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Contents

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From the Managing Editor

Welcome to the first issue of the *Australian Journal of Labour Economics* for 2021. As always, this issue contains articles of interest to academics, practitioners and anyone interested in how labour markets work in Australia and our region. I think readers will find the papers particularly interesting, challenging some of the common policy narratives.

The first paper, by Siddharth Shirodkar and Boyd Hunter of the Australian National University, examines the hypothesis that a discriminatory environment faced by Indigenous business owners affects the success of these businesses. This is important since business ownership provides Indigenous Australians with an opportunity to seek economic independence and greater self-determination. Using an interesting dataset and analysis the authors conclude from their results that the implicit biases of non-Indigenous Australians drives lower levels of Indigenous business ownership. The authors have some interesting (and somewhat controversial) views on what this means for much of the previous research in this area.

The paper by Yonatan Dinku of the Australian National University examines the issue of economic inactive Indigenous youth – defined as those not in employment, education or training (NEET). Given that much of policy is based on the premise that such inactivity has detrimental consequences there is limited empirical evidence on the factors which put young people at risk of economic inactivity. This paper is an important contribution to providing this empirical evidence. A number of individual, household, and local factors are found to explain underlying NEET status.

Gerard Lind and Rebecca Colquhoun provide detailed estimates of gender segregation in the Australian labour market using ABS Labour Force Survey and Census data. Among the main results are findings with important policy implications. Perhaps the most important is that over the last three decades, gender segregation in Australia has not significantly changed across either industries or occupations. Gender segregation across industries is, in general, more resistant to gender integration than across occupations and detailed classifications are more highly segregated than more highly aggregated classifications. Additionally, gender segregation increases as individuals get older and the further they work from urbanised areas. Women continue to have more constrained labour supply choices than men, hindering labour market efficiency and flexibility.

The final paper by Mike Dockery, John Phillimore and Sherry Bawa, of Curtin University, adopts a novel approach to generating a continuous measure of Science, Technology and Mathematics (STEM) intensity. This is employed to model changes in demand for STEM skills, and in other fields, based on changing occupational composition of employment in Australia between the 2006 and 2016 Censuses, and on projected changes to 2024. The results are very interesting and controversial, contradicting some commonly held views on STEM education. Contrary to popular narratives around STEM and the future of work, they find that the changing nature of work is actually reducing the demand for STEM skills relative to skills in other fields of education. The results also suggest that technical and trade jobs account for almost the same level of demand for STEM skills as professional occupations, reflecting the importance of including the VET sector in any STEM agenda. Importantly, the results also suggest that policies to promote ‘women in STEM’ may be misguided. The authors conclude that, if anything, women are benefitting in terms of the demand for their skills by the fact that they are under-represented in STEM and over-represented in key services such as Health and Education. The results in this paper caution against an uncritical acceptance of the need for a higher proportion of people to specialise in STEM fields.

Thanks go to all the authors, editors and referees for contributing to an excellent issue of the journal. Particular thanks are due to Sandie Rawnsley, our Editorial Assistant, for her excellent work in making this issue possible.

Phil Lewis
Managing Editor

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The impact of implicit bias on Indigenous business ownership rates in Australia

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Abstract
Business ownership provides Indigenous Australians with an opportunity to seek economic independence and greater self-determination. However, societal barriers created through systemic discrimination may limit the potential for Indigenous Australians to enter into business. While other research has alluded to the deleterious effect of a discriminatory environment on Indigenous business ownership, much of that research is qualitative and relies on the self-reported experiences of the phenomenon. This paper extends earlier quantitative research that explains lower local rates of business ownership among Indigenous people compared with other Australians using socioeconomic and demographic factors (Shirodkar and Hunter, 2019). Project Implicit developed and collected data from the Implicit Association Test that measures implicit biases against Indigenous Australians, arguably the root cause of systemic discrimination, collecting over 11,000 unique observations from Australians over a decade (Shirodkar, 2019). An ecological regression model of Indigenous business ownership finds that after accounting for other pertinent economic factors, higher rates of implicit bias in Australian regions has a statistically significant and negative relationship with Indigenous business ownership. The result suggests that the implicit biases of non-Indigenous Australians drives lower levels of Indigenous business ownership.

JEL Codes: C21, J15, J70, J71
Keywords: Discrimination, Unconscious bias, Indigenous entrepreneurs

1. Introduction

Systemic racial discrimination in our community has the potential to restrict socioeconomic opportunity and mobility for marginalised groups, and arguably for none more so than Australia's First Peoples. But seldom does our national debate consider if the poor socioeconomic outcomes that Aboriginal and Torres Strait Islander Australians experience result from a discriminatory local environment. Often the complaints of explicit racial discrimination are ignored, dismissed or minimised (Maley, 2018; and Augoustinos, Tuffin and Rapley, 1999).

The manifestation of explicit interpersonal racism may represent but a small symptom of a wider phenomenon that reflect a society's view of a particular group. Such a 'societal view' or implicit societal bias has the potential to taint our perception, thereby distorting pathways and in many cases creating societal barriers to achieving social and economic self-determination.

Business ownership is one pathway to achieving greater economic self-determination, and a driver for Indigenous employment outcomes as well (Hunter, 2014). Growth in the sector and its potential to support Indigenous communities has been well documented (Shirodkar, Hunter and Foley, 2020; Shirodkar, Hunter and Foley, 2018; Dana, 2015; Hunter, 2014; Schaper, 2007; Foley, 2006; Foley, 2003; Altman, 2001; Foley, 2000; and Daly, 1993). Using information from the Australian Census Longitudinal dataset that follows approximately 5 per cent of the Australian population over three Censuses (i.e., over 10 years), Shirodkar, Hunter and Foley (2020) estimate that there were over 19,000 Indigenous business owner-managers at the time of the 2016 Census, but that the rate of Indigenous business ownership was only around 3.7 per cent compared with around 8.6 per cent for non-Indigenous Australia. Shirodkar and Hunter (2019) find that identifying as Indigenous explains a significant proportion of the difference in business ownership rates between Indigenous and non-Indigenous Australians after accounting for other relevant economic and demographic variables. The result indicates a race-related factor is limiting rates of Indigenous business ownership. But Shirodkar and Hunter (2019) could not distinguish if the constraint relates to an external discriminatory environment that supresses Indigenous agency, or if it reflects internalised racism within Indigenous communities, or both. Paradies, Harris and Anderson (2008) provide a useful summary for distinguishing between an external discriminatory environment (encompassing systemic racism and interpersonal racism) and internalised racism. Note that Paradies, Harris and Anderson (2008) recognise the, '… importance of each level of racism, but noted that systemic racism is the level of racism that fundamentally underpins racial/ethnic inequalities in health. Systemic racism is the most pervasive form of racism across a range of life domains such as education, employment and housing.' (2008:4). Arguably, systemic racism is also the underlying phenomenon underpinning socioeconomic inequalities more broadly.

Hunter, Howlett and Biddle (2014) identify that historically, a lack of psychological data limits understanding of discrimination directed at Indigenous Australians. Shirodkar (2019) attempts to address this gap in the literature, presenting never before published social psychology data from Project Implicit's *Implicit*

Association Test (IAT), designed to measure the levels of implicit bias in this country against Australia's First Peoples. Evidence from Shirodkar (2019) suggests that a societal bias may exist in Australia, predisposing the majority of Australian participants of the test to consider Indigenous Australians through a negative lens in almost every setting (see section 3 for a fuller discussion).[1]

This paper builds on the findings from Shirodkar (2019) and Shirodkar and Hunter (2019) to develop an *ecological* regression analysis, testing whether the average IAT D Scores in Australian SA3 regions affect the variation in Indigenous business ownership rates across Australia.[2] This paper establishes that a statistically significant negative relationship exists between levels of measured implicit bias and Indigenous business ownership rates. The results suggest that living in an area with higher levels of bias against Indigenous people can have a highly detrimental effect on local Indigenous business ownership rates, thus reducing prospects for greater Indigenous economic self-determination. The analysis provides evidence to suggest that any bias amongst Indigenous Australians against other Indigenous Australians or 'internalised discrimination' (as measured through Indigenous Australia's IAT D Scores) has no statistically significant correlation with rates of Indigenous business ownership. The implication of these findings is that the challenges to Indigenous entrepreneurship do not necessarily reflect a toxic internal environment in Indigenous communities, but rather an impaired and ultimately prejudicial perception within non-Indigenous communities.

The paper will proceed as follows: Section 2 reviews sociology, psychology and economics literature exploring the links between discrimination and socioeconomic outcomes for marginalised groups, with a focus on implications for business ownership. Section 3 introduces the IAT and reports some of the key findings from Shirodkar (2019). Section 4 presents the ecological regression model testing the correlations between IAT results and Indigenous business ownership rates. Section 5 reports the findings, while section 6 concludes.

2. Literature review

Shirodkar, Hunter and Foley (2018) suggest the bias against Indigenous Australians occurs without awareness of prejudice amongst the majority, meaning the bias is implicit, inherent and unacknowledged, seeping seamlessly into the everyday decision making of societal actors, including those in positions of power. Biddle and Lahn (2016) state 'that most prejudice is implicit and, perhaps even more surprisingly, that implicit discrimination can have a more damaging effect on those who experience it [than conscious or explicit discrimination]' (2016:4). And Zeigert and Hanges (2005) find evidence to suggest that implicit racist attitudes in labour markets interact with a corporate climate for racial bias to predict discriminatory treatment of minorities in relation to hiring decisions.

1 Around 75 per cent of the 11,099 Australians who took part in the test from 2009-2019 received a positive IAT D Score, implying an implicit bias against Indigenous Australian faces.
2 The D Score, which is a standardised unit of measurement for implicit bias, is based on the Cohen's D Score.

Much of the Australian data around discrimination tends to report the causal consequence of direct interpersonal discrimination from its victims. For instance, the 2018 Australian Reconciliation Barometer survey found that 43 per cent of Indigenous Australians reported experiencing at least one form of racial prejudice in the previous six months compared with 20 per cent of non-Indigenous people (see *the Australian Reconciliation Barometer*, 2019). Some research attempts to gain insight into the views of those who are witness to racism, including the *Challenging Racism Project* and the *Scanlon Social Cohesion survey*. But as with all such surveys, an individual often has the incentive to hide their proximity or engagement in socially undesirable acts, such as racism, because such proximity could reflect poorly on their own behaviours and social groupings. And further, claims of bias and racism against Indigenous Australians have historically been discounted or neutralised in mainstream discourses (Maley, 2018; and Augoustinos, Tuffin and Rapley, 1999). These phenomena may reflect an unwillingness to accept that *we* – non-Indigenous Australians – are perhaps major contributors to the challenges that Indigenous Australians face. This is despite the extensive literature that correlates self-reported experiences of discrimination to poor health and wellbeing outcomes amongst minorities, particularly Indigenous Australians (Grollman and Hagiwara, 2019; Paradies, 2018; Bodkin-Andrews and Carlson, 2016; Bodkin-Andrews *et al*. 2013; Paradies, Harris and Anderson, 2008; Bourguignon *et al*., 2006; Spalding, 1999). Pedersen *et al*. (2000) argues that while explicit and 'traditional prejudice' may have subsided in Australia, it has been replaced by 'modern prejudice', described as a more subtle form of prejudice, which contains a veneer of egalitarianism. These scholars argue this modern prejudice, or 'subtle racism', is characterised by a general ambivalence towards minority groups, an approach of attempting to de-racialise (Augoustinos, Tuffin and Rapley, 1999) what may otherwise be seen as discriminatory talks, or to refer to issues of race indirectly.

Additional Australian research also accords with this view of a modern or hidden prejudice existing in Australian discourses. Hage (2014) states that 'Australian racism generally is far less overt and direct, and far less easy to delineate.' (2014:233–234). Seet and Paradies (2015), however, argue that the distinction between 'old racism' – overt and direct racial prejudice – and 'new' or modern prejudice may move the emphasis away from the experiences of actual verbal and physical displays of discrimination that Indigenous Australians and other minority groups still routinely experience.

While old racism may have subsided in day-to-day interactions, the impact of discrimination continues, perhaps manifesting as the more subtle modern prejudice. And its manifestation may occur without our conscious thought, because our prejudicial views may reflect ingrained stereotypes or views about groups that we marginalise, which are difficult to dislodge. Those views may exist contrary to our values of equality and egalitarianism. And if sufficiently widespread and ingrained, may hide within the Australian psyche unchallenged. But the consequence is that our society continues to severely limit the opportunities for marginalised groups to engage freely with the economy and society. It is likely that in both cases – of overt racial prejudice and subtle modern prejudice – implicit bias is the underlying phenomenon that is driving the manifestation of discrimination. And while the presence of a prejudicial social and economic environment remains, however it may manifest, one cannot discount its social and economic effects. We will return to implicit bias and a measurement tool for the phenomenon later.

Studies have described discrimination in labour markets as occurring when individuals, who are equally productive as their peers, are either overlooked, underpaid or treated unequally, because of an observable but immutable difference such as race, gender, ethnicity or ability, to name a few (Biddle and Lahn, 2016; Altonji and Blank, 1994, Arrow, 1972 and Becker, 1957). The result of labour market discrimination is that marginalised groups continue to experience poorer overall life outcomes than other communities, reflected in their lifetime incomes, health outcomes, social mobility and diminished opportunities to maximise their community and economic contributions.

Becker's (1957) seminal work on the economics of discrimination in labour markets established the concept of a 'taste for discrimination' within Caucasian Americans against African Americans. In Becker's model, the production and consumption functions of Caucasians reflect the taste for discrimination as a price premium for avoiding contact with African Americans. He argued that this price premium remained artificially high and that price competitiveness could not erode it away. He surmised that its presence thereby circumvented the low entry cost principle of competitive markets. He used this model to explain much of the significant disparity between the socioeconomic status of Caucasian and African American communities. Arrow (1972) was not satisfied with Becker's taste for discrimination as it added an additional non-economic parameter to the general principle of profit maximisation amongst market participants. He later developed a hypothesis that economic systems may maintain racially exclusive or homogenous networks in order to create 'social capital benefits' amongst the inside group (Arrow, 1998). The benefits more than offset the higher costs of transacting exclusively with insider group peers. The result, he argues, is the radical alteration of resource allocation decisions. Arrow indicates that with social capital, 'discrimination no longer has a cost to the discriminator; indeed, it has social rewards' (1998:98). In effect, Arrow (1998) provided an economic rationale for why racial discriminatory barriers remained and were not sensitive to market power principles.

In Australia, the unique societal prejudices that only Indigenous Australians continue to experience (see Australian Reconciliation Barometer) – resulting from dispossession, massacre, the state stealing one's children and forced assimilation – has also created a persistent discriminatory barrier between Indigenous and non-Indigenous Australians. One cannot ignore how such experiences may continue to limit the prospects for many Indigenous Australians to access the mainstream economy to this day, because arguably, the pre-conditions that resulted in such wanton hostility from our colonial ancestors has never fully disappeared. While we aspire to equality and egalitarianism, and we may genuinely believe in those concepts, our individual and collective views may continue to reflect ideas of racial superiority of one group over another. The result is the creation of a discriminatory backdrop to Australian society, which is so ingrained in our landscape, that we may well seldom recognise it as an abhorrence. A labour market study, Collins (1994), argues that employers (and Australian society as a whole) are geared towards discriminating against minorities, including Indigenous Australians. Booth, Leigh and Varganova (2012) attempt to measure labour market discrimination through a revealed preference approach, finding that CVs with *Indigenous names* are 30 per cent less likely to receive a call back for an interview than CVs with *distinctively Anglo Saxon names*, despite having identical CVs. And Biddle *et al*. (2013) find using self-reported discrimination data that individuals may decrease their labour supply in order to avoid potentially discriminatory situations. But few studies have attempted to understand the possible effects of discrimination on business ownership in Australia. Shirodkar and Hunter (2019) undertake the first quantitative Australian study to look into the matter, finding that differences in identity can explain much of the difference in business ownership rates between Indigenous and non-Indigenous Australia.

Foley (2000) observes that, at great personal cost – and even with the risk of ostracisation from their own community – some Indigenous business owners hide their Indigenous identity from the wider non-Indigenous public. The business owner recognises the crippling effect of discriminatory attitudes on their opportunities to succeed in business. In one example, Foley (2000) accounts for how one Indigenous business owner states he is of 'Spanish descent' if a customer or trade supplier asks. The business owner was forced to cut off contact completely with the Indigenous community stating that, '… if my customers or suppliers knew I was a blackfella I would not last two minutes in this town.' (2000:48). Clearly, coming from a different minority background meant that he would receive a modicum of acceptance from the non-Indigenous community – at the cost of denying his heritage. Foley (2000) reports that despite the man's denials, the situation is a cause of significant anguish, resulting in his children feeling as if the business has made them 'orphans' from their community. But doing so has meant that his family has been able to claw out of poverty, caused by a long period of unemployment prior to going into business.

The trade-off is not unique for Indigenous business owners across Australia. Shirodkar, Hunter and Foley (2020) use the three-wave Australian Census Longitudinal Dataset to identify that between the 2006 and 2016 Censuses, an additional 56 per cent of Indigenous business owners did not self-identify as Indigenous in 2006, but did so by 2016. In contrast, the non-identification rate for the whole Indigenous 15+ population was only 14 per cent over the same period, four times lower. For around a third of the Indigenous business population in 2006, denying their heritage and self-identity was likely the only way they felt they could survive in business in the presence of a racially discriminatory environment. And that was just in the context of something as innocuous as the Census, which only reports de-identified data. In our opinion, the propensity to hide one's Indigenous identity from mainstream society reflects more on Australian society – forcing so many to deny who they, their family, their ancestors and their people are – than on the individuals themselves. In the past 20 years, the number of Indigenous Australians in business has grown rapidly, as have the numbers of Indigenous entrepreneurs who openly identify as Indigenous. Shirodkar, Hunter and Foley (2020) estimate that in the 10 years between 2006 and 2016, the number of Indigenous owner-managers of businesses grew from 10,500 to 19,400 – an 85 per cent increase. Part of the estimates reflects the fact that more Indigenous Australians in business are identifying their Indigenous status than previously. But that does not diminish the likelihood that a substantial proportion of current Indigenous business owners likely did not identify as Indigenous at the latest Census (in 2016), for much the same reasons as previously.

Despite the phenomenon of discriminatory treatment, only a few Australian papers have asserted that discrimination and prejudice have impacts on Indigenous business ownership in Australia, including Shirodkar, Hunter and Foley (2020); Shirodkar and Hunter (2019); Shirodkar, Hunter and Foley (2018); Wood and Davidson (2011); Foley (2006); Foley (2003); Foley (2000) and Dana (1996). In particular, Foley (2003) finds that racial discrimination from mainstream Australia was a common occurrence and a constant presence in the life of the Indigenous entrepreneur, '[t]his was evident when dealing with Government institutions, financiers, creditors and even the entrepreneurs' clientele. To an Indigenous Australian, racial discrimination is a part of life' (2003:17). He also identifies that '[d]iscrimination (racism) is so common to Indigenous Australians that it is only acknowledged when it is physical or exclusionary' (2003:17).

Some research has also raised the phenomenon of internalised discrimination as a possible cause of poorer outcomes for Indigenous Australians. Paradies, Harris and Anderson (2008) identify internalised racism as a type that people within the same racial/ethnic group perpetuate against one another, with the lateral violence that may occur used as evidence of its presence. It presents a contentious issue within Indigenous communities, but the authors suggest that discussion of the phenomenon may well just present a manifestation of ''victim-blaming' discourses that characterise racism as an Indigenous 'problem' rather than recognising it as a consequence of systemic racism within non-Indigenous society.' (2008:5). Following an extensive series of interviews with Indigenous entrepreneurs, Foley (2000) finds some evidence for this behaviour but that the racism the entrepreneurs experience, '… is predominantly directed from the non-Indigenous population, and secondly, it is experienced to a lesser degree from within the Indigenous Australian community.' (2000:51).

Almost all of the Australian research on the impacts of discrimination on Indigenous entrepreneurship is qualitative. Shirodkar and Hunter (2019) undertake the first published quantitative study to determine if a racial element may affect the likelihood of business ownership for Indigenous Australians, once accounting for other demographic and socioeconomic factors. Shirodkar and Hunter (2019) use an individual-level probit cross-sectional estimation to determine the probability of a person entering into business based on characteristics identified in the Australian Census Longitudinal Dataset. The characteristics include Indigenous status, gender, age, income, home ownership, disability, education levels and socioeconomic advantage or disadvantage of their suburb. The study determines that identifying as an Aboriginal and/or Torres Strait Islander Australian in the Census explains between 4–5 percentage points of difference between Indigenous and non-Indigenous business ownership rates, which is statistically significant at the 1.0 per cent level. That is sizeable, considering the Shirodkar, Hunter and Foley (2020) estimates suggest that the rate of Indigenous business ownership sits at around 3.7 per cent compared with around 8.6 per cent for non-Indigenous Australia. But the study provides only a partial response to the question of whether or not discrimination is a confounding factor in the decision of individuals to go into business. Clearly, a racial element exists. The study cannot determine if systematic societal discrimination is the primary cause or if internalised factors within the Indigenous community also play a role. For that, one requires data that can measure the internal psychological factors of a population, which enables an understanding of societal biases. The challenge has been attempting to identify a sufficiently robust measure (Hunter, Howlett and Biddle, 2014). To address the challenge, this paper uses the Implicit Association Test (IAT), offering a means to gain some measurable insight into those internal psychological processes.

3. The Implicit Association Test (IAT)

Greenwald, McGhee and Schwartz (1998) developed the IAT as a *behavioural tool* in social psychology, providing a means to measure implicit attitudes in individuals towards various target concepts. The authors define implicit attitudes as 'actions or judgements that are under the control of automatically activated evaluation, without the performer's awareness of that causation' (1998: 1464). Over time, the concept has become synonymous with the more widely used terms, *unconscious attitudes*, *unconscious bias* and *implicit bias* (Hehman, Flake and Calanchini, 2018; Green *et al.*, 2007; and Nosek, Banaji and Greenwald, 2002).

The IAT technique offers a versatile means to measure inherent attitudes towards a range of concepts including ethnicity, Indigeneity, homosexuality, age, weight, self-esteem, gender, smoking, and even contraceptive use. Many of the US-based IATs have collected millions of observations in free online-based tests. Anyone can participate in an IAT, assuming access to the internet, and can complete the test within 30 minutes. Since participants generally find their own way to perform IATs, a random sampling framework does not apply. But Shirodkar (2019) argues that the shortcoming does not diminish the overall generalisability of the aggregated results. If anything, the average result for even a very large sample may underestimate the extent of implicit bias because of the disproportionately high number of women and left-leaning participants drawn to taking the test (who tend to display on average lower levels of implicit bias). The IAT is widely known for its ability to measure implicit attitudes within individuals—particularly towards marginalised groups, and has been applied extensively in psychology. In addition, it can measure the biases of a person from a marginalised group towards or against their own community, thereby providing a measure of both an external discriminatory environment and internalised racism. Given the large numbers of individuals who participate in online IATs, the real value of the test for economists and sociologists arises from looking at results for large segments of society that have participated in the test.

The most well-known version of the IAT measures US participants' automatic evaluation of African Americans compared with Caucasian Americans. When analysing the data for large samples, the test has displayed predictive validity – arguably the most important form of establishing the validity of a measure – with a number of studies correlating IAT-measured implicit bias with poorer outcomes for the African American community. Hehman, Flake and Calanchini (2017) correlate higher implicit bias in US regions with higher police shootings of unarmed African American men.

Orchard and Price (2017) establish a correlation between the higher levels of racial prejudice and differing birth outcomes of African American and Caucasian babies. And Green *et al*. (2007) find that US doctors with a measured implicit bias against African Americans were on average less likely to prescribe required heart medication to African American patients compared with Caucasian patients.

The studies reveal that the IAT may well capture the previously unmeasurable and often unobservable factors that lead to poorer socioeconomic and health outcomes for some communities compared with others, on a systematic basis. Sociologists such as Bonilla-Silva (2003) suggest that systemic bias in the absence of intentional discrimination leads to 'racism without racists', which accords with the notion in psychology of implicit bias (Payne, Vuletich and Lundberg, 2017). Indeed, Payne, Vuletich and Lundberg (2017) argue that implicit bias may well provide a marker for systemic prejudice (interchangeable with systemic racism). The authors also suggest that implicit bias offers, '… a mechanism that translates systemic prejudice into individual[-level] discrimination.' (2017:239).

Shirodkar (2019) reports IAT data for Australian participants measuring the implicit bias of participants towards Indigenous Australians (the Australian IAT). The study combines the individual results of participants to make general claims about the pool of participants based on different demographic characteristics. The research shows that on average, the 11,099 Australian participants who undertook the test between December 2009 and April 2019 displayed a statistically significant implicit bias against Indigenous faces and in favour of Caucasian faces, with an average IAT D Score of +0.29. The IAT D Score (unit of measuring implicit bias) was comparable in magnitude to that displayed towards African Americans in the US race-based IAT. Around three quarters of participants of the Australian IAT received a positive IAT D Score, implying a bias against Indigenous Australians. The results provide interesting insights about various cross-sections of the participants, including those based on gender, age, ethnicity, occupation, education levels and political persuasions.

The results in Shirodkar (2019) are confronting. If one accepted that the results are capturing a valid societal phenomenon that is generalisable, it suggests that Indigenous Australians are on average likely to experience implicit bias in almost every social setting when in contact with most non-Indigenous Australians and their Indigenous identity is known and/or observable. Having said that, many whose identity is not observable may still be exposed to discriminatory views about Indigenous Australians, but may not feel empowered to refute such claims for fear of having the perpetrator's ire directed at them. Hence the previous example of the Indigenous entrepreneur claiming Spanish descent in order to continue in business.

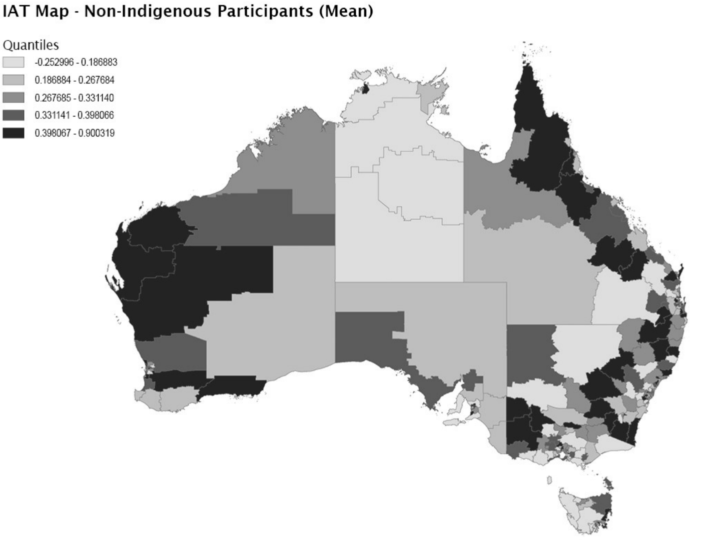
The following section attempts to establish if the Australian IAT results have any explanatory power in determining an impact on Indigenous business ownership rates.

4. Modelling the effect of implicit bias on Indigenous business ownership rates

This paper employs a simple *ecological* regression model specification to understand the extent to which IAT results impact on variations in Indigenous business ownership rates across SA3 regions. We control for a range of regional variables that are associated with higher rates of local Indigenous businesses in the literature (Shirodkar and Hunter, 2019), and test for the significance of the coefficients associated with IAT variables. The model applies a cross-sectional specification, with most of the variables in the model coming from the 2016 Census of Population and Housing. However, the key determinant tested in this paper, the IAT D Scores, treat the entire testing period (2009-2019) as a single sample, since taking a point estimate for 2016 would have severally reduced the sample size. Given the remarkable stability of the IAT D Score over time, this approach does not pose many challenges (Shirodkar, 2019).

