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# Access to Broadband Internet and Labour Force Outcomes: A Case Study of the Western Downs Region, Queensland

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**Abstract**
This paper examines the causal effect of household access to broadband Internet on individuals' labour market outcomes in an Australian rural and regional context. This study uses the survey data of 391 households randomly selected from the Western Downs Region of Queensland, Australia, and employs the propensity score matching technique to make causal inferences. This study also controls selection bias issues – an aspect which has been overlooked in previous studies. This study found that the causal effect of household access to broadband Internet on individuals' labour force outcomes is not statistically significant. This finding can add value to our knowledge of the causal relationship between broadband access and labour force participation. As the rollout of a high-speed broadband network in rural and regional Australia is currently underway, the finding can be considered a benchmark for subsequent assessment of the effects of such infrastructure development on socio-economic outcomes.

**Keywords:** Broadband, Labour force outcome, Propensity score matching, Selection bias, Regional Australia.

**JEL: J2, O3**

## 1. Introduction

The development and deployment of broadband Internet services (hereafter 'broadband') facilitate the flow of information in the digitally connected world. The term 'broadband' commonly refers to high-speed Internet access via a variety of networks, including cable, fibre, wireless and satellite, all of which are faster than analogue dial-up by a huge magnitude. Although broadband refers to high-speed transmission, around the world the threshold varies greatly as does the time involved, especially where the speed/bandwidth is concerned. Broadband in Australia is defined as a minimum download speed equal to or greater than 265 kilobits per second (kbps) and minimum upload speed of 64 kbps (NBN, 2016a). In terms of speed, this is different to what many other developed nations have adopted. For instance, in 2015 the US Federal Communications Commission updated broadband benchmark speeds for the USA to 25 megabits per second (Mbps) for downloads and 3 Mbps for uploads (FCC, 2015). Broadband speed varies a great deal depending on a range of factors, including congestion, location, local conditions, hardware and software, and network traffic. Currently in Australia the National Broadband Network (NBN) is offering five speed tiers – the basic NBN tier is 12 Mbps and the top has download speeds of 100 Mbps and 40 Mbps upload over fibre (NBN, 2016b).

Broadband services are now as important as conventional infrastructure such as the road, railway and electricity networks. It is important for rural and regional communities when making decisions regarding lifestyle choices and location for business. The Internet in general, and high-speed broadband in particular, has increased the speed of information flow in the labour market, essentially reducing frictional or search unemployment. It has also significantly reduced the direct cost of searching and recruiting for job seekers and employers, respectively. A significant number of studies have assessed the benefits of broadband on communities and economies (e.g., Kuhn & Skuterud, 2004; Kuhn & Mansour, 2013; Koutroumpis, 2009; Roller & Waverman, 2001; Shideler et al., 2007). Broadband is a communication technology, and access to this network creates various opportunities and channels that enhance communications between potential employees and employers (Autor, 2001). Evidence suggests that the penetration of broadband increases the probability of employment and labour market participation; for instance, Crandall et al. (2007) found that an increase of three million lines (i.e., a 1% increase in access to broadband) was associated with nearly 300,000 more jobs in the US economy. Using the Ordinary Least Squares estimation, Czernich (2014) found a negative association between availability of broadband via

DSL and unemployment rates in German municipalities, however, an instrument variable approach failed to establish any causal relationship.

Studies on the effects of broadband on employment outcomes have been based on the assumption that individuals' selection of broadband is exogenous in the modelling of this causal relationship. However, theories support the notion that the selection of broadband might be endogenous. For instance, Venkatesh and Brown (2001) confirmed that the adoption of technology in households is associated with an individual's age, income, marital status and the age structure of children in the household. Beard et al. (2012) found that the selection of technology is a matter of choice for users. The desirability of adopting technology varies from person to person, and the variation depends upon the relative advantages of the technology, compatibility, complexity, ease of learning and observability (Rogers, 1995). In line with this argument, access to broadband can also be considered endogenous in the modelling of households' labour market status. Literature provides evidence of a statistically significant association between access to broadband and employment opportunities (Atasoy, 2013; Czernich, 2014). However, none of these studies show any causal relationship between these two variables, because in order to make causal inference, random selection of subjects and their random allocation to treatment and control groups are essential. These methodical issues have been ignored in previous studies. Furthermore, none of the studies on the effects of broadband on the labour market have examined this issue in a rural and regional context.

The main objective of this study is to provide estimates of the causal effect of household access to broadband on labour supply in rural and regional contexts. This study uses primary survey data on the adoption and use of broadband in households in the Western Downs Region (WDR) of Queensland, Australia. In this study, applying the propensity score matching (PSM) technique, we assess the causal relationship between broadband access and employment status. Lane et al. (2016) showed that despite significant improvements in telecommunication infrastructure services, the network capacity in rural and regional Australia remains a major concern. Therefore, research on the influence of broadband on labour market status in Australian rural and regional contexts is significant.

The results will provide potentially useful insights for policymakers. Australia is currently implementing the NBN, which is the biggest and arguably the most important infrastructure project building an accessible, superfast broadband network across the country. The NBN promises social and economic benefits to be delivered as equitably as possible across Australia, particularly for rural and regional households and businesses. The findings of this study will help policymakers understand the potential benefits of the ongoing investment in rural and regional areas.

The remainder of the paper is organised as follows: Section 2 presents the literature review; Sections 3 and 4 present the data and the empirical research strategies, respectively; Section 5 discusses the results; and Section 6 concludes the paper.

