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Sandie Rawnsley
Subscriptions Manager
Australian Journal of Labour Economics
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From the Managing Editor

Welcome to the first issue of the *Australian Journal of Labour Economics* (AJLE) for 2022. In this issue we have a range of articles which will be of interest to our readers covering a range of labour market issues and using a variety of approaches to research.

The first paper by Simone Casey of RMIT University examines the experiences of Australian unemployment payment claimants under the *jobactive* scheme, the main employment services program for Australian job seekers receiving income support. The paper reports the results of a survey conducted by the author on behalf of the Australian Unemployed Workers Union in 2019 of their members about their experience of what the author terms 'coercion' during the *jobactive* era. On indicators like job search support, attending appointments, and activities like Work for the Dole, the results indicate that these requirements did not help unemployment claimants get jobs. Further, the results suggest that significant numbers of respondents felt they were unfairly treated by some employment agencies and scarred by the process. The author suggests that the findings indicate that policy makers should be concerned about the effectiveness of mutual obligation, particularly if the overall intent of labour market programs is increasing economic integration. The results have important implications for improving job-seeker policy.

The paper by Jordy Meekes of Melbourne University, seeks to quantify the economic impact of urban density on individual wages in Australia. The existing literature shows a positive urban density effect on wages, referred to as the urban wage premium. This result is explained by agglomeration mechanisms that affect the benefits and costs of the spatial concentration of economic activity. Increased density can also bring with it costs including crowding and frictions such as increased congestion in urban areas. The paper estimates the size and direction of the net density effect in Australia. HILDA Survey microdata on individuals and regional-level population data, population density effects on individual hourly wages are studied over the period 2001 to 2019. An interesting technique, a flow-based clustering algorithm that uses commuting flows across regions to define spatial units that are characterised by a strong commuting connectivity within each spatial unit. The results suggest that the urban wage premium is conditional on the specific aggregation. The evidence implies that wages increase by 1.6 per cent to 2.7 per cent if local density doubles.

The paper by Austen Peters, Sherry Bawa and Mike Dockery of Curtin University, provides an interesting new approach to estimating the returns to education. The conventional estimates of returns to education examine earnings related to an individuals' years of education, with years spent in education typically inferred from their highest qualification attained. The novelty of the authors' new approach is to account for the actual time individuals may have spent in education by correcting for multiple qualifications obtained and time spent towards qualifications that were not completed. The authors employ data from the HILDA Survey and the ABS to examine the sensitivity of return to education estimates to include these adjustments. Employing these measures, the wage premium associated with each additional year of education reduces the estimated return by 15 per cent. This implies that previous studies may have significantly overestimated the returns to education. However, the returns estimated here are still high implying education is a sound investment. The authors suggest that the results have important policy implications including consideration when setting student contribution fees. The authors also offer important suggestions for further research raised by their analysis.

The final paper in this issue is by Omoniyi Alimi and Jacques Poot of Waikato University and David Maré of Motu Economic and Public Policy Research, Wellington. The paper investigates the contribution of immigration to change in income inequality of New Zealand's urban population (most migrants live in urban areas) and compares that with the contribution of the changing skill composition of the population. In many ways New Zealand's pre-COVID-19 migration narrative is similar to Australia. There have been large numbers of migrants, relative to population – both highly skilled permanent migration and relatively low-skilled temporary migration. Over the relevant period, 1986 and 2013, there has been growing inequality in urban New Zealand which some have attributed to migration. Using a somewhat technical analysis the authors use microdata from six consecutive population Censuses to decompose income inequality into that due to changing skill mix and that due to migration. Inequality is examined for sub-groups of the population according to migrant status so that inequality can be decomposed into that within each sub-group and that between subgroups. Interestingly the results suggest that more than 90 per cent of income inequality in each Census can be attributed to within-group inequality; the growth in the share of the population that is highly skilled and the growth in the share of foreign born in the population both had inequality-increasing effects; and the skill effect exceeded the migration effect. The authors speculate about the impact on inequality when migration numbers return to their post-COVID-19 levels.

I would like to thank authors, the anonymous referees and co-editors for their contributions to the AJLE. Once again special thanks go to the AJLE's editorial assistant, Sandie Rawnsley, for doing an excellent job in making this issue possible.

Phil Lewis
Managing Editor

Back to the future: coercive conditionality in the *jobactive* era

Dr Simone Casey *RMIT University*

Abstract

It had long been established that coercion has been adopted in liberal welfare regimes in advanced capitalist countries to shift people from welfare payments to employment to reduce government expenditure. Dean (2007) associated this with a contractarian set of social obligations that displaced the entitlements of social citizenship. While the scholarly literature on the Australian marketised employment services had evolved into two major tracks using both governance and street-level perspectives, there remained few studies of the experiences of Australian unemployment payment claimants themselves.

This article reports the results of a survey conducted by the author on behalf of the Australian Unemployed Workers Union in 2019 of their members about their experience of coercion during the jobactive era. Jobactive is the main employment services program for Australian job seekers receiving income support. The program commenced in July 2015 and will run until mid-2022. While the data set may reflect the bias of the recruitment group, the size of the sample (n=935) is significant because of the extent of the coercion that was reported. While this coercion has been justified in the shift from passive to active welfare states, the article focuses attention to the ethical basis of the use of coercion in transformative social policy initiatives, particularly in relation to an emergent 'punitive' shift in welfare conditionality studies. It concludes with observations of potential openings for future research as Australia's marketised system undergoes another fundamental reform in 2022.