Access to participants' postcode data provides an opportunity to map individual IAT results to Australian Bureau of Statistics (ABS) statistical areas, on the assumption that the average IAT D Score of participants reflects the general implicit bias of a region. Chart 1 provides a map of non-Indigenous IAT D Scores across Australia. The maps reveals that almost all areas are on average in the positive range of IAT D Scores (i.e., *biased against Indigenous Australians*), barring four regions (two of which had five or fewer observations and were those not included in the regression model). The lowest average non-Indigenous IAT D Score (i.e., the most negative) for a region with at least five observations was recorded in the Huon-Bruny Island SA3 in Tasmania, which interestingly recorded an Indigenous business ownership rate that was more than twice the national average. And the highest average non-Indigenous IAT D Score for a region with at least five observations was the Armidale SA3 in regional NSW, which had a lower than average Indigenous business ownership rate. In order to reduce the impact of outlier results, SA3 regions that contained five or fewer IAT observations were removed from the sample. The distribution of non-Indigenous and Indigenous IAT D Scores by SA3 are provided at Appendix 1.

Chart 1: Map of non-Indigenous IAT D Scores across Australian SA3 regions



The model specification for explaining Indigenous business ownership rates is largely parsimonious. ABS data sources provide the explanatory variables for the economic performance of the region, including incomes, employment rates and education levels. Table 1 provides a list of the economic explanatory variables in the model, including an indication of the relevant literature that supports its inclusion.

The equation below specifies the structure of the model:

$$y_i = X_i\beta + \varepsilon_i$$

where y_i = the proportion of the Indigenous 15+ population that are owner-managers in SA3 region i; and X_i = the vector of determinants of the rate of business ownership in SA3 region i (see table 1). The error term ε_i will account for SA3 regional variations that are not otherwise specified.

Table 1. Determinants of business ownership

Explanatory variables	*Supporting literature*	*Source of data*
Non-Indigenous IAT results by SA3 (2009-2019) as a measure of an external discriminatory environment	Dana, 1996; Foley, 2000; Foley, 2003; Foley, 2006; Wood and Davidson, 2011; Shirodkar, Hunter and Foley, 2018; Shirodkar and Hunter, 2019	IAT results for Australia, Project Implicit
Indigenous IAT results by SA3 (2009-2019) as a measure of an internal discriminatory environment	Foley, 2000; Paradies, Harris and Anderson, 2008	IAT results for Australia, Project Implicit
Education level (number of people with diplomas and advanced diplomas in region divided by the 15+ population) by SA3 in 2016	Schultz, 1972; Delmar and Davidsson, 2000; Foley, 2000; Lazear, 2004; Uhlaner and Thurik, 2007; Acs, Armington and Zhang, 2007; Shirodkar and Hunter, 2019	ABS Census of Population and Housing 2016
Mean total income levels by SA3 in 2015-16	Kuznets, 1971; Lucas, 1978; Schultz, 1990; Wennekers *et al.*, 2007	ABS Estimates of Personal Income for Small Areas (2011-17)
Indigenous employment rate (number of Indigenous employed in full-time or part-time work divided by the 15+ population) by SA3 in 2016	Lucas, 1978; Evans and Leighton, 1990; Krugman, 1991; Meager, 1992; Acs, Armington and Zhang, 2007; Wennekers *et al.*, 2007; Krugman, 2011	ABS Census of Population and Housing 2016
Employment rate (number employed in full-time or part-time work divided by the 15+ population) by SA3 in 2016	Lucas, 1978; Krugman, 1991; Acs, Armington and Zhang, 2007; Krugman, 2011	ABS Census of Population and Housing 2016

External discriminatory environment – reflecting systemic discrimination

The literature review above provides sufficient justification for the inclusion of IAT results. The model incorporates the IAT results for all non-Indigenous Australians who participated in the test by SA3 regions. Removing the results of Indigenous Australians from the IAT score variable means that the model can isolate the specific impact of bias from both populations.

Based on the literature, one would expect that a higher IAT D score (i.e., an implicit bias against Indigenous Australians) would result in lower rates of Indigenous business ownership in region i. That is because the greater latent hostility towards Indigenous Australians would reduce the scope for business ownership. For example, a business owner could face discrimination directly from three points, 1) as a result of customers who do not pay invoices once they find out a business is Indigenous-owned, 2) suppliers who do not extend credit and 3) lenders who may claim that

Indigenous Australians present too much of a risk (Shirodkar, Hunter and Foley, 2018). Additionally, customers may choose not to frequent the business just because they do not want to purchase from an Indigenous retailer, and Indigenous businesses may be shunned from established local business networks.

Internalised racism within the Indigenous community

Internalised racism within the Indigenous community is a contentious topic. It draws upon views of *self-loathing* and *lateral violence* within marginalised groups in relation to their circumstances. Since the IAT data collects results from Indigenous (and non-Indigenous) participants, this ecological analysis provides a means to gauge the potential impact of internalised Indigenous biases on Indigenous business ownership. Given the small number of Indigenous participants who had undertaken the test (N = 410), and given Indigenous participants are only in 180 SA3 regions, the estimation includes SA3 regions that had fewer than six Indigenous IAT D Scores. This may well limit the robustness of any statistical significant result. One could reasonably expect a small negative relationship, if any, between the two variables if both were reliably measured, implying that an increase in IAT D Scores amongst Indigenous Australians will have a negative effect on Indigenous business ownership.

Education levels

Education levels are an important explanatory factor behind business ownership rates (Shirodkar and Hunter, 2019; Acs, Armington and Zhang, 2007; Uhlaner and Thurik, 2007; Lazear, 2004; Delmar and Davidsson, 2000; Foley, 2000; and Schultz, 1978). Shirodkar and Hunter (2019) find that having Diplomas and Certificate level qualifications increased the likelihood of a person entering into business compared to having a university level qualification or a secondary school qualification. The result accords with Lazear (2004), who suggests business owners must be multi-skilled or require a balanced range of skills in order to perform a 'jack of all trades' function. Many small business people are often forced to engage in such a role, given the limited resources that are at their disposal. Diplomas and advanced diplomas provide what Shirodkar and Hunter (2019) refer to as a practical qualification, delivering skills that are more easily deployable across a range of industries, offering a key economic lubricant, particularly in a small business environment.

Average total income levels

Including average total (nominal) income levels provides an approximate measure of a region's affluence compared with other regions, creating strong incentives for business ownership (Kuznets, 1971; and Lucas, 1978). An income variable provides an indication of the average disposable income available in a region. A higher level of income would presumably attract greater numbers of owner-managers. One would assume therefore a positive relationship between the average income in region i and Indigenous business ownership all other things being equal. In international studies looking at business ownership rates, GDP or GNP per capita is used as a measure of income (Wennekers *et al*., 2007; Schultz, 1990). Given that this paper measures cross-sectional differences in the one time-period and in the one country, the ABS's Estimates of Personal Income for Small Areas in 2015-16 will suffice.

Indigenous employment rate

The model includes the rate of Indigenous employment (i.e., Indigenous Australians employed as a share of the 15+ population) as a means of explaining general economic prospects for Indigenous Australians in the region. The variable serves as an anchor of the general opportunities available for Indigenous Australians in the region, with an assumption that higher rates of Indigenous employment results in higher rates of Indigenous business ownership. Presumably then, a general participation effect improves the economic prospects of the entire community assuming all other things being equal. Also note that a reverse causation may also result, since Indigenous businesses are anywhere between 40 to 100 times more likely to hire Indigenous employees compared to non-Indigenous businesses (Shirodkar and Hunter, 2019; and Hunter, 2014). Other studies have also argued the potential for a negative relationship to result, that is, more favourable labour market conditions may reduce the need for necessity business ownership (Wennekers *et al*., 2007; Meager, 1992; and Evans and Leighton, 1990). But perhaps different incentives and opportunity costs apply for those from a majority background to enter into necessity entrepreneurship as opposed to a person from a marginalised background.

Regional total employment rate

The new economic geography literature provides a theoretical basis for understanding the growing disparities in opportunities for different regions based on factors such as infrastructure, degree of urbanisation, and access to physical and human capital, which are functions of transportation costs, economies of scale and factor mobility (Krugman, 1991; Acs, Armington and Zhang, 2007; and Krugman, 2011). The abundance (or lack thereof) of these factors will affect the exploitable opportunities available for business owners. A region's overall employment rate provides a parsimonious measure of overall economic opportunity in a given geography. The employment rate as measured in this paper provides an indication of the share of local 15+ population who are actively productive in the region as at the time of the 2016 Census of Population and Housing. One would assume, therefore, a positive relationship between the employment rate in region i and Indigenous business ownership all other things being equal. Note that Indigenous Australians are included in the calculation of the total employment rate, since they form part of economic capacity of the region. Their exclusion from the calculation could understate the productive capacity of a region. For instance, in certain SA3 regions (particularly in the Northern Territory) Indigenous Australians make up a large share of the workforce.

5. Results

The two ecological regression models are specified as:

1) $y_i = f(constant, x_{1i}, x_{3i}, x_{4i}, x_{5i}, x_{6i})$

2) $y_i = f(constant, x_{1i}, x_{2i}, x_{3i}, x_{4i}, x_{5i}, x_{6i})$

Where y_i = Indigenous business ownership rate for region i; x_{1i} = Average IAT D Score of non-Indigenous participants for region i; x_{2i} = Average IAT D Score of Indigenous participants for region i, x_{3i} = Diploma rate for region i, x_{4i} = Average income level for region i, x_{5i} = Indigenous employment rate for region i, x_{6i} = regional employment rate for region i.

Table 2 provides summary statistics for the models specified above.

Table 2. Summary statistics of model specifications 1) and 2)

Variable	*N*	*Mean*	*Std. Dev*	*Min*	*Max*
y_i = Indigenous business ownership rate	337	0.035	0.025	0	0.198
x_{1i} = Average IAT D Score of non-Indigenous participants (excl. regions < 6 participants)	289	0.307	0.108	-0.253	0.645
x_{2i} = Average IAT D Score of Indigenous participants	186	-0.004	0.351	-0.931	1.177
x_{3i} = Diploma rate	340	0.085	0.017	0	0.127
x_{4i} = Average total income level ('000s)	334	60.490	14.205	41.386	129.254
x_{5i} = Indigenous employment rate	337	0.483	0.126	0	1.23
x_{6i} = regional employment rate	340	0.555	0.075	0	0.784

The difference between the two specifications is that 1) only incorporates non-Indigenous IAT D Scores while 2) also adds Indigenous IAT D Scores as a measure of internalised racism in Indigenous communities. The results reported will primarily focus on specification 1), with a small commentary of the results from 2) at the end of the section.

Table 3 presents the results for each model specified. Initial estimations indicated the presence of heteroscedastic errors, i.e., that $\varepsilon_i \sim (0,1)$ does not hold, and therefore, one cannot assume homoscedastic errors. Using heteroscedasticity-consistent standard errors does not require assuming homoscedasticity (Hayes and Cai, 2007). P-values reported in Table 3 reflect the inclusion of heteroscedasticity-consistent standard errors.

The OLS regression in specification 1) explains roughly 48 per cent of the variation in Indigenous business ownership rates across SA3 regions and the model is jointly significant with an F-value of 52.65. All explanatory variables in the model (apart from the constant and income) are statistically significant at the 1.0 per cent level.

Table 3. Regression models for the determinants of business ownership

Dependent variable: *Indigenous business ownership rate by SA3*	*Specification 1*	*Specification 2*
x_{1i} = Average IAT D Score of non-Indigenous participants	-0.027 (0.002)*** [-0.121]	-0.025 (0.012)** [-0.117]
x_{2i} = Average IAT D Score of Indigenous participants		-0.0004 (0.902) [-0.008]
x_{3i} = Diploma rate	0.543 (0.000)*** [0.324]	0.482 (0.000)*** [[0.328]
x_{4i} = Average total income level ('000s)	0.0004 (0.02)** [0.224]	0.0003 (0.02)** [0.230]
x_{6i} = Indigenous employment rate	0.112 (0.000)*** [0.497]	0.099 (0.000)*** [0.519]
x_{5i} = regional employment rate	-0.120 (0.000)*** [-0.299]	-0.095 (0.002)*** [-0.280]
Constant	-0.014 (0.02)** [NA]	-0.016 (0.088)* [NA]
Number of Observations	289	180
R^2	0.482	0.478
F statistic – joint significance test	52.65	23.92

Note: The table reports the beta coefficients of the explanatory variables. Figures in parenthesis are P-values (reflecting heteroscedasticity-consistent standard errors). Figures in square brackets are standardised coefficients. NA is not applicable. *** denotes statistically significant at the 1.0 per cent level. ** denotes statistically significant at the 5.0 per cent level. * denotes statistically significant at the 10 per cent level.

Importantly, the model shows that the average IAT D score of non-Indigenous participants had a statistically significant negative correlation with the rate of Indigenous business ownership across SA3 regions. The coefficient is -0.027, meaning if the IAT D score of a region increased from 0 (perfectly unbiased) to 1 (highly biased against Aboriginal Australians), the rate of Indigenous business ownership would reduce by 2.7 percentage points all other things being equal. To put that into context, the unadjusted average rate of Indigenous business ownership as measured in the 2016 Census was 2.7 per cent. As such, a highly biased operating environment can have a significant negative effect on Indigenous business ownership. The standardised coefficient (i.e., how many standard deviations a dependent variable will change based on a per standard deviation change in the independent variable) for the non-Indigenous IAT D Score is -0.12, implying that a one standard deviation increase in IAT D scores will result in a 0.12 standard deviation decrease in business ownership rates.

As predicted, the overall diploma rate has a positive coefficient, showing that a 1.0 per cent increase in the region's diploma rate increases the rate of Indigenous business ownership by 0.54 percentage points and the standardised coefficient is +0.32. The size of the result implies that the variable may well be doing more than just having a supply-side effect on business ownership rates. It may well also present the economic 'lubricant' of skilled labour that provides easily deployable skills necessary to make business formation possible across multiple sectors. Further research into understanding the importance of diplomas and other similar qualifications in improving the economic prospects of regions is warranted.

Higher average income levels for SA3 regions increased rates of Indigenous business ownership. For each $10,000 increase in average regional income, the rate of Indigenous business ownership grows by 0.004 percentage points, with a standardised coefficient of 0.22. The result implies that Indigenous business ownership rates are higher in increasingly affluent regions, as expected.

The Indigenous employment rate for a region has a sizeable, positive and statistically significant correlation with the Indigenous business ownership rate. A 1.0 per cent increase in the Indigenous employment rate results in a 0.11 per cent increase in the Indigenous business ownership rate, and the standardised coefficient is +0.50. The result implies that a general Indigenous economic participatory effect likely significantly benefits Indigenous business ownership. The result implies that greater employment conditions for Indigenous Australians will do the most to improve Indigenous business ownership rates compared with any other variable tested. The result is at odds with the notion that improving labour market conditions raises the opportunity cost for business ownership, thereby reducing the rate of business ownership, or perhaps it reflects the different dynamics that apply to marginalised groups. But as this analysis only establishes correlation, the effect may also reflect a reverse causal relationship as suggested in Hunter (2014), who finds Indigenous businesses are much more likely to hire Indigenous workers than non-Indigenous businesses.

Interestingly, the overall employment rate for a region (which includes non-Indigenous and Indigenous employment) has a negative and statistically significant effect on the Indigenous business ownership rate once the region's Indigenous employment rate is included in the model. The negative sign is surprising and somewhat at odds with the positive coefficient for higher average incomes, meaning that the negative coefficient is not a function of affluence necessarily. The result implies that once accounting for Indigenous employment specifically, Indigenous businesses may currently be more abundant in regions that have relatively low overall rates of employment.

Table 3 reveals that the Indigenous IAT D Score variable x_{2i} (in specification 2) had insignificant explanatory power at the 10 per cent level. The variable's inclusion reduced the overall significance of the model from an F value of 52.65 for 1) to an F value of 23.92 for 2). The results imply the inclusion of the Indigenous IAT D Score may misspecify the model. As such, there is no quantitative evidence to suggest that internal biases within Indigenous communities have a meaningful impact on Indigenous business ownership rates. Having said that, the relatively small number of Indigenous IAT observations in many regions means that we should be cautious about interpreting too much from the null result.

6. Conclusion

The quantitative findings of this research supports other evidence from the Indigenous business literature around the negative effects of discrimination (Shirodkar, Hunter and Foley, 2020; Shirodkar and Hunter, 2019; Shirodkar, Hunter and Foley, 2018; Wood and Davidson, 2011; Dana, 1996; Foley, 2006; Foley, 2003; Foley, 2000). The experiences of African Americans attempting to access the mainstream economy formed the basis for the literature around the economics of discrimination as pioneered by American Nobel Laureates, Gary Becker and Kenneth Arrow. This paper attempts to contribute to that body of literature on the economics of discrimination by developing quantitative findings that support the view that implicit racial biases limit economic opportunities for marginalised communities. The situation causes a circumvention of the low entry cost principle of well-functioning markets, thereby resulting in a market failure.

The findings from the ecological regression offer evidence to suggest that societal biases are reducing Indigenous business ownership rates. The use of the Australian IAT, a first in Australian research, shows that the presence of an external biased operating environment curtails rates of Indigenous business ownership across Australia, once other major economic factors are considered. Further, the overall model specification 1) displays a high explanatory power (r^2) of 48 per cent.

The results suggest that the presence of a highly implicitly biased environment reduces opportunities for Indigenous Australians to enter into business. In order to avoid discrimination and survive as a business owner, some must completely or at least partially subsume their self-identity into that of the dominant culture – i.e., identify as non-Indigenous. For those potential entrepreneurs who are unwilling to make such a costly trade-off, the results suggest that society's implicit bias – reflective of systemic racism in Australia – may create an invisible yet impervious barrier into business ownership. For some an infringement on one's integrity may present too high a price to pursue such a life, thereby limiting their participation in enterprise. For those who do subsume their identity, such a decision is likely at great personal cost to themselves, their families and to their community. But wider society may perceive such behaviour as dishonest and by association, the proprietor as untrustworthy, not recognising that society's own implicit biases are the cause of such a drastic action. But Shirodkar, Hunter and Foley (2020) provide irrefutable evidence to show that as recently as 2006, around a third of the Indigenous business owners at that time denied their Indigenous identity in the Census. One must take pause to recognise the magnitude, and the social, economic and personal ramifications of the observation.

This paper finds no evidence to suggest that internalised racism has a statistically significant impact on Indigenous business ownership rates, but we recognise the scope for error to creep into the small number of Indigenous IAT D scores across regions.

Overall the findings largely accord with Foley (2000), who argues the racism that the Indigenous entrepreneur experiences, '… is predominantly directed from the non-Indigenous population, and secondly, it is experienced to a lesser degree from within the Indigenous Australian community.' (2000:51). The results put into question whether a narrative around internalised discrimination actually limits business prospects for Indigenous Australia. As Paradies, Harris and Anderson (2008) suggest, such a narrative may well represent a convenient 'victim-blaming' discourse that characterises racism as an *Indigenous problem*. But it is hard to argue that such a narrative has not influenced much of the research in the Indigenous space. It may well also infiltrate the context in which many well-meaning authors in the Indigenous business literature write within.

The findings of this research have implications for policy makers. One cannot simply focus on improving the skills and capabilities of Indigenous Australians and assume the approach can sufficiently address the persistent gap in socioeconomic outcomes between Indigenous and non-Indigenous Australia. We must recognise the undermining effect of our implicit biases, and the consequences for Indigenous Australians and other marginalised groups. Recognising uniqueness and distinctiveness does not necessarily require the 'othering' and marginalisation of entire subsets of our citizenry. A number of studies have attempted to evaluate treatments to implicit biases, such as implicit bias training, exposure to others' perspectives, induced threats, invoking goals and motivation but they often produce mixed results and the positive benefits if any are relatively weak (Forscher *et al*., 2019, FitzGerald *et al*., 2019, Atewologun, Cornish and Tresh, 2018; and Noon, 2018). Mitchell and Tetlock (2006) argue the inappropriateness of using an individual's IAT score as a measure of prejudice for the purposes of practising anti-discrimination law, although they note the IAT may well still capture implicit associations that individuals make. Such a caution is reasonable, particularly given the potential measurement errors that could creep into an individual's score. But we should also not discount the diagnosis because of the potential ineffectiveness of a single prescription. The criticisms are premised on the notion that the IAT is primarily a means of measuring 'individual-level' bias. This analysis shows that the IAT, arguably, provides greater value when thinking about large subsets of the population. The right psychological tools may not necessarily exist today to address the challenges that affect an individual's level of implicit bias, and indeed, ethical concerns plague any intervention on individuals based on such a test. But that should not discount the potential for this research to diagnose an underlying phenomenon that is rarely explored in Australia. Changing our mindsets requires individuals challenging their own automatic or implicit associations, particularly when they cast an already marginalised group in a negative light. That is an introspective and, ultimately, individual journey for each of us, and not necessarily a role for policy makers. However, policy makers could help create an environment that encourages individuals to question their own immediate and implicit reactions, particularly when those reactions cause harm.

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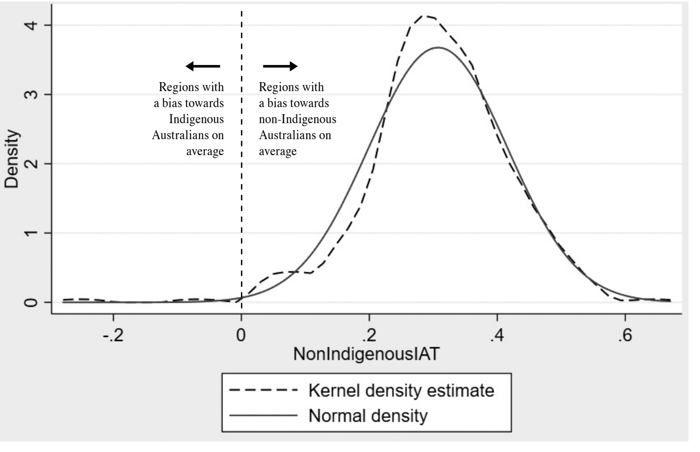
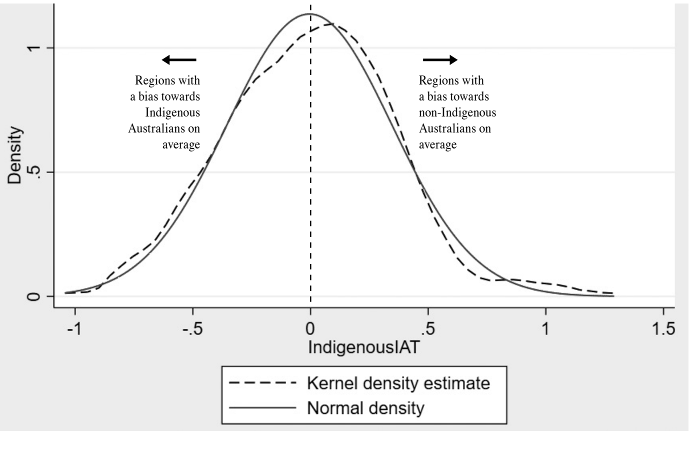
Appendix 1: Distribution of IAT D Scores by SA3 regions

Appendix Figure 1.1. Kernel density estimate of non-Indigenous IAT D Scores by SA3 regions



Notes: Average IAT for at least 5 respondents per region, N = 289

Appendix Figure 1.2. Kernel density estimate of Indigenous IAT D Scores by SA3 regions



Notes: Average IAT, no limit on number of respondents per region, N = 186

A longitudinal analysis of economic inactivity among Indigenous youth

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Abstract

Census and survey data show a high prevalence of youth inactivity among Indigenous Australians. The new Closing the Gap Agreement between the Coalition of Aboriginal and Torres Strait Islander Peak Organisations and the Australian governments at the federal, state and territory level aims to increase the proportion of Indigenous youth (aged 15-24 years) in full-time employment, education or training to 67 per cent by 2031. Understanding the factors that put young people at risk of disengagement from school or the labour market is a requisite for identifying the type and level of support required to increase the engagement of Indigenous Australians with the labour market and education system. However, there is a limited empirical evidence base to guide policy actions. Using data from the Australian Census of Longitudinal Dataset, this study provides extensive profiling of the characteristics of Indigenous youth not in employment, education or training. It also identifies the factors underlying individual-level changes in economic inactivity. The findings suggest that providing well-targeted supports to those who live in disadvantaged circumstances is paramount for mitigating economic inactivity among Indigenous youth.

JEL Codes: I20, J20, J60
Keywords: NEET youth, Indigenous, employment, education, training, Australia

1. Introduction

The 2016 Census shows that over a quarter of a million (278, 408) Australians aged 15-24 years are not in employment, education or training (NEET). Indigenous youth make up 17 per cent of the NEET population while representing only about 5.0 per cent of 15-24 year olds. In particular, 29 per cent of Indigenous youth are not engaged in any employment or educational activity compared with only 8.0 per cent of their non-Indigenous peers (Australian Bureau of Statistics (ABS), 2019).

The assumption that youth inactivity has detrimental personal and societal impacts underpins both the academic literature and policy debate on youth disengagement. In the literature, it is assumed that participation in education, employment, or training keeps young people away from engaging in delinquency and substance use (Maynard, Salas-Wright, and Vaughn, 2015; Melchior *et al*., 2015). Engagement with the labour market and education system at a young age is also vital for personal development and labour market success later in life. While education provides scientific skills that enhance productivity and competency in the labour market (Becker, 2009), employment experience provides on-the-job training and an opportunity to develop a good work ethic (Hopkin, 2012). A growing body of evidence shows that NEET youth have a lifetime of poorer socioeconomic outcomes than otherwise identical individuals. They are at a higher risk of becoming less educated, unemployed and unhealthy future adults (see, Crawford *et al*., 2011; Henderson *et al*., 2017; Ralston *et al*., 2016; Ranzani and Rosati, 2012). The damaging effects of NEET appear to accrue beyond inactive individuals, to impact on society as a whole. Whereas widespread school dropouts by young people can result in suboptimal accumulation of human capital in the society (Catterall, 1987; Leigh, 2008), weak attachments with the labour market can lead to increased welfare spending and reduced tax revenue (Gorjón, de la Rica, and Villar, 2018). In Australia, the overall cost of NEET spells is estimated to be $16 billion per year (Organisation for Economic Co-operation and Development (OECD), 2016).

From a policy perspective, there is a perception that the social and economic returns to eliminating youth disengagement are very large. In this context, Australian governments at national, state and territory levels have been introducing various job and training compacts to curb youth inactivity and help young people grow into healthy, productive, and resilient adults (Council of Australian Governments (COAG), 2009; The Commonwealth Department of Employment, 2013). As such, one of the new Closing the Gap Agreements between the Coalition of Aboriginal and Torres Strait Islander Peak Organisations and the Australian governments at the federal, state and territory level is to increase the proportion of Aboriginal and Torres Strait Islander youth aged 15-24 years who are in employment, education and training to 67 per cent by 2031 (Australian Government, 2020).

Understanding the factors that put young people at risk of being NEET is a requisite for identifying the type and level of supports required and for designing well-targeted policies to mitigate the NEET problem. However, the empirical evidence that rigorously examines the factors driving NEET status among Indigenous Australians is limited. The bulk of research in Australia (reviewed in Section 2) focuses on comparing NEET prevalences across various socio-demographic groups (such as sex, age and Indigenous status) with little attempt to identify the factors underlying NEET status among various youth groups. Using data from the 2011-2016 Australian Census of Longitudinal Dataset (ACLD), this study provides extensive profiling of Indigenous young people who are NEET but also employs a fixed-effects regression to examine the factors driving overtime changes in NEET status at an individual level.

We find that NEETs are a diverse group, and so are the challenges they face. Results from bivariate analyses show that NEET is more prevalent among young people of older ages, without post-school qualifications, with disabilities and who live in remote and low socioeconomic status areas. NEET spells are also more prevalent among females than males. Results obtained with a fixed-effects estimation show that individual, household, and local circumstances constitute an important factor in determining a person's NEET status. A change in NEET status between 2011 and 2016 is strongly associated with changes in disability status, education attainment, household composition, housing condition, residential remoteness, and local socioeconomic status. Together, the findings suggest creating disability-inclusive working and training environments, improving housing conditions and addressing locational disadvantages will be instrumental in tackling the NEET problem among young Indigenous Australians.

The study sheds further light into the literature in different ways. To the best of our knowledge, this is the first study to show the distribution of NEET spells by local socioeconomic status. It is also the first paper to apply a fixed-effects estimation to a nationally representative sample of Indigenous youth. Moreover, the study is the only longitudinal analysis of the dynamics of Indigenous NEET spells.

