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Impact Evaluation of the IMCRC's futuremap® 2018-21

A Report prepared for
Innovative Manufacturing CRC

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Executive Summary

<u>Introduction</u>

In July 2022, the Innovative Manufacturing CRC (IMCRC) engaged the Centre for Transformative Innovation at Swinburne University of Technology to evaluate the impact of their futuremap® workshop and diagnostic tool. In particular, we evaluated the program to better understand the degree in which their clients were engaged with digital technologies and advanced manufacturing relative to their peers within Australia and whether exposure to new processes and technologies translated into improved firm performance.

The diagnostic tool is primarily designed to assess firms' capacity within the following areas

- marketing positioning
- leadership, strategy and change management
- innovation and use of technology
- digital manufacturing (i.e. Industry 4.0)

<u>Key finding 1</u>

Firms participating in the futuremap® workshops were found to be growing faster and innovating more than their closest peers. The key findings are:

- Participation is followed by a statistically significant increase in:
  - turnover sales of 15.5 per cent,
  - wages of 21.5 per cent,
  - and headcount of 6.6 per cent.
- In terms of estimates for compound annual growth rates, participation is associated with increases in turnover sales of 5.76 percentage points, an increase in wages of 1.96 percentage points and an increase in headcount of 2.76 percentage points.
- Participation was associated with increased measures of innovation such as changes in trade mark applications (1.9 per cent), patent applications (0.5 per cent), and design rights applications (1.0 per cent), although the results were not statistically significant.

<u>Key finding 2</u>

Since 2013-14 futuremap® participants have invested more heavily than their peers in branding and marketing, organisational capital, and human capital. However, they have generally invested less in measures of intangible capital such as those involving digital support and digital maturity. This suggests that the marketing of futuremap® was successful at providing firms with training in areas with deficits to help complement their existing strengths.

Finding 3

The average futuremap® participant is a medium sized enterprise which makes them larger than the majority of firms within Australia. Prior to undertaking the workshop, they were experiencing faster growth in turnover, wages, employment and intellectual property than the average Australian business. This means futuremap® is attracting the more ambitious CEOs.

1. Introduction

1.1 Objective, scope and deliverables

The primary aim of this evaluation is to estimate the impact of futuremap®, managed by Innovative Manufacturing CRC (IMCRC) on participating businesses' financial and innovation performance. This evaluation covers businesses participating in the workshop between March 2018 to June 2021.

This impact evaluation study uses the same robust, objective impact evaluation methods developed for previous studies conducted by the Centre for Transformative Innovation. A difference-in-differences analysis framework is used for the evaluation with participating firms designated as the "treatment group" and non-participating firms across Australia form the basis for the control group. A propensity score matching technique is used to identify the nearest matched non-participating firms as control group for each of the participating firms.

This report linked business level records derived from a futuremap® participation survey to Australian Bureau of Statistics (ABS) Business Longitudinal Analytical Data Environment (BLADE) to assess the effect of the program.[1] Specifically, the Business Activity Statement (BAS), Intellectual Property Longitudinal Research Data (IPLORD) and Merchandise Trade databases of BLADE are linked with program participation using participants' Australian Business Number

[1] For more details on BLADE, see Business Longitudinal Analysis Data Environment (BLADE) | Australian Bureau of Statistics (abs.gov.au) (checked on 28-09-2022).

(ABN) as the key linking variable. Throughout the analysis, the unit of analysis is the Australian Business Number, but we use the term firm or business interchangeably.

1.2 Report outline

The remainder of this report is structured as follows. Section 2 provides a brief overview of futuremap® workshop, Section 3 provides a literature review of the economics rationale for such programs and existing evidence of the impacts of the programs from other countries. Section 4 provides a summary of the methodological approach and data. Section 5 presents the empirical findings. Section 6 concludes.

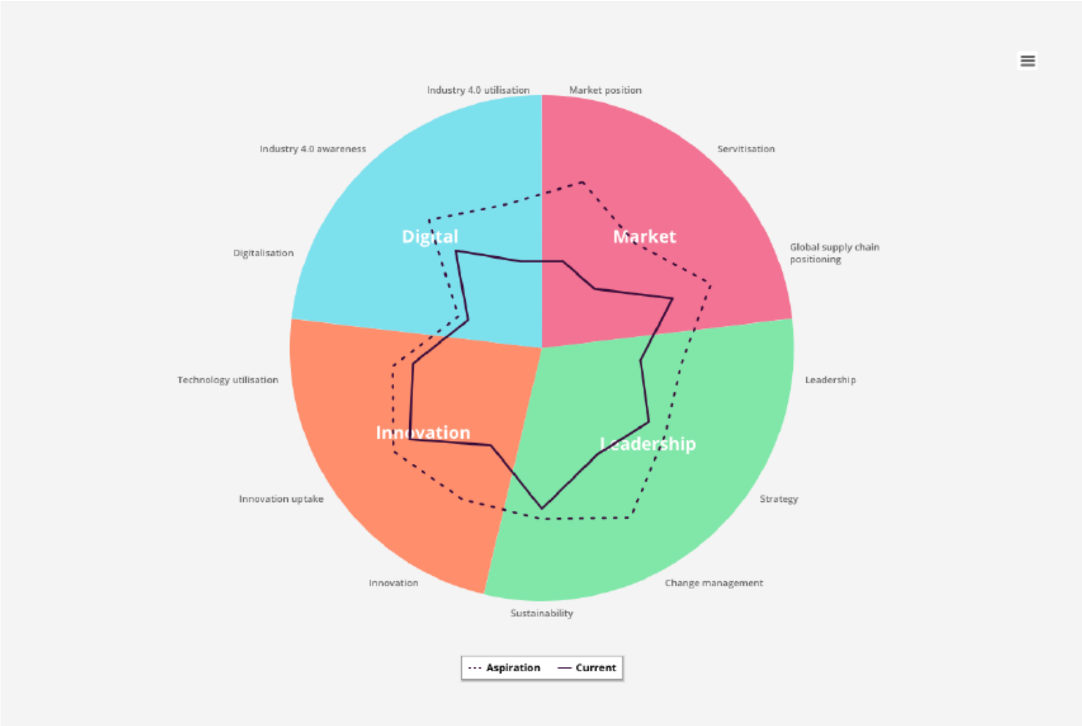
2. futuremap® overview

2.1 futuremap® workshop

The development of futuremap® began in 2018 as a program designed to support the adoption of new technologies for industrial, small and medium sized enterprises (SMEs). The goals of the program are to deliver benefits to Australian manufacturers and the manufacturing industry at-large through facilitating conversation to act as a catalyst to change current practices and attitudes of businesses.

A primary goal of futuremap® is to develop a diagnostic tool to provide participating businesses an opportunity to self-assess their business experiences and ambitions across four spheres: digital technologies, innovation capabilities, market maturity, and leadership. The tool then provides participants a report via a PowerBI platform which has also been aggregated in a way to provide policy makers with crucial data to better understand the capabilities of manufacturing industry within Australia.

Figure 2.1 Example of radar diagram



Source: IMCRC (2022)

Figure 2.1 provides an example of the primary output from the self-assessed survey. The radar diagram maps firms current state of their business as well as their aspirations where they would like to be within two years.

Based on participants responses to the question, the tool also provides businesses links for further reading discussing employing business strategies to create continued, on-going relevance to customers, aligning one's business around strategies and goals, or increasing the value or range of services to customers.

2.2 Participants between 2017-18 and 2020-21

This evaluation utilizes IMCRC's survey response data of futuremap® program participants combined with the databases within BLADE. This date was selected due to financial data not being available after the 2020-21 financial year within BLADE. Of those 768 businesses within the

IMCRC database, 726 were matched within BLADE, a match rate of 94.5 per cent.[2] Specifically, the IMCRC database contains:

- Participants' names and ABNs[3]
- The main industry sector of the participants
- Number of employees (in Australia and Overseas)
- Business' current and aspirational capacity across several dimensions

The IMCRC database provides participant level details of the participating organisations and survey responses for 768 unique businesses which participated between the 2017-18 and 2020-21 financial years (as identified through their ABNs). Table 2.1 documents the distribution of the participants by Commonwealth Industry Growth Sector and the first financial year they participated in a futuremap® workshop.[4] Predominately, participating firms were in advanced manufacturing, consisting just over half the sample. However, 16.4 per cent of the sample did not identify as being within an industry growth sector or fell into a category which was suppressed due to potential data disclosure from small sample sizes.

Table 2.1 Number of futuremap® participants between 2017-18 and 2020-21

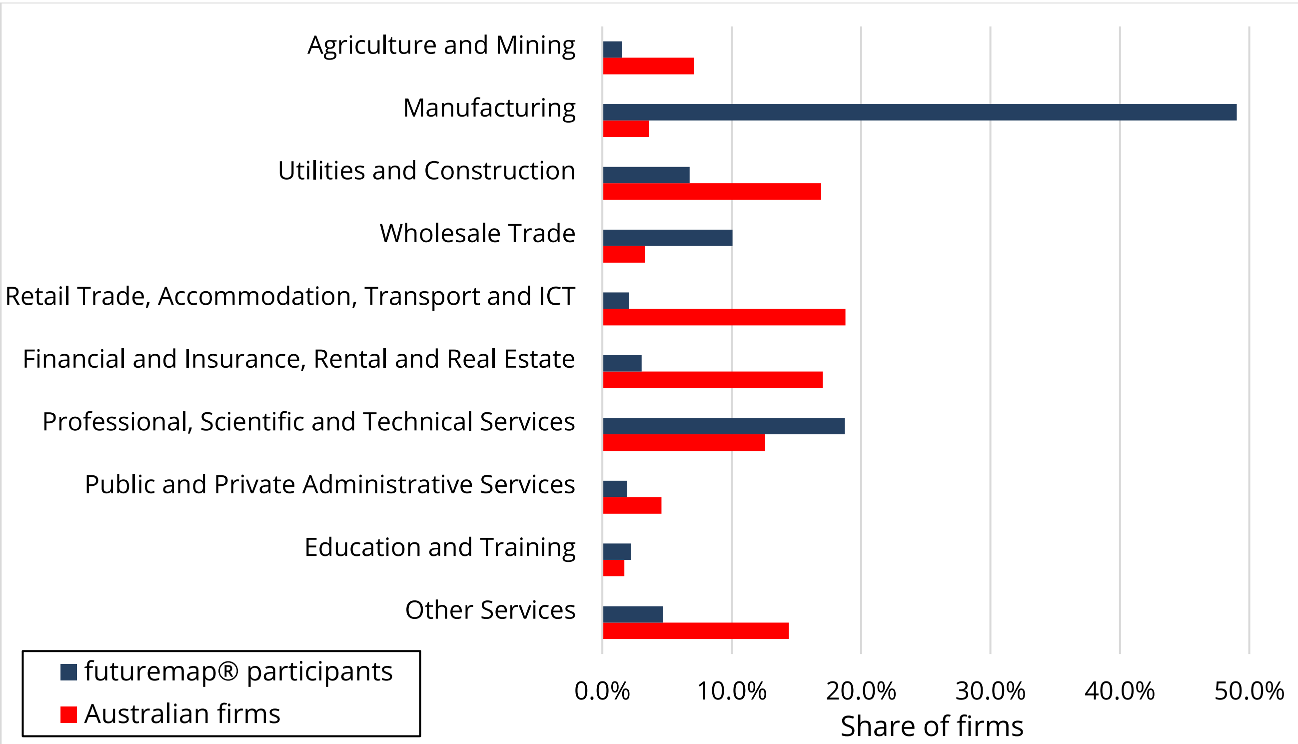
Commonwealth Industry Growth Sector	2017-18	2018-19	2019-20	2020-21	Total
Advanced Manufacturing	41	188	154	30	413
Food and Agribusiness	5	25	34	6	70
Medical Technologies and Pharmaceutical	3	11	12	5	31
Mining Equipment Technology and Service	5	38	13	7	63
Oil, Gas and Energy Resources	11	29	12	13	65
Other / None of the above	10	56	47	13	126
Total	75	347	272	74	768

Source: IMCRC futuremap® survey database

[2] The exact number of participants may not correspond directly to the administrative data due to methodology that the ABS employs to merge the data (many ABNs may be linked to a single firm), the lack of financial data. Similarly, the number of non-participants may be higher than the number of active businesses within Australia as this number includes any entity with an ABN including individuals, trusts and companies.
[3] This data is only used by the ABS to match participation to business-level financial data within BLADE. No identifying information is available to the researchers within ABS' secure data environment.
[4] 43 businesses participated in futuremap® workshops across multiple financial years in the data. The analysis is based on the first financial year of participation.

Figure 2.2 shows the distribution of consolidated primary ANZSIC divisions for the futuremap® participating businesses in the 2020-21 financial year compared to all 2.1 million financially active businesses within Australia.[5] It is clear from the figure that relative to all businesses, futuremap® firms actively recruited manufacturing firms. Likewise, participants were overrepresented in Professional, Scientific and Technical Services and Education and Training. This is consistent with the focus of the IMCRC futuremap® workshop which has a stated purpose to introduce businesses to advanced technologies within the manufacturing sector in Australia.