JEL Codes: E24, J64, P16
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Corresponding author: Email: simone_casey@hotmail.com

Introduction

It had long been established that coercion has been adopted in liberal welfare regimes to shift people from welfare payments into employment so as to reduce government expenditure. Active labour market programs such as those delivered through Australia's marketised employment services are one such example of policies used to effect the transformation from a culture of passive 'welfare dependence' to active citizenship. By the 1990s these active citizenship policies evolved into a set of coercive welfare conditionalities called 'mutual obligations' and included a mandatory work activity called Work for the Dole.

While claimant experiences of coercive enforcement of mutual obligations requirements had been analysed in the *Job Network era* (1998-2009) (e.g. McDonald and Marston, 2005; Marston and McDonald, 2008) there were few studies that documented this in the subsequent *Job Services Australia* (2009-2015) and *jobactive* (2015-2022) eras. Therefore, it was important to observe claimant experiences of coercion in the *jobactive* era because in this stage the active society policies reflected 20 years of marketisation and the intensification of mutual obligation requirements. Consequently, this article reports the results of a large survey of unemployed claimants (n=935) conducted by the author on behalf of the Australian Unemployed Workers Union in 2019. The survey collection instrument was designed to examine the extent of coercion in the *jobactive* era.

In the UK, the introduction of coercion and punitive measures in welfare policy has been described by Wright *et al*. (2020) as 'state perpetrated social harm'. This conceptualisation builds on a growing body of empirical studies that have described the subjective impact of welfare conditionalities which function 'less to discipline poor and marginalised people and more to disqualify them from the entitlements of ordinary citizenship' (McNeill, 2019: 299). Grover (2019) extended this and applied the idea that harsh conditionalities can be conceptualised as a form of 'social murder' because the intentional infliction of poverty through disciplinary policy leads to the ill-health of the poor.

The article proceeds by situating the *jobactive* era within the intensification of coercive conditionality as it evolved in Australia over the past 20 years. It then explains the research methods and provides observations on the strengths and limitations of the survey. The survey results are presented alongside some typical comments that are used to illustrate the subjective harms experienced by the respondents. The discussion situates the survey results within the emerging literature on the punitive shift in welfare conditionality in advanced liberal welfare regimes. The article concludes with some observations about the relevance of the study to future research as Australian labour market programs undergo another era of radical reform with the New Employment Services model due to commence in 2022.

Coercive conditionality in the *jobactive* era

In Australia there was a shift to coercive conditionality in the late 1990s with the restructuring of active labour market policy, the privatisation of government employment services, and the introduction of onerous activities like Work for the Dole.

This shift to coercive conditionalities, or coercive welfare as Dwyer (2004) noted, occurred through waves of reform in which disciplinary labour market programs were initially used as tools for economic integration, but eventually became mechanisms for reducing welfare expenditure.

The Australian version of coercive conditionality had unique features that reflected tensions between competing discourses of choice and personal responsibility. For example, in the late 1990s, the privatisation of employment services was promoted with a vision that New Public Management (NPM) would provide a solution to ineffective public services and that this alternative approach that would provide consumers with 'choice' (Le Grand and Bartlett, 1993). This 'third way' orientation also originally conceived consumers as rational and reflective actors who could make decisions that reflected their economic self-interest, and when given such 'opportunities' would make progress towards self-improvement (Giddens, 1998).

While 'choice' was one of the informing principles of NPM and a justification for privatisation, this notion was soon undermined by the onset of 'work-first' contract conditions and mutual obligation requirements (Howard, 2012). In the Job Network era, the agencies contracted to provide services were subject to 'triple activation' (Van Berkel, 2013) which imposed stricter work first conditions in their contracts for services, which were then converted into targets for individual workers. By the Job Services Australia (2009-2015) and *jobactive* (2015-2022) eras, contractual controls on privatised providers led to so much standardisation that marketisation was described as a failure in the public policy evaluation (Considine *et al*., 2011; 2018).

For the consumers, referred to as 'job seekers', choice was limited by coercive conditionalities including: a requirement to enter into a job plan, providing proof of active job searching; attendance at monthly appointments with job services providers or related support services; mandatory job search; and employability skills training—all as pre-determined by policy makers. These coercive conditionalities limited choice in favour of coercion because of the influence of new-paternalism in which welfare subjects are not trusted to make 'good choices' for themselves (Carney, 2007; Marston and McDonald, 2008). In Lawrence Mead's New Paternalist view, sanctions were justified as tools to achieve behavioural change, that would ultimately lead to better outcomes when unemployed people gained jobs (Mead, 1997).

The Australian model of mutual obligation also involved the use of Work for the Dole, a form of mandatory work activity that was modelled on similar programs in the USA where neo-paternalism had a strong foothold. The adoption of Work for the Dole as a labour market program in Australia, was promoted by the libertarian Centre for Independent Studies (Mendes, 2000). For example, Peter Saunders argued that there was a moral obligation for people receiving unemployment payments to participate in activities that were equivalent to the inconvenience of work so as not to be 'better off' than people in paid work (Saunders, 2004).