2. Literature Review

A multitude of factors could be responsible for the participation of young people in employment, education, or training. Being NEET could be related to poor health, growing up in low-income families, residing in disadvantaged neighbourhoods, or a combination of these and other factors. While it is scanty and highly descriptive, the existing literature in Australia suggests that the NEET group consists of young people with diverse characteristics. The Australian Workforce and Productivity Agency (AWPA) uses data from the 2011 Census and profiles the background characteristics of 15-24 year olds who are NEETs. The study finds higher NEET rates for people with Indigenous background and who have poor English (AWPA 2014). Carcillo *et al.* (2015), drawing on data from the Labour Force Survey and the Household, Income and Labour Dynamics in Australia (HILDA), note that 16-29 year olds who are single parents, live with poor health conditions, have low levels of education and were born to less-educated parents are at a greater risk of falling into the NEET category. Similarly, a study by the OECD uses data from the HILDA Survey for people aged 15-29 years and shows that NEET youth are characterised by being female, being a parent, having a disability, being an Indigenous person or having a migrant background, low vehicle ownership, low levels of education, having less-educated parents and having a broken family (OECD 2016).

Using data from the 1995 wave of the Longitudinal Surveys of Australian Youth (LSAY), Hillman (2005) shows that young people (15-24 year olds) are more likely to become NEETs for up to 13 months if they perform poorly at secondary school, do not have a Year 12 completion certificate, live with a disability and are from culturally diverse backgrounds. The author also shows that NEET status is more prevalent among females, married individuals, and those with children. Stanwick, Forrest and Skujins (2017) use data from the 2003 and 2006 waves of the LSAY and apply logistic regression to identify the factors associated with becoming persistently NEET (i.e., a NEET spell lasting for at least six months). They show that prolonged NEET status is positively associated with being female, having children at the age of 15-19, not completing Year 12, being Indigenous and living in low socioeconomic status communities.

Some issues are worth noting regarding inconsistencies in the literature. Firstly, despite the youth population being defined as people aged 15-24 years in much of the literature on youth disengagement, OECD (2016) and Carcillo *et al.* (2015) include 25-29 year olds in their analysis. Secondly, typically NEET indexes include unemployed people and those not in the labour force if they are not attending an educational institution at a particular point in time. However, the analysis by Hillman (2005) includes only those who are not in the labour force and not in full-time education. Thirdly, except Stanwick, Forrest and Skujins (2017), who use a logit model, all the studies only use cross-tabulations to present NEET rates among various sociodemographic groups such as females, males, Indigenous and non-Indigenous youth. While such studies are vital in informing how a particular youth group fare relative to others in terms of vulnerability to NEET spells, they are limited in providing insights into the reason why the group is at a higher risk of falling into NEET than others. For instance, many of the above studies show that NEET is more prevalent among Indigenous than non-Indigenous youth. However, they do not confirm whether the Indigenous/non-Indigenous gap is inherent to indigeneity or driven by differences in socioeconomic characteristics (such as health, education and wealth) that coexist with indigeneity differences.

One of the key advantages of a regression analysis over a descriptive analysis is that it allows one to examine whether Indigenous youth still have higher NEET rates once other attributes are taken into consideration. This study builds on the existing literature by using a NEET index that is consistent with definitions used in the broader literature and by employing regression models that control for both observed and unobserved differences in individual, family and community circumstances.

3. Data

Our data come from the 2011-2016 Australian Census Longitudinal Dataset (ACLD), which links a representative five per cent sample from the counts in the 2011 Census with corresponding populations in the 2016 Census. There is also a dataset that links a representative five per cent sample from the 2006 Census with corresponding counts in the 2011 and 2016 censuses. However, the 2006 and 2016 samples cannot be used together as individuals who were part of the youth population (15-24 year olds) in

2006 were already in their prime working years (25-34 year olds) in 2016. We choose the 2011-2016 ACLD over the 2006-2011 ACLD since the quality of data linkage is better (and the rate of sample attrition is lower) in the former than the latter.

Though there were minor differences in questionnaire design between the 2011 and 2016 censuses, the way our variables of interest were measured is predominantly the same, and we can observe meaningful longitudinal transitions in the data (see ABS (2019) for more information). It is worth noting, however, that there were some changes in Indigenous status among the linked sample over the period 2011-2016. Of those who were identified as being Indigenous in 2011, 11.3 per cent were identified as being non-Indigenous and 0.53 per cent had not stated Indigenous status in 2016. Of those identified as being non-Indigenous in 2011, 0.58 per cent identified as being Indigenous and 0.61 per cent were unidentified in 2016. Of those who did not state Indigenous status in 2011, 94.6 per cent stated being non-Indigenous, and a further 3.2 per cent stated being Indigenous in 2016.[1] To account for unobserved heterogeneities that lead to inconsistent reporting of one's Indigenous identity, we define the Indigenous population as any individual who was recorded as Indigenous in any of the censuses. This leaves us with about 4,005 observations.

The 2011-2016 ACLD provides a unique opportunity to examine the dynamics of Indigenous youth disengagement from employment, education or training and to identify the factors underlying overtime changes in disengagement status. Although surveys such as the LSAY and HILDA also provide longitudinal samples of the general youth population in Australia, to our knowledge, the ACLD provides the most representative and largest longitudinal sample of Indigenous Australians. It also contains information on a range of relevant topics to our study, such as labour force status, education, health, demography, housing condition, household composition, remoteness, and local socioeconomic status. Table A1 presents a list of relevant background characteristics included in the study.

We use the information provided on individual-level labour force participation (full-time employed, part-time employed, unemployed and not in the labour force) and attendance at educational institutions (full-time student, part-time student and not-attending) on the census night to compute a composite index measuring non-participation in education, employment or training. The NEET variable equals one if a person is non-employed (either unemployed or not in the labour force) and not attending an educational institution, otherwise equals zero. The longitudinal data used in this study show that the NEET prevalence increased from 23.6 per cent to 37.2 per cent between 2011 and 2016. The low NEET rate in 2011 was perhaps because the majority of young people in the sample were required to attend compulsory education.

1 It is worth noting that although people are changing their identity from Indigenous to non-Indigenous at a higher rate (11.3 per cent) than those changing from non-Indigenous to Indigenous (0.53 per cent), because of the large non-Indigenous population size, the number of people switching to an Indigenous identity is over threefold the number switching to a non-Indigenous identity, resulting in a net increase in the number of people who identified as Indigenous over the period 2011-2016.

Our data show 68 per cent of 15-19 year olds are in education compared with only 16 per cent of 20-24 year-olds.[2]

Table A2 presents summary statistics for background characteristics included in the empirical analysis. We note discernible differences in some of the characteristics both cross-sectionally and longitudinally. Cross-sectional comparisons show that a higher proportion of NEETs than non-NEETs live in households where a language other than English is spoken and where at least one household member is non-employed or has a disability. NEETs are also more likely than non-NEETs to live in remote and economically least advantaged areas. On the other hand, a higher percentage of non-NEETs than NEETs undertake voluntary work, live in major cities and live in households with at least one employed member. Between 2011 and 2016, the proportion of young people who were married, with non-school qualifications and who live in households with a Year 12 completed increased substantially. On the other hand, the proportion of NEETs and non-NEETs who live in crowded homes and in households with a non-employed member decreased over the same period.

4. Empirical Approach

The study uses both descriptive (cross-tabulations and graphical presentations) and regression analyses techniques. The former aims to profile the socio-demographic characteristics of NEET youth, whereas the latter aims to examine the factors underlying the incidence and recurrence of NEET spells. In particular, we use fixed-effects regression models to identify the factors that induce an overtime change in NEET status at an individual level. We also use ordered logit models to examine the background characteristics associated with intercensal persistence in NEET status. The descriptive analyses use data from the ABS's TableBuilder and are based on the youth population aged 15-24 years in each relevant census. The regression analyses draw on data from the five per cent sample available in the ABS's DataLab and are restricted to people aged 15-19 years in 2011.

We presume that no single factor is solely responsible for a person's non-participation in education, employment or training and would expect an array of factors to be at play. As indicated in Section 3, the 2011-2016 ACLD includes a wealth of information on potential determinants of NEET status (presented in Table A1). However, individuals may also differ in certain characteristics that we cannot fully observe in the data, and some of the unobserved characteristics may correlate with observed characteristics and NEET status.

2 However, high rates of participation in compulsory education do not necessarily signify regular class attendance by students. Quicke and Biddle (2017) show that irregular class attendance among Indigenous students remain a public policy concern and suggest various policy options to address the problem.

Suppose NEET status of an individual i at time t is determined as follows:

$$NEET_{it} = 1[X'_{it}\beta + \theta_i + \varsigma_{it}] > 0$$

Here, 1[.] is a binary function; $NEET_{it}$ equals one if the person is NEET, otherwise equals zero; X_{it} includes unity and a vector of observable covariates; β is a set of parameters corresponding to X_{it}; θ_i represents time-invariant unobserved effects and; ς_{it} is an error term.

The usual approach to deal with the presence of unobservable differences in panel data models is to use either a fixed-effects or a random-effects estimator. The former allows X_{it} and θ_i to be correlated and produces consistent estimates for β. However, it computes the estimates with a great deal of variation from sample-to-sample and a lesser precision than the latter. The fixed-effects estimator does not allow the estimation of parameters of useful time-invariant observables such as sex. A random-effects estimator does not allow a correlation between X_{it} and θ_i and will produce inconsistent estimates if the unobservables are not randomly distributed. However, it greatly limits the variability of the estimation and gives estimates that are closer, on average, to the true value in a given sample. It also allows the estimation of parameters of interest for time-invariant observables. We use a Hausman test to check whether the fixed-effects model is preferred to the random-effects model. The test rejects the null hypothesis (at Chi2 (22) =1,066.85) in favour of the fixed-effects model.

Notwithstanding the binary nature of the outcome variable, we use a linear fixed-effects model as a benchmark specification. Linear fixed-effects models have some advantages over non-linear variants. Firstly, the estimation of marginal effects is straightforward, and the results are easy to interpret. Secondly, they are more efficient than non-linear fixed-effects estimators, such as the conditional logit models. A conditional logit model drops observations whose value does not switch between 0 and 1 across time and results in a significant reduction in the sample size and degree of precision. The use of a conditional logit model would reduce our sample by 37 per cent.[3]

In our fixed-effects model, identification of the estimates of β comes from the within-individual variation in the time-varying observables. Thus, the consistency of the estimated coefficients rests on the assumption that θ_i is the only source of unobserved heterogeneity. The identifying assumption is that, once we control for all observables and time-invariant unobservables, any change in the observed characteristics is assumed to be exogenous to non-participation in education, employment, or training. The assumption could be violated if there are unobserved time-varying factors driving NEET status that also correlate with X_{it}. Although we cannot be certain what kinds of factors these would be, they would include policies (such as job and training compacts) enacted after the 2011 Census. To bolster the validity of our identifying assumption, we control for several observable characteristics (listed in Table A1) along with a time-dummy to capture census-to-census variations in unobserved factors.

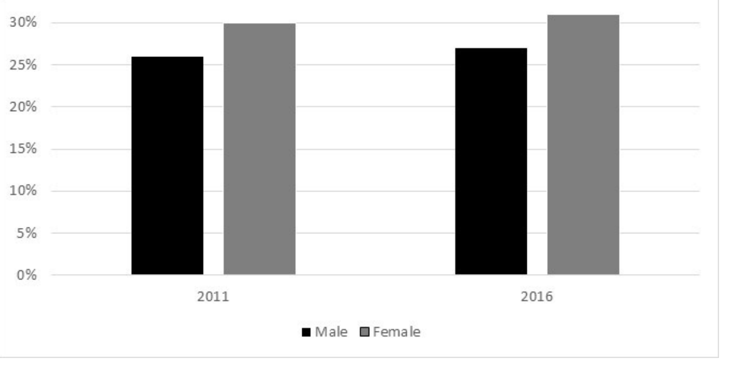
3 Our model assumes linear relationships between the covariates and the outcome of interest despite statistical relationships between a binary outcome and continuous variables (such as age) are generally non-linear. Therefore, we would like to alert readers that our specification may result in biased coefficient estimates and predicted probabilities that fall below zero or over 100 per cent.

5. Results

Descriptive analysis

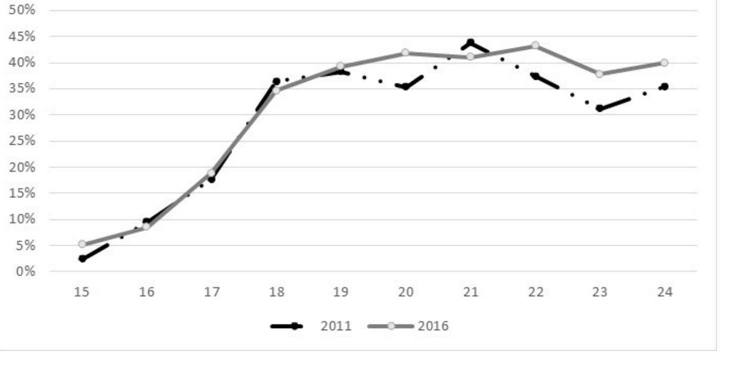
This subsection provides a brief analysis of the profile of NEET youth. Figure 1 shows NEET rates for males and females. NEET is more prevalent among females than males. In 2011, 30 per cent of females were NEET compared with 26 per cent males. For both sexes, NEET prevalence increased by one percentage point between 2011 and 2016.

Figure 1. NEET status by gender



Source: The 2011-2016 ACLD TableBuilder (ABS, 2019).

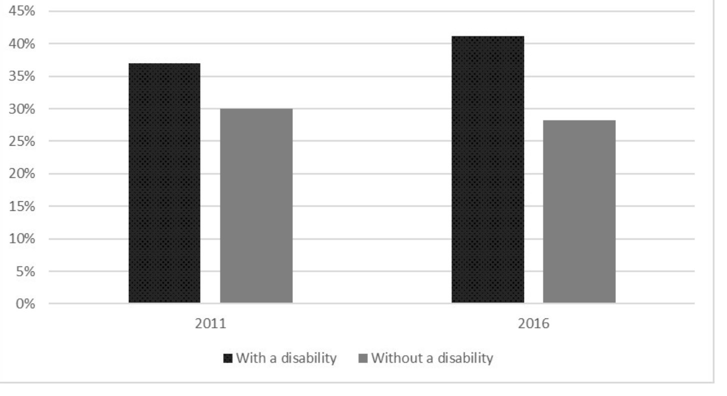
Figure 2. NEET rates by age



Source: The 2011-2016 ACLD TableBuilder (ABS, 2019).

We see in Figure 2 an overall increase in NEET prevalence rates with age. The NEET prevalence in 2011 increased from two per cent for young people aged 15 years to ten per cent for those aged 16 years, and doubled between the ages of 17 and 18 years. While remaining high, the rate zigzagged at the older age brackets with 39 per cent prevalence among 19 year olds and then falling to 35 per cent for 20 year olds before going up to 44 per cent for 21 year olds and dropping back to 31 per cent among 23 year olds and going up again to 35 per cent for 24 year olds. The prevalence in 2016 trended in a similar fashion along with the age profile. The low NEET rates at younger age brackets could be due to youth activation policies in Australia which require young people to be in full-time education, training or employment or a combination of these activities until they turn 17 years (COAG, 2009).

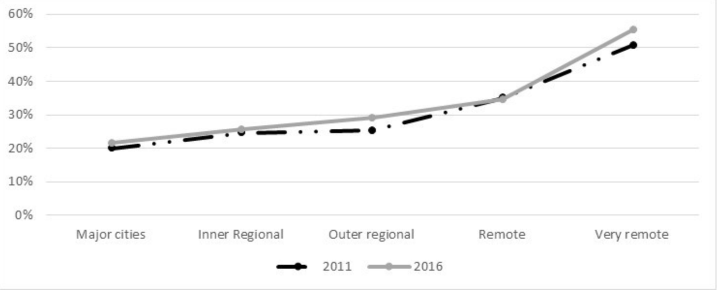
Figure 3. NEET prevalence by disability status



Note: Disability status is defined based on needs for assistance with core activities. People who have reported having needs for assistance with core activities are considered as having a disability.
Source: The ACLD 2011-2016 TableBuilder (ABS, 2019).

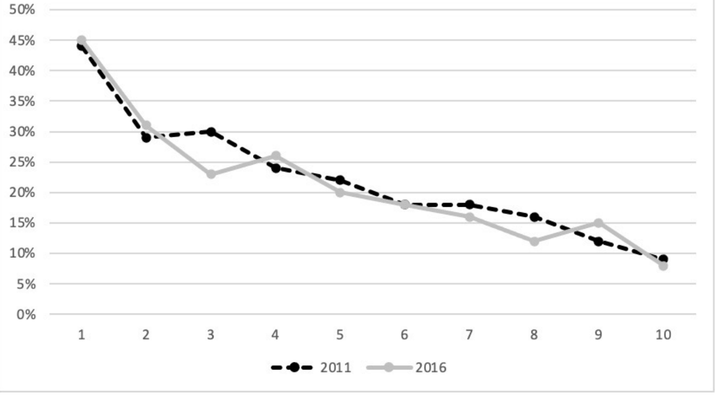
Figure 3 provides NEET prevalence for people who need assistance with core activities and those who do not need assistance. We note that NEET rates are higher among people who need assistance with core activities. The gap almost doubled between 2011 and 2016 (from 7 to 13 percentage points), as the prevalence rate increased substantially for people having disabilities while it fell slightly for those without disabilities. In Figure 4, we depict NEET prevalence rates by geographic remoteness. We note that the risk of falling into NEET increases with remoteness. Over 50 per cent of Indigenous youth who live in very remote areas are NEETs compared with 39 per cent in remote areas, about 26-29 per cent in regional areas and nearly 20 per cent in major cities.

Figure 4. NEET status by remoteness



Source: The 2011-2016 ACLD TableBuilder (ABS, 2019).

Figure 5. NEET prevalence by local socioeconomic status



Source: The 2011-2016 ACLD TableBuilder (ABS, 2019).

We also explore the distribution of NEET prevalences by areas' relative advantages and disadvantages in accessing economic resources, see Figure 5. The ACLD provides a composite index called 'The Index of Economic Resources' that uses household income and wealth and ranks areas in Australia according to relative accesses (or lack of accesses) to economic resources. In the figure, for example, the low deciles represent the presence of many households in the area earning a low income or without house ownership and the high deciles represent many households earning a high income or owning houses. NEET rates fall as access to economic resources improves. In other words, NEET spells are more prevalent in areas where there are fewer households with high income or home ownership. NEET rates are five times higher in economically most disadvantaged areas (Decile 1) than in least disadvantaged areas (Decile 10).

From a policy perspective, the recurrence of NEET spells is also worth discussing. Though we would generally expect most young people to have at least one short NEET spell (up to six months) at some point in time, especially during transitions between education (training) and employment, only a few of them are expected to experience recurring or persistent NEET spells. To get a better insight into the challenges that young people are facing while navigating education and employment pathways, we explore rates of intercensal transition between NEET and non-NEET status. Table A3 shows the NEET recurrence between 2011 and 2016. We note that the rates of transition into and out of the NEET category are similar (34 versus 33 per cent), and the majority (67 per cent) of those who experienced NEET spells in 2011 were also NEETs in 2016.

Regression results

Before proceeding to the main regression results, it is worth noting that about 30 per cent of the young people with records in the 2011 Census do not have linked data to records from the 2016 Census. In traditional longitudinal datasets, a sample attrition (a reduction in sample size) occurs when study participants refuse or are unavailable to provide information. And sample attrition may cause an estimation bias if factors that drive the attrition correlate with outcome variables. In the case of the ACLD, however, the reduction in sample size is likely to be caused by lack of matching identifiers across censuses. Even if we expect this to be independent of individuals' characteristics, we follow Fitzgerald, Gottschalk, and Moffitt (1998) and estimate a logit model of attrition and examine whether the reduction in sample size in 2016 is associated with observable characteristics (including NEET status) in 2011. Table A4 shows that attrition is positively associated with age, disability status and completing Year 12, but negatively correlated with disability status of other household members and their Year 12 completion status. We do not find a significant association between NEET status and attrition. Since our model controls for those characteristics significantly associated with attrition, we do not expect attrition bias to confound our results.

Table 1 presents results from two alternative panel data models. Though our preferred results are those obtained with a fixed-effects specification, we also present results obtained with a random-effects model for the sake of completeness. Looking into the results from the random-effects model, almost all the covariates are significantly associated with NEET status. However, the coefficient estimates tend to be biased for the reasons discussed in Section 4. We see a substantial change in the statistical significance and magnitude of the estimated coefficients when we control for fixed effects.

Table 1. Results from panel data models

Variable	*Random-effects Model*		*Fixed-effects Model*	
	Coef.	*SE*	*Coef.*	*SE*
Age	0.070 *	0.005	0.081	0.068
Female	0.017	0.013		
Married	-0.025	0.021	-0.029	0.034
Living with a disability	0.203 *	0.038	0.260 *	0.101
Speaks other than English	0.051	0.029	-0.067	0.084
Changed usual address	0.003	0.002	0.001	0.001
Year 12 or equivalent	-0.090 *	0.019	0.048	0.034
Certificate level	-0.179 *	0.023	-0.010	0.039
Diploma/Advanced diploma	-0.296 *	0.042	-0.157 *	0.067
Bachelor degree or higher	-0.350 *	0.037	-0.085 *	0.049
Voluntary work	-0.027	0.018	0.010	0.032
Children aged 0-4	0.127 *	0.018	0.150 *	0.035
Children aged 5-14	-0.003	0.014	-0.041	0.027
Anyone else with disability	0.003	0.021	0.020	0.042
Anyone else completed Year 12	-0.060 *	0.016	-0.039	0.034
Anyone else employed	-0.150 *	0.018	-0.129 *	0.038
Anyone else non-employed	0.044 *	0.014	-0.030	0.027
Ethnically mixed household	-0.041 *	0.013	-0.027	0.026
No extra bedroom needed	-0.103 *	0.020	-0.084 *	0.041
Spare bedrooms	-0.110 *	0.020	-0.140 *	0.042
Regional areas	0.018	0.014	0.049	0.054
Remote areas	0.027	0.025	0.122 *	0.085
Local economic resources	-0.016 *	0.002	-0.017 *	0.006
2016 dummy	-0.111 *	0.027	-0.238	0.343
_cons	-0.678 *	0.091	-0.102	0.163
Number of observations	4,005		-0.102	
rho	0.112		0.530	

Note: Coef. refers to coefficients; SE stands for standard error; * statistically significant at the five per cent level.

In looking at the results from our benchmark specification, we note that having needs for assistance with core activities is associated with a 26 percentage point increase in a person's probability of being in a spell of NEET. While people with a severe or profound disability may be permanently unable to work or study, those with a mild or moderate disability may require special assistance (such as mobility and communication aids) to maintain attachment with the labour market or the education system. Thus, the under-provision of such services may result in youth inactivity. Young people with disability may also find it difficult to work or attend educational institutions due to marginalisation by employers and education providers (Cumming and Dickson, 2013).

Living in households with young children (0-4 year olds) also increases the likelihood of falling into NEET by 15 percentage points. This could be because childcare services are inadequate, unaffordable, or poor quality so that families have to resort to home caring for their children. Living in remote areas is also associated with a 12 percentage point increase in the probability of being in a spell of NEET. This is likely to be associated with the scarcity of appropriate employment and training opportunities in those areas.

On the other hand, the probability of being a NEET falls with educational attainment. People with a diploma or advanced diploma and a bachelor degree or higher are 15.7 and 8.5 percentage points, respectively, less likely to experience a spell of NEET. A possible explanation is that higher levels of education provide better employment prospects for Indigenous youth (Birch and Marshall, 2016). We also find that the presence of an employed household member reduces a person's probability of being NEET by 12.9 percentage points. This is because family members with successful labour market engagements might have had a positive influence on young people's perception of the value of education and employment (Hunter and Gray, 2001). The likelihood of falling into NEET is also lower among Indigenous youth who live in uncrowded homes. Youth who live in a house with a sufficient number of bedrooms and those who live in a house with at least one spare bedroom are 8.4 and 14 percentage points, respectively, less likely to be in a spell of NEET than those who live in a house where extra bedrooms are needed. Evidence shows that uncrowded housing provides young people with sufficient space to do homework, study, socialise, practice skills and have quiet time for personal development (Goux and Maurin, 2005; Solari and Mare, 2012) which could translate into enhanced school progression and employability. It is worth mentioning, however, that the observed relationship could be a result of unobserved correlations between uncrowded housing and other household circumstances (such as wealth and income) that positively impact on personal development and economic engagement.

We also find that the economic engagement of Indigenous youth increases with the improvement of local economic conditions. A one decile increase in area-level socioeconomic status is associated with a one percentage point decline in a person’s probability of being NEET. Improvement in local economic conditions could mean that new employment and training opportunities are opening up for young people.

In Section 3, we show that a significant share of our sample changed their Indigenous status between the 2011 and 2016. We restrict the sample to people whose identity was recorded as Indigenous in both censuses to check if our results remain robust. Table A5 shows that the results obtained with the restricted sample are generally consistent with estimates of the full sample.

As reported in Table A3, more than two-thirds of Indigenous youth who were NEETs in 2011 were also NEETs in 2016. Prior research shows that persistently NEET youth are more at risk than those experiencing short NEET spells (Crawford *et al.*, 2011; Samoilenko and Carter, 2015). Unfortunately, the ACLD does not provide data on the length of NEET spells, but shows whether or not a person’s NEET status changed between the 2011 and 2016 censuses. We compute a categorical variable defined as never if the person did not experience a spell of NEET in both 2011 and 2016; ever if the person experienced a spell of NEET either in 2011 or 2016 and; always if the person experienced a spell of NEET in both 2011 and 2016.[4] We use ordered logits (as the variable is coded with increasing order of NEET recurrence) to identify the factors underlying NEET persistence. Results are presented in Table 2. Young people in older age brackets and those who have a disability, live with young children (0-4 year olds) and reside in remote areas are more likely to be NEET in both time periods. On the other hand, those whose highest levels of education are Year 12 and Certificates are less likely to be recurrently NEET. So are those who live in uncrowded homes. The probability of being recurrently NEET also falls with the improvement of local economic conditions.

Table 2. Factors associated with NEET recurrence

Variable	*Never*		*Ever*		*Always*	
	AME	*SE*	*AME*	*SE*	*AME*	*SE*
Age	-0.062 *	0.008	0.033 *	0.004	0.039 *	0.004
Female	-0.020	0.020	0.011	0.010	0.010	0.009
Married	-0.076	0.050	0.040	0.030	0.036	0.023
Living with a disability	-0.038 *	0.052	0.076 *	0.028	0.068 *	0.025
Speaks other than English	-0.038	0.042	0.020	0.022	0.018	0.020
Year 12 or equivalent	0.104 *	0.045	-0.055 *	0.017	-0.049 *	0.015
Certificate level	0.201 *	0.045	-0.106 *	0.024	-0.094 *	0.021
Voluntary work	0.023	0.032	-0.012	0.017	-0.011	0.015
Children aged 0-4	-0.100 *	0.027	0.053 *	0.015	0.047 *	0.013
Children aged 5-14	-0.015	0.021	0.008	0.011	0.007	0.010
Anyone else with disability	-0.036	0.031	0.019	0.016	0.017	0.014
Anyone else completed Year 12	0.046 *	0.024	-0.025 *	0.013	-0.022 *	0.011
Anyone else employed	0.160 *	0.025	-0.085 *	0.014	-0.075 *	0.012
Anyone else non-employed	-0.094	0.023	0.050	0.010	0.043	0.012
Ethnically mixed household	0.008	0.022	-0.004	0.012	-0.004	0.010
No extra bedroom needed	0.073 *	0.022	-0.034 *	0.015	-0.034 *	0.013
Spare bedrooms	0.077 *	0.029	-0.041 *	0.016	-0.036 *	0.014
Regional areas	-0.006	0.022	0.003	0.020	0.002	0.010
Remote areas	-0.117 *	0.037	0.062 *	0.020	0.055 *	0.018
Local economic resources	0.018 *	0.004	-0.009 *	-0.002	-0.009 *	0.002
Number of observations	1,644		1,644		1,644	

Note: AME refers to average marginal effects; SE stands for standard error; * statistically significant at the five per cent level. Highest levels of education such as 'Diploma and advanced diploma' and 'Bachelor degree or higher' are dropped from the models due to a very small number of observations.