Figure 2.2 ANZSIC Divisions between futuremap® and Australia firms in 2020-21



Source: Business Longitudinal Analysis Data Environment (BLADE)

[5] ANZSIC divisions were consolidated due to the small sample of some futuremap® participants within a given ANZSIC division. Financially active is defined by firms with reported, non-zero turnover in their Business Activity Statements.

3. Literature review

3.1 Literature business training

Digital tools such as futuremap® which broaden awareness of new technologies and possibilities of emerging technology trends is not well studied in the economics literature. Insofar as it is intended to catalyse managers to re-think their existing business strategies, it aligns most closely with the existing literature that explores the relationship between management training and firm productivity.

Large persistent differences in productivity between countries and between firms are well acknowledged in the literature (Syverson, 2011). Recent studies are uncovering that a divergence in management practices accounts for the observed persistent gap in productivity (Bloom et al., 2019). Accordingly, firms that invest in improving management practices perform better than those without such investment. One of the effective ways of improving business practice is the offer of subsidised business training and consulting services (McKenzie, 2021).

The overarching goal of business training is to help firms grow, becoming more profitable, competitive and resilient in various business conditions. This could be achieved through better business practices, producing goods more efficiently, lowering costs and expenses and increasing profit margins on the unit. Better marketing practices can expand the customer base. Training may also change the aspirations and mindset of the participants, with enduring effects on business practices and performance. Training programs studied, typically involves a consultant teaching a group of 15 to 40 participants in a classroom setting over 3 to 12 days (McKenzie, 2021). For instance, a business training, Project Growing America through Entrepreneurship (GATE) conducted by the US Department of Labour and Small Business Administration (SBA) starts with a one-to-one assessment, followed by a series of consultation sessions tailored to meet the individual experience, capabilities, circumstances and opportunities (Fairlie et al., 2015). The program also includes classroom training in groups covering the subjects like legal structure, business planning, marketing and advertising. The estimated total cost of training in Project GATE is $1,321 per participant (Fairlie et al., 2015).

However, the key challenge in the program evaluation is to elicit the credible causal effects of training on the participants' performance. Effectively, we need to compare business performance in the post-training period to a counterfactual of what would have happened without training. Relatedly, program participants may have decided to take part in business training regardless of the opportunity of training. Also, even if they do not receive training, they might still grow their businesses. The basic problem is whether firms, usually those aspirational and high-performing, self-select into the program, while those that are happy with their status quo may not take part.

3.2 Randomised experiments

To overcome this identification problem, randomized experiments have been a popular method of assessing impacts on performance (Banerjee et al., 2015). These studies take a group of potential entrepreneurs, and then randomly allocate some firms to be offered training and compare them to a control group of firms that are not offered the training. Comparing outcomes for the treatment group which receives training to the control group that does not then give us an estimate of how much difference training has made in outcomes. The above Project GATE is the largest-ever randomized evaluation of entrepreneurship training with 4,197 potential entrepreneurs randomized at baseline with follow-up surveys after 6, 18 and 60 months (Fairlie et al., 2015). The results found training dramatically increased the likelihood of business ownership by 13 percentage points in the 6 months after training, but dissipate within 18 or 60 months. On average, there is no evidence to suggest that training had enduring effects on business scale, income, profitability, and work satisfaction.

While a different economic context, randomised experiments conducted in developing countries draw similar findings: de Mel et al. (2014) randomly allocated women without businesses to be invited to receive training or not in Sri Lanka. The study has revealed that 70.4 per cent of firms with training had started a business after two years, which can be compared to the 68.6 per cent in the control group without training. A difference – 1.6 percentage points – would be attributed to the receipt of training. However, when it comes to the assessment of other business indicators such as profits, sales and employment, the results are not encouraging. On the other hand, Chioda et al. (2021) find evidence that a 3-week mini MBA program offered to Ugandan high school students was able to provide persistent improvements for firm profitability, capital investment and job creation over 3.5 years. Yet, meta-analyses find overall mixed results. McKenzie (2021) reviewed 15 studies based on randomised experiments with estimates of the impacts of training on profits and 17 studies on sales. Most of the studies have wide confidence intervals for these impacts including the possibility of zero or even negative impacts.

To be fair, several important caveats should be kept mindful. Especially, running experiments in the field is expensive and because of other constraints (such as legal and regulatory requirements), many experiments ended up with sample sizes of 200 to 300 firms. The immediate consequence of this small sample is that statistical tests have less power and the estimates have less precision. This sample issue is also conflated with other technical issues: Outcomes are only realised within a relatively short time frame (e.g. 1 year) after training, incomplete take-up of training and survey attrition. This demonstrates the difficulty of uncovering the causal effects of training on business performance.

Ultimately, regardless of whether the analysis was randomised, the study periods were of a relatively short duration. While looking at historical data, Bianchi and Giorcelli (2022) find evidence that U.S. government-led management training for firms involved in war production in the 1940s had lasting productivity increases up to 20 years after the training, in cases up to 20% higher when compared to non-participants. Those benefits also spilt over to their suppliers.

4. Evaluation method and data

4.1 Difference-in-differences analysis with matching

We implement a difference-in-differences (DID) analysis with a further refinement that the control group is selected by matching participant and non-participants economic characteristics. A more technical discussion of the method and its implementation is provided in Appendices 1 and 2. The basic idea is that we would like to compare the business performance of participants to their performance prior to their participation in the futuremap® workshop. We then normalise this change in performance by comparing it to the change in performance of selected non-participants who appear to have had a similar financial trajectory during the same period prior to futuremap.

We consider nine measures of performance outcomes:

1. Turnover
2. Employment (Wages)

3. Employment (Headcount)
4. R&D expenditures
5. Trademark Applications
6. Patent Applications
7. Design Right Applications
8. Export sales (Merchandise Exports)
9. Import sales (Merchandise Imports)

4.2 Data

To construct the above measures, we use business performance measures available from Business Activity Statement (BAS), Business Income Tax (BIT), Pay-As-You-Go (PAYG), Merchandise Trade (Exports and Imports), and Intellectual Property Longitudinal Research Data (IPLORD) databases within the Australian Bureau of Statistics' Business Longitudinal Analytical Data Environment (BLADE).

The BLADE databases contain integrated financial and business characteristics data for more than 2.1 million active businesses in Australia based on linked databases such as survey data from the ABS (Business Characteristics Survey), Australian Taxation Office (BAS-BIT), IP Australia, Australian Customs and Border Protection (Merchandise Trade), and others. The BAS component used as the primary source of financial records in this report contains all annual reports of turnover provided by businesses with Australian Business Numbers (ABN) in Australia since 2001-02.[6] The Merchandise Trade component likewise contains the exports and imports of goods since 2003-04.

BLADE provides several indicators of business performance derived from Business Activity Statement (BAS) such as turnover and wages. Sales and turnover information are particularly valuable information and relevant for small firms. While some larger firms are required to report exports and imports within BAS, due to the BAS simplification, we instead use businesses' total merchandise exports and imports. As an alternative to wages which is provided in Headcount

[6] Note that the ABS BLADE and its component BAS-BIT database is large and complex and can only be accessed by approved researchers. The database is confidential and results are only released to non-ABS people after scrutiny of the output to ensure no individual business can be identified. These access limitations do not affect the quality of the empirical analysis due to our detailed and thorough analysis.

data is provided within the Pay-As-You-Go database to provide an alternative glimpse to changes in hiring practices.

As a key component of futuremap® is to spur interest in new digital technologies, we further look at R&D expenditures which are eligible for the R&D tax offset which is found within firms' business income tax filings. In a similar vein, we measure firms annual applications in trade marks, patents and design rights. Trade marks can be a measure of new products or services, while patents and design rights provide intellectual property rights to firms for novel innovations.

We exclude businesses with zero values in sales revenues, business income, total expenses, or salary and wage expenses as well as those with missing values in any of the matching variables. In addition, we removed government agencies and education and training firms which participated in futuremap® and those as potential control firms due to the challenges in comparing entities without a clear profit motivation.

To conduct the matching, we ran a series of logistic regressions in which the dependent variable is set to one if a firm attended a futuremap® workshop and zero otherwise. As workshops were conducted in each financial year between 2017-18 and 2020-21, for each financial year, we included the set of participating firms alongside a pool of all potential non-participating firms within BLADE. Matching variables include their logged values of turnover and headcount for each of up to five financial years prior to their participation in futuremap® as well as their turnover growth in that period.[7] In addition, we include 5-year averages of log merchandise exports, log merchandise imports, log patents filed, log trademarks filed, and log design rights filed. Lastly, we include the primary ANZSIC Division of the firm and the first year they filed a BAS which is available in BLADE as a loose proxy for firm age.

Financial information was adjusted for inflation using industry deflators constructed using information from the ABS' Produce Price Indexes with 2021 set as the base year. While these are imperfect measures, these allow us to better account for whether changes in turnover are being driven by higher input prices or higher output. If participating and non-participating firms did not have a full five years of previous turnover and headcount data to use for matching, we

[7] To account for zeros, we take the log of each value and add 1.

ran subsequent logistic regressions with fewer potential lags. Based on the results of the logistic regressions, we then estimate each firms probability of attending a futuremap® workshop. We then create two sets of control groups by selecting the closest 1 and 5 non-participating businesses which have predicted probabilities closest to each participants estimated participation probability. We allow the non-participants to be matched to multiple participating firms (i.e. matching with replacement).

Table 4.1 presents the average characteristics of futuremap® participants and non-participants across Australia from 2013-14 through 2020-21 split into two base periods: a pre-treatment period from 2013-14 to 2016-17 and a post-treatment period from 2017-18 to 2020-21. Each period has summary statistics for the three cohorts, the matched treated participants, and the two sets of control groups.

As seen in Table 4.1, we were able to match 526 of the 726 participants. While some of those missing were government organisations or were within the education and training sector. several firms did not have sufficient information to be included within the logistic regressions, or their predicted probability of participation did not have sufficiently close matches. Due to confidentiality rules, we are unable to report how many fall into each category.

The summary statistics show that the average participant in futuremap® are larger when compared to the population of Australian firms. They report approximately $31.6 million in turnover per financial year between 2013-14 and 2016-17 and employ more than 122.4 people in the same period.[8] The table reports that participants experienced growth in turnover, wages, and headcount in the post-treatment period. However, the control groups also experienced growth, indicating that a more formal analysis to explore potential treatment effects is required.

While the summary statistics do not indicate the share of firms with non-zero exports, we find that the average futuremap® participant exported $660,000 annually between 2013-14 and 2016-17 and imported $1.68 million during the same period. Interestingly, we see eligible R&D expenditures fall for both treatment and control firms as well as the other measures of innovative activities such as trademarking patenting and filing for design rights.

8 Based on the ABS definition of small and medium businesses, the average futuremap® participant falls within the definition of medium-sized businesses.

When compared to data for Australian firms more broadly, while the average futuremap® participant may be considered a medium sized enterprise, they nonetheless are larger than the majority of firms within Australia and over the last decade, are experiencing growth at higher rates than Australian businesses as a whole across the standard financial measures such as turnover, wages, headcount and intellectual property holdings.

Table 4.1 Average business characteristics 2013-14 to 2020-21, by participation status

(a) 2013-14 to 2016-17 Pre-Treatment period

	futuremap®			Matched control (1 NN)			Matched control (5 NN)		
Variable	Count	Mean	SD	Count	Mean	SD	Count	Mean	SD
Real Turnover (Mil $)	526	31.61	73.84	508	38.74	79.21	2452	36.12	76.63
Real Wages (Mil $)	522	6.88	16.57	507	8.02	17.53	2446	7.34	17.01
Headcount	522	122.38	319.74	506	138.34	334.58	2443	126.56	316.29
Real Merchandise Exports (Mil $)	526	0.66	1.48	508	0.69	1.47	2453	0.64	1.41
Real Merchandise Imports (Mil $)	526	1.68	3.76	508	2.69	4.82	2453	2.44	4.52
Real Eligible R&D Expenditures (Mil $)	413	0.52	3.12	371	0.45	2.71	1825	0.33	2.14
Annual Trade mark filings	526	0.32	0.99	508	0.37	1.31	2453	0.27	1.03
Annual Patent filings	526	0.11	0.49	508	0.07	0.41	2453	0.08	0.42
Annual Design right filings	526	0.05	0.26	508	0.02	0.19	2453	0.03	0.21

(b) 2017-18 to 2020-21 Post-treatment period

	futuremap®			Matched control (1 NN)			Matched control (5 NN)		
Variable	Count	Mean	SD	Count	Mean	SD	Count	Mean	SD
Real Turnover (Mil $)	526	34.50	76.02	507	42.20	81.99	2450	40.64	81.50
Real Wages (Mil $)	525	7.43	16.60	507	8.49	17.52	2451	8.13	17.61
Headcount	526	130.58	315.53	506	146.72	337.85	2443	140.74	330.96
Real Merchandise Exports (Mil $)	526	0.76	1.55	508	0.75	1.53	2452	0.69	1.47
Real Merchandise Imports (Mil $)	526	1.78	3.77	508	2.77	4.81	2452	2.59	4.64
Real Eligible R&D Expenditures (Mil $)	383	0.36	1.53	321	0.48	3.17	1619	0.29	2.36
Annual Trade mark filings	526	0.26	0.77	508	0.25	0.88	2452	0.20	0.74
Annual Patent filings	526	0.10	0.42	508	0.05	0.30	2452	0.06	0.33
Annual Design right filings	526	0.04	0.24	508	0.02	0.15	2452	0.02	0.17

5. Results

5.1 Impact of Participation in the IMCRC futuremap® workshops

To estimate the impact of participation in the IMCRC futuremap® on firm performance, we applied a difference-in-differences (DID) method to the merged databases from futuremap® and ABS' BLADE. In a DID model, we regress the log values of an outcome against an indicator variable set to one for treatment firms in the first and all subsequent financial years after participating in a futuremap® workshop (i.e. treatment variable). To control for other time varying factors that may influence the relevant outcomes, the model also includes a set of time indicator variables. This is known also known as a two-way fixed effects model. If we are confident that the model produces causal estimates, we would interpret the coefficient estimate on the treatment variable is an estimate of the percent change in the outcome variable relative to the firm's outcome in the absence of the treatment (i.e. attending the futuremap® workshop). As these estimates are the average increase in the first and subsequent financial years after participating in the workshop, we refer to the treatments effects as "persistent".