Much debate accompanied the introduction of Work for the Dole mutual obligations particularly during the Howard era of welfare reform (Mendes, 2000). While it was originally introduced in the 1986 by a Labor government[1], Work for the

1 As a voluntary labour market program for young long-term unemployed (Sawer, 2000).

Dole was expanded by Australia's conservative governments in the Job Network era to unemployment claimants up to the age of 40. The influence of neo-paternalism was apparent in the way the expansion was justified in contractarian terms, as an obligation on payment claimants to pay back the community for receiving unemployment benefits (Mendes, 2000). Australia's position as a coercive 'workfare' state was also cemented with the Welfare to Work reforms when onerous conditionalities were expanded to more payment recipients, (Carney, 2006; Dean, 2007; McDonald and Marston, 2005)[2].

The *jobactive* era of Australian workfare commenced in 2015, under the administration of a conservative Coalition government who expanded Work for the Dole significantly. When the *jobactive* era started there was an unprecedented expansion of Work for the Dole to unemployment claimants who had been on unemployment benefits for six months or more (DESE, 2020). Another change in September 2018 increased the number of hours of Work for the Dole from 15 to 25 hours per week for all people aged 50 and below for six months of the year[3]. This increase to 25 hours proceeded despite a government funded evaluation of a trial having warned that it could create problems in the quality of activities (Kellard *et al*., 2015)

So, unlike the UK where the Mandatory Work Activity in the Work Programme was disbanded in 2015 amid a range of concerns about its efficacy (DWP, 2012), the Australian version grew larger than it had ever been in the past despite evidence that it did not significantly help people get jobs (Borland and Tseng, 2004). Indeed, the *jobactive* version of Work for the Dole was identified as a 'tree-shaking' policy by Department of Employment[4] officials (Senate, 2017) – that is, a strategy for imposing onerous conditions on welfare recipients to incentivise them to get jobs quickly. Tree-shaking has its foundations in evidence which shows that referral to activities like Work for the Dole tends to cause exit from payments whether people had jobs or not (Borland and Tseng, 2004), with similar observations having been made about use of mandatory work activities in the UK's work programme (Wiggan, 2015).

At the start of *jobactive*, 150,000 job seekers were estimated to need place in a Work for the Dole activity in the first financial year (Senate, 2016: 88-89). This level of referral was remarkable, as Borland and Tseng (2004) noted in their analysis of the *Job Network* version, in 2002-2003 the federal government had provided funding for only 55,000 Work for the Dole places. Because of the unprecedent demand, a new service called Community Work Coordinators was temporarily funded to help source the Work for the Dole activities (DESE, 2020: 15). By the end of the first year 126,000 job seekers had been placed in Work for the Dole activities (Senate, 2017)[5]. The unprecedented demand for Work for the Dole activities continued the following

2 During the JSA era there was a break in the use of Work for the Dole, except as a voluntary activity for the long term unemployed, and to work-off 8 week sanctions.
3 Job seekers aged between 50-54 were also required to participate in Work for the Dole for 15 hours per week.
4 The Department of Employment has had frequent name changes. For convenience this article uses the Department of Employment in the text, while the bibliography refers to the abbreviation DESE.
5 To put this in context that represents about 10 per cent of the job seekers on the 'active' jobactive caseload (as approximately 20 per cent of job seekers had exemptions).

year and between 1 September 2016 and 31 August 2017, there were 118,056 *jobactive* job seekers referred to Work for the Dole activities (Senate, 2017b)[6].

The contract for *jobactive* era employment services providers was used to ensure that Work for the Dole was expanded. This contractualism compelled *jobactive* providers to enforce workfare requirements at the street level. This contractual direction was policed by benchmarking individual provider performance relative to that of other *jobactive* providers. To drive the desired provider behaviour, the Department of Employment also introduced weightings for Work for the Dole performance in the Star Ratings, the performance framework that had been introduced in the Job Network era. The Department of Employment also provided payments to providers to draw on to recover costs related to the administration of Work for the Dole (DESE, 2020).

Employment services providers were also used to enforce participation in Work for the Dole by administering the job seeker compliance sanctioning system. Initially, failure to commence and attend Work for the Dole activities resulted in financial penalties of one day's benefit sanction for every day of non-attendance. At the beginning of the *jobactive* era, 83 per cent of financial penalties were for non-attendance at activities like Work for the Dole (DESE, 2017). In July 2018 a new sanctioning system called the Targeted Compliance Framework (TCF) was introduced (DESE, 2020a). Further analysis undertaken on the TCF data until the end of 2019 showed that financial penalties were applied at double the rate for Work for the Dole activities (Casey, 2020).

The extent of the sanctioning used to enforce Work for the Dole attendance is indicative of how coercive the *jobactive* era was. By the latter years of the *jobactive* era, endemic issues such as poor street-level relations, conflict between job seekers and employment services providers had been described as an abuse of human rights (Raffass, 2017; McKeever and Walsh, 2020). There followed research into how unemployed workers regarded *jobactive* agencies as unhelpful and harmful (O'Halloran *et al*., 2019; 2020).