4 Previous studies use the term 'persistently NEET' to refer to people who experienced a spell of NEET for an extended period of time (usually for over six months). This paper uses term 'recurrently NEET' not to rule out the possibility that those who were NEETs in 2011 may have worked or attended an educational institution before experiencing another spell of NEET in 2016.

6. Conclusion

Using data from the 2011-2016 ACLD, this study provides in-depth profiling of the characteristics of Indigenous NEET youth and examines the factors driving individual-level overtime changes in NEET status. Descriptive results show that NEET is more prevalent among females and young people at older age brackets. Young Indigenous Australians with disabilities and those who live in remote and low socioeconomic status areas also have higher rates of NEET.

Regression results show that individual, household, and local circumstances constitute important factors in explaining the underlying NEET status. In particular, results obtained with a fixed-effects regression show that a young Indigenous person (aged 15-24 years) is more likely to experience a spell of NEET if they experience a disability, live in households with young children (0-4 year olds) and migrate to remote areas. However, their probability of being in a spell of NEET significantly decreases if they obtain a diploma or higher qualification, live in an uncrowded home, someone else in the household is employed, and the economic condition of their area of residence improves.

We also show a strong persistence of NEET status among Indigenous youth, with 67 per cent of the NEETs in 2011 remaining as NEET five years later. Results obtained with ordered logit show that Indigenous youth at older age brackets, with disabilities, from remote and low socioeconomic status areas and who live in crowded homes and with young children are at a higher risk of being recurrently NEET.

Our findings provide key policy insights. While imposing minimum school-leaving ages and mutual obligation requirements could deter inactivity among young people resisting employment and education opportunities (COAG, 2009), a particular policy concern should be directed at providing appropriate supports to those who live in disadvantaged circumstances. Therefore, programs that aim to alleviate the NEET problem among Indigenous youth should:

- create disability-inclusive employment, education, and training environments;
- provide childcare services that are affordable and that meet the needs of Indigenous children and their families;
- improve housing conditions ;and
- address geographic disadvantages in employment and education opportunities.

We want to acknowledge that our analysis does not distinguish between NEETs who are unemployed and those who are not in the labour force. Given that the degree of disengagement from the labour market is different for the two NEET groups, young people in the former group actively seek employment while those in the latter group do not want work or are unable to do so. In future work, we hope to use a larger dataset that will enable us to explore whether different factors are at play for the two NEET categories.

Appendix

Table A1. Variable definition

Variable	*Definition*
NEET	1 if experiences a spell of NEET; 0 otherwise
Age	Age of person in years
Female	1 if female; 0 if male
Married	1 if legally married or lives in a de facto relationship; 0 otherwise
Living with a disability	1 if has needs for assistance with core activities; 0 if does not have need for assistance
Speaks other languages	1 if speaks languages other than English at home; 0 if speaks only English at home
Changed usual address	1 if has changed usual residential address within five years prior the census; 0 otherwise
Level of highest education attained	1 if Year 11 or below; 2 if Year 12 or equivalent; 3 if Year 12 or equivalent; 4 if Diploma/advanced diploma; 5 if Bachelor degree or higher
Voluntary work	1 if does voluntary work for an organisation or group; 0 otherwise
Children aged 0-4	1 if children aged 0-4 years live in the household; 0 otherwise
Children aged 5-14	1 if children aged 5-14 years live in the household; 0 otherwise
Anyone else with disability	1 if anyone else in the household has needs for assistance with core activities; 0 otherwise
Anyone else completed Year 12	1 if the highest year of school completed any household member is Year 12; 0 if the highest year of school completed is Year 11 or below
Anyone else employed	1 if there is an employed household member; 0 otherwise
Anyone else non-employed	1 if there is non-employed household member; 0 otherwise
Ethnically mixed household	1 if Indigenous and non-Indigenous household members live in the house; 0 if all household members are Indigenous
Housing utilisation	1 if extra bedroom is needed; 2 if no extra bedroom is needed; 3 if spare bedrooms available in the house
Remoteness	1 if lives in major cities; 2 if lives in regional areas; 3 if lives in remote and very remote areas
Index of economic resources	This is a ranking of areas (in deciles) in Australia according to relative access and lack of access to economic resources. Low deciles signify the presence of many households in the area earning low income or without house ownership and high deciles signify many households earning high income or owning houses.

Table A2. Summary statistics

	2011				*2016*			
	NEET		*Non-NEET*		*NEET*		*Non-NEET*	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Age	17.704	1.147	16.600	1.368	21.921	1.373	21.940	1.387
Female	0.501	0.500	0.473	0.499	0.529	0.499	0.469	0.499
Married	0.096	0.295	0.027	0.163	0.224	0.416	0.235	0.424
Living with a disability	0.041	0.198	0.033	0.178	0.093	0.290	0.013	0.114
Speaks other languages	0.174	0.379	0.092	0.289	0.183	0.387	0.053	0.225
Changed usual address	0.089	0.285	0.065	0.248	0.085	0.280	0.070	0.256
Year 11 or below	0.758	0.289	0.717	0.451	0.556	0.497	0.189	0.384
Year 12 or equivalent	0.184	0.388	0.210	0.407	0.290	0.454	0.396	0.389
Certificate level	0.056	0.229	0.071	0.257	0.131	0.337	0.292	0.455
Diploma/Advanced diploma	0.003	0.050	0.002	0.045	0.014	0.118	0.056	0.233
Bachelor degree or higher	0.000	0.000	0.001	0.020	0.009	0.094	0.075	0.264
Voluntary work	0.082	0.275	0.142	0.349	0.076	0.265	0.173	0.378
Children aged 0-4	0.355	0.479	0.161	0.367	0.431	0.496	0.170	0.375
Children aged 5-14	0.500	0.500	0.520	0.500	0.376	0.485	0.177	0.382
Anyone else with disability	0.194	0.396	0.149	0.356	0.229	0.420	0.100	0.300
Anyone else completed Year 12	0.370	0.483	0.525	0.499	0.530	0.499	0.806	0.395
Anyone else employed	0.518	0.500	0.753	0.430	0.480	0.500	0.783	0.412
Anyone else non-employed	0.810	0.392	0.587	0.492	0.711	0.454	0.420	0.494
Ethnically mixed household	0.343	0.475	0.489	0.500	0.365	0.482	0.605	0.489
Extra bedroom needed	0.426	0.495	0.204	0.403	0.325	0.469	0.131	0.338
No extra bedroom needed	0.244	0.430	0.319	0.466	0.292	0.455	0.293	0.455
Spare bedrooms	0.329	0.470	0.477	0.500	0.383	0.486	0.576	0.494
Major cities	0.295	0.456	0.400	0.490	0.341	0.474	0.513	0.500
Regional areas	0.417	0.493	0.460	0.498	0.415	0.493	0.396	0.489
Remote areas	0.287	0.453	0.140	0.347	0.244	0.430	0.091	0.287
Local economic resources	2.730	2.310	4.200	2.858	2.873	2.364	4.511	2.822

Note: The data are for unbalanced panel of 4005 observations; SD stands for standard deviation.
Source: The 2011-2016 ACLD DataLab

Table A3. Recurrence in NEET status

2011	*2016*	
	Non-NEET	*NEET*
Non-NEET	66%	34%
NEET	33%	67%

Source: The 2011-2016 ACLD TableBuilder (ABS 2019).

Table A4. Determinates of sample attrition

Variable	*AME*	*SE*
NEET	0.002	0.006
Age	0.017 *	0.007
Female	0.003	0.006
Married	-0.003	0.006
Living with a disability	0.169 *	0.044
Speaks other than English	-0.002	0.008
Changed usual address	0.001	0.001
Year 12 or equivalent	0.145 *	0.044
Certificate level	0.006	0.012
Voluntary work	0.000	0.000
Children aged 0-4	-0.004	0.007
Children aged 5-14	-0.011	0.006
Anyone else with disability	-0.153 *	0.041
Anyone else completed Year 12	-0.147 *	0.041
Anyone else employed	0.005	0.007
Anyone else non-employed	0.017	0.011
Ethnically mixed household	-0.001	0.008
No extra bedroom needed	-0.001	0.006
Spare bedrooms	-0.003	0.009
Regional areas	0.008	0.009
Remote areas	0.022	0.011
Local economic resources	-0.001	0.002
Number of observations	2,434	

Note: AME refers to average marginal effect; SE stands for standard error;
* statistically significant at the five per cent level.

Table A5. Estimates for a subsample of young people whose identity recorded as Indigenous in both 2011 and 2016

Variable	*Random-effects Model*		*Fixed-effects Model*	
	Coef.	*SE*	*Coef.*	*SE*
Age	0.058 *	0.007	0.055	0.083
Female	0.011	0.015		
Married	-0.026	0.027	-0.034	0.043
Living with a disability	0.201 *	0.052	0.222 *	0.121
Speaks other than English	0.068	0.036	-0.077	0.095
Changed usual address	0.002	0.002	0.001	0.001
Year 12 or equivalent	-0.084 *	0.026	0.074	0.043
Certificate level	-0.176 *	0.030	-0.018	0.049
Diploma/Advanced diploma	-0.255 *	0.026	-0.169 *	0.079
Bachelor degree or higher	-0.312 *	0.056	-0.074	0.081
Voluntary work	-0.044	0.024	0.029	0.039
Children aged 0-4	0.139 *	0.023	0.149 *	0.039
Children aged 5-14	0.002	0.018	-0.062	0.033
Anyone else with disability	0.014	0.029	0.011	0.050
Anyone else completed Year 12	-0.058	0.021	-0.046	0.040
Anyone else employed	-0.173 *	0.027	-0.168 *	0.042
Anyone else non-employed	-0.037 *	0.018	-0.032	0.032
Ethnically mixed household	-0.063 *	0.020	-0.029	0.046
No extra bedroom needed	-0.085 *	0.026	-0.081 *	0.040
Spare bedrooms	-0.126 *	0.027	-0.156 *	0.048
Regional areas	0.027	0.087	0.073	0.070
Remote areas	0.010	0.032	0.269 *	0.131
Local economic resources	0.015 *	0.003	-0.015 *	0.007
2016 dummy	-0.132 *	0.060	-0.118 *	0.417
_cons	-0.471 *	0.118	-0.394	1.421
Number of observations	3,289		3,289	
rho	0.050		0.531	

Note: Coef. refers to coefficient; SE stands for standard error; * statistically significant at the five per cent level.

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Analysis of gender segregation within detailed occupations and industries in Australia

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Abstract

This study provides new and detailed estimates of gender segregation in the Australian labour market. Using ABS Labour Force Survey and Census data, we explore and decompose long-term trends of segregation and integration by employing a shift-share analysis and index measures across time, age and space. We find that over the last three decades, gender segregation has not significantly changed across either industries or occupations. Gender segregation across industries is, in general, more resistant to gender integration than across occupations and detailed classifications are profoundly more segregated than top-level classifications. Additionally, gender segregation increases as individuals get older and the farther they work from urbanised locations. We show that decades of gender equality policy have not had a major impact on minimising labour market segregation. Women continue to have more constrained labour supply choices than men, hindering labour market efficiency and flexibility.

JEL Codes: J16, J20, J21, J24, J30, J70
Keywords: employment, gender, occupational segregation, industrial segregation

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1. Introduction

Perhaps the biggest change to Australia's labour force in the past century is who does the work. Only 43 per cent of women participated in the labour market in 1989; 30 years later, this has risen to 61 per cent. In that time, the female share of total employment has gone from 36 per cent to 47 per cent.[1] Women now make up close to half of all workers in Australia.

These shifts have coincided with major reforms to the institutions, laws and incentives that shape the working lives of men and women. The federal Equal Pay cases of 1969–1975, *Sex Discrimination Act 1984*, *Affirmative Action (Equal Employment Opportunity for Women) Act 1986*, various child care payments, the *Paid Parental Leave Act 2010* and the introduction of flexible working provisions have all contributed to the higher rate of female participation. Despite this, analysis into the gender makeup of the labour market has found that gender segregation remains stubbornly persistent throughout the Australian labour market (Gregory and Duncan, 1981; Kidd and Meng, 1997; Lee and Miller, 2004).

Gender segregation exists when the mix of men and women in certain jobs does not match the gender balance of the overall labour force. It includes segregation across occupations and industries, working hours (with more women working part-time than men) and in the job hierarchy (with men occupying the lion's share of senior positions, also known as vertical segregation). This has been the subject of renewed policy attention, with a recent Australian Government *Strategy to Boost Women's Workforce Participation* (Department of the Prime Minister and Cabinet, 2017) and parliamentary inquiry (Finance and Public Administration References Committee, 2018).

Such segregation presents three key challenges to labour market and societal outcomes. Most fundamentally it constrains labour supply choices of individuals by limiting the range of jobs that are realistically available to them. Secondly, the constraint could limit women's earning potential and increase the gender wage gap (unlike the international literature, the Australia evidence is mixed on this point, Cassells *et al*. (2009) provides a summary). Thirdly, at the macro level, lesser mobility between 'male' and 'female' occupations hampers labour market efficiency and flexibility, with higher unemployment and skill gaps (Anker, 1997).

Renewed policy attention has not been met with renewed evidence. The most recent Australian sex segregation studies were conducted in the early 2000s, when signs of gender integration were minimal and slowing. Additionally, the existing literature often relies on high-level job breakdowns, understating the level of gender segregation and covers only short or discontinuous time series, which cannot show changes in segregation over time. This paper addresses these gaps using detailed occupation and industry data sourced from the Australian Bureau of Statistics (ABS) Labour Force Survey (LFS) time series, which were not available at the time of the previous studies. Our analysis uses a combination of indices and descriptive analysis to determine the extent of, and trends within, gender segregation in Australian over the last three decades.

1 Data sourced from ABS (2020) Labour Force, Australia, for persons aged 15 years and over.

The next section of this paper synthesises the literature on occupational and industrial gender segregation. The Methodology section outlines the study design, which data sets were used in analysis and the appropriate empirical methods chosen to quantify the current extent of gender segregation in Australia's workforce. The Descriptive Analysis sets out the data at broad occupation and industry classifications. The Measures of Segregation section employs a shift share analysis to decompose the increase in the female share of employment into growth and composition effects. It also measures gender segregation across time, age groups and locations using the index of dissimilarity (ID). The Conclusion summarises the findings, discusses policy implications and identifies future research directions.

2. Literature review

While the causes and consequences of gender segregation in the labour market are well documented – Anker (1998) provides the most thorough account – this paper is focussed on the measurement and change in the degree of segregation in labour markets. Segregation is often measured using various indices with Duncan and Duncan's (1955) ID being regularly used in the literature. Others include Karmel and Maclachlan's (1988) 'IP' index and the marginal matching index (MM) of Blackburn, Jarman and Siltanen (1993). We discuss the advantages and disadvantages of different indices in the Methodology section.

Australian studies provide mixed evidence on trends in segregation with most showing little or no change for over a century. Lewis (1985) conducted the longest study, with analysis back to 1891. Lewis showed the ID was largely unchanged from 1891 until the 1960s and 1970s, when segregation fell by around 8 per cent. Most of this occurred in the first half of the 1970s, with integration slowing up to 1981. Conversely, Karmel and MacLachlan (1988) found segregation actually increased slightly over 1960s and 1970s. In more recent decades, Rimmer (1991) and Lee and Miller (2004) found no change in segregation through the 1980s and early 1990s. On the other hand, Watts (2003) reports a 6 per cent reduction in segregation measures between 1986 and 2002 with the IP index.

International comparisons reveal current levels of segregation in Australia to be around average for developed economies (Blau and Khan, 1996; Jarman *et al*., 1999; OECD, 2002; Dolado, Felgueroso, and Jimeno, 2003). Segregation fell by around 20 per cent in the United States in the 1970s and 1980s, with little change since (Blau, Simpson and Anderson, 1998; Blau, Brummund and Liu, 2013). The United Kingdom also saw a rapid fall in the 1980s (Hakim, 1992). Anker (1998) and Anker, Helina and Ailsa (2003) report modest gender integration across a sample of developed countries, Latin American countries and Middle Eastern countries in the 1980s and 1990s. However, segregation was stable or increasing in some Asian countries and the transitional economies of Eastern Europe.

The OECD (2002) and Dolado, Felgueroso, and Jimeno (2003) find that the ID increases with age within several countries, including Australia. The authors suggest that segregation is falling overtime with more gender balance in successive cohorts. However, it could also suggest that segregation varies over the life course, irrespective of cohort effects. Later life events are likely to increase segregation, like having children (OECD, 2002) or marrying (Lewis, 1985). Some Australian studies have found contrary evidence, with lower levels of segregation for older workers (Lewis, 1985; Lee and Miller, 2004).

The studies above have focused on gender segregation across occupations. Very few have also considered segregation across industries. Blau and Khan (1996) reported IDs for occupations and industries for 10 industrialised countries in 1985-88. In this study, industrial segregation was considerably lower than occupational segregation (around 5-10 percentage points), with Australia reporting below average occupational segregation and average segregation for industrial segregation.

In addition to the different jobs that men and women do, the workforce is also segregated in terms of *how* men and women work. Women are more likely to be employed part-time and use flexible work arrangements, this seems to be primarily due to their cultural role of needing to balance the responsibilities of work and care. Around 46 per cent of women worked part-time in 2019, compared with 19 per cent of men.[2] The limited availability of part-time work in selected occupations and industries can reinforce patterns of gender segregation (Department of Employment, 2017). However, part-time work is becoming more gender integrated, with increasing numbers of men working part-time, and a wider distribution of part-time working arrangements across the labour market (Watts, 2003).

One key weakness of segregation studies is that many are limited to very high-level occupational breakdowns in compiling their index measures (Hakim, 1992; Jarman *et al*., 1999). This is particularly true for cross-country studies where matching of detailed occupation categories is difficult. The broad categories ignore all of the variation and gender segregation between occupations within them, and their use therefore understates the degree of segregation. For example, Preston and Whitehouse (2004) showed that 37.3 per cent of women were working in female-dominated occupations (greater than 70 per cent female) in 2002 when counting the 1 digit occupations, but the number climbed to 55.8 per cent for 2-digit occupations and 62.6 per cent for 4-digit occupations. The 'true' level of segregation is an elusive concept to measure. At a micro level, even relatively well-integrated occupations often have workers segregated by gender across firms (Blau, Simpson and Anderson, 1998).

A second issue is that (the lack of) movements in the global measure of segregation given by an index does not give any information about underlying changes in the labour market. Despite the stagnant index measures in Australia, there are many counter-balancing shifts in individual occupations. Preston and Whitehouse (2004) showed that 46 per cent of women and 34 per cent of men in Australia worked in occupations that became more gender integrated between 1996 and 2002, while 34 per cent of women worked in female-dominated jobs that became more female-dominated and 18 per cent of men worked in male-dominated jobs that became more male-dominated.

2 Data sourced from the ABS (2020) Labour Force, Australia, for persons aged 15 years and over.

A third challenge is distinguishing between *horizontal* and *vertical* segregation. Horizontal segregation refers to work of different but equal types. Vertical segregation refers to work of different and unequal types that exist along a hierarchy in terms of pay, authority, status and other dimensions. Blackburn, Brooks and Jarman (2001) argue that vertical segregation is the primary concern because it relates specifically to the inequality of segregation. However, attempts to quantify vertical segregation are limited by the need to rank job types according to highly subjective vertical dimensions such as status. Watts (2003) argues that case study approaches will enable greater understanding, albeit limited in scope and generalisability.

In summary, the literature on occupational gender segregation shows that there has been little progress on gender integration of the Australian labour market over the last century, with the exception of a period through the 1960s and 1970s. This is despite the female employment rate and share of the labour force rising dramatically over the same period. Segregation exists horizontally and vertically, although the vertical component of segregation is difficult to measure. It also exists in the different ways of work, with more women working part-time and flexibly than men. There are some marked weaknesses in the literature: the most recent studies are now over 15 years old, many studies use broad occupational categorisations instead of detailed ones, few studies consider industrial segregation at all, and there is a limited understanding of counteracting movements beneath the headline index measure of segregation.

3. Methodology

The aim of this study is to provide new estimates of gender segregation in the Australian labour market. The methodology builds on the existing literature in several ways. We update old data; there are no estimates of segregation in Australia in this millennium. We look at occupational and industrial segregation; the latter has largely been ignored in the literature, despite also contributing to the gender pay gap. We use the 30-year LFS time series, which was not available at the time of previous studies. This series provides consistent and detailed industry and occupation categories across the series which allows us to measure change in segregation over an extended period. This is particularly useful given the economy has restructured considerably away from manufacturing and towards services. The 3- and 4-digit data in the series also allows greater accuracy than the often used high-level, 1-digit job categories.

Shift share analysis

We employ a shift share analysis to determine the source of changes in female share of employment. This analysis distinguishes between changes to a certain occupation's/industry's share of total employment and changes to the gender composition of those occupations/industries (Olivetti and Petrongolo, 2016).

To make this distinction, the equation below was applied to Australia's labour market:

$$\Delta l_{ft} = \sum_j \alpha_{fj} \Delta l_{jt} + \sum_j \alpha_j \Delta l_{fjt} \qquad (1)$$

with l_{ft} denoting the change in female employment, l_{jt} representing the female share of labour in the occupation/industry j, l_{fjt} denoting the share of female employment in occupation/industry j while $\alpha_{fj} = (l_{fjt} + l_{fjy-t})/2$ and $\alpha_j = (l_{jt} + l_{jt-1})/2$ are decomposition weights.

Equation 1 can be divided into two components, with the first component signifying change in the female share of employment attributed to changes in the occupation's/industry's employment share within the total economy. For example, if there is strong growth in demand for midwives (the most 'female' occupation), there will likely be a shift toward female employment due to changes *between* occupations. This change is referred to as the 'between effect'.

The second component of the equation reflects variations in female employment due to alterations to the gender composition of occupations/industries. For example, if more women start working in mining (the most 'male' industry), there will be a shift toward female employment due to changes *within* industries. This is known as the 'within effect'.

Indices of segregation

Index calculation has characterised empirical investigations into segregation for some time, resulting in several suitable indices being available and appropriate for this study. These indexes of segregation represent the extent to which distinct groups, like men and women, are unevenly distributed across certain social constructs. Here, this refers to occupations and industries.

The ID can be written as;

$$ID = \frac{1}{2} \sum_{i=1}^{n} \left| \frac{F_i}{F_T} - \frac{M_i}{M_T} \right| \qquad (2)$$

where n is the number of occupations, F_i is the number of females employed in a certain occupation/industry i, F_T is the total number of employed females and vice versa for M_i and M_T.

The ID signifies the proportion of a particular gender that would need to move occupations/ industries, without replacement, in order to create a uniform distribution of the population (Cortese, Frank, and Cohen, 1976). Its value is maximised at 1 when each occupation/industry contains only one gender, and minimised at zero when the proportion of each group in each occupation/industry is consistent with the proportion in the workforce as a whole.

There are some weaknesses of the ID. Watts (1992; 2003) outlines these in detail, including the failure of the ID to be independent of changes to the occupation structure of the labour force and the gender share of total employment.

Karmel and Maclachlan's (1988) IP index does meet Watts' criteria and is the main alternative index to the ID. The key difference is that the ID represents the share of either sex which must relocate, without replacement, to achieve zero segregation whereas the IP represents the share of either sex which must relocate, with replacement (Cortese *et al*., 1976; Watts, 1992).

Given the criticisms of the ID, both indices were tested in the analysis with negligible differences between them. While the values of each index differ (by construction), the overarching trends and insights are the same. We have not shown the IP analysis here, however, we can report that the two series have a correlation coefficient of 0.97 for 3-digit industries and 0.94 for 4-digit occupations. Given the ID is the most used index in the literature and there are few differences between the overarching trends in the indices, the ID was used for the analysis in this paper.

Data sources

Analysis in this paper focuses on gender distribution at a very detailed occupational and industrial classification level in Australia. In order to do this, ABS LFS data was primarily relied upon as it allows for analysis at the detailed level of both occupational (4-digit) and industrial (3-digit) classifications. The LFS is formed on a multi-stage area sample of approximately 26,000 private dwellings, covering roughly 0.32 per cent of the civilian population of Australia aged 15 years and over. The LFS survey first begun in 1985, making it a useful dataset for analysing segregation over time. LFS data from 1985-2019 was employed in this study.

The ABS's Census of Population and Housing is used where detailed breakdowns were not available in the LFS, including for the age group analysis and some locational analysis. This Census has been conducted every five years since 1911 and provides a comprehensive snapshot of the nation, counting respondents based on where they were located on the designated Census night. Data collected relates to a broad range of characterising fields, some of which include family size, marital status, occupations, languages spoken, country of birth and income.

Due to our reliance on LFS and Census data, an understanding of the occupational and industrial classification system employed by the ABS is necessary for making sense of the paper's findings. Industries and occupations are classified according to the Australian and New Zealand Standard Classification of Occupations (ANZSCO) and the Australian and New Zealand Standard Industrial Classification (ANZSIC), respectively.

ANZSCO is a skill-based classification for all occupations and jobs in the Australian and New Zealand labour markets. The framework has several hierarchical levels, which are grouped based on similarities in skill sets. The broadest classification level, denoted by a 1-digit code, is referred to as Major Group, followed by Sub-Major Group (2-digit), Minor Group (3-digit), Unit Group (4-digit) and then the most detailed classification of Occupations (6-digit).

For industries, individual businesses are assigned particular industry classifications, based on a businesses' predominant activity. The highest level within ANZSIC is denoted by one letter codes, named Divisions, followed by Subdivisions (2-digit), Groups (3-digit) and Classes (4-digit) being the most precise classification.

An example of the occupational and industrial classification structure is shown in Table 1.

Table 1. Example of classification levels

Source	*Digits*	*Level*	*Description*
ANZSCO	1-digit	Major Group	2 Professionals
	2-digit	Sub-major Group	23 Health Practitioners
	3-digit	Minor Group	231 Medical Practitioners
	4-digit	Unit Group	2312 Specialist Medical Practitioners
	6-digit	Occupation	231211 Anaesthetist
ANZSIC	1-digit	Division	E Construction
	2-digit	Subdivisions	30 Building Constructions
	3-digit	Groups	301 Residential Building Construction
	4-digit	Classes	3011 House Construction

Source: ABS (2006) ANZSCO; ABS (2006) ANZSIC.

4. Descriptive analysis

Analysing the female share of employment across top-level occupations and industries provides initial insight into the gender composition of the Australian workforce. The significant variance in female shares of employment across occupations discussed in the Literature Review section of this paper is clearly shown in Table 2. For example, in 2019, one in ten Australians employed as Machinery Operators and Drivers were female, compared to roughly three in four employed as Clerical Administrative Workers, representing a 65 percentage point difference.

Table 2 shows there has been minimal change in 30 years for three occupation groups; Clerical and Administration Workers, Sales Workers and Labourers. The female share increased substantially in four occupation groups, with two trending towards integration and two trending towards re-segregation, increasingly dominated by females (Community and Personal Service Workers and Professionals).

Table 2 highlights the large share of female employment in traditionally ‘female’ industries, such as Education and Training, and relatively low shares in traditionally ‘male’ industries, such as Construction. Similar to occupational segregation at the 1-digit level, a 66 percentage point difference can be seen between the industry with the highest female share of employment (Health Care and Social Assistance) and the industry with the lowest (Construction). Like occupations, there was a mixture of movements in the female share between 1989 and 2019. The female share has been steady in six of 19 industries, it is increasing in 11 industries and decreasing in two industries. Of those industries where the female share is increasing, nine are integrating and two are re-segregating.