## 2. Research Evidence

The main mechanisms through which access to and use of broadband services contribute to labour market participation are searching and applying for jobs online. Job searching is a process of information gathering: some traditional job-searching options are informal referrals from friends and relatives, media advertisements and public employment offices (Weber & Mahringer, 2008). However, newly developed mechanisms such as social networking and social media can provide employment-related information more quickly and to a wider audience than other means in this information age.

Several studies have assessed the effects of broadband network deployment and its penetration on macroeconomic outcomes, including employment and gross domestic product growth (Katz et al., 2010; Atasoy, 2013). Some more recent literature have explored the effects on local business and entrepreneurship development. For instance, scholars are increasingly focusing on the effects of high-speed broadband on issues of regional development (Grubesic and Mack, 2015), on business innovation and entrepreneurship development (Alam and Adeyinka, 2016; Tranos and Mack, 2016) and on knowledge-intensive firms' differential performances (Mack and Rey, 2014) or firm-level productivity (Haller et al., 2015).

From a theoretical perspective, broadband lowers the transaction costs of initial employment for both employers and employees, and thus raises overall output and productivity. Katz et al. (2010) studied the employment and economic impact of network externalities by splitting Germany into two regions – a high *Landkreise* (average broadband penetration rate of 31% of the population) and a low *Landkreise* (average rate of 24.8%) – and found the type of effects that the broadband network has, varies by region. Although the impact of broadband on employment is slightly negative in the lower-penetrated areas during the first three years, after this time the level of impact in both regions is the same.

A growing amount of literature has reported a significant positive relationship between access to the Internet and employment growth at national and local levels. An early study, using longitudinal data on Internet use and subsequent employment, found the Internet's influence on unemployment durations in the USA was insignificant (Kuhn & Skuterud 2004). However, studies by Champion et al. (2012), Beard et al. (2012) and Kuhn and Mansour (2013) found a significant positive influence of the use of broadband on the reduction of unemployment in the USA.

Champion et al. (2012) examined the association between access to the Internet at home and the probability of employment for both males and females in the USA. The study modelled labour market outcome as a linear function of home access to the Internet. The control variables included were age, educational attainment, ethnicity, race, language spoken at home and marital status. This research found that access to the Internet at home increases the probability of being employed by 37% and 34% for females and males, respectively. The study provided further evidence that home access to the Internet reduces the costs associated with labour supply and shifts some work from offices to homes.

In another empirical study, Beard et al. (2012) examined the impact of three kinds of internet – public, dial up and broadband – on job searching, and thereafter on labour market participation, using USA labour market data. They used multinomial logit regression analysis augmented with the pairwise matching technique. They found that access to broadband at home or in public places reduces the probability by 50% that an unemployed person ceases job searching, compared to their non-user counterparts. Kuhn and Mansour (2013) suggested that unemployed people who look for work online are employed in about 25% less time than those who do not search for work online. Their study used the linear probability model of binary outcome – that is, either looking for or not looking for jobs online. Using growth in the Internet over time across states in the USA, Stevenson (2008) examined the relationship between job-searching behaviour and changes in access to the Internet. The study found evidence that increasing Internet penetration is positively associated with a growth in sending out resumes, looking at job advertisements and people contacting employers directly. Kolko (2012) reported a statistically significant positive relationship between broadband access and employment growth in the USA – one standard deviation change in broadband access is associated with a 0.085 standard deviation change in employment growth.

Beyond the USA, some studies have investigated the relationship between Internet-based job searching and labour market outcomes in Germany, South Korea and the UK (Suvankulov &

Lau, 2011; Green et al., 2012). The key finding of these studies was that using the Internet for job searching reduces unemployment significantly. Using national panel data, Suvankulov and Lau (2011) examined the impact of job searching through broadband on the probability of re-employment in Germany and South Korea. They assumed that job searches through the Internet were an endogenous variable. Controlling for endogeneity by using Hausman-Taylor instrumental variable techniques, their study found that online job seekers have a higher probability of being employed.

In contrast, Australian studies on the effect of broadband access on economic outcomes are macro in nature. Using the computable general equilibrium model of the economy, ACIL Tasman (2004) found broadband access has a positive impact on employment growth and projected that the average annual growth in the number of people employed in the state of Victoria, Australia, resulting from broadband adoption was 0.5% between 2004 and 2015.

In summary, the direction of a causal relationship between broadband services and employment growth is ambiguous (Kolko, 2012). Some studies have examined the effects of broadband access on economic outcomes, including employment and wage rates, at both macro and micro levels (Crandall et al., 2007; Lehr et al., 2005). Studies on the economic benefits of broadband at the household level appear to be limited; none have examined this causal relationship at the household level in a rural and regional Australian context. Most studies have also focussed on assessing and comparing the causal effects of broadband deployment on labour market outcomes between urban and rural areas. Variations *within* rural and regional areas have received very little attention. A study with a regional Australian perspective is significant, as the Internet – especially high-speed broadband – is supposed to improve job matching because asymmetries and search costs are reduced (Stevenson, 2009). Also, the issue of selection bias with regard to the choice of broadband has been overlooked in previous research; hence, the estimates are not reliable. In this paper, we overcome the issue by using the PSM technique and thereafter investigating the issue in a regional area in Australia.