The Australian Unemployed Workers Union Survey

The conditions outlined above led to the revival of the Australian Unemployed Workers Union (AUWU) in 2014, which grew to become a large, organised interest group. As Peillon (1998) and Tyler (2015) argued coercive relations generate resistance, and this explains why the AUWU gained so much momentum in this late stage of mutual obligation in Australia. The AUWU contributed their members' experience's to reports (e.g. Bennett *et al*., 2018) which identified experiences in which unemployed workers felt punished by Work for the Dole, and were instrumental in campaigning for a parliamentary inquiry into *jobactive* in 2018 (Senate, 2019).

6 It is also of note that 35,000 job seekers who were referred to Work for the Dole did not commence, meaning they either exited unemployment payments, found a job or were exempted on medical grounds.

Research methods

In the context of evidence on harms caused to job seekers in the *jobactive* era, the survey described in this study was conducted among AUWU member to examine the extent of coercion in relation to *jobactive* era mutual obligation rquirements[7]. These 'mutual obligations' included establishing a job plan, regular face-to-face appointments with *jobactive* providers, proof of 20 job applications per month, mandatory employability skills training, and activities like Work for the Dole for six months every year[8].

The topics covered in the survey were informed by existing research into aspects of the employment services that are relevant to critical welfare conditionality analysis of coercion. Consequently, the survey questions were designed to explore the extent to which respondents believed they had choice, whether the requirements were fair, if they received useful support from *jobactive* providers, whether the activities had helped them, and the accessibility of complaints processes. Three of the questions specifically explored perceptions of the fairness of payment suspensions and sanctions, and asked respondents to comment on how they had survived when they had lost payments because of sanctions.

The survey instrument consisted of 31 questions that used either the five-point Likert rating scale or a yes/no response, as well as 5 open-ended opportunities for comments. Respondents were able to skip questions and this led to irregular response tallies that ranged between 935 for demographic questions to 525 for questions on sanctions. The survey instrument was tested with AUWU members to ensure the questions would be understood by the intended audience and to avoid policy and academic jargon. As with any survey design there is room for improvement on the factors, semantics and expression if the instrument is to be drawn on in the future.

AUWU members were invited to participate in the survey via an email to an electronic mailing list of 17,000 members and this was also promoted on Twitter and Facebook social media accounts. The researcher adhered to ethical processes in relation to informed consent by explaining the purpose of the survey in the cover letter email and web postings, by identifying that the results would be published as a report, that participation was voluntary, and that responses would be de-identified. To maintain consistency with ethical processes relating to informed consent, only the data and qualitative responses that were published in the original AUWU report have been analysed for this article, and to preserve participant anonymity, only broad demographic data such as age range, gender, and type of employment service is reported.

Limitations

There were both strengths and limitations to this survey that may be of interest to other researchers, particularly those undertaking large scale independent research

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7 The survey was used for a AUWU report that was presented to government officials to propose a review of mutual obligation (AUWU, 2019).

8 It should also be noted there were also increasing levels of online self-service involving a Digital Dashboard for monitoring job search, appointments and online reporting of attendance at activities like *Work for the Dole*.

with marginal populations. A key strength was a comprehensive survey sample was achieved as a result of the AUWU's trusted status with marginalised unemployment claimants. In that respect it is notable that there were more participants in this survey than in the Government's consultations on *jobactive* reforms (n=188) (McPhee, 2018).

Against this, a limitation to the study is that the respondent cohort was acessed solely through the AUWU's mailing list and social media sites. To this extent the sample has potential for bias as unemployed workers often sign-up to the AUWU mailing list because they have either already had a negative experience with employment services or know of someone who has. It is also worth noting that the reformation of the AUWU can be seen to have been a consequence of the shift to punitive conditionality which motivated otherwise disempowered individuals to collectivise by joining a social movement. This goes in some part towards explaining the overall negative weighting of the survey results on choice and empowerment, that temper claims of generalisation to the broader population of the unemployed.

However, there are two points to make in relation to generalisations around the AUWU survey. First, the overall weighting of negative experiences has been demonstrated in other small Australian studies and in evidence provided to parliamentary inquiries. Second, the scale of the data collected in this survey was large enough to facilitate secondary statistical analysis to assess the validity of the factors in the survey tool (O'Halloran *et al*., 2021). This statistical analysis validated the recurrence and relevance of the themes of choice, fairness, disempowerment and coercion in the extensive respondent commentary collected in the survey. It also concluded that six factors are important elements of job seeker service experience: usefulness, client centredness, feedback and complaints, psychologically positive, fairness, and rapport. Through this statistical analysis it has been possible to develop a rating scale (O'Halloran *et al*., 2021) that will be of interest to the international community seeking standardised measures through which to evaluate participant views of activation programs and employment services in diverse social policy settings.

Results and Analysis

Overall, the results indicated that most respondents were deprived of choice over the activities they were made to undertake, that these activities were not viewed as being useful or helpful, and in fact, they were perceived as being punitive. The survey results indicate the overall number of responses for each section of questions and discuss the dominant results. Examples from the free-text commentary are used to illustrate the respondent experiences.

In terms of broad demographics of the respondent cohort (n=935), 43 per cent were male, 54 per cent were female, and 3 per cent percent did not identify as either or preferred not to say. A broad breakdown by age indicated that 57 per cent of participants were aged under 55 and 32 per cent aged between 55 and 65. Analysis of the Qualtrics collection indicators suggested the respondents were distributed across Australia.