Table 2. Female share of employment in industries and occupations, 1989-2019

Classification	*1989*	*1999*	*2009*	*2019*	*Change 1989-2019*
Occupations					
Managers	28.96	28.38	34.51	38.22	9.26
Professionals	43.80	47.86	51.46	54.53	10.72
Technicians and Trades Workers	11.05	12.69	13.83	15.78	4.73
Community and Personal Service Workers	63.61	66.58	69.57	70.55	7.24
Clerical and Administrative Workers	73.92	76.34	75.73	73.20	-0.73
Sales Workers	60.02	61.35	62.50	60.85	0.82
Machinery Operations and Drivers	16.64	11.83	8.48	10.46	-6.17
Labourers	35.97	35.52	35.54	34.18	-1.79
Industries					
Agriculture, Forestry and Fishing	28.79	31.03	31.38	31.69	2.90
Mining	10.74	10.13	13.31	16.49	5.75
Manufacturing	26.89	26.40	27.25	26.80	-0.09
Electricity, Gas, Water and Waste Services	12.19	18.63	20.61	24.89	12.69
Construction	13.15	12.68	12.04	11.89	-1.26
Wholesale Trade	31.86	33.02	32.05	32.33	0.47
Retail Trade	55.48	54.43	56.30	55.66	0.18
Accommodation and Food Services	56.32	54.60	55.95	54.79	-1.52
Transport, Postal and Warehousing	19.42	24.02	24.05	21.76	2.34
Information Media and Telecommunications	36.61	43.60	42.00	38.49	1.88
Financial and Insurance Services	52.80	55.02	52.63	50.20	-2.61
Rental, Hiring and Real Estate Services	39.81	44.10	52.27	48.74	8.93
Professional, Scientific and Technical Services	46.65	42.59	43.69	42.34	-4.31
Administrative and Support Services	48.84	51.13	52.28	53.53	4.69
Public Administration and Safety	38.23	41.91	46.49	50.80	12.57
Education and Training	62.10	66.43	69.35	71.16	9.06
Health Care and Social Assistance	74.90	77.57	79.11	78.00	3.10
Arts and Recreation Services	47.00	44.28	47.68	49.69	2.69
Other Services	40.92	37.69	43.28	46.31	5.39

Source: ABS, Labour Force, Australia, Detailed, Quarterly, Nov 2019.

The data above captures the average gender shares across broad 1-digit industry and occupation classifications. However, more detailed breakdowns reveal much greater variation in segregation. For example, the most female 4-digit occupations within the 1-digit Manager group is Child Care Centre Managers (91.4 per cent) and the least female is Construction Managers (9.7 per cent), while an average occupation is Advertising, Public Relations and Sales Manager (38.1 per cent). Taking segregation analysis beyond the 1-digit classifications is relatively uncommon in this field. The index measures adopted later in this paper will show that detailed analysis indicates much higher levels of overall gender segregation in the labour market than broader classifications.

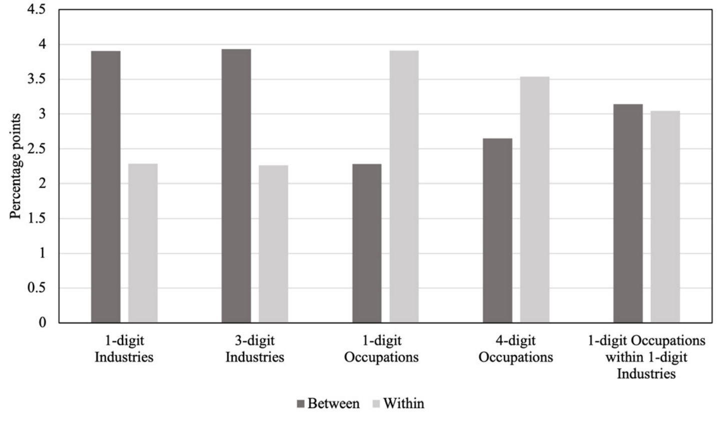
Overall, the descriptive analysis has highlighted persistently segregated occupations and industries. There were mixed trends over time, although it was most common for the female share to have increased in jobs over the last 30 years. This includes instances of both integration, where the gender balance is now more equal, and segregation, where already female jobs are becoming more female-dominated. The female share was steady in some jobs and actually decreased in a small sub-set of occupations and industries. The next section will explore the impact of these trends on the overall level of gender segregation in the Australian labour market.

5. Measures of segregation

Shift share analysis

The female share of total employment has increased from 39.9 per cent of the workforce in 1987 to 46.1 per cent in 2019, a rise of 6.2 percentage points in three decades.[3] As mentioned above, a shift-share analysis quantifies how much of this change in female share of employment is due to growth of specific occupations or industries, known as ‘between effects’, and how much is due to alterations in the gender composition of occupations or industries, known as ‘within effects’. This analysis has been carried out for industries at the 1-digit and 3-digit level, for occupations at the 1-digit and 4-digit level, and for occupation by industry cross tabulations at the 1-digit level. The results of this decomposition can be seen in Figure 1.

Figure 1. Shift share analysis for industries and occupations



Source: ABS, Labour Force, Australia, Detailed, Quarterly, Nov 2019.

3 Data sourced from ABS (2020) Labour Force, Australia.

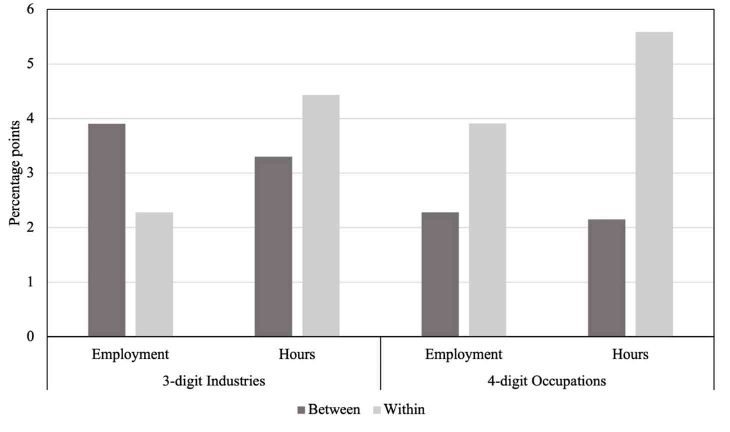
For industries, between effects account for a larger proportion of the rise in female employment share than within effects, with the opposite being true for occupations. Considering 1-digit industries, between effects accounted for 3.9 percentage points of the 6.1 percentage point rise in the female share of employment (63.5 per cent of the shift), and within effects accounted for 4.2 percentage points (36.5 per cent). This means that growth of industries that employ mostly women account for more of the change than a balancing of the gender mix within industries. For 1-digit occupations, between effects only account for 2.3 percentage points (36.8 per cent of the shift) while within effects account for 3.9 percentage points (63.2 per cent). This means that the occupation within effect has played a larger role than the between effect. These findings suggest that industries have been more resistant to gender integration than occupations.

The second key observation from Figure 1 is the difference between parent and detailed classifications of industries and occupations. There is a negligible difference between the results for 1-digit and 3-digit industries, however, there is a noticeable difference between 1-digit and 4 digit occupations. For the detailed 4-digit occupations, between effects are 0.4 percentage points higher than the 1-digit analysis, and within effects are lower by the same margin. Therefore, some changes within broad occupation groups reflect changes between more detailed occupations underneath the parent classifications.

Since the distribution of occupations varies across industries, a proportion of the between-occupation effects could be explained by the expansion of industries in which traditionally female roles are over-represented (Olivetti and Petrongolo, 2016). We see this in the final set of columns decomposing the change in gender share of employment for 1-digit occupations classed within 1-digit industries. The divergent results for industries and occupations converge, with between and within effects near evenly balanced at around 3 percentage points each. This indicates that some of the shift in female share that was caused by a changing industry composition (between effects) came from the changing gender mix within occupations that made up those industries (within effects). Conversely, some of the shifts within occupations came about because some industries were growing more than others (between effects).

Figure 2 presents the shift share analysis across 4-digit occupations and 3-digit industries, calculated across jobs and total hours worked. In presenting a comparison of integration trends by hours worked and the number of jobs, the analysis accounts for the inherent differences in instances of part-time employment between sexes. Within effects are stronger when decomposing the shift in hours worked compared to jobs worked (employment). This is most clear for industries, where the relative contribution of within and between effects is inverted for hours and employment. The smaller between effects when counting hours most likely reflects the higher rates of part-time work in the typically female industries that have seen strong growth, such as education and healthcare (there is only a small difference in between effects for occupations). The higher within effects suggests that the jobs that have seen gender integration have also seen more women working full-time than in previous decades.

Figure 2. Shift share analysis for jobs and hours



Source: ABS, Labour Force, Australia, Detailed, Quarterly, Nov 2019
Note: When comparing the shift share across hours and employment the difference in total increase in female's share of employment across this period (6.2 percentage points) and hours worked (7.7 percentage points).

The shift share analysis has measured the source of the rising female share of employment over the last three decades. The composition of the effects depends on whether jobs are categorised by industries, occupations or a combination of the two. The higher within effects suggests that there may have been a greater degree of gender integration for occupations than industries. However, this analysis captures both 'male' jobs that have become more integrated and 'female' jobs that have become more segregated, both of which contribute to a higher female share of employment. The next section measures the overall change in segregation via the ID, presenting which forces have contributed to the observed trends.

Index of dissimilarity

The ID measure of gender segregation within industries and occupations across the past 30 years is given in Table 3. We see that gender segregation across the detailed classifications is more profound. Around 33 per cent of workers across 3-digit industries would need to move industries in order to create a uniform distribution of genders across industries but around 40 per cent would need to move at the 3-digit level in 2019. For occupations, around 37 per cent would need to move between 1-digit occupations while 51 to 58 per cent would need to move between 4 digit occupations. In other words, there is a much more gender segregation when industries and occupations are broken down to a detailed level which more closely reflects real differences between jobs.

Table 3. Gender segregation in industries and occupations, 1989-2019

	Classification	*1989*	*1999*	*2009*	*2019*	*Change 1989-2019*
Industries	1-digit (n=19)	0.321	0.304	0.323	0.328	0.007
	3-digit (n=290)	0.381	0.363	0.406	0.402	0.021
Occupations	1-digit (n=8)	0.388	0.401	0.388	0.367	-0.020
	4-digit (n=468)	0.574	0.568	0.548	0.519	-0.055
	1-digit (n=152)	0.505	0.492	0.473	0.448	-0.057
Industries x occupations	1-digit (n=152)	0.505	0.492	0.473	0.448	-0.057

Source: ABS, Labour Force, Australia, Detailed, Quarterly, Nov 2019.

Gender segregation is more profound in occupations than industries. The ID for 1-digit occupations is around 7 percentage points higher than 1-digit industries, despite there being eight occupations and 19 industries defined at that classification level. Consistent with findings for other developed countries (Blau and Khan, 1996), this indicates that gender roles are more strongly aligned to the type of work we do, rather than the workplace (or industry) in which we do it. Still, segregation remains for both occupations and industries, and the final row of Table 3 shows that segregation is higher again at the intersection of the two.

The ID for 1-digit occupations within 1-digit industries ranges from 44 to 50 per cent, much higher than the 32 per cent and 38 per cent for 1-digit industries and occupations. Again, this indicates that there is a higher level of segregation when we consider finer breakdowns. The added implication here is that men and women who have the same occupation will tend to work in traditionally male or traditionally female industries.

Perhaps most importantly, we see that there have been only very modest reductions in gender segregation over the last three decades. The 4-digit occupation ID had a consistent (yet very slight) downward trajectory, finishing 5.5 percentage points lower in 2019 than 1989. Similarly, the ID for 1-digit industries by 1-digit occupations fell by 5.7 percentage points. The other series showed almost no change. This degree of change is greatly overshadowed by the rise in overall female labour force participation of 18 percentage points over the same period.

By these measures, there has been little change in the level of occupational and industrial segregation in the Australian labour market. At most, there is less than 5.7 per cent fewer workers who would need to change jobs to achieve gender integration across the workforce than 30 years ago. The result is similar to some previous Australian analysis of occupational segregation, which found declines in segregation of similar scale, particularly in the 1970s (Lewis, 1985) and 1990s (Watts, 2003). The slow pace of change aligns with the United States experience, where there was a distinct period of integration between 1970 and 1990 but little progress since then (Blau, Brummund and Liu, 2013).

This lack of movement in the ID is somewhat hard to reconcile with those of the previous section where we saw that between 38 per cent and 62 per cent of the rise in the female share of employment has come from changes within occupations and industries. One possible explanation is that some occupations have become more gender balanced, like managerial professions, while others have become less balanced and specifically more female, such as Health Professionals and Educational Professionals (Preston and Whitehouse, 2004).

Table 4, adapted from Preston and Whitehouse (2004), confirms these trends. It gives the share of employment in occupations and industries that were integrated, segregated or had a stable gender mix between 1988 and 2019. A job was classified as 'integrating' (or 'segregating') if the gender mix was closer (or further away) to the overall mix across the labour force in 2019 than 1989. A job was classified as 'stable' if the gender mix did not shift by more than 3 percentage points. Further, the table divides jobs into whether one gender was over-represented in 2019; this indicates the direction of integration or segregation, for example, whether a traditionally 'male' job now has a higher share of females.

Table 4. Employment shares of occupations and industries that became more gender integrated/segregated from 1989-2019, by gender representation

		Occupations		*Industries*	
		% *of female employment*	% *of male employment*	% *of female employment*	% *of male employment*
Integrating	Females over-represented*	27.0	14.1	9.5	8.0
	Males over-represented*	11.1	24.4	6.0	12.9
	Total**	**38.1**	**38.6**	**15.6**	**20.9**
Segregating	Females over-represented*	32.0	8.4	45.9	16.7
	Males over-represented*	3.4	12.1	5.0	16.4
	Total**	**35.5**	**20.5**	**51.0**	**33.1**
Stable***	Females over-represented*	21.8	6.9	21.3	12.2
	Males over-represented*	3.6	32.8	10.8	31.9
	Total**	**25.4**	**39.7**	**32.1**	**44.2**

* 'Over-represented' means a higher gender share in the industry or occupation than the gender share of total employment across all jobs in 2019
** Totals do not sum to 100% because some occupations were missing data in 1989
*** 'Stable' means the gender mix of the occupation or industry did not change by more than 3 percentage points
Source: ABS, Labour Force, Australia, Detailed, Quarterly, Nov 2019

We observe divergent patterns across occupations and industries. While many jobs are integrating, others are segregating, and others still are not changing much at all. In line with the ID measurements, occupations were more likely to be integrating than industries. Around 38 per cent of men and women work in occupations that have been integrating in the last 30 years, but only 15-20 per cent work in industries than have been integrating. Likewise, industries are more likely to be stable or segregating than occupations.

A large number of female-dominated jobs are becoming more female-dominated (more segregated). Around one third of women work in occupations (32.0 per cent) where females are increasingly over-represented. For industries, it is nearly half of all women (45.9 per cent). This includes jobs like teachers, receptionists, clerks and bookkeepers. In contrast, only 11.1 per cent of women work in occupations and, 6.0 per cent work in industries, that are becoming more gender integrated, but where males are still over-represented. These are most commonly specialist manager roles, for example, finance managers. This suggests that significant barriers still need to be overcome for women to enter traditionally male fields.

Between a quarter and a half of men and women work in jobs where the gender mix has been relatively stable. Men were more likely than women to work in these unchanging jobs. They include construction, building, trade and manufacturing jobs for men. For women, they include care, nursing, administration and hospitality jobs.

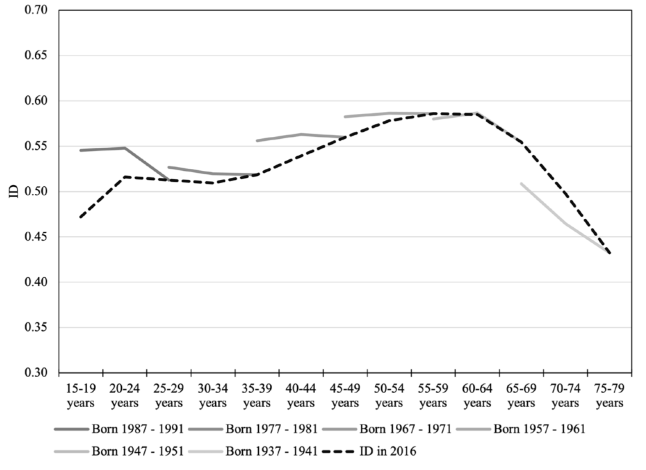
The ID analysis above has shown that more detailed classifications reveal a greater extent of segregation, occupations are more segregated than industries and that gender divides also occur at the intersection of occupations and industries. While occupations are more segregated overall, there has been more progress towards integration than in industries, albeit modest. This aligns with the within effects of the earlier shift-share analysis. Breaking down the trends reveals significant counter-balancing forces of integration and segregation underlying the aggregate ID measure.

Segregation and age

The gendered patterns of participation over the life course is a key feature of the Australian labour force. Women are more likely than men to stop or reduce labour participation around child rearing years and the participation rate does not fully recover in later years, at both the intensive and extensive margin. This section explores the implications for segregation over the life course.

Figures 3 and 4 present ID values for gender segregation across age groups for 4-digit occupations and 3-digit industries, respectively. The figures show the ID across age groups in 2016 as well as cohorts spaced 10 years apart, from those born in 1937-41 to those born in 1987-91. Comparing the two sets of data highlights how variation across ages groups reflect the different life courses of successive cohorts of workers (OECD, 2002).

Figure 3. Cross-cohort comparisons of ID by age, 4-digit occupations



Note: Cohorts are not constructed with longitudinal data, they are 'synthetic cohorts' constructed from cross-sectional data across ABS Census years
Source: ABS Census of Population and Housing, 2006, 2011 and 2016

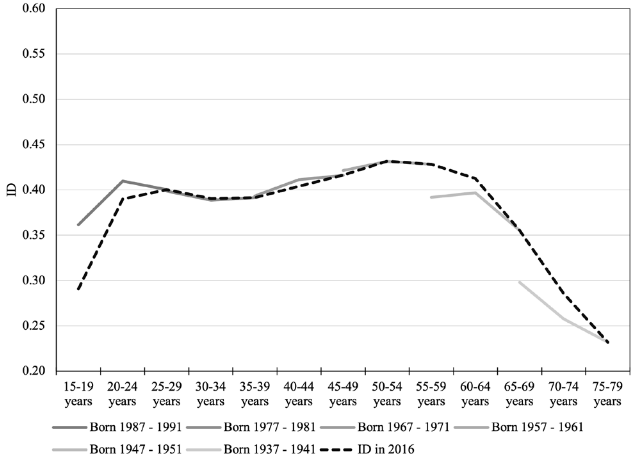
Firstly, considering the dotted line for the ID in 2016. There is a clear pattern of increasing segregation as Australians grow older, with segregation peaking around 50 to 64 years of age for both industries and occupations. These results are consistent with international studies from the OECD (2002) and Dolado, Felgueroso, and Jimeno (2003), but they are contrary to Australian studies from Lee and Miller (2004) and Lewis (1985), which both show occupational segregation falling consistently with age.

One likely explanation for the rising segregation over the life course is that over time many women move into more 'family friendly' jobs because they bear the overwhelming majority of caring responsibilities in most family units. This may also contribute to vertical segregation as women do not advance to higher status positions as often as men at later career stages.

Part of the pattern could also come from cohort effects, whereby the rates of segregation are lower for younger workers as new generations are entering non-traditional fields at higher rates. This appears evident for occupations (Figure 3), where the ID for each subsequent cohort is somewhat below the previous cohort (note later/younger cohorts are to the left of the chart).

The changes are less pronounced for industries than occupations, particularly between the ages of 20 and 60 years (Figure 4). This is true for both the overall variation across ages (dotted line) and the differences between cohorts (solid lines). As with earlier observations, this reflects the slower integration of industries and lower levels of segregation in industries overall. It could also reflect the different career paths over the life course, with workers more likely to move between occupations within the same industry than change industry altogether.

Figure 4. Cross-cohort comparisons of ID by age, 3-digit industries



Note: Cohorts are not constructed with longitudinal data, they are 'synthetic cohorts' constructed from cross-sectional data across ABS Census years
Source: ABS Census of Population and Housing, 2006, 2011 and 2016

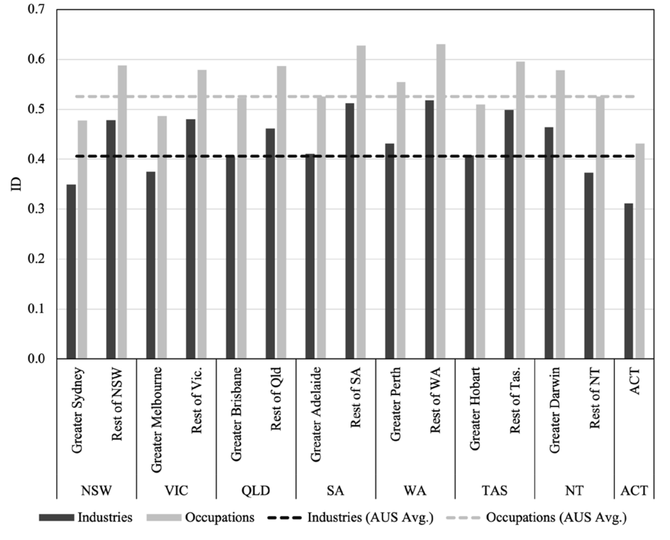
Finally, there is a marked fall in segregation in the later years for both occupations and industries. This may be driven by earlier exits from the labour force in traditionally gendered jobs, for example, a younger average retirement age in construction for men or nursing for women. Similarly, the patterns across cohorts indicate that segregation later in working life is increasing rather than decreasing for more recent cohorts. This could be due to workers in those aforementioned 'gendered' jobs' staying in the labour force for longer in more recent years.

Segregation and location

The data thus far has assessed segregation for Australia as a whole. However, there are large differences between locations, which are explored in this section by comparing capital cities with regions, and then across local areas of varying density.

Figure 5 shows the average ID for capital cities and the balance of state, using ABS Census data. Segregation is greater in the regional areas than the capital cities of all jurisdictions and like earlier data, the ID for industries is higher than the ID of occupations in each location.

Figure 5. Segregation for 4-digit industries and 4-digit occupations, capital cities and the balance of state, 2016

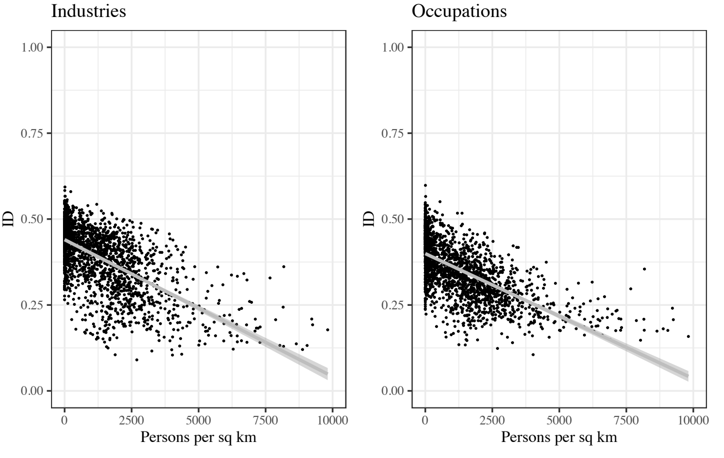


Source: ABS Census of Population and Housing, 2016

The overall levels of gender segregation are distinctly lower in Sydney, Melbourne and, in particular, Canberra (the ACT). A large proportion of the workforce in these jurisdictions is employed in service sectors that have a large share of female employment. By contrast, the level of segregation was much higher in regional Queensland, South Australia, Western Australia and Tasmania where male-dominated industries, such as agriculture, mining and manufacturing, play a much larger role in the economy.

Figure 6 takes this analysis further by considering segregation in local areas, as defined by the ABS Statistical Area Level 2 (SA2). There are 2310 SA2s in Australia and they typically correspond to an area the size of a suburb. The industry and occupation ID is plotted against population density for each location. The ID is based on the employment of the residents in each location (rather than the place of work).

Figure 6. Segregation and population density of local areas (SA2), 1-digit industries and 1-digit occupations, 2016



Note: SA2s with a population fewer than 1,000 persons were excluded in order to ensure meaningful ID estimates.
Source: ABS Census of Population and Housing, 2016; ABS, Population and Age by Sex, Regions of Australia, 2016

The scatterplots show a clear trend of declining ID for areas of greater density. An inner city location or inner ring suburb of more than 5,000 persons per sq km has an ID of around 0.25 for industries and 0.20 for occupations. This rises to 0.31 (industries) and 0.37 (occupations) in middle and outer ring suburbs with population densities around 1,500 persons per sq km, and further to around 0.40 (industries) and 0.45 (occupations) in regional areas. There is much more variability in low density locations, which is partly due to the low number of workers. To quantify the relationship with a simple OLS regression: an increase of 1000 persons per sq km is associated with a fall in ID of 1.8 percentage points for industries ($r2 = 0.15$, $p < 0.001$) and 3.6 percentage points for occupations ($r2 = 0.39$, $p < 0.001$).

The lower ID for more urbanised locations could be driven by 'between effects' in the underlying industrial and occupational structure (as noted with the interstate and intercity differences above). It could also be driven by differences within industries and occupations. That is, one industry in a regional labour market may be more segregated than the same industry in a city labour market, these are the 'within effects'.

Following the technique of Blau and Hendricks (1979), we decompose the variation between Australian capital cities and regions by comparing the ID to the national average. Table 5 details the within effects, between effects and a residual. The residual component is described by Blau and Hendricks (1979) as an interaction of the within and between components, however, this has been criticised by Anker (1998) as uninterpretable. Nevertheless, the residual is reported here for completeness.

Table 5. Decomposition of ID deviation from national average, 2016

		Decomposition (% pts)			*Share of deviation (%)**		
	Deviation	*Within*	*Between*	*Residual*	*Within*	*Between*	*Residual*
Industries (4-digit)							
Greater Sydney	-5.7	-3.5	-2.7	0.5	-52.7%	-39.6%	7.7%
Rest of NSW	7.2	5.6	2.0	-0.4	69.8%	25.0%	-5.2%
Greater Melbourne	-3.1	-2.3	-1.4	0.5	-54.4%	-32.9%	12.7%
Rest of Vic.	7.4	6.4	1.3	-0.3	80.1%	15.8%	-4.0%
Greater Brisbane	-0.1	-0.6	0.5	0.1	-55.2%	39.9%	4.9%
Rest of Qld	5.6	3.5	2.5	-0.4	54.6%	38.7%	-6.7%
Greater Adelaide	0.5	1.1	-0.5	-0.1	65.1%	-31.3%	-3.6%
Rest of SA	10.6	9.2	2.0	-0.6	78.5%	16.6%	-4.9%
Greater Perth	2.5	0.6	2.1	-0.1	19.8%	75.3%	-4.9%
Rest of WA	11.2	8.3	4.4	-1.4	58.9%	31.0%	-10.2%
Greater Hobart	0.1	4.5	-2.9	-1.5	50.8%	-32.5%	-16.7%
Rest of Tas.	9.3	8.6	1.0	-0.4	85.6%	10.2%	-4.2%
Greater Darwin	5.8	3.3	2.2	0.3	57.2%	37.7%	5.1%
Rest of NT	-3.3	3.1	-2.3	-4.1	32.7%	-24.4%	-42.9%
ACT	-9.5	0.9	-7.0	-3.4	7.9%	-61.6%	-30.5%
Occupations (4-digit)							
Greater Sydney	-4.8	-2.1	-2.9	0.2	-39.8%	-56.7%	3.5%
Rest of NSW	6.3	3.4	3.1	-0.2	51.1%	46.5%	-2.4%
Greater Melbourne	-3.9	-1.9	-2.2	0.2	-44.9%	-50.2%	4.9%
Rest of Vic.	5.3	3.3	2.2	-0.2	58.4%	38.4%	-3.2%
Greater Brisbane	-0.3	-0.2	-0.2	0.1	-45.3%	-31.1%	23.6%
Rest of Qld	6.2	3.2	3.4	-0.4	45.3%	48.8%	-6.0%
Greater Adelaide	0.0	0.6	-0.7	0.1	41.8%	-49.0%	9.2%
Rest of SA	10.2	6.2	3.4	0.6	60.6%	33.8%	5.6%
Greater Perth	2.9	1.3	1.6	0.0	43.7%	56.3%	0.0%
Rest of WA	10.5	5.4	6.9	-1.8	38.4%	49.1%	-12.5%
Greater Hobart	-1.5	1.2	-2.1	-0.6	30.3%	-53.2%	-16.5%
Rest of Tas.	7.0	4.5	2.7	-0.2	60.7%	36.0%	-3.3%
Greater Darwin	5.3	0.9	4.4	0.0	17.6%	82.2%	-0.2%
Rest of NT	0.0	2.0	1.2	-3.3	31.1%	19.0%	-49.9%
ACT	-9.4	-2.3	-6.2	-0.9	-24.1%	-65.9%	-10.0%

* This is the share of the absolute value of the components. This accounts for components with opposite signs, for example, the within and between component in Greater Adelaide.