For each outcome, we estimated four difference-in-differences models.[9] In Model 1, we performed 1NN matching and the difference-in-differences regressions included all financial years from 2003-04 through 2020-21 (or 2019-20 for outcome variables which were not available in 2020-21). In Model 2, we again use 1NN matching, but have restricted the period for the difference-in-differences regression from 2013-14 through the last year available in the data. The rationale behind this choice is that older data may skew the results if there have been recent structural changes in firms performance and older behaviour may not need to be as comparable between firms for a comparison on how futuremap® impacts their performance today. Models 3 and 4 are the same as Models 1 and 2, respectively except that they use the 5NN control group as the comparison group.

The t-tests of pre-treatment means (provided in Appendix 2, Tables A2.2 and A2.3) generally show the pre-treatment means for the matching characteristics between the treatment firms (futuremap® participants) and control firms for the matched 1NN control group are not statistically different. This suggests that on a first pass, the common trends assumption is

[9] See the discussion in Appendix 1 and 2 for more details.

satisfied. When comparing the pre-treatment period innovative outcomes for design rights and patenting, we found the differences were statistically different, suggesting, futuremap® participants were more active in those areas prior to their engagement with futuremap. Those differences were not found within the 5NN results. Therefore, given the matched 5NN results have better pre-treatment t-tests, we prefer the 5NN results in combination with the shorter pre-treatment period as our preferred results. It should be noted that where results differ significantly, we should be cautious in our interpretations.

Within a follow-up analysis in which we run regression models in a relative event study time framework (see Table A2.4 in Appendix 2), the results suggest that firms participating in futuremap® workshops tend to experience statistically significant growth in their financial metrics in the preceding financial year and intellectual property filings in the two preceding financial years prior to attending the workshops. This suggests, the propensity score matching does not fully control for the selection into treatment. Therefore, even where we find evidence of positive and statistically significant coefficient estimates, we want to be cautious to interpret these as fully causal. Nevertheless, the results do indicate some optimism for the potential in a causal relationship between the IMCRC and financial outcomes. Each outcome is discussed within a separate subsection below.

Impact on turnover

Table 5.1 presents the coefficient estimates for the treatment effects of futuremap® participation on firm turnover. The average effects across the four models range between 9.1 per cent to 15.5 per cent, however, the coefficient estimate is statistically different from zero only within the last model. Within that model, the 95 percent confident intervals suggest that the range of estimates can vary from a low of 3.0 per cent to a high of 28.0 per cent. Relative to the findings found in the literature review in Section 3, the average estimate results are aligned, but on the high side given both the intensity of the workshop and the length of time in which the impact is measured over. However, given the likely positive selection into the program, it is plausible that these firms have the resources and capabilities to quickly adapt new knowledge and translate it into new sales.

Table 5.1. Estimated impact of futuremap® on real turnover (% change)

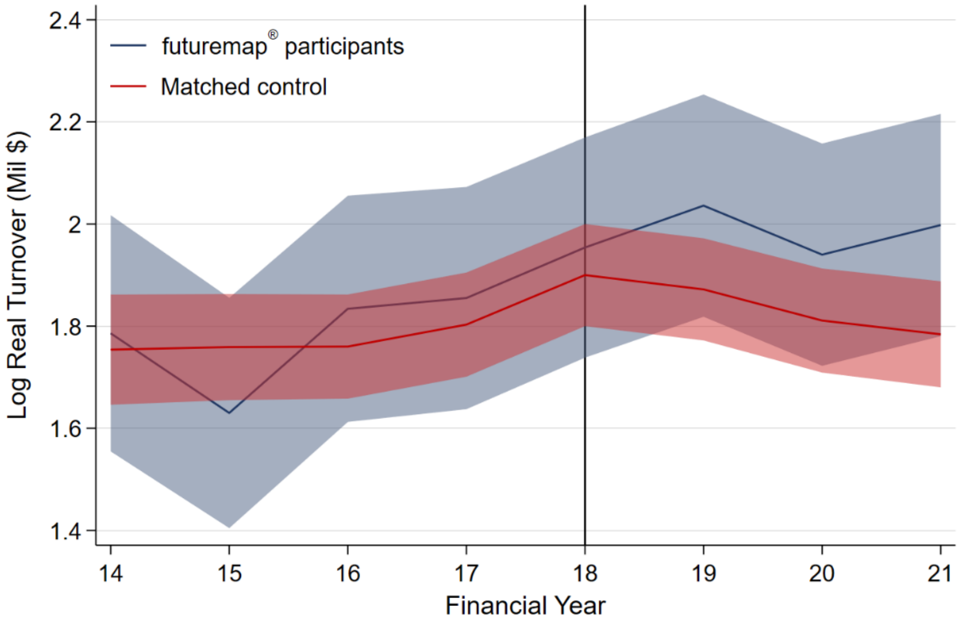
Average	Lower	Upper	Firms	Model
9.1%	-8.0%	26.2%	1,049	Control Group: 1NN; Period: 2003-04 to 2020-21
11.4%	-3.5%	26.3%	1,049	Control Group: 1NN; Period: 2013-14 to 2020-21
12.1%	-2.2%	26.4%	3,023	Control Group: 5NN; Period: 2003-04 to 2020-21
15.5%*	3.0%	28.0%	3,023	Control Group: 5NN; Period: 2013-14 to 2020-21

Notes: Estimates are based on difference-in-differences analysis of participating futuremap® firms compared to different sets of non-participating firms. Models 1 and 2 uses one propensity score matched non-participating firm for each treated firm as control. Models 3 and 4 uses five propensity score matched non-participating firms. Lower and upper bounds are approximated 95% confidence intervals. * indicates estimates are statistically different from zero at the 5 per cent level of significance.

As mentioned above, the matched 5NN group is our preferred control group. If we interpret model 4 by noting that after firm's participate in futuremap®, on average their turnover is 15.5 per cent higher than it would be given the relative growth rate of the firms in the control group. As noted however, we cannot fully discount the possibility that the result is zero given that the 95 per cent confidence interval crosses zero.

Yet as we find in the event study results as well as the plotted year trends found in Figure 5.1, we see some evidence that the futuremap® participants are growing at a higher rate when compared to their matched controls. Thus we should be cautious in interpreting these results as fully causal, although as seen in the secondary results in the appendix, the growth in the prior financial year is statistically significant only at the 10 per cent level. Nonetheless, they reflect that futuremap® is considered a useful source of knowledge on new manufacturing technologies and management strategies that are relevant to some of the most successful Australian manufacturing firms.

Figure 5.1. Estimated mean real turnover (mil $) across financial years



Notes: Estimates are estimated means and 95% confidence intervals for futuremap® participants and the 5NN control group from between the 2013-14 financial year and 2020-21 financial year. The vertical line at 18 represents the first year that some firms in the sample receive the treatment (i.e. participated in the futuremap® workshop).

Impact on wages

Table 5.2 presents the coefficient estimates for the treatment effects of futuremap® participation on wages. The average effects across the four models range between 7.2 per cent to 21.5 per cent with only the models in which we remove the earlier period data. This could reflect changes in the treatment groups productivity over time that will not be fully captured within the fixed effects.

The 95 percent confident intervals suggest that the range can vary from a low of -14.2 per cent to a high of 31.7 per cent suggesting that the estimates are not overly precise and can vary depending on the specification chosen.

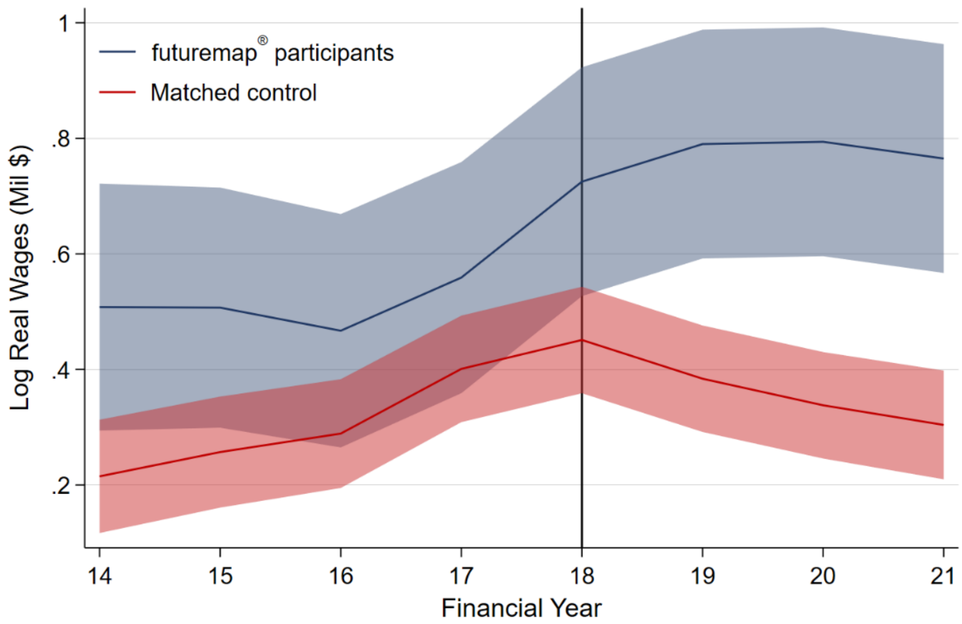
Table 5.2. Estimated impact of futuremap® on real wages (% change)

Average	Lower	Upper	Firms	Model
7.2%	-14.2%	28.6%	1,048	Control Group: 1NN; Period: 2003-04 to 2020-21
16.9%*	2.4%	31.4%	1,048	Control Group: 1NN; Period: 2013-14 to 2020-21
12.3%	-3.6%	28.2%	3,022	Control Group: 5NN; Period: 2003-04 to 2020-21
21.5%*	11.3%	31.7%	3,022	Control Group: 5NN; Period: 2013-14 to 2020-21

Notes: Estimates are based on difference-in-differences analysis of participating futuremap® firms compared to different sets of non-participating firms. Models 1 and 2 uses one propensity score matched non-participating firm for each treated firm as control. Models 3 and 4 uses five propensity score matched non-participating firms. Lower and upper bounds are approximated 95% confidence intervals. * indicates estimates are statistically different from zero at the 5 per cent level of significance.

Figure 5.2 provides the trends for log wages between the treated and control groups between the 2013-14 and 2020-21 financial years. These results suggest that in the pre-treatment period, the matched control group appears to be growing faster than the futuremap participants, yet we see a divergence in the post-treatment period. Indeed, we see some evidence of real wages falling for those firms since the 2017-18 financial year.

Figure 5.2. Estimated mean real wages (Mil $) across financial years



Notes: Estimates are estimated means and 95% confidence intervals for futuremap® participants and the 5NN control group from between the 2013-14 financial year and 2020-21 financial year. The vertical line at 18 represents the first year that some firms in the sample receive the treatment (i.e. participated in the futuremap® workshop).