## 3. Methodology

### 3.1 The study area

The WDR of south east Queensland, Australia, was selected as the study area for this research. The region's Local Government Area covers 38 004.7 km$^2$. There were 33 494 people residing in the region in 2015. The key centres in terms of population and economic activity are Dalby, Chinchilla, Miles, Tara, Jandowae and Wandoan (Figure 1). The region's economy is based on a strong mineral and energy resources sector, including coal, coal seam gas and liquefied natural gas, and agricultural and farming sectors with livestock, timber, cotton and grain production (Alam & Salahuddin, 2015). The region is rich and dominating in south east Queensland, with booming mining and growing food-processing sectors – it is considered one of the emerging energy- and resource-based areas in Australia. Despite its significant economic potential, the region lacks business diversity compared with some other regional areas in Australia (Alam & Shahiduzzaman, 2015).

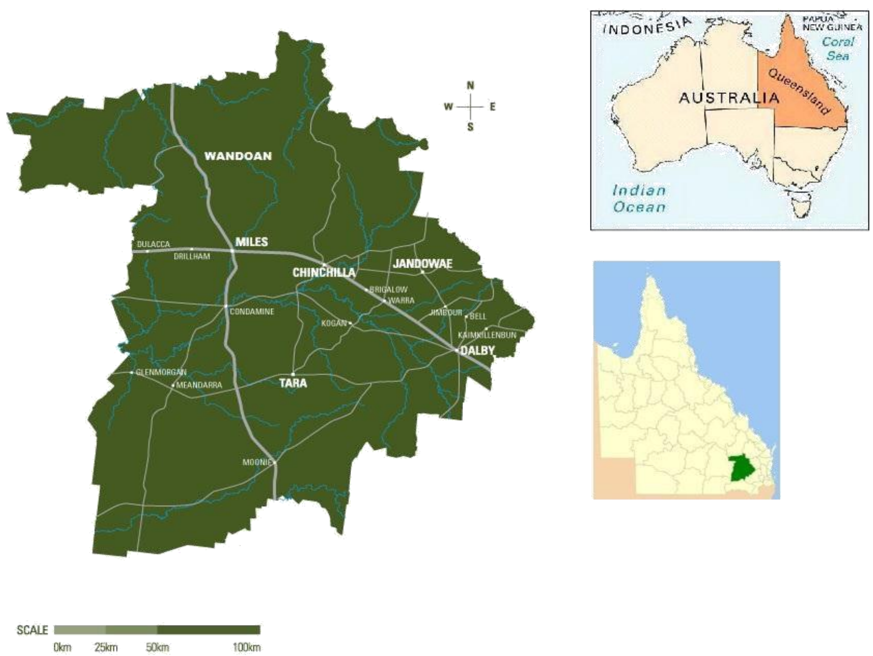


**Figure 1:** Map of the Western Downs Region study area

The region's unemployment rate is lower than that of Queensland: the unemployment rate of 3.8% was significantly lower than the averages for Queensland (5.9%) and Australia (5.5%) in 2015. This creates labour and skills shortages due to the growth of the energy and resources sectors and the associated support service industries.

### 3.2 Sampling and data description

The sample selection, based on the geographic distribution of the households, was representative of households in the region. The Local Government Area comprises four Statistical Local Areas – Chinchilla, Dalby, Miles-Wandoan and Tara. When deciding on the number of samples from each of these areas, the sample size was based on the population of each statistical area so that the sample is representative of the population. Questionnaires were distributed in-person to randomly selected households, and residents over 18 years of age were invited to complete the survey questionnaire. Within each household, survey participants were selected using the next-birthday method. There were 391 completed survey questionnaires in the final sample. The gender division of the respondents was 54% female and 46% male. The age groups of the respondents ranged from 18–24 years to 65+ years. The sample was dominated by respondents in the 35–44 and 45–54 year age groups (19.18% and 21.99%, respectively), while 16% of the respondents were 65+ years old.

## 4. Empirical Strategies

### 4.1 Selection bias

Theoretically, access to broadband or any type of Internet facilities is not random – some forms of precondition are required. For instance, having Internet connectivity or even a computer at home requires payments for the hardware, software and services as well as a strong motivation for their usages on the part of users, along with a certain level of digital literacy. Therefore, access to broadband at home is conditional upon individuals' observed as well as unobserved characteristics. Therefore, the issue of selection bias arises. Table 1 shows the mean differences between the two groups of individuals – with and without access to broadband at their homes – based on observable characteristics. These differences may serve as a confounding factor in a simple linear regression model to study such a causal relationship. Therefore, the application of a single equation regression model to assess the causal relationship will not be able to control selection bias issues.

**Table 1:** Mean differences between groups (access and no access to broadband) based on individuals' observable characteristics

| Variables | Have no access to broadband | Have access to broadband | Difference | Significance level (t-statistics) |
|---|---|---|---|---|
| Employment | 0.76 | 0.90 | (0.14) | (2.19)** |
| Age (years) | 3.85 | 3.60 | (0.25) | (1.09) |

| | | | | |
|---|---|---|---|---|
| Highest educational attainment | 3.00 | 3.72 | (0.721) | (4.44)* |
| No. of computers at home | 2.31 | 5.6 | (3.29) | (11.09)* |
| No. of household members | 2.31 | 2.81 | (0.58) | (3.37)* |
| Average household income | 3.63 | 4.60 | (0.96) | (3.54)* |
| Spending for Internet | 4.77 | 3.30 | (1.46) | (3.51)* |
| Ethnicity | 1.87 | 1.98 | (0.10) | (3.45)* |

Note: * and ** indicate 1% and 5% level of significance, respectively.