Source: ABS Census of Population and Housing, 2016.

The table shows that both within and between effects are present. The two largest and most dense labour markets – Sydney and Melbourne – have lower IDs that the national average and between a third and half of the deviation is balanced across within and between components. The highest IDs are in regional Western Australia and South Australia where much of the deviation is due to within effects. The lowest ID is in the ACT and this is largely due to 'between effects', which owes to the dominant public sector.

The results point to a mix of between and within effects driving the lower segregation in more urbanised locations. This means that women have greater opportunities in bigger cities due to both the structure of the economy and the gender balance within industries and occupations. There are multiple possible drivers for this: higher wages in cities make the trade-off between work and care more attractive, shorter commute times and greater access to services make the work-care balance more manageable, higher housing costs require a greater household income (noting that women are most often the secondary earner) and there may be greater cultural acceptance of gender equality in cities.

6. Conclusion

There are five key findings of this research. First, detailed occupations and industries are profoundly more segregated than top-level occupations and industries. Second, little change has occurred in segregation across both industries and occupations in the past three decades. Third, industries are more resistant to integration than occupations. Fourth, segregation increases as workers get older. Vertical segregation, work-family dynamics and cohort effects are all likely contributors to this. And fifth, more urbanised locations have more gender integrated labour markets, which is due to both the structure of the local economies (between effects) and greater gender balance within industries and occupations.

The major implication of these findings is that decades of gender equality policy have not had a substantial impact on the gender balance across the jobs that men and women do. Women still have more constrained labour supply choices, hindering labour market efficiency and flexibility. Further work can be done on understanding and addressing the economic, social and cultural barriers to gender integration in the labour market, particularly on dimensions of vertical segregation and restructuring of the labour market post-COVID-19. Given progress is likely to be slow into the future, there is need for complementary work on how traditionally female jobs are valued (or undervalued). At least for wages, a reassessment of 'women's work' may be a faster route to gender equality.

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Changing demand for STEM skills in Australia and gender implications

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Abstract

A method is developed for measuring the intensity with which skills in science, technology, engineering and mathematics (STEM) are used in different occupations based on workers' field of education of their highest qualification and weighted by the wage premium associated with that level of qualification. This is used to model changes in demand for STEM skills, and in other fields, based on the changing occupational composition of employment in Australia between the 2006 and 2016 censuses, and on projected changes to 2024. The approach offers a number of advantages over previous measures used to define STEM workers. Most importantly, by generating a continuous measure of STEM-intensity rather than a binary STEM versus non-STEM definition, it incorporates VET qualifications rather than just university level qualifications, and allows for transferability of STEM skills to what might be considered 'non-STEM' jobs. Contrary to popular narratives around STEM and the future of work, we find that the changing nature of work is actually reducing the demand for STEM skills relative to skills in other fields of education. Health stands out as the field in which the demand for qualifications has been growing most strongly. We also find that technical and trade jobs account for almost the same level of demand for STEM skills as professional occupations, reflecting the importance of including the VET sector in any STEM agenda. While governments have actively sought to promote 'women in STEM', our results suggest that, if anything, women are benefitting in terms of the demand for their skills by the fact that they are under-represented in STEM, and over-represented in key services such as Health and Education. We caution against an uncritical acceptance of the need for a higher proportion of people to specialise in STEM fields. More explicit and testable statements of the rationales and assumptions behind STEM definitions and associated policy are needed to further advance skills forecasting and the appropriate role, if any, of a unique STEM agenda within that framework.

JEL Codes: J16, J20, J21, J24, J30, J70
Keywords: employment, gender, occupational segregation, industrial segregation

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Introduction

The need to increase the level of skills and qualifications of the Australian workforce in the fields of science, technology, engineering and mathematics (STEM) features regularly in narratives of the future of work. Enhanced productivity through the development of a workforce with high STEM capacity across many industry sectors is seen as key to innovation and competitive advantage, and thus for continued economic growth and employment in high wage jobs. So too, is it seen as essential that the workers of the future embrace automation and increased use of data and information sciences in the workplace. Given the under-representation of women in STEM subjects in school and post-school education (Department of Industry, Innovation and Science 2019, Marginson *et al*. 2013, Office of the Chief Scientist 2016, Wajngurt and Sloan 2019), there has been a concerted push to encourage women into STEM careers as part of this agenda to embrace the evolving nature of the jobs of the future.

Despite a continuing focus on promoting a STEM savvy workforce, it is difficult to point to a clear evidence-base to support the assumptions underlying this narrative. In large part this is due to definitional and measurement issues, with ambiguity surrounding exactly what fields of education should be included as 'STEM' and how to identify STEM requirements of jobs or workers. In much of the empirical research that seeks to capture the prevalence of STEM capabilities in the Australian workplace, the notion of what represents a 'STEM worker' or a 'STEM job' is binary – that is to say, they are categorised as either STEM or non-STEM. In Australia, the assignment of a person as a STEM worker is often based on whether they hold a university degree or higher qualification in the disciplines of Natural and Physical Sciences, Information Technology or Engineering and Related Technologies (see, for example, Healy, Mavromaras and Zhu 2011; PwC 2015: 14). In reality, of course, different jobs require varying levels of STEM skills and the focus on university qualifications disregards the potentially important contribution of STEM-related skills accrued at the level of vocational certificates and diplomas.

In this paper we propose a method for measuring the 'STEM-intensity' of jobs at a relatively detailed level of classification of occupations, based on the qualification profile of workers by occupation using data from the Australian Bureau of Statistics (ABS) Census of Population and Housing. The measurement approach is designed to address two key challenges to measuring the STEM content of jobs: it generates a continuous measure of the demand for STEM skills within a job, rather than a binary divide, and incorporates vocational level qualifications from Certificate Level 3 and above. Using this measure, it is possible to infer the changes in demand for skills in STEM and in other fields associated with past and projected changes in the occupational composition of employment in Australia. This approach is used to describe how the demand for STEM skills is evolving in the Australian labour market, and the differential implications for the demand for skills held by men and women.

We find little support for the notion that the changing nature of work has heightened demand for STEM skills relative to skills in other fields of education over the past decade, or that it will do so in the near future given existing projections for employment by occupation. Health stands out as the field of education in which the demand for qualifications has been growing most strongly. Moreover, women have, if anything, benefitted in terms of the demand for their skills by the fact that they are under-represented in STEM relative to men, and over-represented in employment in key services such as Health and Education. We caution against an uncritical acceptance of the need for a higher proportion of people to specialise in STEM fields, and call for greater clarification around the justification for such policies to guide measurement issues and, thereby, ensure claims and assumptions can be subject to testable hypotheses.

Background

Claims of the need to increase the proportion of the workforce with STEM qualifications typically follow three main, interrelated lines of argument: that it would boost economic growth; the jobs of the future will increasingly demand STEM skills; and that employers face shortages of STEM qualified workers (Australian Industry Group 2013, 2015; Bradley *et al*. 2008; Dawkins 1988; Department of Jobs, Tourism, Science and Innovation [JTSI] 2019; Office of the Chief Scientist 2013, 2015, 2016; PwC 2015). Similar arguments focus on the requirement, more specifically, for higher-level STEM skills such as university degrees and PhDs. As there is a strong correlation between studying STEM subjects in secondary school and entry into university level-STEM courses, there is concern at what is seen as a declining interest, participation and performance in STEM in schools in Australia, particularly for girls (Office of the Chief Scientist 2012, Rothwell 2013, Timms *et al*. 2018). This progression of students from STEM in schools to post-school courses and eventually into STEM jobs invokes the metaphor of the 'STEM pipeline', extended to the 'leaky pipeline' with reference to people who divert into other courses or into non-STEM jobs (Cannady *et al*. 2014, Metcalf 2010).

The demand for labour and skills is a derived demand related to the output of goods and services in the economy and the production technologies (functions) with which they are produced. Conceptually, we can think of changes in the demand for STEM skills as coming from four sources: 1. changes in the overall level of output; 2. changes in the composition of *existing* goods and services in the output mix; 3. changes in production technologies; 4. the development of entirely new goods and services, and their associated production functions.

A fundamental role of the education and training system is to embody into the emerging labour force the knowledge and expertise needed to meet the requirements of the economy. Hence, a key reason for trying to anticipate the future skill needs – such as STEM – is to minimise mismatch between the skill requirements of industry and the skills possessed by the workforce in order to maximise output. The Australian Industry Group (AIG) (2015), for example, argues there is an urgent need to lift the level of STEM qualified employees. The AIG point to evidence from the ABS that '… STEM skills jobs grew at about 1.5 times the rate of other jobs in recent years' (2015: 5); and to international evidence that '… 75 per cent of the fastest growing occupations require STEM skills and knowledge' and in the US 'STEM employment grew three times more than non-STEM employment over the past 12 years' (p. 8).

However, evidence on the existence of emerging shortages of STEM workers is inconclusive. Healy *et al*. (2011) found mixed evidence of the presence of skills shortages in STEM, with signs of shortages most acute in engineering, while Norton (2016) argues Australia actually has more science graduates than the labour market can absorb in related jobs. There is also evidence that women who complete university degrees in a STEM field experience worse labour market outcomes than other female graduates upon labour market entry (Li *et al*. 2017) and across their working lives (Dockery and Bawa, 2018).

Existing empirical projections of future employment for Australia use generic time series methods that rely heavily on past aggregate trends, with *ad hoc* industry-specific adjustments (see for example Department of Employment, Skills, Small and Family Business 2019). Other projections are based either on employer survey data (e.g., Deloitte Access Economics 2014), on nationally representative household data such as the Household, Income and Labour Dynamics in Australia (HIILDA) survey or the ABS Survey of Income and Housing (SIH) (Borland and Coelli 2017); or the Australian panel component of the international adult skills data collection Programme for the International Assessment of Adult Competencies (PIAAC). Recent empirical studies of the labour market effects of automation have been based on a similarly naïve approach, one that applies a fixed view of the task composition of workers' jobs. This has led to the publication and popularisation of research findings that speculate up to 40 per cent of jobs will become redundant as a result of automation (Frey and Osborne 2013, Committee for Economic Development of Australia [CEDA] 2015).

Of course, all projection exercises are inherently difficult, but even more so when predictions or assumptions are sensitive to future technological innovations. Fifty years ago, for example, no Australian consumers were purchasing mobile phones, personal computers or microwave ovens, or receiving MRI scans. The internet had yet to be introduced. None of the jobs associated with these products and services existed. There is also potential endogeneity between the level of education and skills of the workforce and what is produced. By generating a strong supply of workers with qualifications used in the production of particular goods and services, a country may be able to develop a comparative advantage in those industries. This is particularly desirable if those industries are seen to offer high paying and high quality jobs. Among many others, the Office of the Chief Scientist argues that the promotion of STEM is key to shaping our industrial fortunes:

> "Australia's future is not one of vastly lower wage rates seeking to compete in low-end manufacturing. Our future lies in creating a high technology, high productivity economy; to innovate and to compete at the high-end of provision. To do so, the technical skills and scientific awareness of the entire workforce must be raised." (Office of the Chief Scientist 2012:12)

The argument is that, in the emerging knowledge economy, it is the innovators who will capture higher returns, and STEM is critical to innovation. As Marginson notes, "Many of the data-based international comparisons in education and innovation policy are centred explicitly on the STEM disciplines" (2015: 23).

Taking stock of, or projecting the demand for, STEM skills is further complicated by measurement and definitional issues. Highlighting the lack of a clear rationale for grouping the fields of science, technology, engineering, and mathematics together, various analysists have called for the inclusion of other fields, such as adding an M (medicine/health) or A (arts) in the definition, making it STEMM or STEAM. Among others, Card and Payne (2017) argue that nursing should be included in STEM, arguing that nursing requires the same prerequisites as many other STEM programs such as maths, chemistry and biology. Wajngurt and Sloan (2019) recommend adding Arts into the traditional definition of STEM, changing it to STEAM to make it more inclusive of women and students who are uninterested in traditional fields of STEM, further arguing that STEM and the arts are not mutually exclusive. Vestberg (2018) argues for the incorporation of humanities because of their importance in providing a 'moral and cultural' compass to transform technological innovations into improvements in human wellbeing (cited in Jobs Queensland 2019: 65). Boy (2013) also recommends a shift to STEAM to promote creativity, problem solving and the 'possibility of longer-term socio-technical futures'. Among others, Bequette & Bequette (2012), Costantino (2017), Maeda (2013), Rolling (2016) and Vestberg (2018) also support STEAM as the definition, arguing that science and arts are complementary and, further, that the STEM subjects alone will not lead to the innovation the 21st century demands. In contrast, May (2015) warns that the inclusion of the Arts threatens to dilute the potential of the STEM agenda to promote innovation.

Similarly, Oleson *et al*. (2014) point out that, like researchers, government agencies vary considerably on which fields of education and occupations should be considered as STEM. The Australian Bureau of Statistics, for example, includes qualifications in Agriculture, Environmental and Related studies (ABS 2014), as does the Office of the Chief Scientist (2016) and the Western Australian State Government in the definition used for its STEM skills strategy (JTSI 2019).

Compounding the question of the disciplinary boundaries of STEM is the question of the level of qualifications. The use of a bachelor degree as the STEM entry level has been criticised both in Australia (Korbel 2016, Siekmann 2016) and in the US (Rothwell 2013) for overlooking a significant contribution of the vocational education and training (VET) sector. Siekmann (2016) argues that accurate labour market predictions and workforce planning in the face of the restructuring of labour and industries requires consideration of all education sectors.

The use of a binary STEM versus non-STEM divide has itself been criticised. STEM skills are transferable between jobs that are considered STEM and non-STEM jobs, as are non-STEM skills, and STEM graduates work in a variety of jobs outside their original field of study (Korbel 2016, Office of the Chief Scientist 2016). Metcalf (2010) criticises the 'leaky pipeline' analogy for failing to recognise the value of this transferability and varied career pathways involving multiple ways of entering and re-entering STEM. Rothwell (2013) and Siekmann and Korbel (2016a, 2016b) propose continuous indices of science and maths intensity or of workers' STEM skills by occupations as a better method for measuring STEM jobs, in line with the approach we develop in the following section.

Measuring the STEM-intensity of jobs

The STEM tag is often assigned to people rather than to jobs, so the 'STEM workforce' refers to people with qualifications in STEM fields (for example, Office of the Chief Scientist 2016). For the purposes of this analysis, we include the fields referred to by the Australian Council of Learned Academies (ACOLA) as the 'core' STEM disciplines, or the Australian Standard Classification of Education (ASCED) fields of Natural and Physical Sciences (NPS), Information Technology (IT) and Engineering and Related Technologies (ERT) (see Healy *et al*. 2011, Marginson *et al*. 2013: 30, Siekmann and Korbel 2016a: 6; and ABS 2001 for details on ASCED). Imposing a somewhat arbitrary threshold level of qualification, the 'STEM workforce' could be defined as the set of persons holding such university level qualifications in one of those fields. This approach is depicted in Table 1, which shows 2016 Census data for employed persons that hold a post-school qualification by broad ASCED field, with the shaded area representing the STEM workforce.

Being based on the characteristics of workers, not on the characteristics of jobs, this definition takes a purely supply-side perspective. It also leads to a binary distinction between STEM and non-STEM workers. Here we propose and develop a measure of the intensity with which STEM skills are used in different occupations, allowing us to estimate how the demand for STEM skills is changing based on the changing occupational composition of the employed workforce. An important innovation in this method is that it provides for a more nuanced treatment of skill level. It can be seen from Table 1 that the NPS field has the highest proportion of post-school qualifications at the postgraduate degree level, and at the bachelor's degree level and higher (88.0 per cent). However, a substantial proportion of workers with qualifications in the fields of IT and ERT have a diploma or advanced diploma as their highest post-school qualification. As discussed above, it would seem important that such non-university qualifications be taken into account in any assessment of the demand for STEM skills or of the STEM capability of the workforce.

We concentrate on occupational classifications as the best indicators of the type of jobs involved in the various production functions. Since 2006, occupations have been classified in official Australian statistical collections using the Australian and New Zealand Standard Classification of Occupations (ANZSCO) (ABS 2006). The ANZSCO structure consists of eight major occupational groups, under which there are four finer levels of definition: 43 sub-major groups; 97 minor groups, 358 unit groups, and 998 'occupations'. The conceptual model underlying the classification framework defines jobs on the basis of their attributes in terms of the combination of skill levels and skill specialisation. A job is seen as a set of tasks performed in employment (whether as an employee or self-employed), and occupations as a grouping of jobs requiring the performance of similar sets of tasks: that is, tasks performed at a similar skill level and involving a similar skill specialisation.

The measure of STEM-intensity here is calculated at the level of the 97 minor groups. Relative to the major and sub-major groups, which are largely distinguished on the basis of skill level, minor groups within each sub-major category are distinguished from one another '… mainly on the basis of a finer application of skill specialisation than that applied at the sub-major level' (ABS 2006: 4). Skill specialisation refers to:

- Field of knowledge required
- Tools and equipment used
- Materials worked on
- Goods or services produced.

When disaggregated to a fine enough level, a particular occupation should consist of a set of jobs that involve much the same work, irrespective of their associated geographical location, industry sector, contractual status or various other dimensions of that job. We can infer that such a set of jobs involves a given level of skill, relates to a common field of knowledge and utilises similar technologies. Take, for example, the minor group 'Database and Systems Administrators, and ICT Security Specialists'. Whether working in mining, financial and insurance services or arts and recreation services, we would anticipate persons in that occupation to undertake similar tasks and, in doing so, apply similar skills, knowledge and technologies. On this basis, we argue that the changing occupational composition of the workforce can be used to proxy change in the nature of work. If it is possible to link STEM skill requirements to occupations, then it is possible to relate changing occupational composition – past and projected – to changing requirements for STEM skills. This is done by a cross-tabulation of the skill level and field of education of workers' post-school qualifications for each of 97 minor-group occupational categories for Australia.

Table 1. Employed persons with post-school qualifications by field of education and highest level of qualification: Australia 2016

Field of education	*Level of education not stated/ inadequately described*	*Certificate*	*Diploma/ advanced diploma*	*Bachelor's degree*	*Graduate diploma/ certificate*	*Post-graduate degree*	*Total*	*Persons with post-school qualifications*
	%	%	%	%	%	%	%	
Natural and Physical sciences	1.7	4.2	6.2	59.4	2.6	26.0	100.0	231,080
Information technology	3.7	12.2	17.9	42.9	3.6	19.8	100.0	274,920
Engineering and related technologies	2.1	65.4	10.2	17.0	0.6	4.7	100.0	1,170,252
Architecture and building	2.0	76.0	7.9	10.1	0.7	3.2	100.0	474,196
Agriculture, environmental and related studies	2.4	49.8	18.4	20.9	1.8	6.7	100.0	168,830
Health	3.3	13.1	18.1	47.5	6.1	11.9	100.0	799,564
Education	1.7	11.0	10.1	49.1	16.2	12.0	100.0	586,189
Management and commerce	3.0	25.7	23.6	30.2	4.0	13.5	100.0	1,592,254
Society and culture	2.0	27.1	18.2	34.7	5.1	12.8	100.0	921,815
Creative arts	1.7	14.8	25.4	48.0	2.8	7.2	100.0	290,661
Food, Hospitality and Personal Services	2.3	73.3	21.8	2.6	0.1	0.0	100.0	384,836
Mixed field programmes	72.2	22.8	4.2	0.6	0.0	0.1	100.0	10,574
Inadequately described/not stated	42.7	26.2	7.8	18.7	0.9	3.7	100.0	289,616

Source: ABS 2016 Census of Population and Housing, retrieved from online Tablebuilder facility.

To approximate STEM skill requirements by occupation, we consider a matrix consisting of a separate table such as Table 1 for employed persons in each of the 97 minor group (or '3-digit') occupations. We also retain Census categories of 'not fully defined' (nfd), giving 134 occupational classifications in total.[1] With reference to all persons working in an occupation, the proportion with post-school qualifications in STEM fields can be calculated as a measure of the 'intensity' with

1 For example, within the major group of '2 Professionals', the 3-digit table from the Census includes a category of '200 Professionals, nfd' including employed persons who were identified as professionals, but could not further be allocated to a sub-major group. Sub-major groups also include nfd categories: the sub-major group of '26 ICT Professionals' includes a category of '260 ICT Professionals, nfd', along with '261 Business and systems analysts', '262 Database and systems administrators' and '263 ICT Network and support professionals'. For completeness, we have retained these 'nfd' categories in the analysis.

which STEM skills are used in each occupation. To overcome the arbitrary dichotomy in which STEM qualifications are defined only at the bachelor's degree or above, we instead incorporate all post-school qualifications within the STEM fields and apply a weighting based on the level of education.

This begs the question of what weighting to apply to different educational levels. Ideally, the weighting should relate to the intensity of STEM knowledge or skill. One option would be to use an approximation of the typical number of years of education required to complete each qualification, on the assumption that STEM-intensity increases directly with time spent in training and education. A robustness check following this approach is presented in Appendix 3. Our preferred approach is to infer the level of skill embodied in each qualification level on the basis of its associated wage premium realised in the labour market since, in theory, such wage differentials equate to differences in marginal productivity. This takes into account both the supply side (i.e., training and education outputs) and the demand side for such qualifications. A wage equation was estimated using the pooled sample of employees from HILDA waves 2001 to 2017. In the model the dependent variable is the logarithm of hourly real wages expressed in 2017 dollars, and we control for key supply side characteristics, such as gender, age, marital status and migrant background (see Appendix 1 for detailed results). We also include dummy variables for the workers' highest level of post-school qualification attained corresponding to those in Table 1, along with dummy variables for completion of Year 12 and completion of Year 11 or below. The model is estimated with bachelor's degree as the omitted or base category. Under this specification, the coefficient on each post-school qualification variable corresponds to the average per cent increase or decrease in wages associated with attaining that level of qualification relative to a person who has attained a degree.

The estimated coefficients from the wage equation are shown in Table 2. By example, the coefficient of 12.9 indicates that a person with a postgraduate degree earns, on average, 12.9 per cent higher hourly wages than similar persons with a bachelor's degree. A worker with a Certificate level III/IV, on the other hand, typically earns 27.8 per cent lower. From this we can derive expected earnings at each level of qualification relative to a degree holder. Given that, in theory, earnings equate to productivity, these relativities can be used as a basis to assign weights to different levels of qualification, as shown in the final column of Table 2. By construction, the implied weight or level of STEM skills associated with a worker with a bachelor's degree held in a STEM field is equal to 1. A postgraduate qualification carries a 56 per cent higher weighting than a Certificate III/IV level qualification, reflecting the estimated differences in wages between workers with those qualification levels.

Table 2. Weightings assigned to workers' STEM qualifications by level of education

	Regression Coefficient (%)	*STEM skill weighting*
Postgraduate (masters/doctorate)	12.9	1.129
Graduate diploma or certificate	4.8	1.048
Bachelor's or honours degree	—	1.000
Advanced diploma or diploma	-17.1	0.829
Certificate level III or IV	-27.8	0.722
Completed Year 12	-26.0	n.a.
Completed Year 11 or lower	-37.8	n.a.

The STEM skill intensity is calculated for each occupation as:

$$S = \frac{(0.722N_{Cert} + 0.829N_{Dip} + 1.000N_{Degree} + 1.048N_{Grad.dip} + 1.129N_{Higher.deg})}{N_{Total}} \qquad \text{(Equation 1)}$$

where N_{Cert}, N_{Dip}, N_{Degree}, $N_{Grad.dip}$, and $N_{Higher.deg}$ respectively refer to the number of persons employed in the occupation with a certificate, diploma, bachelor's degree, graduate diploma/certificate and higher degree in a STEM field. The denominator, N_{Total}, is the total number of persons employed in the occupation, encompassing those with and without post-school qualifications. Hence an occupation's STEM 'skill intensity' is directly related to the proportion of workers with their post-school qualification in a STEM field, and the level of those qualifications.

Potentially the measure ranges from zero, if no workers in an occupation held a post-school qualification in a STEM field; to 1.129 if every worker in the occupation held a postgraduate degree in a STEM field. It is true that the employment of persons with STEM qualifications in an occupation does not necessarily equate to 'use' or demand for those particular skills. Some people with STEM qualifications will be employed in an occupation and not be using their STEM skills. Equally, some people with no formal STEM skills will be employed in jobs where having STEM skills would increase their productivity, and their employers would prefer that they did hold such skills. Such a direct matching is not required with this approach. All that is required for the measure to be valid is that people with STEM qualifications are disproportionately allocated, through the various labour market processes, to occupations in which those skills are most valued or most in demand.

While assigning a weighting of 1 to a bachelor's degree is somewhat arbitrary, it makes no difference to the results as to which qualification level is chosen as the base category or what the base value is set to: any changes would simply result in scaling the measures generated up or down proportionately. However, choosing a bachelor's degree as the unitary base offers some consistency with existing studies which only consider a person to be part of the STEM workforce if they have a bachelor's degree or higher. A limitation is that it is not possible to take account of STEM skills embodied in peoples' school level qualifications – ideally one would like to know the extent of STEM subjects that workers had undertaken in their Year 12 graduation, and whether this was associated with their occupational destination.

A second limitation is that the Census variable used to capture level of education aggregates all certificates into a single category incorporating certificates from Level I to Level IV. However, the variable for highest level of post-school qualification in HILDA includes only certificates III and IV at the certificate level. Generally returns to certificate levels I/II are lower than to completion of Year 12, and thus the wage premium associated with certificates and estimated using the HILDA data would over-estimate the wage premium associated with certificates more generally as defined in the Census. However, this is likely to have minimal effect in our case. An analysis of the more detailed level of qualification data for the 2016 Census reveals that virtually all certificates held in the STEM fields are in fact at the certificate III/IV level, with less than one-fifth of one per cent of certificate holders reporting certificates at the I/II level. Hence the wage premium of -27.8 per cent associated with certificate Level III/IV relative to a bachelor's degree, as estimated from HILDA, is the most appropriate one to use in applying weights to STEM qualifications.

Third, the returns to different levels of qualification estimated using HILDA apply to qualifications in all fields, not just to STEM. In reality, wage relativities associated with different levels of qualification may vary substantially across fields of education: a diploma in IT may be associated with a very different return to a diploma in hospitality, for example. Following the logic of using expected wages as a measure of STEM skills, ideally it is the returns to qualifications specific to STEM fields of education that would be used. These are difficult to estimate because field of highest post-school qualification has only been collected in HILDA's supplementary education modules contained in the Wave 12 and Wave 16 surveys, but potentially could be done using just cross-sectional estimates or replicating the approach of Dockery and Bawa (2018). Restricting the data to Waves 12 and 16 only and estimating the return to STEM qualifications returns a marginally lower premium to a postgraduate degree (10.8 per cent), a higher return for a graduate diploma (+8.5 per cent) and similar returns for other qualifications (-16.5 per cent for an advanced diploma/diploma and -28.1 per cent for a certificate, relative to a degree). Hence using STEM specific returns should not greatly alter the general findings. An advantage of using the more general weighting is that it can also be applied for comparisons with other fields, as is done below.

Which are the STEM jobs?

The resulting STEM skill-intensity measure calculated for all minor group occupations using 2016 Australian Census data is presented in Appendix 2, while Table 3 reports the 25 most STEM intensive and 25 least STEM intensive occupations, along with the derived STEM-intensity measure.[2] As would be expected professional occupations,

2 Occupational categories of 'not further defined', such as '260 ICT Professionals, nfd' have been excluded for the purposes of Table 3, but have been included in all relevant calculations.

notably in engineering and ICT, feature prominently among the list of STEM-intensive occupations. Engineering professionals top the list as the occupation with the most heavily STEM qualified workforce. However, many occupations classified within the major category of '3 Technicians and Trades workers' also appear in the top 25 STEM intensive occupations, and even one from the lower skilled major group of machinery operators and drivers (stationary plant operators). Employment in such occupations would be neglected under those approaches to measuring STEM skills which use a bachelor's degree as the minimum level of qualification required to be considered a 'STEM worker'. Indeed, using the wage premium associated with each qualification level to weight STEM skills intensity implies that technicians and trades workers accounted for almost the same proportion of employment of STEM skills (28.6 per cent) in 2016 as professional workers (29.6 per cent), followed by managerial occupations (14.8 per cent).