Impact on headcount

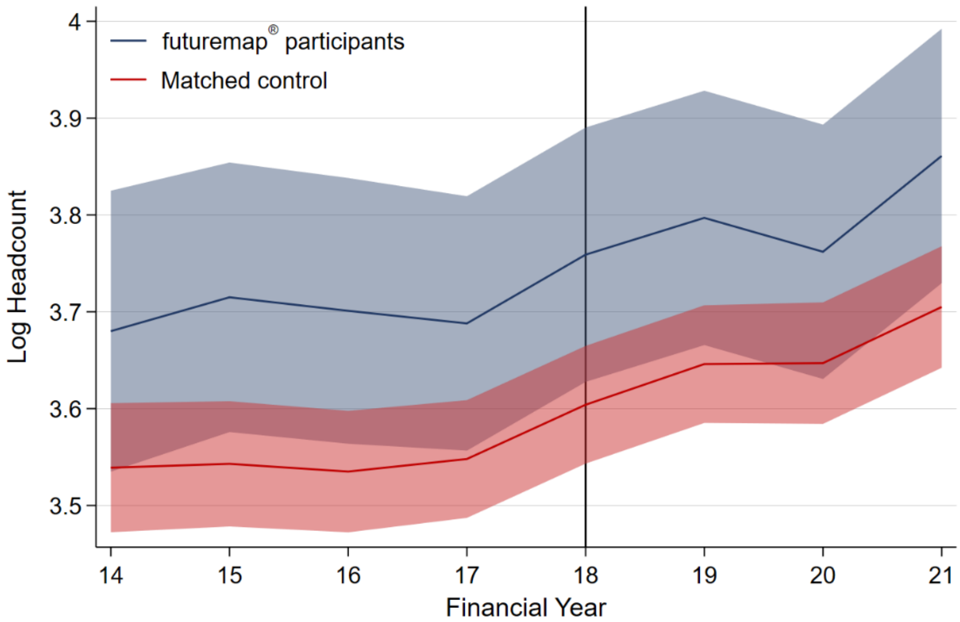
Table 5.3 presents an alternative measure for employment by exploring the coefficient estimates for the treatment effects of futuremap® participation on headcount. Unlike the estimates for wages, each model coefficient estimates are statistically significant. The average effects across the four models was stable and ranged between 6.6 per cent to 7.3 per cent. The 95 percent confident intervals suggest that the range can vary from a low of 0.6 per cent to a high of 13.6 per cent.

Table 5.3. Estimated impact of futuremap® on headcount (% change)

Average	Lower	Upper	Firms	Model
7.1%*	0.6%	13.6%	1,049	Control Group: 1NN; Period: 2003-04 to 2020-21
7.1%*	2.0%	12.2%	1,049	Control Group: 1NN; Period: 2013-14 to 2020-21
7.3%*	2.0%	12.6%	3,023	Control Group: 5NN; Period: 2003-04 to 2020-21
6.6%*	2.3%	10.9%	3,023	Control Group: 5NN; Period: 2013-14 to 2020-21

Notes: Estimates are based on difference-in-differences analysis of participating futuremap® firms compared to different sets of non-participating firms. Models 1 and 2 uses one propensity score matched non-participating firm for each treated firm as control. Models 3 and 4 uses five propensity score matched non-participating firms. Lower and upper bounds are approximated 95% confidence intervals. * indicates estimates are statistically different from zero at the 5 per cent level of significance.

Figure 5.3. Estimated mean headcount across financial years



Notes: Estimates are estimated means and 95% confidence intervals for futuremap® participants and the 5NN control group from between the 2013-14 financial year and 2020-21 financial year. The vertical line at 18 represents the first year that some firms in the sample receive the treatment (i.e. participated in the futuremap® workshop).

Impact on real R&D expenditures

Table 5.4 presents the coefficient estimates for the treatment effects of futuremap® participation on real R&D expenditures. As neither the ABS nor the ATO require firms to record their total R&D expenditures, this is a measure of businesses' R&D expenditures that are eligible for the R&D tax offset within their income taxes. As noted earlier, the data on Business Income Tax is available only through the 2019-20 financial year, so the estimates of the treatment effects are not as long lasting as those found in the previous results within Tables 5.1 through 5.3.

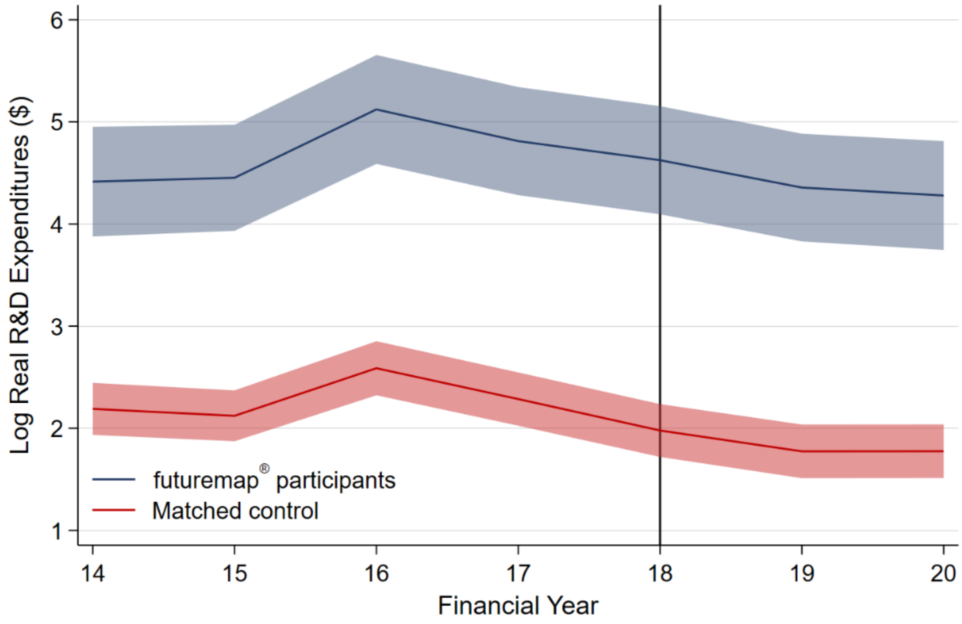
However, none of these results are statistically significant at the 5 per cent level of significance and moreover we see large swings between negative and positive averages. The average effects across the four models range between -8.4 per cent to 25.7 per cent. Figure 5.4 sheds some light in the negative coefficients. We can see for both the treatment and control firms, the average expenditures on R&D has been falling since the 2015-16 financial year. This is consistent with the summary statistics found in Table 4.1. This fall is not limited to firms within our sample and has been observed in national level trends.

Table 5.4. Estimated impact of futuremap® on real R&D expenditures (% change)

Average	Lower	Upper	Firms	Model
3.3%	-55.1%	61.7%	0,856	Control Group: 1NN; Period: 2003-04 to 2019-20
-8.4%	-61.7%	44.9%	0,800	Control Group: 1NN; Period: 2013-14 to 2019-20
25.7%	-25.5%	76.9%	2,428	Control Group: 5NN; Period: 2003-04 to 2019-20
-3.7%	-51.5%	44.1%	2,290	Control Group: 5NN; Period: 2013-14 to 2019-20

Notes: Estimates are based on difference-in-differences analysis of participating futuremap® firms compared to different sets of non-participating firms. Models 1 and 2 uses one propensity score matched non-participating firm for each treated firm as control. Models 3 and 4 uses five propensity score matched non-participating firms. Lower and upper bounds are approximated 95% confidence intervals. * indicates estimates are statistically different from zero at the 5 per cent level of significance.

Figure 5.4. Estimated mean real R&D expenditures ($) across financial years



Notes: Estimates are estimated means and 95% confidence intervals for futuremap® participants and the 5NN control group from between the 2013-14 financial year and 2019-20 financial year. The vertical line at 18 represents the first year that some firms in the sample receive the treatment (i.e. participated in the futuremap® workshop).

Impact on trade mark applications

Table 5.5 presents the coefficient estimates for the treatment effects of futuremap® participation on trade mark applications. We find only statistically significant coefficient estimates in Model 3. Across all four models, the average effects across the four models range between 1.9 per cent to 3.6 per cent with the 95 percent confident intervals ranging from a low of -2.1 per cent to a high of 6.5 per cent. The magnitudes of the results are relatively modest when compared to the financial variables. Similar to the R&D measurements, data on trade mark applications within BLADE were only available through the 2019-20 financial year.

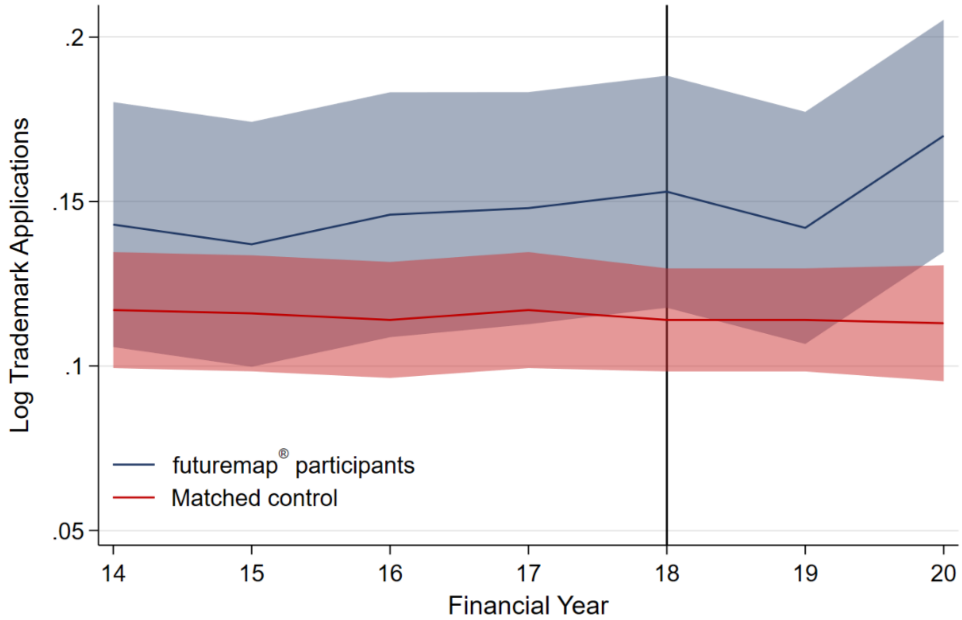
It should be noted that while there is evidence that SMEs do not necessarily disclose their intellectual property at the same rates relative to larger firms as a strategy to maintain a competitive edge, insofar as the control groups are similarly secretive due to their selection being based on various financial metrics for size, their underlying IP strategies should remain similar and that these would suggest real growth. However, these results could be confounded if the firms strategies on publicising IP were to change as a result of futuremap.

Table 5.5. Estimated impact of futuremap® on trade mark applications (% change)

Average	Lower	Upper	Firms	Model
3.0%	-0.5%	6.5%	1,049	Control Group: 1NN; Period: 2003-04 to 2019-20
1.4%	-2.1%	4.9%	1,049	Control Group: 1NN; Period: 2013-14 to 2019-20
3.6%*	0.7%	6.5%	3,023	Control Group: 5NN; Period: 2003-04 to 2019-20
1.9%	-1.2%	5.0%	3,023	Control Group: 5NN; Period: 2013-14 to 2019-20

Notes: Estimates are based on difference-in-differences analysis of participating futuremap® firms compared to different sets of non-participating firms. Models 1 and 2 uses one propensity score matched non-participating firm for each treated firm as control. Models 3 and 4 uses five propensity score matched non-participating firms. Lower and upper bounds are approximated 95% confidence intervals. * indicates estimates are statistically different from zero at the 5 per cent level of significance.

Figure 5.5. Estimated mean trade mark applications across financial years



Notes: Estimates are estimated means and 95% confidence intervals for futuremap® participants and the 5NN control group from between the 2013-14 financial year and 2019-20 financial year. The vertical line at 18 represents the first year that some firms in the sample receive the treatment (i.e. participated in the futuremap® workshop).

Impact on patent applications

Table 5.6 presents the coefficient estimates for the treatment effects of futuremap® participation on patent applications. For patent applications, none of the four model coefficient estimates were statistically significant at the 5 per cent level, yet the estimates were consistent with the averages ranging from 0.5 per cent to 1.6 per cent.