A seminal work by Rosenbaum and Rubin (1983) introduced the PSM technique as an alternative econometric approach to reduce the observed and unobserved biases significantly, though not eliminate them totally, in a non-experimental study setting. An advantage of using the PSM lies with its ability to control unobserved self-selection bias based on participants' observed characteristics (Caliendo et al., 2005).

For causal inference with observational data, instrumental variable (IV) regression and Heckman's two-step regression have been suggested in the literature (Camerson & Trivedi, 2005). However, IV regression typically reduces the precision of causal inference, and the robustness of Heckman's two-step regression is presently under scrutiny in different literature bodies because of assumptions related to its distribution of error terms (Kiiza & Pederson, 2012). In this context, PSM is considered comparatively robust because of the existence of no assumption about the error terms and a lack of requirement for any functional form of a model to conduct an empirical study (Cameron & Trivedi, 2005).

### 4.2 Propensity score matching (PSM) technique

Rosenbaum and Rubin (1983) defined PSM as the conditional probability of receiving a treatment (i.e., access to broadband) given socio-economic and demographic characteristics, as illustrated below (in order to keep this paper succinct, we avoided technical details of PSM here – interested readers can consult Guo and Fraser (2015) for details):

$$p(X) \equiv P_r(D = 1|X) = E(D|X) \qquad (1)$$

where 0 means no access to broadband and 1 means access to broadband. $D = \{0,1\}$ and $X$ is a vector of multidimensional pretreatment characteristics such as socio-economic and demographic characteristics. $p(X)$ is the propensity score. If a population of units denoted by $i$ is known, then the Average Treatment Effect on the Treated (ATT) is estimated as follows:

$$ATT \equiv E\{Y_{1i} - Y_{01} | D_i = 1\}$$

$$ATT = E[E\{Y_{1i} - Y_{0i} | D_i = 1, p(X_i)\}]$$

$$= E[E\{Y_{1i} | D_i = 1, p(X_i)\}] - E[E\{Y_{0i} | D_i = 0, p(X_i)\}] \quad (2)$$

where $Y_{1i}$ is a potential outcome for an individual with access to broadband, and $Y_{0i}$ is without any access. The following two balancing properties need to be satisfied to derive (2) given (1):

Property 1: If $p(X)$ is the propensity score; then $D \perp X \mid p(X)$, and

Property 2: If $(Y_1 Y_0) \perp (D \mid X)$; then $(Y_0 Y_1) \perp D \mid p(X)$.

The main objective of the PSM technique is to estimate an appropriate comparison between two groups of individuals who have access and who do not have access to broadband, conditioned on observable characteristics. Based on the propensity score, individuals belonging to the above mentioned two groups were selected on the basis of similarities in observed characteristics. This assumed no selection bias based on unobserved characteristics.

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PSM technique requires matching algorithms such as nearest neighbour, caliper and radius, stratification and interval, and kernel matching (Becker & Ichino, 2002). A one-to-one nearest neighbour (NN) matching approach is selected because of its popularity (Bajracharya & Amin, 2013; Caliendo & Kopeinig, 2008). We also checked the balancing property, and if the matching quality was not up to the mark, we changed matching algorithms to confirm that the balancing property was satisfied. In this study, NN caliper matching algorithms sufficiently fulfilled the balancing property.

An important step is to check the overlap and the region of common support between treatment and control groups. This was done to ensure that two groups of individuals in this study with vastly different propensity scores were not compared (or matched). The one-to-one matching is confined to individuals who are found within the 'region of common support'. We present the finding graphically, because the most straightforward approach is a visual analysis of the density of the distribution of the propensity score in the treatment and control groups. Once the region of common support has been defined, an individual that falls outside the region of common support has to be disregarded.

### 4.3. Sensitivity analysis: hidden bias test

The matching technique to estimate average treatment effects has been popular in the literature, however, examining the sensitivity of the estimated results by checking hidden bias has become an increasingly important approach (Becker & Caliendo, 2007). If there are unobservable variables that simultaneously affect treatment and control variables, a hidden bias arises. Previous research has suggested addressing this problem using the bounding approach (Rosenbaum, 2002, cited in Becker & Caliendo, 2007). In the literature, two kinds of statistics have been proposed for continuous and binary types of outcome variables, respectively. For binary types of outcome variables, the Mantel and Haenszel (MH) statistic is suggested (Becker & Caliendo, 2007). The test statistics are as follows:

$$Q_{MH} = \frac{|Y_1 - \sum_{s=1}^{s} E(Y_{1,s})| - 0.5}{\sqrt{\sum_{s=1}^{s} Var(Y_{1,s})}}$$

$Q_{MH}$ is bounded by two bounds, namely, $Q_{MH}^{+}$ and $Q_{MH}^{-}$, which are as follows:

$$Q_{MH}^{+} = \frac{|Y_1 - \sum_{s=1}^{s} |\overline{E}_2^{+} - 0.5}{\sqrt{\sum_{s=1}^{s} Var(\overline{E}_2^{+})}}$$

$$Q_{MH}^{-} = \frac{|Y_1 - \sum_{s=1}^{s} |\overline{E}_2^{-} - 0.5}{\sqrt{\sum_{s=1}^{s} Var(\overline{E}_2^{-})}}$$

The $Q_{MH}^{+}$ statistic adjusts the MH statistic downwards for positive (unobserved) selection, and $Q_{MH}^{-}$ adjusts the MH statistic downwards for negative (unobserved) selection. If $e^{\gamma} = 1$, the bounds are equal to the base scenario of no hidden bias. As Becker and Caliendo (2007, p. 74) noted, "With increasing $e^{\gamma}$, the bounds move apart, reflecting uncertainty about the test statistics in the presence of unobserved selection bias".