Given the disagreement over whether medicine should be considered a STEM discipline, it is interesting to note that three medical professions rank amongst the seven least STEM intensive occupations: midwifery and nursing professionals, health therapy professionals and medical practitioners.

Table 3. Twenty-five most and least STEM-intensive occupations, 2016

Highest STEM-Intensity (S.I.)		*Lowest STEM-intensity (S.I.)*	
Occupation	*S.I.*	*Occupation*	*S.I.*
Engineering Professionals	0.834	Hairdressers	0.004
Business & Systems Analysts, Programmers	0.721	Midwifery & Nursing Professionals	0.007
ICT Network & Support Professionals	0.641	Health Therapy Professionals	0.013
Mechanical Engineering Trades Workers	0.590	Legal Professionals	0.019
Electricians	0.584	Child Carers	0.020
Natural & Physical Science Professionals	0.570	Personal Assistants & Secretaries	0.020
Air & Marine Transport Professionals	0.565	Medical Practitioners	0.022
Database & Systems Administrators, ICT Security Specialists	0.564	Health & Welfare Support Workers	0.025
Automotive Electricians & Mechanics	0.557	Accountants, Auditors & Company Secretaries	0.025
ICT Managers	0.516	Receptionists	0.025
Fabrication Engineering Trades Workers	0.500	Social & Welfare Professionals	0.026
Panelbeaters, Vehicle Body Builders, Trimmers & Painters	0.490	Plumbers	0.028
ICT & Telecommunications Technicians	0.486	Education Aides	0.031
Electronics & Telecoms. Trades Workers	0.456	School Teachers	0.032
Wood Trades Workers	0.384	Bricklayers, & Carpenters & Joiners	0.033
Printing Trades Workers	0.356	Personal Carers & Assistants	0.034
Building & Engineering Technicians	0.334	Food Trades Workers	0.035
Agricultural, Medical & Science Techns.	0.314	Hospitality Workers	0.038
Miscellaneous Specialist Managers	0.258	Glaziers, Plasterers & Tilers	0.038
Construction, Distribution & Production Managers	0.229	Checkout Operators & Office Cashiers	0.038
Tertiary Education Teachers	0.222	Education, Health & Welfare Services Managers	0.039
Textile, Clothing & Footwear Trades Wrkrs	0.206	Sports & Fitness Workers	0.041
Stationary Plant Operators	0.203	Personal Service & Travel Workers	0.042
Misc. Technicians & Trades Workers	0.178	Financial & Insurance Clerks	0.042
Contract, Program & Project Administrators	0.177	Accounting Clerks & Bookkeepers	0.042

Note: 3-digit occupational categories of 'not further defined' excluded from this Table.

The logic behind our application of the intensity measure in the analysis that follows is that the fine-level occupational classifications can be used to differentiate between jobs in line with their requirements for STEM skills and knowledge. An important test of the validity of this assumption is that the relative ranking of occupations in terms of their STEM-intensity should be quite stable over time. The quantum of the measure will change, by definition, with changes in the supply of STEM skills – if more workers gain post-school qualifications in STEM fields, the measured intensity will increase – and this may be unrelated to requirements of jobs.

It is the stability of the relative ranking of occupations that is critical. To test this, the STEM-intensity measure was also generated for each occupation using the 2006 Census data. The straight correlation between the 2006 and 2016 measures, at 0.99, is almost unitary. More importantly, the rank correlation of the occupations is 0.94, demonstrating strong persistence in the differences in STEM requirements between different occupations over time. Large changes in rank occur primarily for the 'nfd' categories with very few workers, and hence their measured STEM-intensity will be sensitive to changes in the qualifications held by a small number of workers. However, as the number of workers in these categories is small, such changes will have minimal impact on the results. The 2016 STEM-intensity for each occupation, and their ranks for 2006 and 2016 can be seen in Appendix 2.

This gives us confidence that changes in employment by occupation can be used as a robust measure of changes in the demand for STEM skills in the labour market. Further, changes in STEM requirements can be approximated wherever employment data by occupation is available or can be inferred, such as between regions or industries, between different time periods, and for future projections. The following sections look retrospectively at changes in STEM requirements in the Australian labour market between 2006 and 2016, and then changes in STEM requirements based on existing national employment projections.

Recent trends in employment in STEM occupations

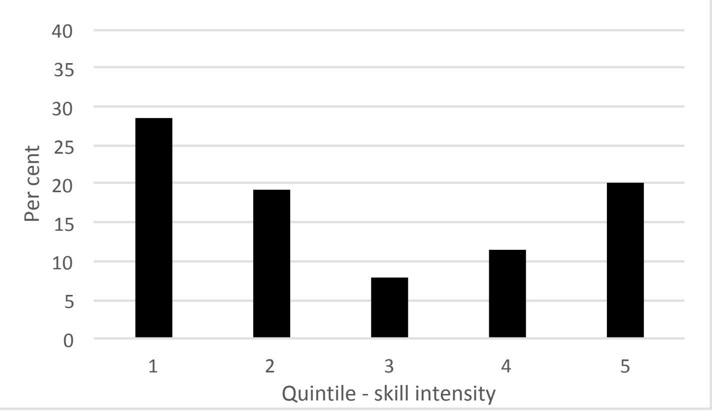
To assess the relative growth of STEM employment, counts of employed persons in the 2006 Census were divided into quintiles according to the STEM-intensity of their occupation as derived in 2016. That is, into the one-fifth of workers with the lowest STEM-intensity in their jobs, followed by the next fifth, and so on to the 20 per cent of workers in occupations with the highest STEM-intensity. With the Census recording 8.94 million Australians in employment in 2006, each quintile contains around 1.79 million workers. We then looked at how the number of workers employed in those occupations changed in the decade between 2006 and 2016.

In total, employment in Australia grew by 17.4 per cent in the decade between the 2006 and 2016 censuses.[3] As Figure 1 shows, it was the least STEM-intensive jobs that grew most quickly, with the number of jobs in those occupations increasing by 28.4 per cent, more than 50 per cent faster than employment growth overall. Employment in jobs in the top quintile of STEM-intensity also expanded more rapidly than the overall workforce, increasing by 20.2 per cent over the decade. Jobs in occupations with moderate STEM-intensity (from the 3rd and 4th quintiles) grew markedly more slowly. In fact, over half of all jobs growth (54 per cent) was observed in jobs in the bottom two quintiles of STEM-intensity. Rather than a general increase in requirements for STEM skills, the picture is more one of a 'shrinking middle' featuring growing demand for jobs that are very STEM-intensive and for those with low STEM requirements. The pattern also fits with perceptions of technological

3 Calculations exclude persons for whom occupation was inadequately described or not stated. These amounted to 1.7% of employed persons in Australia in the 2016 census, and 1.8% in the 2006 Census.

change contributing to 'jobs polarisation' in which there is an increase in the share of high-skilled and low-skilled jobs, at the expense of middle-skilled jobs (Borland and Coelli 2017: 381).

Figure 1. Percentage growth in jobs from 2006 to 2016, by quintile of STEM skill intensity



This same analysis can be repeated for the individual fields within STEM (Figure 2), and for the non-STEM fields of education (Figure 3). Figure 2 contains the respective employment changes by quintile of skills intensity for the Natural and Physical Sciences (NPS); Information Technology (IT); and Engineering and Related Technologies (ERT). It can be seen that jobs growth in the top quintile of skill intensity for NPS and ERT contributed to the faster growth of STEM-intensive jobs, with jobs making intensive use of skills in NPS leading the way. The fifth of jobs in occupations with the highest skill intensity in NPS in 2006 increased in number by 27.3 per cent between 2006 and 2016 (Figure 2(a)). However, structural change over the past 10 years appears to have been relatively neutral in terms of the share of jobs with intensive demand for IT skills, and to significantly reduce the share of jobs requiring skills in the field of ERT.

Structural change in the labour market, as proxied by changing occupational composition, strongly favoured jobs demanding health skills and qualifications (Figure 3(c)). Jobs in occupations in the highest quintile in terms of their intensity of health-related skills and qualifications grew by 34.9 per cent between 2006 and 2016, double the rate of overall employment growth. These 20 per cent of jobs in 2006 accounted for 40 per cent of all jobs growth over the 10 years. Interestingly, the field of Society and Culture was also strongly favoured by structural change, with the top quintile contributing 37.0 per cent of all jobs growth. This is notable given the arguments noted above that STEM needs to incorporate humanities to become 'STEAM'. There appears to have been a stronger shift to jobs utilising these skills than STEM skills, for which the top quintile of jobs in 2006 had a 23.2 percentage share of subsequent jobs growth. Changing occupational composition of the labour market also appears to have favoured qualifications in education, but worked against the fields of Agriculture, Environmental & Related Studies; Architecture and Building; and Food, Hospitality & Personal Services.

Figure 2. 2006-2016 growth in jobs by skill-quintile, individual STEM fields

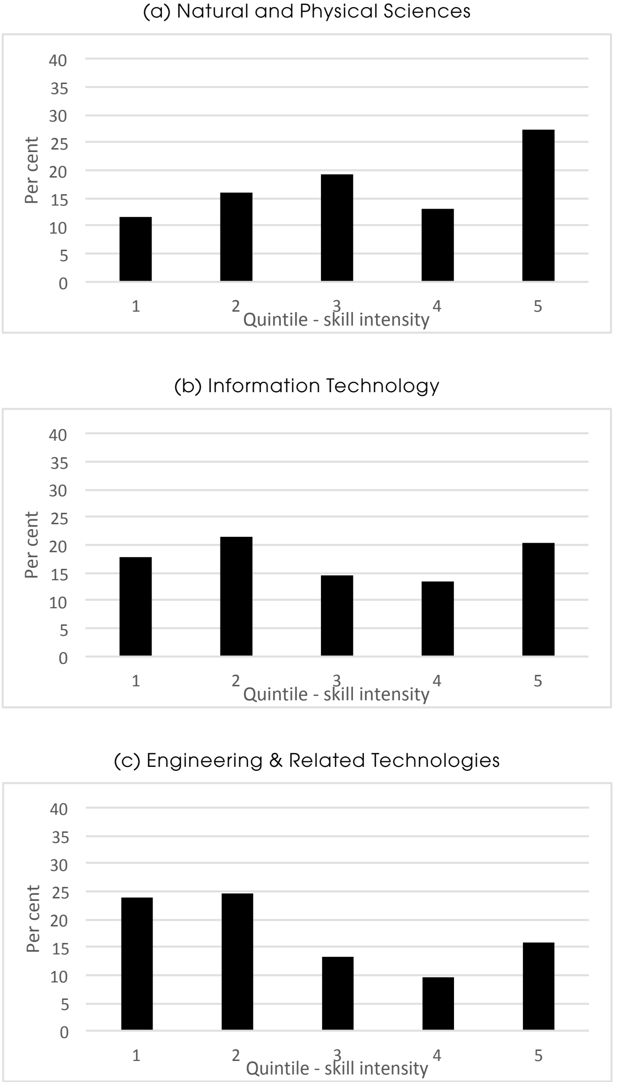
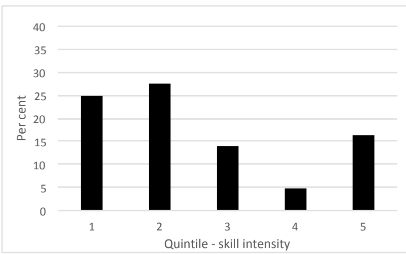
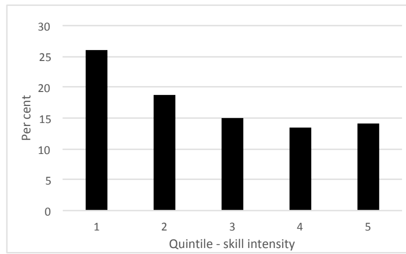


Figure 3. 2006-2016 growth in jobs by skill-intensity decile, non-STEM fields

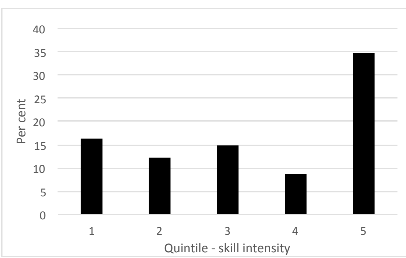
(a) Architecture and Building



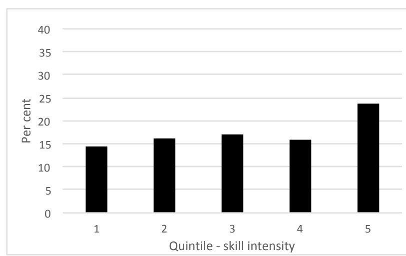
(b) Agriculture, Environmental and Related Studies



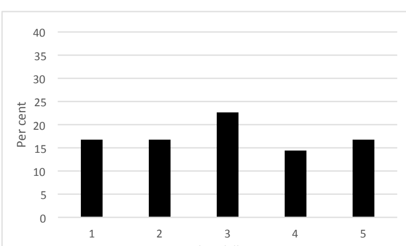
(c) Health



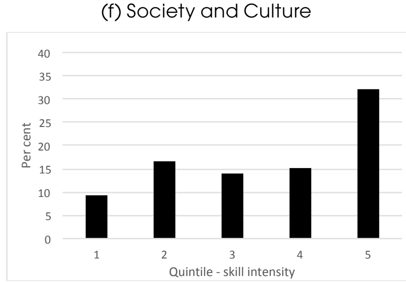
(d) Education



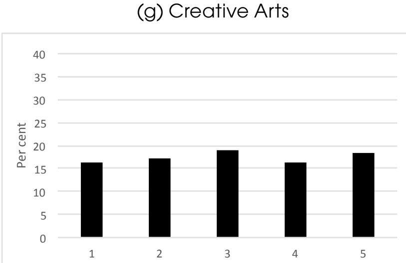
(e) Management and Commerce



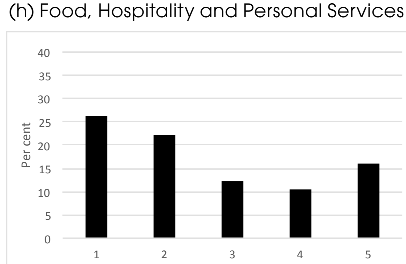
(f) Society and Culture



(g) Creative Arts



(h) Food, Hospitality and Personal Services



A more direct measure of changing skill requirements can be derived by calculating the change in employment weighted by skill intensity. Again, this can be done for STEM skills overall, as well as for the individual fields and for non-STEM fields. The results of this exercise, shown in Table 4, suggest that growth in demand for STEM skills associated with the changing occupational profile of employment, at 17.3 per cent, has actually been substantially slower than overall growth in skills across all fields (21.5 per cent). Growth in demand for NPS skills was on par with overall (weighted) skills growth, with higher growth for IT skills and very low growth in demand for skills in the ERT field. Changing employment by occupation increased demand at a stronger rate for Health (35.9 per cent), Society and Culture (29.0 per cent) and Education (24.3 per cent). In terms of the absolute number of employed persons weighted by skill level, the largest increase was observed for Management and Commerce, followed by Health and Society and Culture.

Table 4. Change in skill requirements: STEM and non-STEM (employed persons weighted by skill level)

	Weighted employment			*Per cent growth*
	2006	*2016*	*Change*	
STEM	**1,181,533**	**1,385,791**	**204,258**	**17.3**
Natural & Physical Sciences	187,185	227,356	40,170	21.5
Information Technology	192,774	250,410	57,635	29.9
Engineering & Related Technologies	801,573	908,026	106,453	13.3
Non-STEM				
Architecture and Building	305,585	355,667	50,082	16.4
Agriculture, Environmental & Related	124,467	135,889	11,422	9.2
Health	536,504	728,926	192,422	35.9
Education	449,246	558,434	109,188	24.3
Management and Commerce	1,173,464	1,379,822	206,358	17.6
Society and Culture	629,419	812,242	182,823	29.0
Creative Arts	218,086	261,311	43,225	19.8
Food, Hospitality & Personal Services	238,497	280,543	42,045	17.6
All Fields	**4,856,800**	**5,898,623**	**1,041,823**	**21.5**

Projected growth in demand for STEM skills

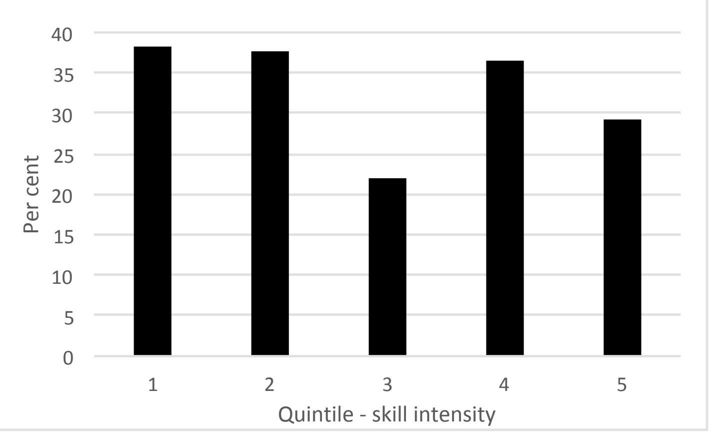
The estimates above offer little support for the view of growing demand for STEM skills in the Australian labour market over the 10 years from 2006 to 2016, relative to skills in other fields. By necessity of having to rely on the five-yearly Census data to obtain sufficiently detailed data on workers' qualification levels by field of education and occupation, this provides a somewhat rear-mirror view of changes in the nature of work, whereas much of the STEM narrative appeals to supposed changes in demand associated with 'the future of work'. Having developed measures of STEM-intensity by occupation, and of skill-intensity for other fields, it is a mechanical procedure to project future trends in skills demand based on projections of employment by occupation. The Department of Education, Skills, and Employment (DESE) regularly produces such a set of projections, and at the time of writing projections were available to 2024.[4] Available down to the 4-digit ANZSCO level, the projections are generated using time-series forecasting methods applied to past trends supplemented by '… adjustments made to take account of research undertaken by the National Skills Commission and known future industry developments'. The projections are for total persons employed (including full-time and part-time employment), consistent with the Census data used above.

The Department projects total employment of 13.9 million persons by 2024, an increase of 32.7 per cent over the 2016 ABS Census count. Applying the STEM-intensity coefficients by occupation, we can impute the changing demand for STEM skills associated with those projections. Sorting the 2016 data into quintiles of employment by STEM skill-intensity, Figure 4 shows the projected growth in employment in occupations in each of those quintiles from 2016 to 2024. It can be seen that the Department's projected trends in employment by occupation imply an ongoing shift in occupational structure of the labour market away from STEM skills. Growth is projected to be highest in the two quintiles with lowest requirement for STEM skills: 38.3 per cent in the first quintile and 37.6 per cent in the second quintile, respectively. The one-fifth of jobs with the highest STEM skill requirements are projected to grow by just 29.2 per cent.

Jobs in the occupations in the two quintiles (or 40 per cent of jobs in 2016) with the lowest STEM requirements are expected to account for 46.4 per cent of all employment growth, compared to 40.2 per cent for the two quintiles with the highest STEM requirements. As with trends from 2006 to 2016, there is evidence of a polarisation or 'disappearing middle' in the distribution of jobs according to demand for STEM sills.

4 The data were downloaded from https://lmip.gov.au/default.aspx?LMIP/EmploymentProjections on 23 July, 2020. The webpage also contains a description of the forecasting methodology. The responsible Department at the time these projections were published was the Department of Employment, Skills, Small and Family Business (DESSFB).

Figure 4: Percentage growth in jobs from 2016 to 2024, by quintile of STEM skill intensity



The occupational intensity of skill use by different fields of education can be used to make an assessment of future growth in skills demand associated with the projected changes in employment by occupation, as was done above for past trends in Table 4. Importantly these provide some gauge of the magnitude of projected skill demands as well as percentage changes. We can see in Table 5, demand for STEM skills is projected to be marginally higher than the growth in skills overall, but this is due only to the strong projected growth in demand for IT skills. A number of the non-STEM fields of education are projected to experience stronger growth in percentage terms than STEM, including (in order) Architecture and Building; Health; Society and Culture; and Creative Arts.

In terms of the absolute numbers, as opposed to percentage changes, a substantial increase in skills-weighted employment is projected for the STEM fields taken together. However, for individual fields of education, the increases are projected to be largest for Management and Commerce, Society and Culture, Engineering and Related Technologies and Health.

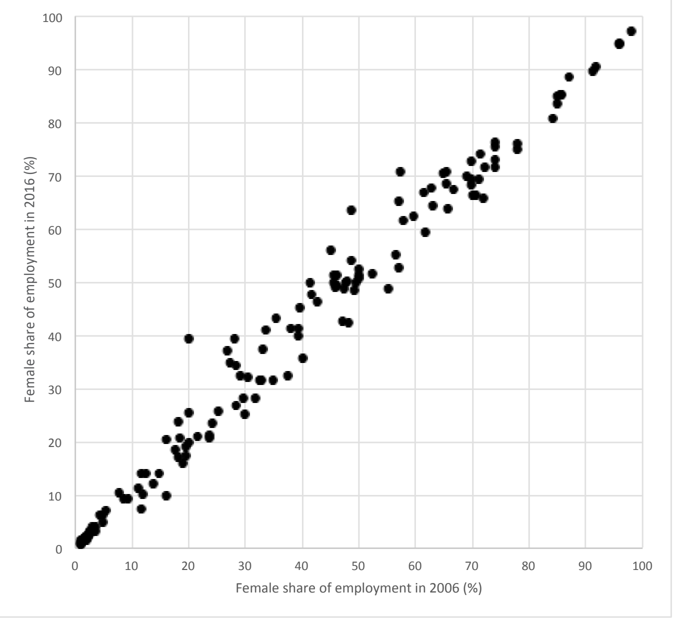
Table 5. Projected changes in skill requirements: STEM and non-STEM (employed persons weighted by skill level), 2016-2024

	Weighted employment			*Per cent growth*
	2016	*2024*	*Change*	
STEM	**1,385,791**	**1,882,867**	**497,076**	**35.9**
Natural & Physical Sciences	227,356	298,023	70,667	31.1
Information Technology	250,410	377,175	126,765	50.6
Engineering & Related Technologies	908,026	1,207,669	299,644	33.0
Non-STEM				
Architecture and Building	355,667	493,573	137,906	38.8
Agriculture, Environmental & Related	135,889	176,366	40,477	29.8
Health	728,926	1,004,591	275,665	37.8
Education	558,434	740,358	181,924	32.6
Management and Commerce	1,379,822	1,795,249	415,427	30.1
Society and Culture	812,242	1,118,360	306,118	37.7
Creative Arts	261,311	356,829	95,518	36.6
Food, Hospitality & Personal Services	280,543	371,034	90,491	32.3
All Fields	**5,898,623**	**7,939,226**	**2,040,603**	**34.6**

Changes in skills demand by gender

As noted, there has been a concerted effort on the part of government to encourage women into STEM, as they are typically under-represented among students in STEM subjects at school and in post-school courses, such as engineering and IT. In this section, we consider how the changing occupational composition of employment affects demand for skills in jobs held by women and men. While it may seem a bit old-fashioned to talk of 'men's jobs' and 'women's jobs', the truth is that occupational segregation by gender is still quite an entrenched feature of the Australian labour market. As the scatter plot in Figure 5 demonstrates, there is close to a 1 to 1 correspondence between the gender distribution within occupations in 2006 and the distribution 10 years later. The occupations that were female dominated in 2006 were similarly female dominated in 2016, such as Personal Assistants and Secretaries (98.1 per cent of workers were female in 2006 versus 97.2 per cent in 2016), Receptionists (96.0 per cent v. 94.8 per cent) and Child Carers (95.9 per cent v. 95.1 per cent). The male dominated end of the spectrum is populated by trade occupations, including Bricklayers, Carpenters and Joiners (0.9 percent female in 2006, 0.8 per cent in 2016), Fabrication Engineering Trades Workers (0.9 per cent v. 1.0 per cent) and Automotive Electricians and Mechanics (1.0 per cent v. 1.4 per cent).

Figure 5. Female share of employment by occupations: 2016 versus 2006



Source: ABS 2016 Census of Population and Housing, retrieved from on-line Tablebuilder facility.

Taking the skill-intensity of each occupation, skills demand by field of education was calculated for the jobs held by women and by men in 2006 and 2016. The skills intensity of jobs is based only on the occupation specific intensity measures generated from the 2016 Census data as described above. Hence, the estimated changes in skills demand are associated purely with changes in employment by occupation, and unrelated to changes in educational attainment of the labour force. The results are presented in Table 6, which is essentially a decomposition by gender of the figures presented in Table 4. A number of salient points can be seen from this exercise. Changes in employment levels by occupation between 2006 and 2016 saw a huge increase in demand for skills in the field of Health for women. This can be seen in terms of both the percentage growth (38.3 per cent) and in absolute numbers: an estimated increase in skill-weighted employment of 140,000, almost double the contribution of the STEM fields combined (Table 6(a)). In absolute terms, changes in employment also imply large increases in skills demand for women in the fields of Society and Culture and Management and Commerce.

An additional column, headed ‘Growth share’, has been added to Table 6 (a) and (b). This reports the change in skill-weighted employment as a proportion of the total change (male and female) in skill weighted employment across the labour market. It can be seen from the final row, that most of the increase in skill-weighted employment went to jobs held by women (59.0 per cent share) rather than to men (41.0 per cent share). It can also be seen that increased employment in occupations requiring skills in the fields of Health, Society and Culture made substantial contributions to women capturing a disproportionate share of growth in skilled employment.

Table 6. Changes in skill requirements by gender: STEM and non-STEM (employed persons weighted by skill level), based on 2006 and 2016 employment by occupation

(a) Females

	Weighted employment			*Per cent growth*	*Growth share (%)*[a]
	2006	*2016*	*Change*		
STEM	**306,816**	**380,410**	**73,594**	**24.0**	**7.1**
Natural & Physical Sciences	88,539	113,129	24,590	27.8	2.4
Information Technology	65,352	82,113	16,761	25.6	1.6
Engineering & Related Technologies	152,925	185,168	32,243	21.1	3.1
Non-STEM					
Architecture and Building	51,823	64,560	12,737	24.6	1.2
Agriculture, Environmental & Related	44,153	50,531	6,377	14.4	0.6
Health	365,832	505,916	140,083	38.3	13.4
Education	307,598	395,927	88,328	28.7	8.5
Management and Commerce	618,375	737,263	118,888	19.2	11.4
Society and Culture	359,437	485,554	126,117	35.1	12.1
Creative Arts	107,381	133,401	26,020	24.2	2.5
Food, Hospitality & Personal Services	128,165	150,436	22,272	17.4	2.1
All Fields	**2,289,580**	**2,903,998**	**614,418**	**26.8**	**59.0**

(b) Males

	Weighted employment			*Per cent growth*	*Growth share (%)*[a]
	2006	*2016*	*Change*		
STEM	**874,717**	**1,005,381**	**130664**	**14.9**	**12.5**
Natural & Physical Sciences	98,647	114,226	15580	15.8	1.5
Information Technology	127,422	168,297	40875	32.1	3.9
Engineering & Related Technologies	648,649	722,858	74209	11.4	7.1
Non-STEM					
Architecture and Building	253,763	291,107	37344	14.7	3.6
Agriculture, Environmental & Related	80,313	85,358	5045	6.3	0.5
Health	170,672	223,010	52338	30.7	5.0
Education	141,648	162,507	20859	14.7	2.0
Management and Commerce	555,088	642,558	87470	15.8	8.4
Society and Culture	269,982	326,688	56706	21.0	5.4
Creative Arts	110,705	127,910	17205	15.5	1.7
Food, Hospitality & Personal Services	110,333	130,106	19773	17.9	1.9
All Fields	**2,567,220**	**2,994,625**	**427405**	**16.6**	**41.0**

Notes: a. Percentage share of all (male plus female) weighted growth from 2006-2016.

Comparing Tables 6(a) and (b) it can be seen that men and women are employed in relatively equal numbers in skill-weighted terms for the field of Natural and Physical Sciences, but there are around half as many women as men in the field of IT and around one-quarter as many in the field of Engineering and Related Technologies. So, is the relatively minor contribution of projected employment growth in STEM-intensive occupations for women simply a consequence of their stark under-representation in those jobs? The answer is clearly 'no'. For both men and women, changes in employment occupation point to slower growth in skills demand in the STEM fields than for all fields. Hence, if anything, men experienced a lower increase in skills demand because of their over-representation in STEM-intensive occupations. However, there was a narrowing of the gender divide in STEM related occupations over that decade, with women's employment in STEM intensive occupations growing more rapidly than for men.