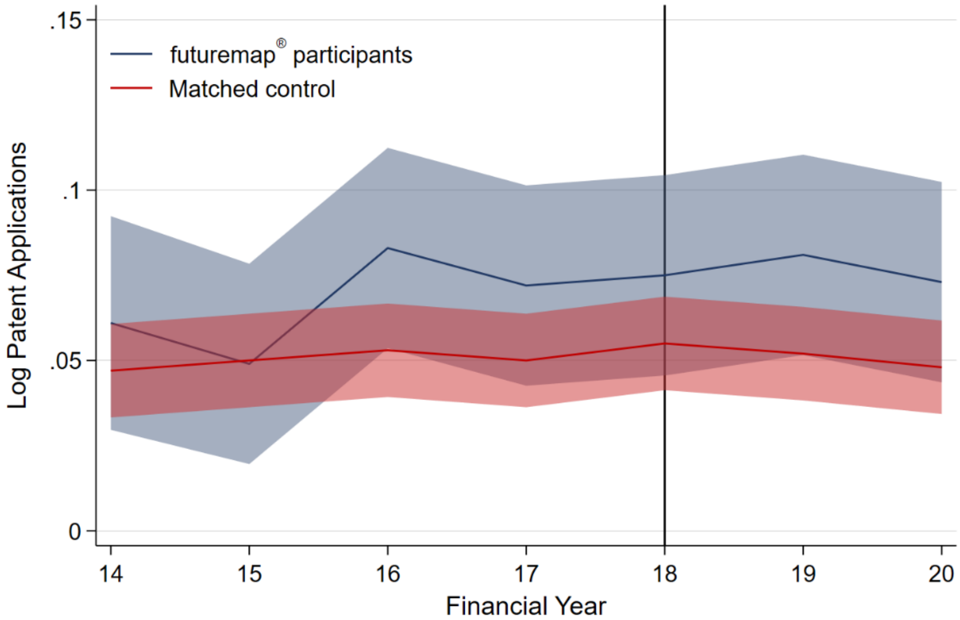
Similar to the earlier innovation measures, the coefficient estimates for patent applications are modest, suggesting that there is not significant evidence that futuremap® had fast-acting impact on innovation. However, given the lead time required for changes in the inputs of R&D to result in real outputs, these results should not be suggestive that the program was ineffective, particularly given that patent application data was available only through the 2019-20 financial years.

Table 5.6. Estimated impact of futuremap® on patent applications (% change)

Average	Lower	Upper	Firms	Model
1.6%	-0.2%	3.4%	1,049	Control Group: 1NN; Period: 2003-04 to 2019-20
1.0%	-0.8%	2.8%	1,049	Control Group: 1NN; Period: 2013-14 to 2019-20
1.0%	-0.8%	2.8%	3,023	Control Group: 5NN; Period: 2003-04 to 2019-20
0.5%	-1.1%	2.1%	3,023	Control Group: 5NN; Period: 2013-14 to 2019-20

Notes: Estimates are based on difference-in-differences analysis of participating futuremap® firms compared to different sets of non-participating firms. Models 1 and 2 uses one propensity score matched non-participating firm for each treated firm as control. Models 3 and 4 uses five propensity score matched non-participating firms. Lower and upper bounds are approximated 95% confidence intervals. * indicates estimates are statistically different from zero at the 5 per cent level of significance.

Figure 5.6. Estimated mean patent applications across financial years



Notes: Estimates are estimated means and 95% confidence intervals for futuremap® participants and the 5NN control group from between the 2013-14 financial year and 2019-20 financial year. The vertical line at 18 represents the first year that some firms in the sample receive the treatment (i.e. participated in the futuremap® workshop).

Impact on design rights applications

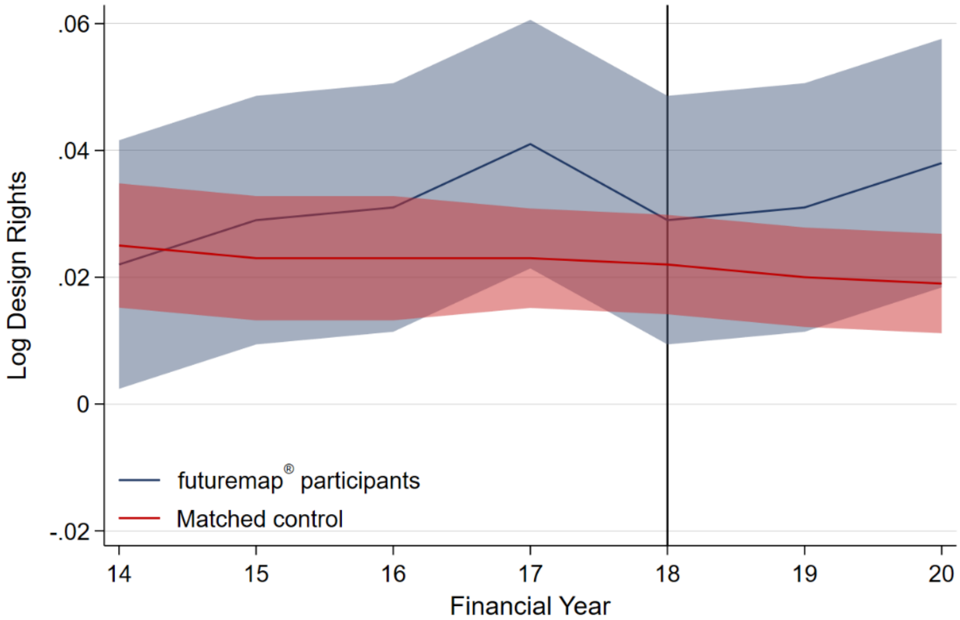
Table 5.7 presents the coefficient estimates for the treatment effects of futuremap® participation on design rights. As noted in the previous results for measures of innovation, none of the coefficient estimate results were statistically different from zero. Again, the results remained similar across the specifications, the average ranging between 1.0 per cent and 1.1 per cent.

Table 5.7. Estimated impact of futuremap® on design rights applications (% change)

Average	Lower	Upper	Firms	Model
1.1%	-0.5%	2.7%	1,049	Control Group: 1NN; Period: 2003-04 to 2019-20
1.1%	-0.5%	2.7%	1,049	Control Group: 1NN; Period: 2013-14 to 2019-20
1.0%	-0.4%	2.4%	3,023	Control Group: 5NN; Period: 2003-04 to 2019-20
1.0%	-0.4%	2.4%	3,023	Control Group: 5NN; Period: 2013-14 to 2019-20

Notes: Estimates are based on difference-in-differences analysis of participating futuremap® firms compared to different sets of non-participating firms. Models 1 and 2 uses one propensity score matched non-participating firm for each treated firm as control. Models 3 and 4 uses five propensity score matched non-participating firms. Lower and upper bounds are approximated 95% confidence intervals. * indicates estimates are statistically different from zero at the 5 per cent level of significance.

Figure 5.7. Estimated mean design rights applications across financial years



Notes: Estimates are estimated means and 95% confidence intervals for futuremap® participants and the 5NN control group from between the 2013-14 financial year and 2019-20 financial year. The vertical line at 18 represents the first year that some firms in the sample receive the treatment (i.e. participated in the futuremap® workshop).

Impact on exports

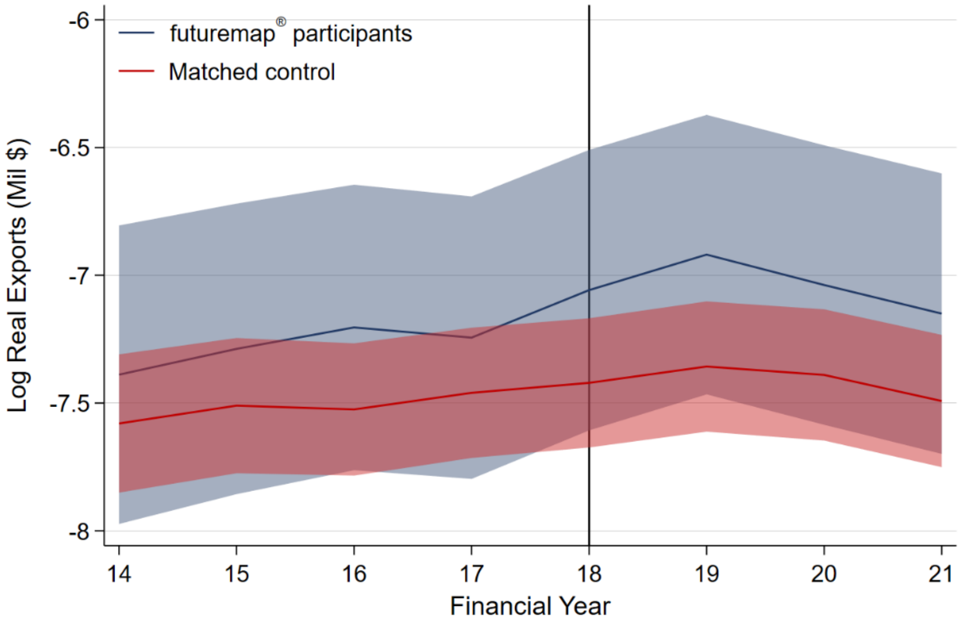
Table 5.8 presents the coefficient estimates for the treatment effects of futuremap® participation on real exports. The average effects across the four models range between 13.0 per cent to 28.3 per cent with none of the models being statistically significant. The 95 percent confident intervals for the models suggest that the range can vary from a low of -17.5 per cent to a high of 56.7 per cent suggesting that while the average results are positive, the estimates are not overly precise.

Table 5.8. Estimated impact of futuremap® on real exports (mil $) (% change)

Average	Lower	Upper	Firms	Model
16.0%	-17.5%	49.5%	1,049	Control Group: 1NN; Period: 2003-04 to 2020-21
13.0%	-15.4%	41.4%	1,049	Control Group: 1NN; Period: 2013-14 to 2020-21
28.3%	-0.1%	56.7%	3,023	Control Group: 5NN; Period: 2003-04 to 2020-21
20.8%	-2.7%	44.3%	3,023	Control Group: 5NN; Period: 2013-14 to 2020-21

Notes: Estimates are based on difference-in-differences analysis of participating futuremap® firms compared to different sets of non-participating firms. Models 1 and 2 uses one propensity score matched non-participating firm for each treated firm as control. Models 3 and 4 uses five propensity score matched non-participating firms. Lower and upper bounds are approximated 95% confidence intervals. * indicates estimates are statistically different from zero at the 5 per cent level of significance.

Figure 5.8. Estimated mean real exports (mil $) across financial years



Notes: Estimates are estimated means and 95% confidence intervals for futuremap® participants and the 5NN control group from between the 2013-14 financial year and 2020-21 financial year. The vertical line at 18 represents the first year that some firms in the sample receive the treatment (i.e. participated in the futuremap® workshop).

Impact on imports

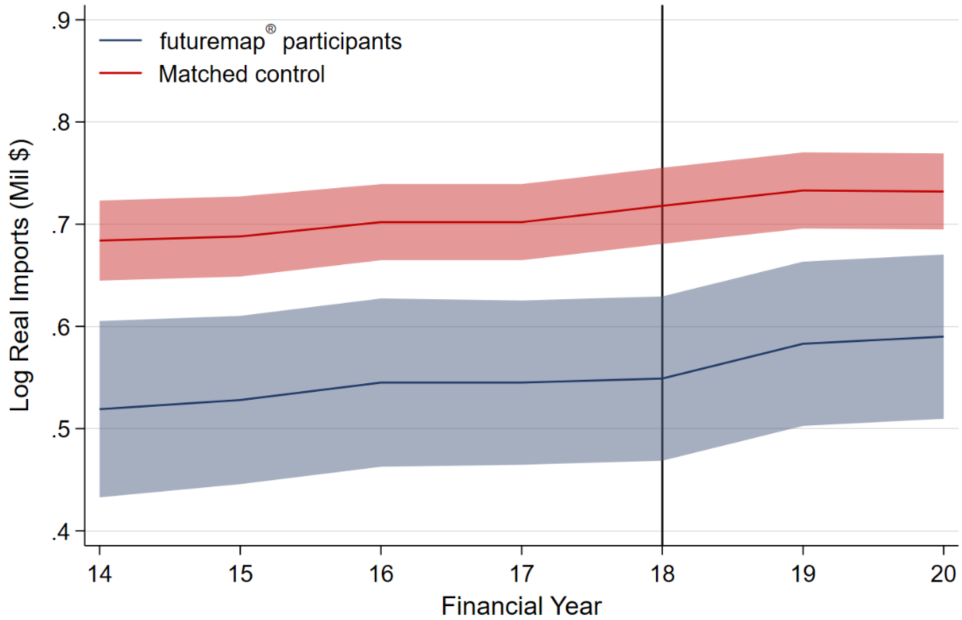
Table 5.9 presents the coefficient estimates for the treatment effects of futuremap® participation on real imports. The average estimated effects across the four models range are not statistically significant, but are consistent and range between 0.6 per cent and 2.0 per cent. The 95 percent confident intervals suggest that the range can vary from a low of -2.9 per cent to a high of 5.3 per cent.

Table 5.9. Estimated impact of futuremap® on real imports (mil $) (% change)

Average	Lower	Upper	Firms	Model
1.2%	-2.9%	5.3%	1,049	Control Group: 1NN; Period: 2003-04 to 2019-20
2.0%	-1.3%	5.3%	1,049	Control Group: 1NN; Period: 2013-14 to 2019-20
0.6%	-2.7%	3.9%	3,023	Control Group: 5NN; Period: 2003-04 to 2019-20
1.5%	-1.4%	4.4%	3,023	Control Group: 5NN; Period: 2013-14 to 2019-20

Notes: Estimates are based on difference-in-differences analysis of participating futuremap® firms compared to different sets of non-participating firms. Models 1 and 2 uses one propensity score matched non-participating firm for each treated firm as control. Models 3 and 4 uses five propensity score matched non-participating firms. Lower and upper bounds are approximated 95% confidence intervals. * indicates estimates are statistically different from zero at the 5 per cent level of significance.