The Job Plan

The first group of questions related to the requirement to sign a job plan. The job plan serves three roles in the administration of coercive conditionality.

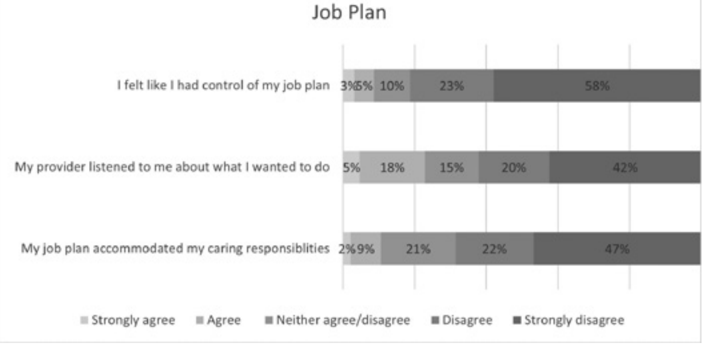
First, signing it is an administrative condition of payment eligibility. Not signing a job plan results in disqualification from unemployment benefits. In the *jobactive* era, job seekers were given 48 hours of 'think time' to sign the job plan, before their payment was suspended and if they continued to refuse to sign it, their payment was cancelled.

Second, the job plan acts as a social security law 'contract' that binds unemployment benefit claimants to meet activation conditions or face sanctions. Most of these conditions are pre-determined in policy made by the Department of Employment. For example, the minimum number of appointments the job seeker must attend a month, participation in pre-employment activities, a requirement to attend job interviews, and complete proof of job search, and at six-monthy intervals participate in an activity such as Work for the Dole. As such, the job plan is an instrument of enforcement and a mechanism through which sanctions can be applied under Australia's social security laws.

Third, the job plan is an instrument of notification under social security law. It communicates notification of the consequence of non-compliances under social security law. It therefore contains a written warning about the penalties for not complying and this notification is supposed to be reinforced whenever it is reviewed or updated.

Given its overall importance in the enforcement of social security conditionalities, the survey explored questions about choice in the job plan, as reported in Figure 1. Respondents (n=814) were asked questions about control of the job plan, choice over activities in the job plan, and flexibility of the job plan in relation to caring responsibilities.

Figure 1. Choice in the job plan



Source: data derived from survey.

The results show that 81 per cent of respondents disagreed (Disagree/Strongly disagree) with the statement that they had control over their job plan, 62 per cent did not feel the *jobactive* provider listened to them about what they wanted to do, and 69 per cent indicated that the job plan did not accommodate their caring responsibilities.

These results indicate that the requirement to support a job plan is perceived by participants as restricting choice, especially as signing a plan is a precondition of receiving payments. It therefore functions as an instrument of coercion, wherein pre-populated requirements are used to enforce conditionalities. The respondent commentary suggested that for many, the job plan itself was signed under duress:

> *I was in the hands of a customer service officer who told me 'if you don't sign, you can't get paid'. I have signed under duress.*

This duress reflected the lack of choice and disempowerment survey respondents reported about their ability to influence the kinds of activities they were required to do.

Appointments

In the *jobactive* era the frequency of appointments was determined by providers – except for job seekers under the age of 30, who were required to meet face to face at least once per month. However, *jobactive* providers could determine appointment frequencies based on the servicing strategies they developed when they applied for the contracts.

Figure 2. Provider appointments

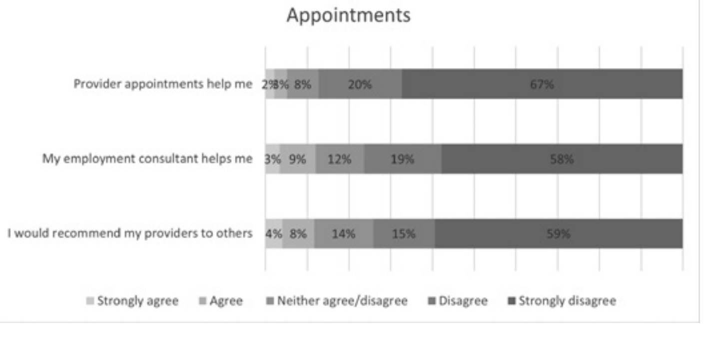


Figure 2 shows that of the respondents (n=782), 87 per cent did not find appointments useful, 77 per cent did not find their advisor helpful, and 74 per cent would not recommend their provider to others.