Like women, men also experienced a very high increase in skilled employment in Health (30.7 per cent), but they did not capture anywhere near the share of skilled employment growth that women did because of the under-representation of skilled males in Health. Essentially, structural change in the labour market over the decade from 2006 to 2016 shifted strongly in favour of demand for women's skills because of their over-representation in Health, Society and Culture and Education.

The corresponding tables comparing skill-weighted employment by field of education in 2016 and in 2024, based on the (then) DESSFB's employment projections, are presented in Table 7. This is calculated assuming constant employment shares by gender within occupations in 2016 and 2024, which, as shown in Figure 5, seems a justifiable approximation. Following our methodology, the Department's projections for growth in employment by occupation imply an increase in skill-weighted employment that will be shared relatively evenly between men (51.2 per cent) and women (48.8 per cent). In this case, forecast structural change does contribute to a strong increase in demand for STEM skills for men, due largely to projections for a big increase in employment in occupations intensive in Engineering and Related Technology skills and a very high rate of growth in demand for IT skills. Projections for strong growth in occupations requiring skills in the field of Architecture and Building also translate to increased skills demand for men. However, it remains the case that the projections imply the share of growth in skills demand predicted to be captured by women due to their over-representation in the fields of Health, Education and Society and Culture is greater than the share captured by men due to their over-representation in the STEM fields.

Table 7. Projected changes in skill requirements by gender: STEM and non-STEM (employed persons weighted by skill level), 2006 and 2024

(a) Females

	Weighted employment			*Per cent growth*	*Growth share (%)*[a]
	2016	*2024*	*Change*		
STEM	**380,410**	**503,292**	**122,882**	**32.3**	**6.0**
Natural & Physical Sciences	113,129	148,009	34,880	30.8	1.7
Information Technology	82,113	115,937	33,824	41.2	1.7
Engineering & Related Technologies	185,168	239,346	54,178	29.3	2.7
Non-STEM					
Architecture and Building	64,560	87,056	22,496	34.8	1.1
Agriculture, Environmental & Related	50,531	65,386	14,855	29.4	0.7
Health	505,916	702,547	196,632	38.9	9.6
Education	395,927	526,939	131,012	33.1	6.4
Management and Commerce	737,263	959,454	222,191	30.1	10.9
Society and Culture	485,554	674,924	189,370	39.0	9.3
Creative Arts	133,401	180,704	47,303	35.5	2.3
Food, Hospitality & Personal Services	150,436	200,292	49,856	33.1	2.4
All Fields	**2,903,998**	**3,900,594**	**996,596**	**34.3**	**48.8**

(b) Males

	Weighted employment			*Per cent growth*	*Growth share (%)*[a]
	2016	*2024*	*Change*		
STEM	**1,005,381**	**1,379,575**	**374,193**	**37.2**	**18.3**
Natural & Physical Sciences	114,226	150,014	35,787	31.3	1.8
Information Technology	168,297	261,237	92,941	55.2	4.6
Engineering & Related Technologies	722,858	968,323	245,465	34.0	12.0
Non-STEM					
Architecture and Building	291,107	406,517	115,410	39.6	5.7
Agriculture, Environmental & Related	85,358	110,979	25,622	30.0	1.3
Health	223,010	302,044	79,033	35.4	3.9
Education	162,507	213,419	50,913	31.3	2.5
Management and Commerce	642,558	835,795	193,237	30.1	9.5
Society and Culture	326,688	443,436	116,748	35.7	5.7
Creative Arts	127,910	176,125	48,215	37.7	2.4
Food, Hospitality & Personal Services	130,106	170,742	40,636	31.2	2.0
All Fields	**2,994,625**	**4,038,631**	**1,044,006**	**34.9**	**51.2**

Notes: a. Percentage share of all (male plus female) weighted growth from 2016-2024.

Conclusions and discussion

We argue that the methodology developed for this report offers important advantages over previous approaches to measuring the demand for STEM skills in the Australian workforce and for monitoring changes in that demand. The most significant enhancement is the move away from a binary definition of STEM and non-STEM workers to one that embodies STEM qualifications at all levels from certificate III/IV and above, and takes account of the transferability of STEM skills across occupations. This captures the demand for tradespeople and technicians with STEM qualifications that are often at the root of skills shortages, and a group that is excluded in approaches that use a bachelor's degree as the minimum qualification to be deemed a 'STEM' worker. While the approach requires assumptions regarding the weightings attributed to different levels of qualifications, these have not been chosen arbitrarily but are based on earnings differentials. Indeed, by this measure, many of the most STEM-intensive occupations are trades and technical occupations, including Mechanical Engineering Trades workers coming in at sixth out of 134 ANZSCO 3-digit categories. Workers in the Technical and Trades occupations are calculated to have accounted for almost the same level of STEM skills in 2016 as professional workers.

Second, the approach is not affected by supply-side changes, such as rising credentialism. With STEM-intensity by occupation defined in a given base year (in our case 2016), imputed changes in STEM employment arise purely through changes in employment by occupation, not changing educational attainment of the workforce. This contrasts with other approaches which would directly infer rising STEM demand if the number of graduates from STEM courses increased in the workforce. We caution against the interpretation of the weighted employment measure as a 'quantum' of STEM skills or STEM demand, but rather it should be used for comparative purposes; that is, to measure changes over time and differences between subsets of the workforce. Additionally, the approach can be used to assess changes in demand for qualifications for any grouping by field of education, including for the sub-fields within STEM, for different variations of STEM (such as STEMM or STEAM) and for non-STEM fields.

Contrary to much of the narrative surrounding STEM and the 'future of work', our results suggest that changes in the occupational structure of the workforce over the decade from 2006 to 2016 reduced the demand for STEM skills relative to other qualifications. Rather than a broad-based increase in employment in jobs utilising STEM skills, there has been a polarisation – or 'shrinking middle' – with jobs with very high STEM-intensity and jobs with very low STEM-intensity growing more rapidly than average. By a considerable margin, it is skills in Health that saw the greatest increase in demand from changing employment patterns between 2006 and 2016, and growth in demand for skills in the fields of Society and Culture and in Education also outpaced STEM. Employment projections to 2024 suggest demand for STEM and non-STEM skills will grow at a relatively similar pace.

The results are clearly inconsistent with what would be expected given popular narratives around STEM and the future of work and their associated policy prescriptions. Moreover, when it comes to the demand for their skills, women appear to be benefitting from their under-representation in STEM: policies to get women into

STEM fields and courses could be characterised as ‘pushing them off a winning horse’. While this analogy does not take into account other attributes of the jobs requiring those skills, such as status, pay and security, there is also evidence that women in STEM-related work fare badly on a number of dimensions of job quality (Dockery and Bawa 2018).[5] While these results may seem surprising they probably should not be, given that as economies develop and wealth increases, the services sector of the economy increases in importance (Buera and Kaboski 2012). As discussed, there is no consensus on exactly which fields of education should be included as STEM, and we have used a restrictive definition based on the ‘core’ fields of the Natural and Physical Sciences, Information Technology and Engineering and Related Technologies. Several Australian agencies include the field of Agriculture, Environment and Related Studies in their preferred definitions of STEM (ABS 2014, JTSI 2019, Office of the Chief Scientist 2016). Had we adopted that expanded definition, we note that the key results would have been even more pronounced, given that that field is relatively male dominated and has displayed low growth in skills demand.

Our estimates of changing skills demand, both historically and looking forward, suggest that the occupational restructuring of the workforce will increase demand for workers with qualifications in the educational fields of Society and Culture and in the Creative Arts more than in STEM. This is interesting in view of the calls for the inclusion of the Humanities and Arts in ‘STEAM’ and the Commonwealth Government’s announcement in June of 2020 of an amended fee structure for university courses that ‘incentivises students to make more job-relevant’ decisions about their education.[6] The Minister’s statement indicated the reforms are aimed at reducing the relative costs in areas of employment growth and demand, leading to more ‘job-ready’ graduates. Some effects of the proposed changes will be to substantially increase student contributions to the costs of courses in humanities (Society and Culture), while reducing student contributions in health, nursing, teaching and the STEM fields (Cassells and Bond-Smith 2020). Our results would suggest these effects are consistent with the stated aim of promoting participation in areas of growth when it comes to reducing student contributions in health and education, but not in incentivising students away from the humanities and toward STEM.

Limitations and possible extensions

While we argue the method developed to measure changes in the demand for STEM skills offers some important advantages over previous approaches, we by no means intend to suggest it is ideal or should even be considered a preferred method for measuring the STEM content of jobs. That will often depend on the particular research or policy context with which measures are being used. The approach does not take account of part-time employment or hours of work. This can perhaps be justified

5 We fully endorse policies to address gender-based discrimination and bias due to gender stereotypes that limit women’s opportunities, and acknowledge these are important issues in STEM. However, those issues must be addressed as principles of fairness and equality (and in all fields), not to fit narratives around skill shortages.

6 https://ministers.dese.gov.au/tehan/job-ready-graduates-power-economic-recovery.

since the skills intensity measure relates to skills needed for a position irrespective of the hours supplied: an engineer working half-time still needs an engineering degree, not half a degree. It would be data intensive, but the approach can be readily extended to incorporate hours worked, and this may have significant implications relating to inferences of skills demand by gender.

As noted, the methodology means that results are not affected by a general increase in the proportion of workers holding qualifications, only by changes in employment by occupation. This also means that a broad-based increase in STEM content across all jobs, rather than occupational change favouring STEM-intensive jobs, would not be detected by our methodology as an increase in demand for STEM skills. The most probable candidate for such a change is the growing need for ICT (information communication and technology) skills across jobs. However, it could be argued that a general increase in the need for STEM competencies, such as in IT, does not necessarily translate into a need for more people to specialise in STEM, but simply the incorporation of such basic competencies into other curricula.

An associated limitation is that the quantification of STEM-intensity relies on the field of education of workers' highest post-school qualification and does not take into account prior learning in STEM. While the Census is the only feasible source of detailed breakdowns of employment by occupation and qualification to support the modelling undertaken here, it does not provide information on science and mathematics subjects or level completed at high school. How completion of STEM subjects at high school relates to occupational destination and earnings would allow us to more accurately model STEM skills demand and to pick up more broad based changes in skill requirements.

Having data on field of *highest* post-school qualification only similarly leads to the neglect of other post-school qualifications gained. This would include, for example, workers who gained an initial degree in engineering, but who go on to gain a postgraduate qualification in management. Healy *et al*. (2011) also note the example of those who gain an undergraduate degree in mathematics or science and become teachers. Typically, their highest qualification is a graduate diploma or master's in education, and thus their STEM qualifications would not be captured by the methodology. Data providing a full inventory of workers' STEM skills and qualifications would provide for a more nuanced assessment of changes in skills demand.

Potential extensions or refinements of the approach include defining STEM-intensity at a more detailed level of classification of occupations and/or qualifications and allowing for part-time/full-time status of workers. However, the more detailed the occupational classification used as the basis for defining STEM-intensity, the more one will counter issues with small cell counts. Concerns over the appropriateness of the weightings applied by level of qualification could readily be assessed by testing the sensitivity of key findings to alternative weightings. Note that the common approach of defining STEM workers as those with a degree or higher is also an implicit weighting, and a special case of our approach (i.e., a weighting of one for a bachelor's degree and higher and zero otherwise). Even for those arguing that the focus for STEM capacity should be at the university level, our approach at least places greater weighting on higher degrees over undergraduate degrees.

Some critical reflections on STEM

Another element of the methodology ripe for sensitivity analyses is the choice of what fields of education to include in STEM. A challenge in determining the appropriate fields to include is the lack of a clear statement of the rationale behind the grouping of a particular set of fields together as STEM (or STEMM or STEAM). Ideally, such decisions in the modelling approach would be geared to answer specific questions or provide specific information, however, no explicit motivation seems to have been provided to guide the definition of STEM.

Much of the narrative surrounding STEM relates to what are seen as growing skills needs in response to the changing nature of work, suggesting that growing demand is common to each of the fields. However, there is little evidence to support this from the analysis. Our results suggest that changes in employment by occupation have reduced the STEM-intensity of employment overall. The long term structural shift away from manufacturing in the Australian economy is likely to have been a significant factor driving this result, with manufacturing identified as the most common industry of employment for STEM qualified workers (Office of the Chief Scientist 2016: 20). It is clearly demand for qualifications in the field of Health that have grown most as a result of the changing occupational distribution of work over recent years, perhaps offering support for the inclusion of medicine in an expanded STEMM. The conclusions drawn with respect to STEM would have been dramatically different if qualifications in the field of Health had been included in the definition of STEM, given the weighted increase in employment in Health between 2006 and 2016 was almost as great as for the three core STEM fields combined. However, if fields are included on the basis of exhibiting growing demand, the whole argument becomes circular. Moreover, the pattern of change within individual STEM fields is far from uniform, with demand for qualifications declining in ERT in relative terms, and IT being the only STEM field in which jobs that intensively use those qualifications have grown faster than average between 2006 and 2016. IT is also the only field to see above-average growth in skill demand in coming years, based on occupational projections.

As noted, there is a possibility that the methodology has failed to detect a more general or broad based increase in STEM content across all occupations. However, again the evidence casts doubt on this – the ‘shrinking middle’ pattern of growth in occupations by quintile of STEM-intensity shows that in fact there has been strong growth in occupations with the very lowest level of STEM-intensity. There is an associated policy question of whether the priority for the education system should be to promote greater general STEM literacy or strengthen capacity at the more elite level. Arguments of the need to position ourselves as an ‘innovation nation’ to maintain our competitiveness and standard of living would seem more compatible with increasing capacity at the elite level and with higher growth in STEM-intensive occupations. The latter trend is not evident in the data.

In developing the methodology to assess changes in the demand for STEM qualifications, note that the approach taken for STEM as a whole could equally be applied to the individual STEM fields and to other fields of education. So while the approach was motivated by the STEM narrative, nothing different was done from the more general case of trying to forecast skills demand by field of education. Without some additional (and testable) information specific to those fields, there seems little to be gained from grouping them together from the perspective of forecasting skills demand.

The rationale for grouping science, technology, engineering and mathematics together may lie in pedagogical issues: common challenges in science education and communication. Indeed a substantial STEM education literature has emerged (see, for example, Freeman, Marginson and Tytler 2015). However, we believe the development of explicit and testable statements of rationales and assumptions behind STEM definitions and associated policy is necessary to further advance skills forecasting and the appropriate role, if any, of a unique STEM agenda within that framework.

Finally, we note that all the analysis in this paper is based on data collected and projections prepared prior to the outbreak of COVID-19, and does not take into account the potential impact of the pandemic on the Australian labour market. It is fair to assume those impacts will include a bleaker aggregate employment outlook, and a further relative increase in demand for skills and qualifications in the field of Health.

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Appendix 1: Wage equation results

Table A1. Estimated Regression coefficients - dependent variable = natural logarithm of real hourly wage; HILDA 2001-2017

		Standard		
Parameter	*Estimate*	*Error*	*t Value*	*Pr > |t|*
Intercept	2.522	0.032	78.82	<.0001
Wave (1-17)	0.012	0.000	29.31	<.0001
Female	-0.090	0.007	-13.08	<.0001
Age in years	0.042	0.002	24.67	<.0001
Age-squared	-0.045	0.002	-20.89	<.0001
Married	0.082	0.006	14.37	<.0001
Female – number of kids	-0.026	0.006	-4.36	<.0001
Female – number of kids squared	0.002	0.001	1.38	0.1678
Has long-term disability	-0.070	0.007	-9.50	<.0001
Country of birth				
Australia	–			
English Speaking country	0.035	0.011	3.33	0.0009
Non-English speaking country	-0.071	0.010	-7.26	<.0001
Works part-time	0.028	0.006	4.80	<.0001
Tenure – years in current occupation	0.010	0.001	11.16	<.0001
Tenure-squared	-0.015	0.003	-5.87	<.0001
Proportion of time in unemployment[a]	-0.486	0.028	-17.32	<.0001
Highest post-school qualification				
Postgraduate degree	0.129	0.015	8.66	<.0001
Graduate diploma or certificate	0.048	0.014	3.55	0.0004
Bachelor's degree	–			
Diploma or advanced diploma	-0.171	0.012	-14.49	<.0001
Certificate Level III or IV	-0.278	0.009	-30.59	<.0001
Completed Year 12	-0.260	0.010	-26.81	<.0001
Year 11 and below	-0.378	0.010	-37.65	<.0001
Mean (log wage)	3.349			
Observations	136,699			
Individuals	21,755			
R-squared	0.23			
F-test (20 degrees of freedom)	546.88			<.0001

Notes: a. since leaving full-time education.

Appendix 2: Occupations by 2016 STEM-intensity, ANZSCO 3 digit level

ANZSCO code	*Occupation (ANZSCO minor-group)*	*STEM Intensity*	*2016 Rank*	*2006 Rank*
233	Engineering Professionals	0.834	1	1
261	Business and Systems Analysts, and Programmers	0.721	2	2
263	ICT Network and Support Professionals	0.641	3	5
230	Design, Engineering, Science and Transport Professionals, nfd	0.593	4	3
323	Mechanical Engineering Trades Workers	0.590	5	7
260	ICT Professionals, nfd	0.588	6	9
341	Electricians	0.584	7	6
234	Natural and Physical Science Professionals	0.570	8	4
231	Air and Marine Transport Professionals	0.565	9	8
262	Database and Systems Administrators, and ICT Security Specialists	0.564	10	10
321	Automotive Electricians and Mechanics	0.557	11	11
320	Automotive and Engineering Trades Workers, nfd	0.552	12	13
135	ICT Managers	0.516	13	14
310	Engineering, ICT and Science Technicians, nfd	0.511	14	12
322	Fabrication Engineering Trades Workers	0.500	15	17
324	Panelbeaters, and Vehicle Body Builders, Trimmers and Painters	0.490	16	15
313	ICT and Telecommunications Technicians	0.486	17	16
342	Electronics and Telecommunications Trades Workers	0.456	18	18
340	Electrotechnology and Telecommunications Trades Workers, nfd	0.408	19	26
394	Wood Trades Workers	0.384	20	21
300	Technicians and Trades Workers, nfd	0.377	21	19
392	Printing Trades Workers	0.356	22	20
312	Building and Engineering Technicians	0.334	23	22
200	Professionals, nfd	0.326	24	23
311	Agricultural, Medical and Science Technicians	0.314	25	24
139	Miscellaneous Specialist Managers	0.258	26	25
133	Construction, Distribution and Production Managers	0.229	27	27
242	Tertiary Education Teachers	0.222	28	29
510	Office Managers and Program Administrators, nfd	0.211	29	54
393	Textile, Clothing and Footwear Trades Workers	0.206	30	28
712	Stationary Plant Operators	0.203	31	35
130	Specialist Managers, nfd	0.198	32	30
700	Machinery Operators and Drivers, nfd	0.196	33	36
399	Miscellaneous Technicians and Trades Workers	0.178	34	37
511	Contract, Program and Project Administrators	0.177	35	38
731	Automobile, Bus and Rail Drivers	0.174	36	41
111	Chief Executives, General Managers and Legislators	0.170	37	33
224	Information and Organisation Professionals	0.170	38	40

ANZSCO code	*Occupation (ANZSCO minor-group)*	*STEM Intensity*	*2016 Rank*	*2006 Rank*
110	Managers, nfd	0.167	39	34
710	Machine and Stationary Plant Operators, nfd	0.157	40	44
711	Machine Operators	0.154	41	50
839	Miscellaneous Factory Process Workers	0.151	42	56
390	Other Technicians and Trades Workers, nfd	0.151	43	32
899	Miscellaneous Labourers	0.150	44	49
225	Sales, Marketing and Public Relations Professionals	0.143	45	42
149	Miscellaneous Hospitality, Retail and Service Managers	0.140	46	45
232	Architects, Designers, Planners and Surveyors	0.135	47	43
890	Other Labourers, nfd	0.132	48	82
733	Truck Drivers	0.125	49	51
220	Business, Human Resource and Marketing Professionals, nfd	0.125	50	52
590	Other Clerical and Administrative Workers, nfd	0.124	51	39
732	Delivery Drivers	0.119	52	62
721	Mobile Plant Operators	0.115	53	60
730	Road and Rail Drivers, nfd	0.114	54	58
831	Food Process Workers	0.112	55	67
441	Defence Force Members, Fire Fighters and Police	0.112	56	48
442	Prison and Security Officers	0.108	57	53
131	Advertising, Public Relations and Sales Managers	0.107	58	47
330	Construction Trades Workers, nfd	0.105	59	69
821	Construction and Mining Labourers	0.102	60	65
591	Logistics Clerks	0.100	61	61
610	Sales Representatives and Agents, nfd	0.099	62	46
500	Clerical and Administrative Workers, nfd	0.099	63	72
240	Education Professionals, nfd	0.097	64	55
561	Clerical and Office Support Workers	0.096	65	70
132	Business Administration Managers	0.095	66	63
140	Hospitality, Retail and Service Managers, nfd	0.093	67	57
832	Packers and Product Assemblers	0.090	68	77
741	Storepersons	0.089	69	73
530	General Clerical Workers, nfd	0.088	70	71
611	Insurance Agents and Sales Representatives	0.087	71	59
600	Sales Workers, nfd	0.085	72	64
540	Inquiry Clerks and Receptionists, nfd	0.084	73	80
142	Retail Managers	0.081	74	68
800	Labourers, nfd	0.080	75	86
830	Factory Process Workers, nfd	0.080	76	84
541	Call or Contact Centre Information Clerks	0.079	77	66
599	Miscellaneous Clerical and Administrative Workers	0.073	78	81
250	Health Professionals, nfd	0.073	79	83

ANZSCO code	*Occupation (ANZSCO minor-group)*	*STEM Intensity*	*2016 Rank*	*2006 Rank*
811	Cleaners and Laundry Workers	0.073	80	91
841	Farm, Forestry and Garden Workers	0.073	81	88
121	Farmers and Farm Managers	0.073	82	87
891	Freight Handlers and Shelf Fillers	0.068	83	104
251	Health Diagnostic and Promotion Professionals	0.064	84	79
630	Sales Support Workers, nfd	0.063	85	126
362	Horticultural Trades Workers	0.063	86	89
440	Protective Service Workers, nfd	0.063	87	108
141	Accommodation and Hospitality Managers	0.062	88	90
212	Media Professionals	0.062	89	78
222	Financial Brokers and Dealers, and Investment Advisers	0.061	90	85
223	Human Resource and Training Professionals	0.060	91	74
249	Miscellaneous Education Professionals	0.056	92	96
612	Real Estate Sales Agents	0.056	93	93
550	Numerical Clerks, nfd	0.056	94	92
532	Keyboard Operators	0.055	95	94
621	Sales Assistants and Salespersons	0.053	96	98
361	Animal Attendants and Trainers, and Shearers	0.053	97	97
211	Arts Professionals	0.052	98	95
639	Miscellaneous Sales Support Workers	0.051	99	100
210	Arts and Media Professionals, nfd	0.048	100	105
332	Floor Finishers and Painting Trades Workers	0.046	101	103
512	Office and Practice Managers	0.045	102	101
531	General Clerks	0.043	103	113
851	Food Preparation Assistants	0.043	104	119
551	Accounting Clerks and Bookkeepers	0.042	105	109
552	Financial and Insurance Clerks	0.042	106	111
451	Personal Service and Travel Workers	0.042	107	106
452	Sports and Fitness Workers	0.041	108	102
134	Education, Health and Welfare Services Managers	0.039	109	110
631	Checkout Operators and Office Cashiers	0.038	110	121
333	Glaziers, Plasterers and Tilers	0.038	111	107
431	Hospitality Workers	0.038	112	116
351	Food Trades Workers	0.035	113	124
423	Personal Carers and Assistants	0.034	114	123
331	Bricklayers, and Carpenters and Joiners	0.033	115	112
270	Legal, Social and Welfare Professionals, nfd	0.032	116	75
241	School Teachers	0.032	117	114
422	Education Aides	0.031	118	122
420	Carers and Aides, nfd	0.029	119	125
334	Plumbers	0.028	120	115

ANZSCO code	*Occupation (ANZSCO minor-group)*	*STEM Intensity*	*2016 Rank*	*2006 Rank*
272	Social and Welfare Professionals	0.026	121	117
542	Receptionists	0.025	122	127
221	Accountants, Auditors and Company Secretaries	0.025	123	120
411	Health and Welfare Support Workers	0.025	124	118
400	Community and Personal Service Workers, nfd	0.023	125	99
253	Medical Practitioners	0.022	126	129
521	Personal Assistants and Secretaries	0.020	127	130
421	Child Carers	0.020	128	132
271	Legal Professionals	0.019	129	128
252	Health Therapy Professionals	0.013	130	131
254	Midwifery and Nursing Professionals	0.007	131	133
391	Hairdressers	0.004	132	134
360	Skilled Animal and Horticultural Workers, nfd	0.000	133	31
450	Sports and Personal Service Workers, nfd	0.000	134	76

Appendix 3: Robustness check – weighting qualification level by years of education

The changes in skill requirements in STEM and in individual fields of education between 2006 and 2016, as reported in Table 4, were recalculated with the qualifications weighted by the years of education typically required to gain the qualification, instead of by the associated wage premium. The years to gain a qualification is calculated as the sum of typical years of schooling and the typical years in post-school education and training. Twelve years of schooling is assumed for qualifications at the bachelor's degree level and above. For lower level qualifications, the average completed years of schooling for persons holding that qualification is calculated from 2016 Census data. Time taken to complete each level of post-school qualification was taken from the 'volume of learning' typically associated with different qualification levels, as given in the 2013 Australian Qualifications Framework (Australian Qualifications Framework Council 2013). The average years of education assumed for each broad post-school qualification level took into account the proportion of employed persons with qualifications at the more disaggregated level using Census data (e.g., the proportion of people with Certificate level I, II, III and IV in 2016 is accounted for in estimating the average time taken for the broader 'Certificate' category). The estimates range from 12.36 years for a Certificate to 17.55 years for completion of a PhD. Standardising the time taken to complete a Bachelor's degree (15.75 years of education) to equal one results in the following measure of skill intensity for field of education j within each occupation i:

$$S_{j,i} = \frac{(0.785N_{Cert.j,i} + 0.834N_{Dip.j,i} + 1.000N_{Degree.j,i} + 1.086N_{Grad.dip.j,i} + 1.114N_{Higher.deg.j,i})}{N_{Total.i}} \quad \text{(Equation 2)}$$

Comparing Equation 2 with Equation 1, it can be seen that weighting qualifications by their associated time in education, rather than their associated wage premium, results in a very similar, albeit slightly flatter, gradient by qualification level. Accordingly, the estimates of growth in skill demand by field of education vary only marginally, and the key findings are unaffected, as can be seen by comparing Table A3 to Table 4. Weighting qualifications on the basis of their associated years in education, the demand for STEM skills increased by 16.9 per cent between 2006 and 2016, lower than the 21.3 per cent growth in demand for skills across all fields. This compares to estimates of 17.3 per cent for STEM and 21.5 per cent overall using the original approach.

Table A3. Change in skill requirements: STEM and non-STEM (employed persons weighted by years of education required to attain skill level)

	Weighted employment			*Per cent growth*
	2006	*2016*	*Change*	
STEM	**1,227,431**	**1,435,278**	**207,847**	**16.9**
Natural & Physical Sciences	187,249	227,365	40,116	21.4
Information Technology	194,411	252,302	57,891	29.8
Engineering & Related Technologies	845,770	955,610	109,840	13.0
Non-STEM				
Architecture and Building	325,376	378,150	52,775	16.2
Agriculture, Environmental & Related	129,524	141,216	11,692	9.0
Health	542,524	736,615	194,091	35.8
Education	454,604	565,281	110,677	24.3
Management and Commerce	1,197,188	1,406,433	209,245	17.5
Society and Culture	641,866	828,703	186,837	29.1
Creative Arts	220,753	264,353	43,601	19.8
Food, Hospitality & Personal Services	253,902	298,569	44,668	17.6
All Fields	**4,993,167**	**6,054,598**	**1,061,431**	**21.3**

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