Figure 5.9. Estimated mean real imports (mil $) across financial years



Notes: Estimates are estimated means and 95% confidence intervals for futuremap® participants and the 5NN control group from between the 2013-14 financial year and 2019-20 financial year. The vertical line at 18 represents the first year that some firms in the sample receive the treatment (i.e. participated in the futuremap® workshop).

Discussion

As discussed previously, it is likely that businesses self-select into futuremap® relative to the population of Australian firms. futuremap® participants tend to fit within the definition of SMEs, yet nonetheless are larger in terms of sales and employees, while also more likely to be engaged in innovating activities such as R&D and patenting.

Such self-selection has important implication on a program impact evaluation with observational data such as reported here. Because we as the analysts have no direct control on the data generation process or on how the samples whose data being observed were selected, the estimates can suffer from the aforementioned selection bias due to observed and unobserved factors that affect both decisions to participate in the program and the intended outcomes from the program.

In this evaluation, we implemented difference-in-differences (DID) framework with matching to reduce the self-selection bias by eliminating the influence of unobserved and time invariant factors[10] through comparing the change in the performance of the participant with non-participants, before and after the program. Effectively, we differenced out any time-invariant confounding effects that could lead to biased estimates.

DID estimation can minimise self-selection bias however, we still had to deal with potential bias caused by unobserved but time varying factors such as a sudden change in managerial strategy. Implicit in the DID is the common trend assumption which states that the changes in the performance of both participants and non-participants are the same in the absence of the program intervention. In practice, we ensured that the common trend assumption was not violated by selecting only “similar” non-participants as the control group using firm-level pre-participation variables. In practice, these common trends do not fully hold when looking at differences in the trends for the logged level of those same variables. This difference suggests that we should be cautious before asserting causality, yet the consistent magnitude of the results suggest that it is likely that futuremap® had a positive contribution towards firm growth.

Despite being cautious in regards to causal interpretations, these results suggest that participating firms are growing faster than similar non-participating firms. This suggests that the IMCRC is able to identify and attract firms with a certain level of managerial or innovative capacity that is not directly observable with the financial data. This could provide a useful tool to follow up with previous participants and provide policy makers with unique insights into the aspirations of an elite group of manufacturing firms in Australia.

[10] Factors which do not change over time but determine whether or not a firm participated in the program and correlate with the outcomes being evaluated.

5.2 Measures of investment into intangible capital

A noted goal for futuremap® is to act as a catalyst for firms investment into new digital technologies and innovative management. These metrics can be hard to measure, but nonetheless are understood to constitute intangible capital for businesses.

This capital can consist of past expenditures on staff training and professional development, innovation, marketing, management expertise and workplace relations that are expected to have a lasting benefit for firms (Webster, 1999, 2000).

Accounting for intangible capital and investment is important for the same reasons that fixed capital and investment are regarded as important. Forms of investment

- Are a source of future productivity growth
- Contribute toward and result from a trade cycle
- Are necessary for the health and future existence of a business

Corrado et al. (2005) classified intangibles into

- Computerized information or knowledge embedded in computer programs and software
- Innovative property or knowledge acquired through scientific research and development and non-scientific discovery and development, inventive and creative activities
- Economic competencies or knowledge embedded in firm-specific human training and structuring of firm resources (market research and branding as well as business process re-engineering).

To determine whether futuremap® participants are investing in intangible capital and how they compare to their peers across Australia, we developed several indexes of intangible capital using survey responses from the Business Characteristics Survey (BCS).

Collecting data on workplace reforms, Information Technology (IT) systems, training and marketing are challenging as firms do not collect information on these expenditures (either in-house or through contractors) in a systematic and consistent way. The ABS understood that if they asked firms for their expenditure on these items they would get many missing observations. Accordingly, the approach taken by the ABS, and indeed similar surveys in Europe and New Zealand, is to ask several questions about their activity to which the firm would only need to answer yes or no.[11]

These binary – yes/no – responses to questions are not as precise as reporting actual investment expenditures but Australian research has revealed a reasonable correlation between both types of metrics (Jensen and Webster, 2009). Therefore, we take these indices as a second-best measure of intangible investment. The following indices have been developed due to their direct representation of common types of intangible capital:

- Digital support: the number of different categories of employee delivering IT support within the business (e.g. IT specialists, contractors, etc.).

- Digital maturity: the number of different ways the business is digitally engaged with its stakeholders, and which aspects of their productive activities are automated (e.g. do their IT systems link with those of their suppliers? Are their stock management, invoicing, production or logistics automated?, etc.).

- Branding and marketing: the number of different ways in which a business changed its market methods, branding, design, advertising medium, etc. in the last year.

- Organisational capital: the number of different ways the business changed its management processes, business practices, external relations, operational processes, etc.

- Human capital: did the business deliver training specific to the new products or processes, did they expand the structured training delivered to employees, etc.

Each of these indices is a composite measure of between 2 and 11 individual question responses in the BCS. All but two questions are binary variables across the set of indexes asking a business whether they did or did not engage in a particular activity in the previous 12 months. All five indexes are reported for every firm participating in the BCS.

[11] See Chappell and Jaffe (2018)

These indexes are reflective of the intangible capital embedded within that business. Using them to analyse investment activities is made possible by the assumption that the activities included in the BCS impose a cost on businesses (in the form of time, money, effort and other resources, as well as an opportunity cost). For example, if a business indicates on the BCS that their digital support is delivered by specialists employed by the business, we can assume this poses a cost in the form of wages on that business.

Likewise, if a business hires contractors to deliver these services. Based on this assumption, we can infer that a business which employs both IT specialists and contractors to deliver their digital support is likely to be investing more in their IT capabilities than a business only investing in digital support from a single source.

In the context of branding and marketing, a business that confirms in the BCS that they have introduced a new marketing campaign is indicating they have invested in designing, testing and delivering this campaign. They can be said to have invested more in branding and marketing capital in that reference period that a business that has not designed, tested or delivered any new marketing campaigns. Further, this assumption is bolstered by the fact that some questions in the BCS are targeted at innovative activities (i.e. businesses confirm they have engaged in 'new or significantly improved' marketing methods). Under this key assumption, our indices of intangible capital allow us to compare businesses based on the number of unique activities they are engaged in. In short, a business with a higher index score in a given variable has confirmed they are engaged in more activities indicative of some investment in intangible capital.

Table 5.10 presents the basic definition of the various intangible indexes and the types of measurements they cover. Using the BCS, we develop five measures of intangible capital, digital support, digital maturity, branding and marketing, organisational capital, and human capital.

Table 5.10. Intangible capital index definitions

Digital support	Provision of IT Support includes: Persons working in the business - IT specialists; Persons working in the business - not IT specialists; Supplier of software or hardware; Contractors or consultants; and Other
Digital maturity	Systems link automatically with Suppliers'; business systems; Customers' business systems; Own systems - Reordering replacement supplies; Own systems - Invoicing and payment; Own systems - Production or service operations; Own systems - Logistics, including electronic delivery; Own systems - Marketing operations; and Other
Branding and marketing	Number of new or significantly improved marketing methods; Joint marketing or distribution collaborative arrangement; Significant changes to the aesthetic design or packaging of goods or services; New media or techniques for product promotion; New methods of product placement or sales channels; New methods of pricing goods or services; spending on innovative new marketing methods and Other marketing method.
Organisational capital	Reforms to Operational processes including Methods of manufacturing or producing goods or services; Logistics, delivery or distribution methods for goods and services; Supporting activities for business operations; Other operational processes; expenditure on new organisational/managerial processes; reforms to organisational/ processes including knowledge management processes; major change to the organisation of work; new business practices for organising procedures; new methods of organising work responsibilities and decision making; new methods of organising external relations with other businesses or institutions; and other organisational/managerial processes.
Human capital	Training specific to development or introduction of new goods, services, processes or methods; compared to previous year. Structured/formal training for employees increased, decreased or stayed the same.

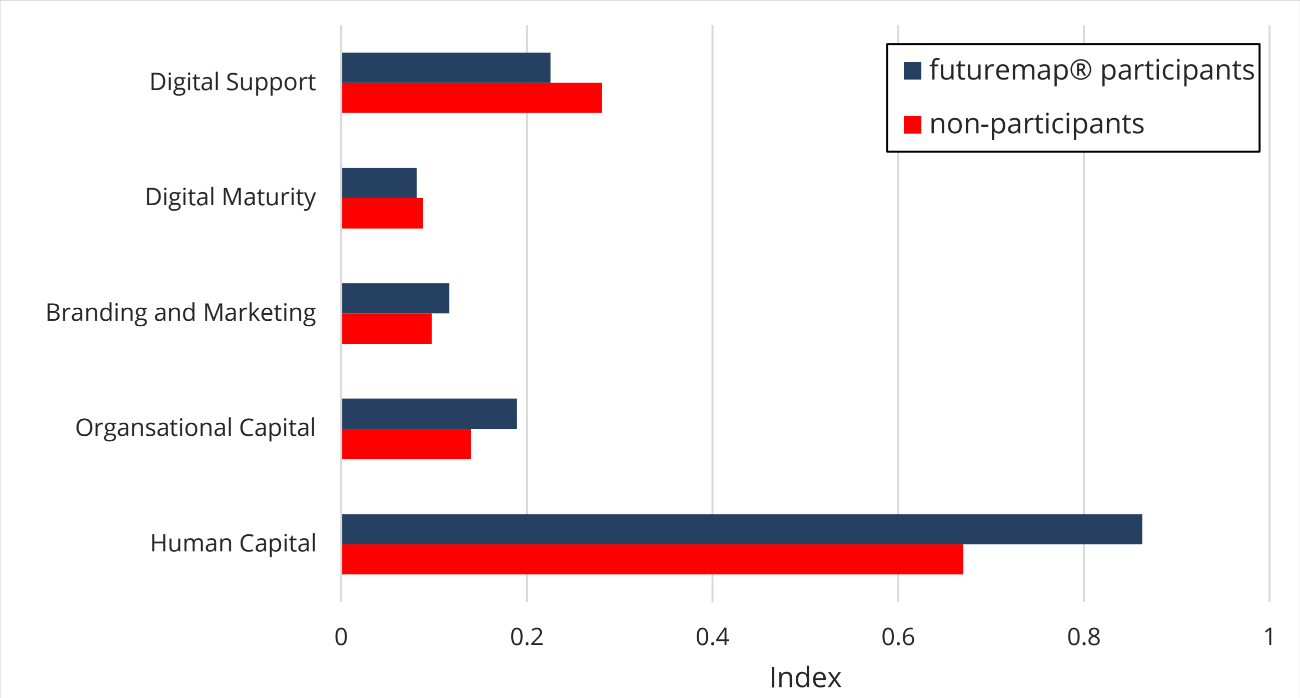
Notes: Definitions constructed by authors using survey responses found within the BCS.

For futuremap® participants which have also been selected within the BCS since 2014-15, we compare their investment in these areas relative to their Australian peers in the same period. Those results are presented in Figure 5.10. As participation in the BCS is not common, we are not able to track their changes over time in a meaningful way.

These results suggest the investment in intangible capital between participants and non-participants suggest some interesting variations between the firms. In particular, we see participants were more likely to invest in Branding and Marketing, Organisational Capital and Human Capital relative to their peers. The magnitudes across indexes are not directly comparable, but we can compare the relative index averages between participants and non-participants. We see amongst the three indexes in which participants exceed the non-participants, the indexes ranged between 19.3 per cent higher (branding and marketing) and 35.3 per cent higher (organisational capital). This suggests that futuremap® participants are generally investing more in operational and human management processes and engaging in more branding and marketing efforts.

On the other hand, these firms were less likely to be investing in digital support and digital maturity relative to their peers. As this period also includes financial years prior to firms participations, this is consistent with the participants decisions to engage with futuremap® as they have identified existing gaps in their knowledge relative to their Australian peers.

Figure 5.10 Intangible capital indexes by futuremap® participation status



Source: Business Longitudinal Analysis Data Environment (BLADE)

6. Conclusions

Information plays a significant role in identifying the market opportunities, products and the characteristics of consumers. Yet the mere existence of information and resources generally is insufficient for firms to integrate that information into their business. The first hurdle, small and medium sized firms confront is being aware of the cutting edge in processes. The second, is converting that knowledge into practice. For both aspects, educational and government institutions are a critical component to unlocking that information for businesses. However, existing evidence provides conflicting conclusions with regards to the effectiveness of these solutions, suggesting that it is just as important on how the information is transmitted to businesses as providing those with information.

This report aims to provide an evaluation of the impact of the IMCRC futuremap® workshop and tool over the period of March 2018 to June 2021. The analysis is based on linked survey data of participants in futuremap® workshops and ABS BLADE database.

Acknowledgements

Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the IMCRC or ABS. All results have been reviewed to ensure that no confidential information is disclosed. We wish to thank Simon Dawson, Jason Coonan and David Chuter at the IMCRC for the use of the futuremap® participant survey data and confidence to fund the research; Talei Parker, Laura Brazier, Lisa Commens, Molly Chapman, Sandra Flynn, Ben Harrington, and everyone behind the scenes from the ABS for making the analysis of the ABS data possible.