4.4 Estimation of propensity score

Literature has suggested using logit, probit and linear probability to estimate propensity scores (Caliendo & Kopeinig, 2008). However, it is further suggested that in principle, any discrete choice model can be used because researchers are not interested in variable coefficients; hence, model choice is not critical here. The logit model has more density mass in the bounds and the most prevailing PSM (Guo & Fraser, 2015), hence, we used logit in the following form:

$$P\left(Y_i \middle| X_i = x_i\right) = E(Y_i) = \frac{e^{x_i \beta_i}}{(1 + e^{x_i \beta_i})} \tag{3}$$

After model selection, we required its specification. We specified the model based upon economic theory and previous literature. To specify Equation (3), we followed Venkatesh and Brown (2001) who suggested that adoption of technology is a consumption good and the demand for its household consumption is a function of household income and residents' age, education and gender. As broadband is a communication technology in a household setting, the demand for its household consumption can be specified as follows:

$$P_i(Y_i = Internet_i) = f(age, gender, income, education) \tag{4}$$

In Equation (4), access to broadband at home $(Internet)_i \in (0,1)$. If $Y_i = 1$, a household has broadband access, and $0$ otherwise. A household without broadband access at home does not necessarily indicate that it does not have another form of Internet access including narrowband and dial up. On the right-hand side of Equation (4), the respondent's age is denoted by *age*, gender by *gender*, monthly household average income by *income*, and the level of highest education by *education*. Literature has suggested that omitting an important variable may increase bias in the resulting estimates (Caliendo & Kopeinig, 2008). Therefore, in order to reduce the risk of the omitted variable problem, we extended Equation (4) by including two additional control variables: (i) type of occupation if employed, which was denoted by *occupation*; and (ii) the respondent's ethnicity, which was denoted by *ethnicity*. We included *occupation* and *ethnicity* to capture motivation of the respondents to use broadband for job searching. Occupation has also been used as a proxy for unobserved skills in the literature (Levenson & Zogni, 2007), therefore, we can assume occupation as a proxy for wage. We defined two categories of occupations – white collar jobs such as manager, technician, professional and administration, and blue collar jobs. We considered ethnicity, because we assumed Aboriginals and Torres Strait Islanders are less motivated compared to other Australians regarding the use of broadband for job searching. Following Kuhn and Skuterud (2004), Weber and Mahringer (2008), and Championet et al. (2012), we extended the model for PSM estimation as follows:

$$P_i[(Y_i = Internet_i \mid (0,1)] = f(age, gender, income, education, occupation, ethinicity) \quad (5)$$

## 5. Variable Descriptions

5.1. Outcome variable: employment vs unemployment status

Although labour force status is a multi-faceted variable, in some literature it has been defined in terms of being employed or unemployed (Champion et al., 2012; Kuhn & Mansour, 2013). Following the previous studies, our dependent variable was whether a respondent was either employed or unemployed or not in the labour market during the time of data collection. In the survey, 47.32% reported they were full-time employed, 15.37% reported they were part-time employed, 12% reported they were self-employed and 12% reported they were retired; the remaining 13.31% were unemployed, including students involved either with full-time or part-time study. For this research, excluding retired people, we combined full-time, part-time and self-employed to make a single category: employed. The remaining respondents were combined to make another category: unemployed.

5.2. Dependent variable for PSM

The main dependent variable was access to broadband at the household level. The variable was measured by asking a household member about their access to broadband. We coded this binary outcome variable as 1 if a member of the household indicated the availability of broadband, and 0 otherwise. Our survey showed that about 83% of households have access to broadband, and the majority of these are through wireless (40.3%) and ADSL/ADSL2+ (32%).

5.3. Other control variables for PSM

The variables age and education were measured in years on the basis of reporting by the respondents. Comparative statistics of the variables in the two groups are presented in Table 2. The table shows that those who have access to broadband have a statistically significant level of higher participation in the labour force and a higher level of educational attainment. Given the differences between these two groups, we can conclude that the people who have broadband access are more empowered and motivated to participate in the labour force.

