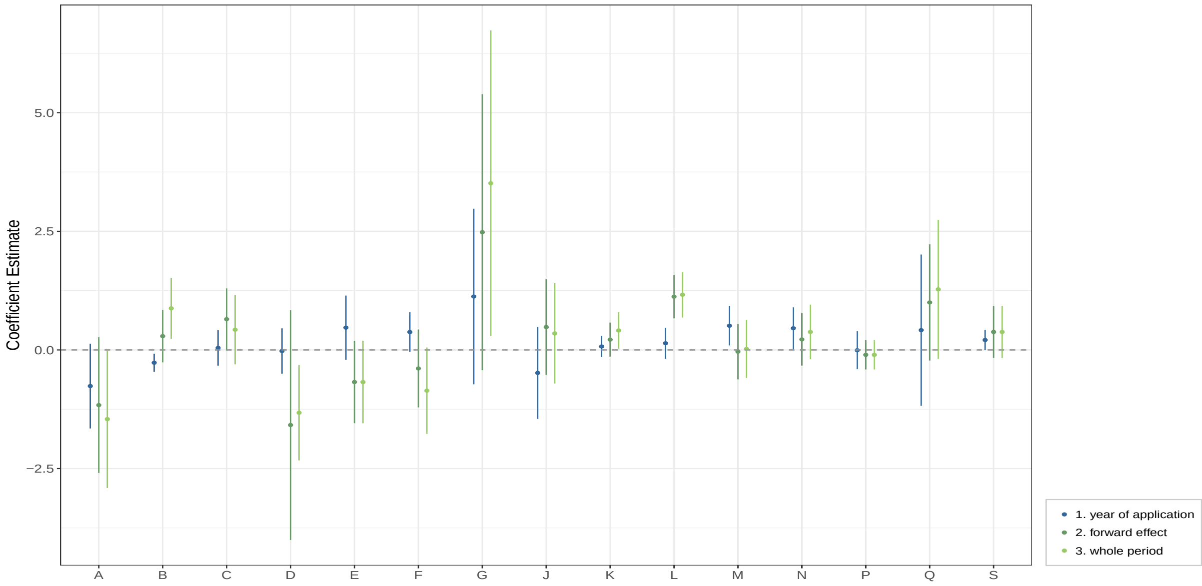

Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(1)$.

Figure 11: Productivity and commercial business networks by industry




Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(1)$.

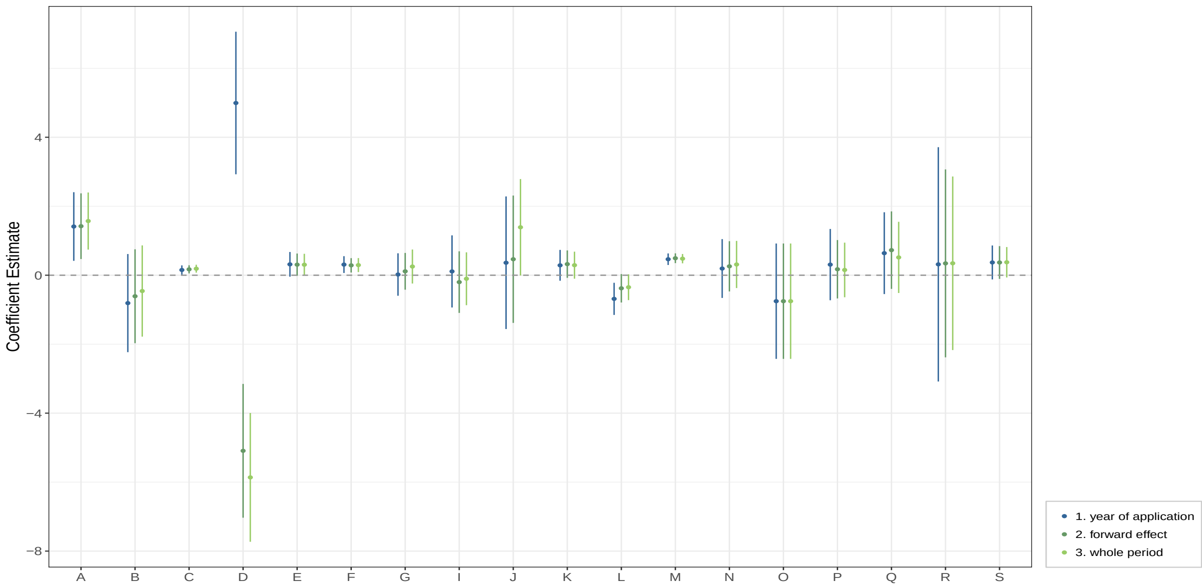
Figure 12: Productivity and shared directors business networks by industry




Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(1)$.