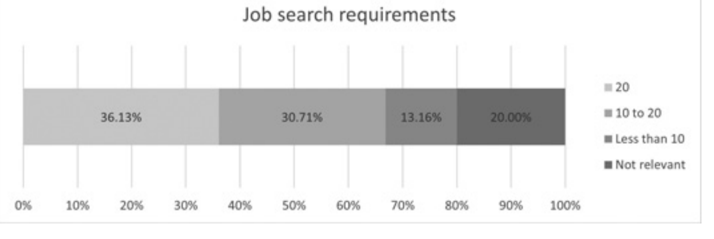
The results in relation to appointments reinforce O'Halloran *et al.* (2019) finding that participants saw little benefit in attendance at appointments. This view was expressed in commentary which highlighted how respondents believed appointments were a waste of time:

> *Appointments are a waste of time, and petrol. I've been with four different providers over the last 9 years and haven't felt helped, supported – hence the reason I am still unemployed. I had a consultant promise to do a practice interview with me at our next appointment, but then at the appointment tell me that anything I need to know about interviews, I can find online. I've had appointments cancelled five minutes beforehand, pity it takes 20 minutes to drive to an appointment.*

Support for Job Search Activities

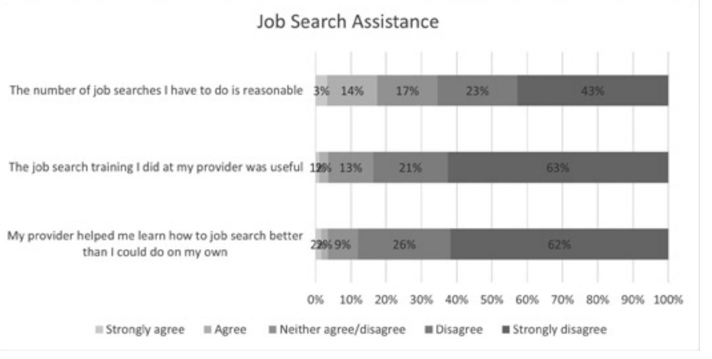
Proof that participants were involved in job search activities was a crucial requirement in the *jobactive* era. In 2019, job search requirements involved providing proof of up to 20 job applications per month, with evidence including email confirmations from employers or job application acknowledgement messages from job search websites. While providers were contractually directed to make nuanced decisions about the right levels of job searches, Figure 3 shows that of the (n=755) respondents, 66 per cent were required to provide proof of 10-20 job applications per month. The results are a concern because, as the Parliamentary Inquiry into *jobactive* (Senate, 2018) showed, onerous job search targets caused distress for unemployed workers in locations where there are few actual jobs to apply for.

Figure 3. Participants job searches per month



A series of survey questions assessed whether the number of job searches was reasonable and whether *jobactive* providers provided useful job search training and support. Figure 4 shows that of the respondents (n=769) to these questions, 66 per cent did not find the job search requirements reasonable, 84 per cent did not find job search training useful, and 88 per cent did not get assistance from their provider in learning how to conduct a job search that was better than the knowledge they already had access to themselves.

Figure 4. job search assistance



The fact that that job search benchmarks were not regarded as being reasonable means that there was a perception of unfairness. This unfairness was compounded by the fact that *jobactive* providers were not reciprocating this activity by providing practical assistance such as with job search training.

This lack of practical assistance was also reflected in the responses to the survey questions about receiving financial support that would enable them to achieve their employment goals or enable them to get work. Of the respondents (n=525), 64 per cent did not receive funding for their own employment goals.

Some examples of respondent commentary that practical assistance was not available included:

> *Have been refused each time I've asked for assistance – petrol voucher to be able to attend interview and for clothes for interviews... disgraceful and frankly inexcusable!!*

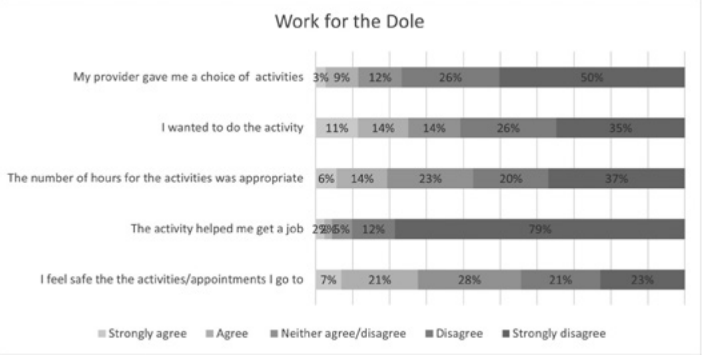
> *Glasses renewed - required for everything further than 5cm from my face. Clothing after a house fire burned all my clothes – have been told funding for an interview outfit and/or shoes and/or training etc is only available if I am 100% guaranteed a job as a result*

> *The current provider has already stated that they will not help me with any clothes or studies and will also not be referring me to any employers. I am therefore not sure what the purpose of seeing them is.*

Work for the Dole

The survey questions on Work for the Dole focused on eliciting respondent views on levels of choice and whether the activities helped them get a job. Figure 5 shows that of respondents (n=783), 76 per cent did not get to choose activities, that 61 per cent did not want to do the activities, that 91 per cent did not find the activity useful for helping them get a job.

Figure 5. Work for the Dole



These results reflect the extreme level of coercion that unemployment claimants experienced in the *jobactive* era. This extreme coercion was reflected in the respondent commentary about not having choice over the Work for the Dole activity, even when they were then expected to attend for 25 hours per week, for six months of every year:

> *They had already chosen my Work for the Dole activity with no consultation*

Further, respondents commented on how Work for the Dole activities were not customised to their individual needs, how they were poorly resourced and did not help get people jobs:

> *The project is a sham, it provides no meaningful tasks, it has at least seven participants, the project is supposed to be a gardening project. This project takes place in the backyard of a house ... This project is being conducted on the cheap. Donated plants, clay soil, huge sods of soil that appear to have come from a construction site. Second-hand equipment, no gloves supplied... unless you are prepared to use pre-worn. It is a disgrace, nothing less than a sham.*

For others, Work for the Dole was described as causing psychological harm:

> *My Work for the Dole experience gave me such anxiety that I developed heart palpitations and my job provider just told me I was being over dramatic!! We weren't given jobs to do just forced to sit in a basement doing nothing all day.*

One respondent commented on how a *jobactive* provider had imposed additional requirements to get job seekers to do more hours, and for more than six months:

> *At one of my appointments they tried to extend my Work for the Dole to 24 hours a week and lengthen my six months to eight months because I came into my work for dole late.*

This appears to have been because of confusion about policy rules without regard for the job seeker's rights or consent.