**Table 2:** Descriptive statistics

| Variables | Percentage | Std. Err. |
|---|---|---|
| Employment status | | |
| Employed | 74.69 | 0.02 |
| Otherwise | 25.31 | 0.02 |
| Gender | | |
| Female | 54.48 | 0.02 |
| Male | 45.52 | 0.02 |
| Age (years) | | |
| 18-24 | 9.45 | 0.01 |
| 25-34 | 17.14 | 0.02 |
| 35-44 | 19.18 | 0.02 |
| 45-54 | 21.99 | 0.02 |
| 55-64 | 16.11 | 0.02 |
| 65+ | 16.11 | 0.02 |
| Highest education level | | |
| Less than primary | 3.58 | 0.00 |
| Primary | 7.93 | 0.01 |
| High school | 39.39 | 0.02 |
| Trade/Certificate/Diploma | 29.92 | 0.02 |
| Bachelor | 13.81 | 0.02 |
| Post graduate | 5.37 | 0.01 |
| Occupation | | |
| Blue-collar jobs | 62.66 | 0.02 |
| White-collar jobs | 37.34 | 0.02 |
| Average household income | | |
| $19,999 or less | 5.63 | 0.01 |
| $20,000–39,999 | 16.11 | 0.02 |
| $40,000–59,999 | 11.76 | 0.02 |
| $60,000–79,999 | 15.35 | 0.02 |
| $80, 000–119,999 | 14.32 | 0.02 |
| $120,000 & above | 36.83 | 0.02 |
| Ethnicity (Aboriginal and Torres Strait Islander) | | |
| Yes | 4.35 | 0.01 |
| No | 95.14 | 0.01 |

## 6. Results and Discussion

6.1. Results

A cross-tabulation of labour market outcomes of the two groups of households (mean difference) showed a high level of employment among broadband users compared to those who did not have broadband access (Table 1). Results from a binary logistic regression model to calculate propensity score are presented in Table 3. The results show that the effect of access to broadband on labour market outcome is not different to zero because the estimated coefficient is not statistically insignificant at the 5% level.

**Table 3:** Logistic regression of access to broadband

| Variables | | Coeff. | z-value |
|---|---|---|---|
| Male | | -0.16 | (0.51) |
| Age groups (years) | | | |
| | 18-24 | 0.49 | (0.39) |
| | 25-34 | 1.84 | (2.49)* |
| | 35-44 | 0.84 | (1.50) |
| | 45-54 | 1.20 | (2.07)* |
| | 55-64 | -0.04 | (0.09) |
| Education | | | |
| | Primary | 0.29 | (0.35) |
| | High school | 0.63 | (0.88) |
| | Trade/Certificate/Dip | 1.33 | (1.66) |
| | Bachelor | 2.10 | (2.04)* |
| | Post graduate | 0.19 | (0.19) |
| White-collar job | | 0.10 | (0.24) |
| Average household income groups | | | |
| | \$20,000–39,999 | 1.30 | (2.25)* |
| | \$40,000–59,999 | 1.17 | (1.82) |
| | \$60,000–79,999 | 2.54 | (3.41)** |
| | \$80, 000–119,999 | 2.64 | (3.28)** |
| | \$120,000 & above | 1.40 | (2.41)** |
| Ethnicity | Yes | 1.45 | (2.46)* |
| Constant | | -1.187 | 1.22 |
| LR ratio | | 62.105 | |
| Prob>LR | | 0.00 | |
| McFadden's $R^2$ | | 0.18 | |
| *N* | | 391 | 391 |

Note: *, ** and *** mean 1%, 5% and 10% level of significance, respectively.

Next, we implemented the PSM procedure using *psmatch2* command in Stata (Leuven & Sianesi, 2003). Through this command in Stata, we performed both propensity score calculation and the subsequent balancing property check. Our specified logit model satisfied the balancing property. Further, we checked the overlapping condition between the two groups. For doing so, the most straightforward approach was by a visual analysis of the densitiy distribution of the propensity in both groups (Caliendo et al., 2005; Dehejia & Wahba, 2002); Figure 2 presents this result. The left-hand side of the graph presents the propensity score distribution for the untreated group and the right-hand side presents the distribution for the treated group. It can be seen from the graph that the distribution of the propensity score for each group overlaps with the other, indicating that there are no further issues such as an invalid result. This issue arises if the distributions do not overlap.

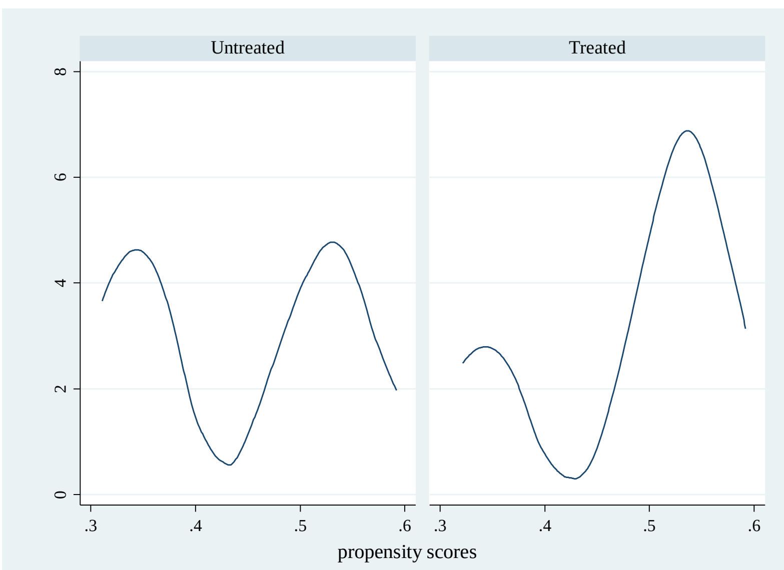


**Figure 2:** Common support or overlap

The first row of Table 4 presents the mean difference in the level of participation in the labour force from the unmatched sample (i.e., full-sample). The extent of the effect on this unmatched sample presents simply an estimate of the difference in the levels of participation from the original sample. This estimate does not take into account the selection bias. The estimated difference is 14 percentage points, which is statistically significant at the 5% level (t-value of 4.28). This implies that the level of labour force participation is 14 percentage points higher among the households with broadband access compared to households without access to broadband. This result is largely consistent with previous findings, including those of Champion et al. (2012), Kuhn and Skuterud (2004), and Webner and Mahringer (2008).