Appendix 1 Method

A1.1 Difference-in-differences (DID) analysis

We derived average treatment effects on the treated as our estimate of the impact of the IMCRC futuremap® program on participants' export performance using a quasi-experimental method known as difference-in-differences (DID). To implement the method, we required observable data on the export performance of participating and non-participating firms before and after the futuremap® workshop. In the stylised diagram in Figure A.1 below, the observed data are labelled with "green" coloured labels T0 and C0 (corresponding to the average performance of participants and non-participants <u>before</u> workshop participation, respectively) and T1 and C1 (corresponding to the average performance of participants and non-participants <u>after</u> workshop participation, respectively).

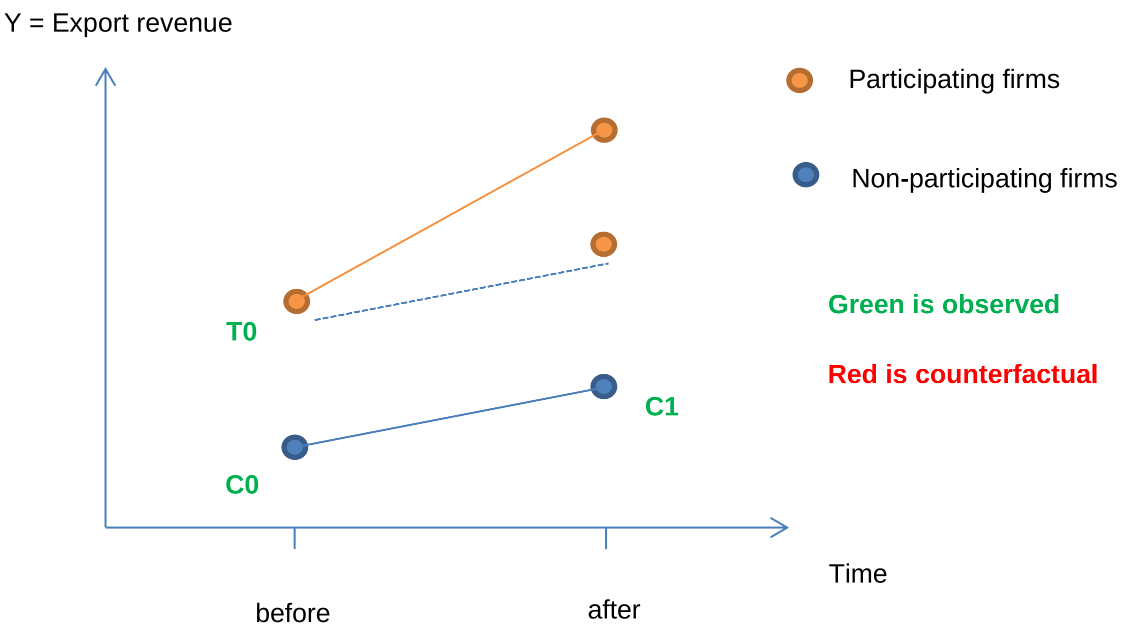


Figure A.1: Impact evaluation with before and after data

Naïve impact estimates

Given the observed data as defined above, one naïve estimate of the impact is to compare the difference in average export performance (Y) at points T1 and C1 (that is, $Impact_{Naive1} = Y_{T1} - Y_{C1}$). This naïve estimate is usually produced when we do not observe before and after data. The problem with this naïve estimate is we do not know whether participating firms are always superior to non-participating firms. Note that Figure A.1 is drawn such that $Y_{T0} > Y_{C0}$ to illustrate the possibility that participating firms may in fact have better export performance even before the program.

Another slightly less naïve estimation method that people can use when before and after data are available is to measure impact as: $Impact_{Naive2} = Y_{T1} - Y_{T0}$. This estimate is an improvement over the previous one since it does not suffer from the "upward bias" from any pre-existing superior performance of the participating firms. That problem is avoided by making a comparison based only on the performance of the participating firms. However, there is still another problem in terms of completely attributing the change in the performance of participants ($Y_{T1} - Y_{T0}$) to the IMCRC futuremap® workshop participation. It is plausible that some of the measured improvement in participating firms' performance comes from other unobserved reasons unrelated to the futuremap® workshop participation. In Figure A.1, this possibility is illustrated by the counterfactual point T1' to denote the average export performance ($Y_{T1'}$) had there be no futuremap® workshops. The closer T1' is to T1, that is as $Y_{T1'}$ closer to Y_{T1}, then the more severe the misattribution problem from using $Impact_{Naive2}$ measure.

DID impact estimate

To address the attribution bias problem of $Impact_{Naive2}$, we can redefine the impact measure as:

$$Impact = Y_{T1} - Y_{T1'} \tag{A1.1}$$

The problem with implementing the measure $Impact$ in (A2.1) is that it involves $Y_{T1'}$ which is an unobserved counterfactual. The difference-in-differences approach solves this problem by making a reasonable assumption that whatever unobserved factors there are which are unrelated to futuremap® workshop participation, they affect performance before and after the program for both participants and non-participants in a similar way. This assumption is also known as the common trend assumption as shown in Figure A.1 above by the common slopes of the lines C0-C1 and T0-T1'.

Under the common trend assumption, we can estimate $Y_{T1'} - Y_{C1}$ as $Y_{T0} - Y_{C0}$ such that the impact of futuremap® workshop participation can be measured as:

$$Impact_{DID} = Y_{T1} - Y_{T1'}$$

$$= (Y_{T1} - Y_{C1}) - (Y_{T1'} - Y_{C1})$$

$$= (Y_{T1} - Y_{C1}) - (Y_{T0} - Y_{C0})$$

$$= (Y_{T1} - Y_{T0}) - (Y_{C1} - Y_{C0}) \qquad \text{(A1.2)}$$

where in the third line we substitute $Y_{T0} - Y_{C0}$, which is observable, for $Y_{T1'} - Y_{C1}$ which is unobserved. Thus, $Impact_{DID}$ is essentially computed based on the difference of two observed differences and hence where the difference-in-differences term comes from.

A2.2. Basic DID

This and subsequent sections and Appendix 2 provide a more technical discussion of the implementation of the DID method in this report. Denote program participation status as D_{it} where $D_{it} = 1$ if firm i participates in the IMCRC futuremap® workshop in financial year t and $D_{it} = 0$ otherwise. Denote X_{it} as the corresponding vector of observed covariates of firm and program characteristics. Denote Y_{it}^1 as the observed outcome (say, export revenues) and Y_{it}^0 as the unobserved (counterfactual) outcome.

Hence, $E[Y_{it}^1|X_{it}, D_{it} = 1]$ is the observed average outcome of participating firms conditional on X_{it} and $E(Y_{it}^0|X_{it}, D_{it} = 1)$ is the counterfactual average outcome of participating firms had they not participated. The impact of trade promotion program is measured by the average treatment effect on the treated (ATT) denoted by τ:

$$\tau = E(Y_{it}^1|X_{it}, D_{it} = 1) - E(Y_{it}^0|X_{it}, D_{it} = 1) \qquad \text{(A1.3)}$$

In equation (A1.3), τ measures the average change in the outcomes of participating firms as the difference between observed average outcomes after treatment and counterfactual average outcomes had the firms not received the treatments. It is clear that to obtain an unbiased estimate of τ we need an unbiased estimate of $E(Y_{it}^0|X_{it}, D_{it} = 1)$, the counterfactual average outcome. An obvious candidate is to use the average outcome of a selected group of non-participants, which we call as the control group. This control group would need to be identified by taking into account any potential non-randomness or endogenous selection in program participation.

In other words, we need to select the control group such that relevant firm characteristics are comparable in both groups. We did this in two ways. First, we implemented the basic difference-in-differences method. The main idea was to use the longitudinal nature of survey and the databases available within BLADE. Specifically, we used the repeated observations of the same firms across the years in order to control for time invariant and unobserved characteristics that lead to systematic selection to participating in futuremap®. Using difference-in-difference, we estimated τ by comparing the change in the various outcomes of participants before and after the treatment to the change in the same outcomes of non-participants before and after the treatment. This is shown in equation (A1.4) below:

$$Y_{it} = X_{it}\beta + \tau D_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \text{(A1.4)}$$

Note that in specifying equation (A1.4), we assume the conditional expectation function $E(Y|X, D)$ is linear and any unobserved firm characteristics is decomposable into a time-invariant firm specific fixed effects (μ_i), common across firms year effect (λ_t) and a random component (ε_{it}). The introduction of the covariates (X) linearly may lead to inconsistent estimate of τ due to potential misspecification (Meyer, 1995; Abadie, 2005). In order to avoid this problem, we followed Volpe Martincus and Carballo (2008) and augment the difference-in-differences analysis with a matching analysis as described below.

A2.3 Matched DID

As discussed above, a key identification assumption of the DID method is the common trend assumption. To minimize the possibility that this assumption is violated, we needed to make sure that the control group, that is the set of non-participants, are as "similar" as possible to the participants. This is particularly important when we know that program participation is not random, that is when there is any systematic selection bias into attendance. The matched-DID impact measure aims to address the problem by making a slightly weaker assumption that there is a common trend once participants and non-participants are matched on observable characteristics.

The matched difference-in-differences method can estimate treatment effects without imposing the linear functional form restriction in the conditional expectation of the outcome variable is (Arnold and Javorcik, 2005; Görg et al 2008). The matching method part controls for any endogenous selection into programs based on observables (Heckman and Robb, 1985; Heckman et al 1998). The difference-in-differences part of the method controls for endogenous selection into programs based on time invariant unobservables. Therefore, the matched difference-in-differences estimate of the treatment effects (τ) is the difference between the change in the outcomes before and after program participation of treated firms and that of matched non-participating firms. Any imbalance between the treated and control groups in the distribution of covariates and time-invariant effects is controlled for. Note however that we still need to assume that there are no time-varying unobserved effects influencing selection into treatment and treatment outcomes (see Heckman et al., 1997; Blundell and Costa Dias, 2002).

In practice, the estimation of τ (treatment effects) was conducted in two stages. First, control group members were identified using a matching method such as the propensity score matching (explained below). Second, equation (A1.4), without the X covariates, was estimated using the treated group and matched control group as the sample.

Propensity score matching

The basic idea of propensity score matching is to pair participating firms to most similar non-participating firms using a propensity score. The propensity score was estimated as the predicted probability of a firm to participate in the program based on observed covariates, $P(X)$, which do not include the outcome measures. By doing this, we control for observable sources of bias in the estimation of the treatment effect (selection on observables bias). In order to estimate, $P(X)$, we controlled for observed factors that determine firms selection into the programmes and export performance, so that programme participation and programme outcomes are independent. The similarity of two given firms was then assessed by how close their propensity scores are.

In this report, we use the following similarity criteria to select the participants and non-participants in computing the $Impact_{DID}$:

1. The nearest neighbour (NN1): For each participant, select one non-participant with the most similar propensity score.

2. The five nearest neighbours (NN5): For each participant, select five non-participants with the most similar propensity scores.

To produce relatively reliable estimates of the propensity scores, Volpe Martincus and Carballo (2008) and the literature they cite[12] suggest that we take into account factors that are correlated with different stages of firm development. Firms at different levels appear to have different level of awareness of available programs and technologies. In addition, their needs and obstacles also vary, implying different requirements and expectations from participation in programs and workshops.

In practice, our choice of matching variables was limited by how rich the database we worked with. For this report, we estimated the propensity score as the predicted probability of participating in the IMCRC futuremap® workshop conditional on:

- Previous five years of turnover
- Previous five years of headcount
- Merchandise exports
- Merchandise imports
- Type of legal organisation (i.e. public company, private company, trust, sole proprietor)
- Patents
- Trademarks
- Design Rights
- ANZSIC division
- First year of financial information in BLADE

Outside of turnover and headcount where we used individual lagged values to help control for trends, we averaged the past five years of values for the remaining financial information in order to avoid endogeneity problem in the matching process.

[12] See, as cited in Volpe Martincus and Carballo 2008, Kedia and Chhokar 1986; Naidu and Rao 1993; Diamantopoulos et al., 1993; Naidu and Rao 1993; Moini 1998; Ogram 1982; Seringhaus 1986; Kotabe and Czinkota 1992; Francis and Collins-Dodd 2004.

The propensity matching approach was implemented using the *psmatch2* command in Stata software based on the following constructed variables:

1. Beginning with the 2017-18 financial year. identify treated and non-treated firms. $D_i = 1$ if $D_{it} = 1$ for the year t. Otherwise, $D_i = 0$. The variable D_i is the dependent variable for psmatch2.

2. For that year, construct the covariates vector X_{it} consists of the variables described above. For the case of the 2017-18 financial year, compute the pre-2017-18 average values of each components in X_{it} across the years for each firm and ensure the lagged values of turnover and headcount are available. Denote this average values as X_{ipre}; this covariate vectors is the independent variables for psmatch2.