The respondents were also asked about whether they felt the activities they were required to participate in were safe. On this question 44 per cent indicated that did not find the activities safe, implying that nearly half of them were coerced to attend activities that they did not think met work, health and safety standards.

There is evidence of the dangers involved in activity participation. For instance, in 2016 a young man died in an accident at an activity (DESE, 2020c). This incident was subject to legal proceedings in which it was determined the risks of the activity had not been managed effectively and that the *jobactive* provider had been negligent. In response to that incident the Department of Employment introduced stronger risk management processes (DESE, 2020c) but these additional controls were not sufficient to make the respondent's feel safe:

> *I was injured on a work site while participating in a Work for the Dole activity. Every cost that I have had to incur for my ongoing recovery from that injury no matter the amount had to be paid by me first before the second in charge of the Work for the Dole scheme in Australia… I have NO confidence at all in this program. You are NOT I repeat NOT covered by standard workers compensation for accident on ANY Work for the Dole activity.*

Respondents described how they believed lack of safety at Work for the Dole activities reflected the general disrespect with which they were being treated because they were unemployed. This disrespect was described as justified because being unemployed was regarded as on a par with being a criminal:

> *I felt that my Work for the Dole placement was inconsiderate of workers' reasonable access to amenities, or safety (my foot went through a badly-placed piece of plywood, and the incident was*

> *disregarded). I was bullied, and mostly relegated to dusting shelves in very hot conditions, with nowhere to sit outside break times – very demoralising, and not very good for my health! The atmosphere of the place, and treatment of the workers, made us feel like juvenile delinquents.*

These comments suggest that Work for the Dole the activities did not have to meet the standards of safety that are required in workplaces. The participants were assigned a lesser form of citizenship because the unemployed are regarded as being worth less than other citizens.

In summary, the results about the job plan, appointments, job search and practical assistance and Work for the Dole indicated the majority of the survey respondents had little choice over activities, that respondents were not listened to about what they wanted to do, and that these activities did not help them get jobs:

> *I am sick to death of being forced to apply for jobs that I know I will never get! I am sick to death of being forced to attend appointments with employment service providers who don't give a fuck about me! I am sick to death of being forced to do useless activities like Work for the Dole program, job club and Certificate II and III courses!*

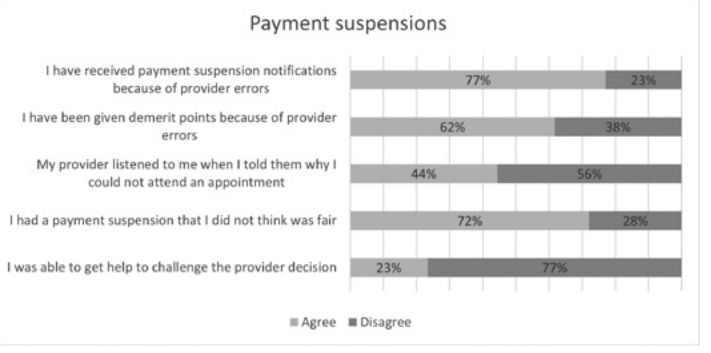
The respondent commentary indicated frustration at the lack of support and anger at the perceived pointlessness of the activities they were required to attend while being threatened with sanctions if they did not.

Payment suspensions

The final three survey questions explored respondents' perceptions of the fairness 'job seeker compliance system' which consisted of automatic payment suspensions, demerit points and benefit payment sanctions. Automatic payment suspensions had been part of the job seekers compliance system for many years. Demerit points were introduced with the TCF in 2016 and in this new system demerits led to financial sanctions that increased severity from 1, 2 and 4 weeks. It is important to note in the early stages of TCF, there was an increase of 70 per cent increase in payment suspensions which were generated because of changes in the automation of attendance reporting processes (Henrique-Gomes, 2019).

Figure 6 shows that of the 511 respondents to these questions, 77 per cent had automatic payment suspensions caused by provider errors, 62 per cent had received demerit points because of provider errors, and 72 per cent indicated they had received unfair payment suspensions. A further 77 per cent of respondents disagreed with the statement that they were able to get help to challenge a provider decision.