**Table 4:** PSM estimate of ATT

| Variable | Sample | Treated | Controls | Difference | S.E. | t-stat |
|---|---|---|---|---|---|---|
| Employment Status | Unmatched | 0.78 | 0.54 | 0.24 | 0.06 | 4.28 |
| | Matched | 0.57 | 0.54 | 0.03 | 0.09 | 0.35 |

The second row of Table 4 presents the estimated ATT based on the propensity score matched sample of 223 who had only fulfilled the region of common support condition. We found that the estimated difference is 12%, which is statistically insignificant at the 5% level (t-value of 0.63). The estimated effect size is 2% lower than the previous unmatched finding. Therefore, we conclude that the state of labour force participation among the households who have access to broadband is different from the households who do not have access to broadband, but the difference is not statistically significant.

Next, we explored the characteristics of both matched and unmatched observations with results displayed in Table 5. PSM estimates the ATT only from a small subset of the total sample who meet a stringent set of matching criteria. Based on the balancing criteria described earlier, we found that for all variables selected to measure the propensity score, the mean differences between the treatment and control groups after matching is performed become statistically insignificant because of their small t-statistics. Therefore, we concluded that the balancing property is satisfied.

**Table 5:** Mean of control variables by matching status from PSM analysis

| Variables | Unmatched /matched | Mean | | %bias | t-test | |
|---|---|---|---|---|---|---|
| | | Treated | Control | | t-value | p> \|t\| |
| Gender | Unmatched | 0.44 | 0.52 | -14.5 | -1.05 | 0.29 |
| | Matched | 0.51 | 0.51 | 0.0 | 0.00 | 1.00 |
| Age | Unmatched | 3.6 | 3.9 | -18.7 | -1.49 | 0.13 |
| | Matched | 3.5 | 3.8 | -18.0 | -0.91 | 0.37 |
| Education | Unmatched | 3.68 | 3.06 | 57.2 | 4.14 | 0.00 |
| | Matched | 2.84 | 3.15 | -20.0 | -1.61 | 0.11 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Occupation | Unmatched | 0.41 | 0.19 | 47.7 | 3.23 | 0.00 |
| | Matched | 0.15 | 0.20 | -11.6 | -0.72 | 0.47 |
| Avg. household income | Unmatched | 4..42 | 3.45 | 54.7 | 4.28 | 0.00 |
| | Matched | 3.08 | 3.60 | -29.0 | -1.61 | 0.11 |

| Sample | Pseudo R-square | LR $Chi^2$ | P > $Chi^2$ | Mean Bias | Median Bias |
|---|---|---|---|---|---|
| Unmatched | 0.08 | 27.80 | 0.00 | 38.6 | 47.7 |
| Matched | 0.04 | 6.46 | 0.26 | 17.5 | 18.0 |

To check the robustness of the estimated ATT, we implemented the NN matching approach in Stata 13 using the command -*teffects nnmatch*-. The estimated ATT is 0.20 with a z-value of 1.69 and p-value of 0.09. Though the size of the estimated effect is smaller, it is positive and statistically significant at the 5% level.

We then conducted a sensitivity analysis by checking for hidden bias. Treatment effects in observational studies may have a potential selection bias problem generated by hidden bias because of unobservable counterfactuals. The results are reported in Table 6.

**Table 6:** Sensitivity analysis

| Gamma | Q_mh+ | Q_mh- | p_mh+ | p_mh- |
|---|---|---|---|---|
| 1 | 1.73583 | 1.73583 | .041297 | .041297 |
| 1.05 | 1.52781 | 1.94888 | .06328 | .025655 |
| 1.1 | 1.32761 | 2.15026 | .092153 | .015767 |
| 1.15 | 1.1366 | 2.34314 | .127853 | .009561 |
| 1.2 | .953928 | 2.52825 | .17006 | .005732 |
| 1.25 | .778884 | 2.70624 | .218024 | .003402 |
| 1.3 | .610832 | 2.87769 | .270655 | .002003 |
| 1.35 | .449216 | 3.0431 | .326638 | .001171 |
| 1.4 | .293541 | 3.20292 | .384554 | .00068 |
| 1.45 | .143368 | 3.35754 | .443 | .000393 |
| 1.5 | -.001696 | 3.50733 | .500677 | .000226 |
| 1.55 | -.092038 | 3.65262 | .536666 | .00013 |
| 1.6 | .043483 | 3.79368 | .482658 | .000074 |
| 1.65 | .174837 | 3.93079 | .430604 | .000042 |
| 1.7 | .302287 | 4.06418 | .381217 | .000024 |
| 1.75 | .426069 | 4.19408 | .335029 | .000014 |
| 1.8 | .5464 | 4.32067 | .292395 | 7.8e-06 |

| | | | | |
|---|---|---|---|---|
| 1.85 | .663479 | 4.44415 | .253512 | 4.4e-06 |
| 1.9 | .777487 | 4.56469 | .218436 | 2.5e-06 |
| 1.95 | .888592 | 4.68243 | .187111 | 1.4e-06 |
| 2 | .996946 | 4.79752 | .159395 | 8.0e-07 |

Under the assumption of no hidden bias – that is, gamma = 1 – the $Q_{MH}$ test statistic provides a similar statistic of 1.73583, indicating the overall treatment effect appears to be fairly robust to the selection of hidden bias. Therefore, the results suggest that broadband does not have any statistically significant positive impact on households' labour supply decisions in the study area.