3. The control group is defined as the nearest neighbour (or five nearest neighbours) matched by psmatch2 using the variables in steps 1 and 2.

4. If five years of lagged values for treatment firms are not available re-run the matching for firms with between 1 and 4 lags to find matches for those firms.

5. Re-do steps 1 through 4 for the financial years: 2018-19, 2019-20, and 2020-21.

Appendix 2 Matching analysis results

A2.1 Propensity score matching

As discussed in Appendix 1, to account for the possibility of systematic selection into participation in futuremap®, we implemented the propensity score matching approaches and produce difference-in-differences (DID) estimates of the program impacts on matched control groups. Table A2.1 summarises the coefficient estimates of propensity equations. Table A2.2 summarises the matching results.

Table A2.1: Propensity score matching coefficient estimates

	Dependent Variable: Attended futuremap® workshop in 2017-18
2016-17 Log Real Turnover	0.240
	(0.451)
2016-17 Log Headcount	0.149
	(0.725)
2015-16 Log Real Turnover	-0.030
	(0.397)
2015-16 Log Headcount	-0.258
	(0.715)
2014-15 Log Real Turnover	0.022
	(0.465)
2014-15 Log Headcount	0.163
	(1.006)
2013-14 Log Real Turnover	-0.127
	(0.423)
2013-14 Log Headcount	0.518
	(1.052)
2012-13 Log Real Turnover	-0.017
	(0.438)
2012-13 Log Headcount	0.103
	(0.781)
2011-12 Log Real Turnover	-0.030
	(0.356)
2011-12 Log Headcount	-0.239
	(0.455)
Mean Log Real Merchandise Exports	0.135**
	(0.064)
Mean Log Real Merchandise Imports	0.062
	(0.065)
Public Company	-0.448
	(1.285)
Private Company	0.521
	(0.757)
Mean Log Patents Filed	0.386
	(0.931)
Mean Log Trademarks Filed	-0.148
	(0.641)
Mean Log Design Rights Filed	1.095
	(1.367)
Real Turnover Growth	0.000
	(0.006)
First Year with Financial Indicators	Included
ANZSIC Division Indicators	Included
Observations	96,669
Pseudo R-Squared	0.217

Table A2.1 is example of one of the 20 logistic regressions used to calculate propensity score estimates for the matching procedure. A total of 96,669 firms were included in this example propensity score matching estimation. These numbers are lower than the summary statistics of potential firms in Australia due to missing values in one or more covariates as well as excluding any firm in the control group.

The coefficient estimations are not generally statistically significant. Given the large degree of multicollinearity in the variables, this is to be expected. However, in the case for predicting values, multicollinearity does not impact the quality of the results.

A2.2 t-tests of pre-program means

Based on the estimated coefficient summarized in Table A2.1, we computed propensity scores. These propensity scores were used to identify the most similar non-participants as the matched control group. We identified the nearest neighbour and five nearest neighbours from the pool of non-participants. Table A2.2 provides the summary of t-tests of differences in the means in average export performance before program participation (pre-2011) between participants and non-participants matched using the propensity matching model (PSM2).

Table A2.2: Difference in pre-program outcomes of participants (P) and non-participants (NP) for the 1NN Matched Sample; PSM2

	Non-Participants		Participants		
	N	Mean	N	Mean	t-stat
Lag (1 Year) Log Real Turnover	529	2.09	534	2.02	0.55
Lag (1 Year) Log Headcount	529	3.69	534	3.75	-0.65
Lag (2 Years) Log Real Turnover	529	1.92	534	1.92	0.02
Lag (2 Years) Log Headcount	529	3.64	534	3.69	-0.57
Lag (3 Years) Log Real Turnover	515	1.85	518	1.82	0.15
Lag (3 Years) Log Headcount	498	3.65	492	3.72	-0.81
Lag (4 Years) Log Real Turnover	495	1.95	498	1.79	1.01
Lag (4 Years) Log Headcount	476	3.67	472	3.71	-0.48
Lag (5 Years) Log Real Turnover	482	1.83	482	1.73	0.61
Lag (5 Years) Log Headcount	467	3.55	454	3.67	-1.15
Lag (6 Years) Log Real Turnover	453	1.75	462	1.73	0.11
Lag (6 Years) Log Headcount	418	3.62	426	3.69	-0.62
Mean Log Real Merchandise Exports	529	-6.96	534	-7.30	0.95
Mean Log Real Merchandise Imports	529	-4.51	534	-4.92	1.15
Mean Log Patents Filed	529	0.03	534	0.05	-1.69*
Mean Log Trademarks Filed	529	0.12	534	0.12	-0.01
Mean Log Design Rights Filed	529	0.01	534	0.02	-1.72*

Notes: *, **, *** denotes statistically significant estimate at 10, 5, and 1% level. Null hypothesis is that the difference in means is zero.

Table A2.2 shows the differences in pre-program participation averages for participants and non-participants in the 1NN matching sample. The results suggest that the sample is well matched, the t-stats suggest that the mean pre-program outcomes for futuremap® participants are not statistically different from the non-participants outside of design rights filed and patents filed. In both cases, it is only statistically significant at the 10 per cent level of significance. These suggest that non-participants were less likely to have filed design rights and patents relative to the futuremap® participants prior to the workshops.

Table A2.3: Difference in pre-program outcomes of participants (P) and non-participants (NP) for the 5NN Matched Sample; PSM2

	Non-Participants		Participants		
	N	Mean	N	Mean	t-stat
Lag (1 Year) Log Real Turnover	2576	2.04	534	2.02	0.15
Lag (1 Year) Log Headcount	2576	3.67	534	3.75	-1.07
Lag (2 Years) Log Real Turnover	2576	1.89	534	1.92	-0.23
Lag (2 Years) Log Headcount	2576	3.61	534	3.69	-1.15
Lag (3 Years) Log Real Turnover	2496	1.87	518	1.82	0.40
Lag (3 Years) Log Headcount	2429	3.61	492	3.72	-1.40
Lag (4 Years) Log Real Turnover	2401	1.89	498	1.79	0.84
Lag (4 Years) Log Headcount	2333	3.61	472	3.71	-1.32
Lag (5 Years) Log Real Turnover	2337	1.79	482	1.73	0.45
Lag (5 Years) Log Headcount	2232	3.57	454	3.67	-1.23
Lag (6 Years) Log Real Turnover	2230	1.77	462	1.73	0.31
Lag (6 Years) Log Headcount	2070	3.60	426	3.69	-1.08
Mean Log Real Merchandise Exports	2576	-7.44	534	-7.30	-0.46
Mean Log Real Merchandise Imports	2576	-4.83	534	-4.92	0.30
Mean Log Patents Filed	2576	0.04	534	0.05	-1.59
Mean Log Trademarks Filed	2576	0.10	534	0.12	-1.51
Mean Log Design Rights Filed	2576	0.02	534	0.02	-1.30

Notes: *, **, *** denotes statistically significant estimate at 10, 5, and 1% level. Null hypothesis is that the difference in means is zero.

Table A2.3 shows the differences in pre-program participation averages for participants and non-participants in the 5NN matching sample. Similar to the 1NN results in Table A2.2, the results suggest that the sample is well matched for the financial variables. The t-stats suggest that the mean pre-program outcomes for futuremap® participants are not statistically different from the non-participants. Unlike, in the case for innovation variables, we see that the differences in design rights and patents are not statistically significant.

A2.3 Relative-time, event study estimation results

As an alternative to the difference-in-differences approach to estimating treatment effects, we can estimate the results using a relative-time event study approach in which we include a series of indicator variables set to one if a business will attend a workshop in two financial years (i.e. Treatment in t-2) up to a business attended a workshop 3 financial years prior. The benefit of this approach is that it allows us to get some indication on whether the treated firms performance is changing relative to the control group prior to receiving treatment.

These results, shown in Table A2.4 suggest despite the mean financial characteristics not being statistically different in the pre-period between participants and non-participants, there is evidence that the participant firms were growing faster in the financial years leading up to their participation in futuremap®.

Overall, this suggests that we should be cautious when interpreting the results of the difference-in-differences results as the propensity score modelling has not fully controlled for businesses selection into treatment. What this means in practice is that more successful firms relative to the average firm in Australian are more likely to be engaging in workshops that provide training and introduce the firms to new technologies. Given those restrictions, it is not possible to fully disentangle these effects from the impact that futuremap® has in enabling firms to adopt new innovative strategies or technologies.

Table A2.4: Estimates of treatment effects for various outcomes using relative-time, event study approach for 1NN sample

	Log Turnover	Log Wages	Log Headcount	Log R&D	Log Trademarks	Log Patents	Log Design Rights	Log Exports	Log Imports
Treatment (t-2)	0.116*	0.036	0.014	0.531**	0.029	0.010	0.007	0.125	-0.011
	(0.067)	(0.061)	(0.021)	(0.237)	(0.018)	(0.009)	(0.008)	(0.154)	(0.012)
Treatment (t-1)	0.183**	0.122*	0.041	0.085	0.024	0.015	0.006	0.132	-0.004
	(0.080)	(0.070)	(0.027)	(0.308)	(0.019)	(0.010)	(0.008)	(0.180)	(0.017)
Treatment (t)	0.200**	0.210**	0.080**	0.246	0.034	0.019*	0.013	0.178	0.004
	(0.091)	(0.087)	(0.033)	(0.366)	(0.023)	(0.011)	(0.009)	(0.186)	(0.021)
Treatment (t+1)	0.194*	0.214*	0.101***	-0.311	0.011	0.014	0.017	0.235	0.041
	(0.118)	(0.112)	(0.037)	(0.452)	(0.029)	(0.016)	(0.011)	(0.209)	(0.031)
Treatment (t+2)	0.190	0.250*	0.095**	-1.578	0.078	-0.009	0.020	0.148	0.071
	(0.145)	(0.132)	(0.048)	(0.982)	(0.057)	(0.031)	(0.024)	(0.249)	(0.073)
Treatment (t+3)	-0.219	-0.107	-0.093					0.163	
	(0.300)	(0.332)	(0.058)					(0.426)	
Year fixed effects	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	8,948	8,912	8,643	5,429	7,965	7,965	7,965	8,998	7,965
Firms	1,049	1,048	1,049	800	1,049	1,049	1,049	1,049	1,049
R-Squared	0.020	0.025	0.074	0.009	0.002	0.003	0.001	0.014	0.041

Notes: *, **, *** denotes statistically significant estimate at 10, 5, and 1% level. Dependent variables are the variable described in each column. Sample includes the 1NN propensity score matched control group.

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Glossary

Confidence interval	A 95% confidence interval means if the analysis is replicated with 100 times with possibly different samples, the true value of the population parameter of interest (the impact of futuremap® workshops) will be observed in the interval 95 times.
Control group	The control group consists of firms who did not participate in the program but are otherwise similar to the participating firms. To obtain unbiased impact estimates, the average change in the relevant outcomes of participating firms is compared to the average change in the same outcomes of the firms in the control group.
Counterfactual	In program impact evaluation with observational data, the counterfactuals refer to the unobserved outcomes of participants had they not participated in the programs.
Difference-in-difference	An empirical technique to account for potential selection into treatment when treatment effect is to be estimated with non-experimental data. Instead of taking average difference in outcomes of treatment and control groups to measure treatment effect, difference-in-differences (also known as DID) takes the difference between the average change in outcomes of the treatment group and the average change in outcomes of the control group.
Economically significant	This concept concerns with the magnitude of the impacts and to be contrasted with the concept of statistical significance. An estimated impact may be statistically significantly different from zero. However, the magnitude of the impact may be too small to be considered as significant in economic terms. This is also known as importance measure.

Impact	Impact is the change in the financial performance (turnover, wages, headcount, R&D expenditure) of the IMCRC futuremap® workshop participants.
Lower bound	Lower bound refers to the lower limit of any reported 95% confidence intervals.
Matching	In this evaluation, matching is a data driven approach to ensure two given firms are "similar" to each other in the matching characteristics or in terms of the probability to be in the treatment group.
Naïve estimate	Naïve estimate refers to impact estimates derived from a simple difference between export performance before and after program participation or between export performance of participants and non-participants.
Propensity score	Propensity score refers to the predicted probability of a given firm is participating in IMCRC futuremap®, conditional on firms observed characteristics.
Propensity score matching	This refers to matching based on a comparison of the propensity score defined above. Two firms are matched if their propensity scores match.
Robust estimate	This concept refers that the estimates are robust to variation in model specifications.
Treatment group	In this evaluation, treatment group refers to participating firms/businesses in the futuremap® workshops.
Time invariant factors	Factors which values are fixed/constant across time.
Unobserved factors	In this evaluation, they refer to factors which are not recorded in the data, but they determine whether or not a firm participated in the program and are correlated with the outcomes being evaluated.
Upper bound	Upper bound refers to the upper limit of any reported 95% confidence intervals.