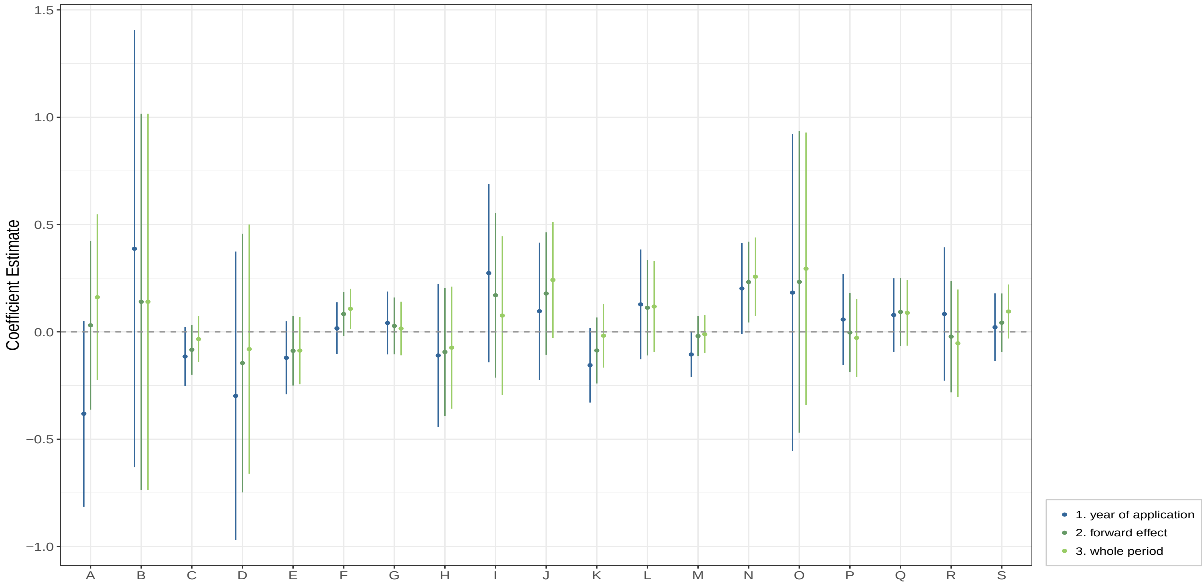
## E.6 Sales and business networks by industry

Figure 13: Sales and R&D business networks by industry



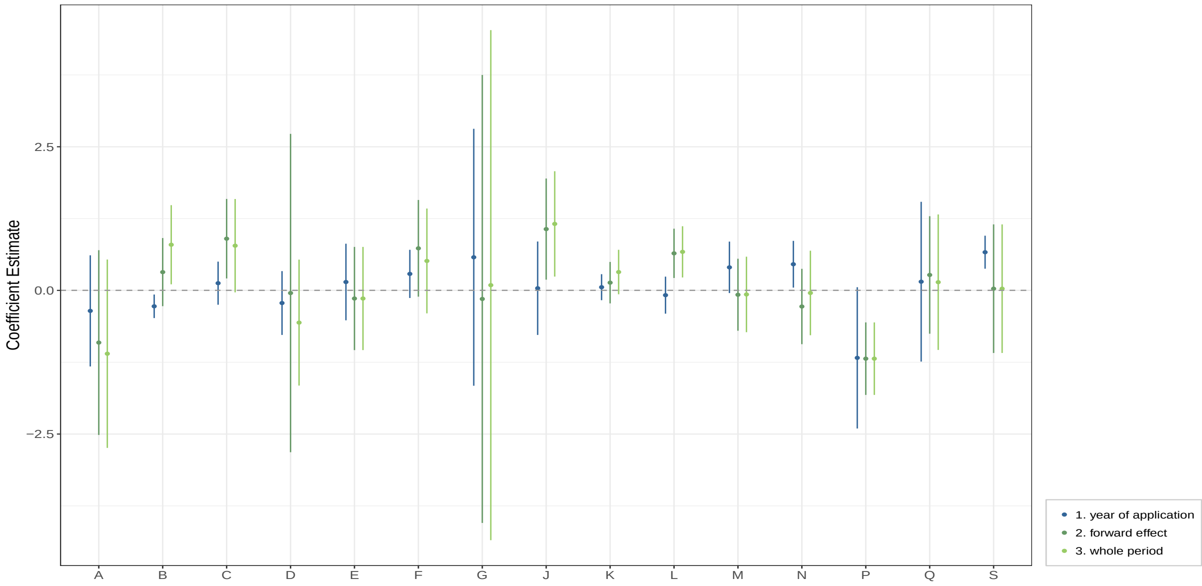

Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(2)$.

Figure 14: Sales and commercial business networks by industry




Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(2)$.