## 6.2. Discussion of the results

Although a growing volume of literature has reported a significant positive relationship between access to the Internet and employment status at national and local levels, our causal study has found evidence that contradicts previous findings. For instance, Dettling (2015) found that residential broadband Internet access across states in the USA increased labour force participation for married women, but no corresponding effect on single women or men. Similar results were observed by Champion et al. (2012) where home Internet access was found to be highly correlated with employment. The no significant effect of broadband on labour supply in this study means that residents in the study area were not reaping the benefits of broadband infrastructure deployment. First, this may be due to the methodological differences in our study which addresses selection bias issues.

Second, the impact of communication technology requires a 'critical mass' before it is felt (Salim et al., 2016). A critical mass may not have developed in the study region yet, particularly given that the rollout of the NBN only started in the area late in 2016 and is not due to be completed until 2018. The NBN and its rollout plan have been subject to ongoing battles between Australia's two major political parties. Due to a reliance on copper wire, wireless and satellite networks, the realised economic benefits such as telework, eBusiness and video conferencing have not expanded across the study region. Recent research in the Western Downs region confirmed that many smaller towns have limited or no access to wired broadband and remain highly reliant on wireless/mobile broadband (Lane et al., 2016). Overall, rural areas are disadvantaged with limited options in choosing a provider, slower speeds, smaller data quotas and higher prices compared to their urban counterparts (RTIRC, 2015). However, there has been some improvement with the country's average peak download speed reaching 43 megabits per second in the first quarter of 2016 – up 6.8% compared to the same quarter in the previous year (Akamai, 2016). Therefore, achieving the critical mass will require both time and a consistent government policy.

Third, the current Coalition-led Federal Government is aiming to complete a nationwide rollout of the NBN by 2020, but with a different political commitment to its predecessor and by using a mix of technologies such as fibre-to-the-node (FTTN) and the existing hybrid fibre coaxial (HFC) networks. This mix is in contrast to the fibre-to-the-premises (FTTP) network adopted by the Labor Government in 2009. It is observed that the Coalition's NBN plan is faster (6–8 years sooner) and more cost effective (A$20–30 billion) than the previous government's plan mainly because of a switch from the FTTP to a mixed fibre/copper-based network. But this has raised concern that Australia risks falling behind the rest of the developed world if the whole country is not connected through high-speed fibre optic cable, especially if the rural and remote locations are to remain connected primarily through wireless and satellite networks. This also raises the prospect of a greater digital divide between inner regional and rural/remote areas. This disparity requires an immediate policy intervention in order to provide faster, affordable and equitable broadband services to all citizens irrespective of their geography.

Fourth, our findings hint at a possible mechanism of personal and social networking for employment-related information and employment opportunities in the rural and regional areas where the households are relatively more homogeneous and are connected with each other very intimately.

## 7. Conclusion

This study examined the causal relationship between households' access to broadband and labour force status in a rural and regional Australian context. Existing literature provided evidence that access to broadband increases the probability of labour force supply, however, most of these studies assumed an exogenous nature of the key explanatory variables of interest, which remains a key weakness of past research. Using the PSM technique, we found evidence that access to broadband at home does not increase labour supply in the study area. This requires further explanation as to why the PSM technique does not provide any evidence of an effect of broadband on labour market status.

The rollout of the NBN is yet to be completed, particularly outside metropolitan areas in Australia. The current broadband services in the study area are through fibre, satellite and mobile connections. However, most households in the study area, particularly outside of the towns, are connected via copper, 3G and 4G mobile networks, and satellite devices. There is considerable dissatisfaction among residents in the study region in terms of the speed of Internet downloads and uploads (Alam & Salahuddin, 2015). Therefore, it is too early to conclude that broadband has a definite positive effect on labour force participation in rural and regional Australia.

Assessing causality is critical for the telecommunications policy debate about whether broadband services generate employment opportunities, particularly because output and employment growth are key goals of the NBN in Australia. Lack of a causal relationship between broadband access and employment does not mean that broadband infrastructure investment is not desirable for rural and regional communities. Broadband might offer benefits not fully captured by employment or wage growth in the early stages of the network's deployment. Households use broadband services for a wide range of day-to-day activities, including education, health services, e-commerce and e-governance. The study area has been experiencing energy and resources booms during recent years, which have created employment opportunities not only for skilled workers but also for semi- and non-skilled workers who may not be technologically savvy.

The results of this research should be considered in the light of the following limitations. First, the dataset was drawn from a particular region; hence, the sample size is not representative of the entire regional Australia. Different regions of Australia are diversified in terms of population characteristics, geography and their economy. To derive any generalised results, future research should consider data collected from a variety of locations across regional Australia. Second, a major limitation of the PSM technique is that it assumes the selection of broadband as a function of observed variables. Although PSM is the most popular method used by researchers to control selection bias in assessing causality, there might be many unobserved household characteristics and regional-level confounding factors that may influence the selection of broadband in regional Australia. Third, people generally have a low level of mobility geographically in rural and regional areas; they may look for employment locally. In such a case, the influence of broadband on employment outcomes may be low. We leave these issues for further research.

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