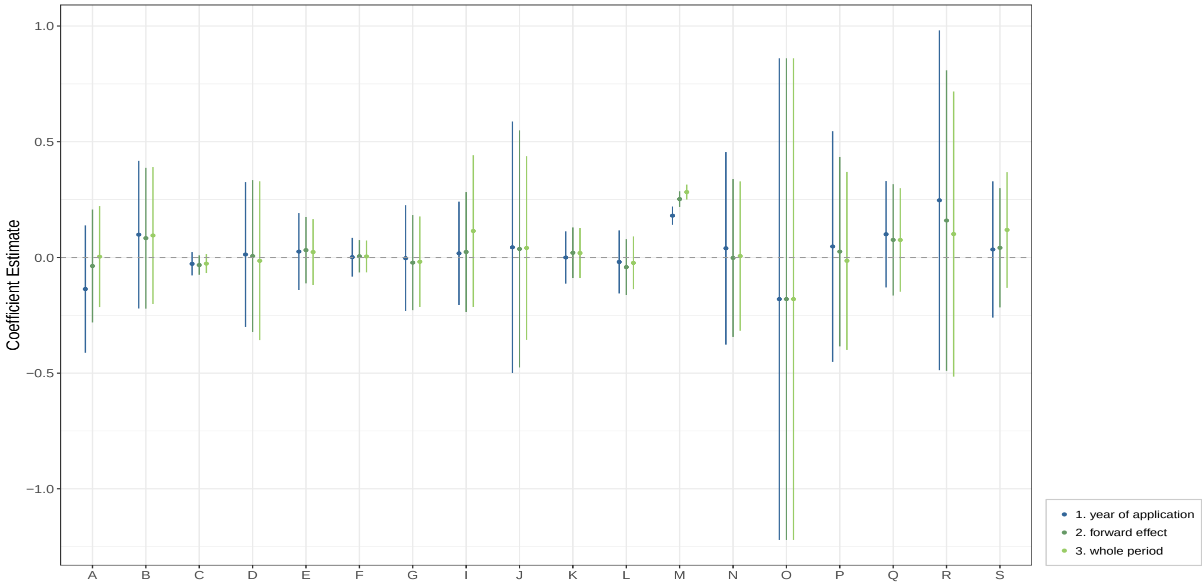
Figure 15: Sales and shared directors business networks by industry




Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(2)$.

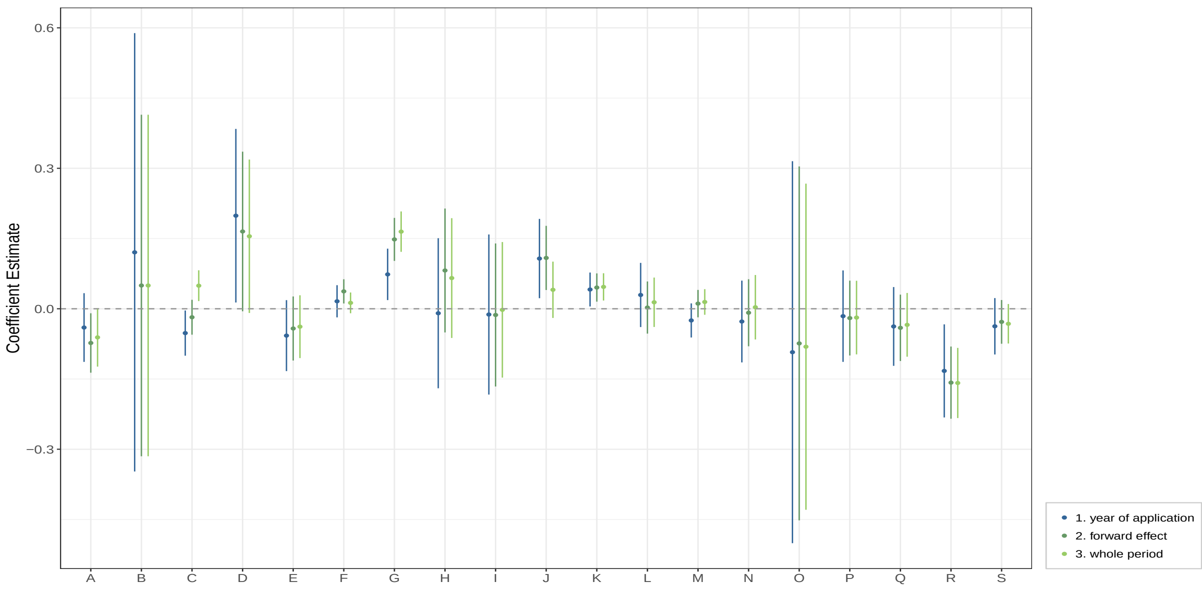
## E.7 Innovation and business networks by industry

Figure 16: Innovation and R&D business networks by industry




Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(3)$.

Figure 17: Innovation and commercial business networks by industry




Note. $95\%$ CIs for the coefficients of $BusinessNetworks$ for three scenarios for each industry from fitting $(3)$.

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