Figure 6. Payment suspensions



While the results do reflect the early implementation and training problems with the TCF, they also indicated an overwhelming perception among respondents of unfairness in the system. The respondent commentary provided examples of the way in which errors and unfairness were prevalent and led to the perception that the compliance system itself was punitive:

> *I have been suspended several times in the last 12 months, even when I notified them of non-attendance.*

The commentary also showed how providers forced job seekers into resolving problems that were generated by the new information technology (IT) system's requirements for online reporting:

> *When the demerits system came in, I called the agency and I had to resubmit job searches that were missing (they weren't missing, I met the search for that month, but I still had to do it all anyway).*

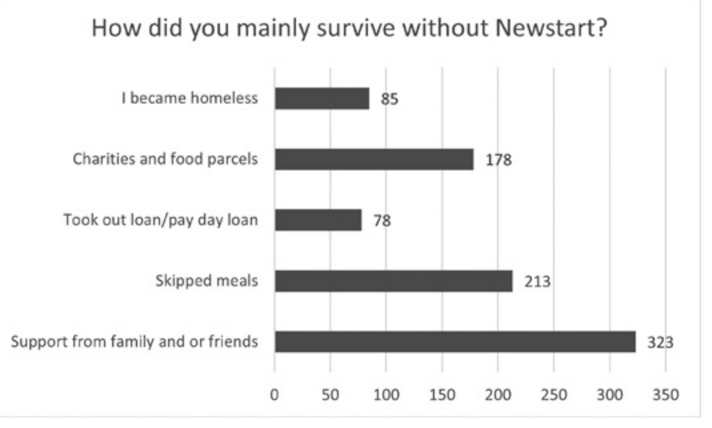
The onus of correcting IT system errors was borne by job seekers even when providers agreed that the job seeker had not been at fault:

> *I got fined for not attending an event I had proof I was at the job provider agreed with this I still lost money. I spent over 8 hours on the phone over 2 days trying to sort it out.*

The impact of financial penalties

The survey question on the impact of financial penalties enabled respondents to select from the list of values indicated in Figure 7. These values were used because of knowledge about the impacts of sanctions and the question also included a free text commentary field. Figure 7 shows how respondents (n=525) indicated they survived when their job seeker payments were sanctioned or cancelled. While the majority indicated they relied on support from family and friends and skipping meals, a significant number of respondents indicated they had become homeless.

Figure 7. Consequences of financial penalties



The commentary showed how respondents developed a range of strategies to cope with the loss of payments:

> *Sell belongings, stop paying bills, didn't renew licences and tickets, cut back to bare minimum essentials.*
>
> *Used an equity facility on my mortgage and put my super into retirement mode to withdraw from it.*
>
> *Used up my savings.*
>
> *Used whatever I had saved to get by, skipping meals, working out which bills I could afford to not pay.*
>
> *I actually lost $50 of my Newstart, which meant I then had to go and borrow that money from a payday lender or ask family and friends. Most of the time, I tried to just skip meals.*

Some of the respondents described their view that it was better to cancel unemployment payments so as to avoid being treated ‘like a criminal’:

> *Will be all of the above when I cancel the payment myself. I literally cannot meet my obligations going forward and the stress of being treated like a criminal for that may kill me.*

This kind of commentary highlights the extent to which respondents experienced forms of suffering also expressed as despair:

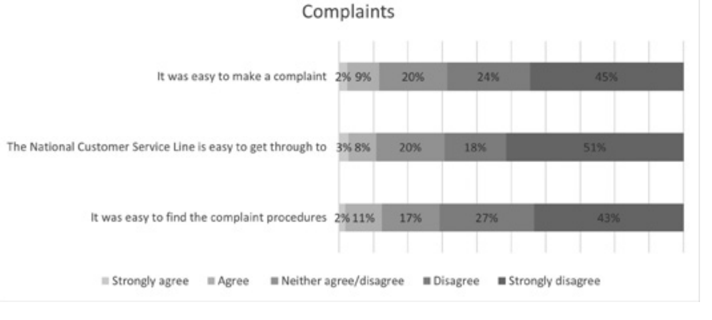
> *I absolutely despair. I’ll be cancelling my own payment in the future for my own health and the health of my career. I cannot meet my obligations because of ill health and caring responsibilities. Sooner or later every provider I have had has been aggressive to the point of driving me to suicidal ideation, or deliberately impose requirements that cannot be met… I’ve literally been told by others I’m worthless, that Work for the Dole is about the best I can aspire to (I have a PhD). It’s designed to break us.*

Complaints and the Right to Social Security

Questions about access to complaints processes were included in the survey because they are an indicator of empowerment as well as of administrative fairness. The survey interrogated this by asking respondents about how easy it was to make complaints about employment services.

Figure 8 shows that of the respondents (n=765), 69 per cent did not find it easy to make a complaint, 69 per cent did not find the National Customer Service Line (for complaints) easy to get through to, and 70 per cent did not find it easy to find information about how to make complaints.

Figure 8. Access to complaints



Further, there were numerous comments that indicated that complaints processes were not promoted by *jobactive* providers, and that respondents were deterred from complaining because it would not yield any positive results:

> *Didn't know I could complain but doubt any of it would help anyway*

> *Easy to make a complaint, but to get action or feedback it was impossible*

The overall levels of disempowerment were reflected by the respondents commentary that making a complaints would lead to retribution:

> *I attempted to lodge a complaint and was advised to take it up at the job agency where the only person manning the office was my job support provider. There is no accountability and Centrelink clients are passed back and forth between two agencies who have no interest in them.*

> *In order to complain about the jobctive provider I had to get a form from their office! Totally unacceptable when they are bullies. My payments would have got cut off, there is no help for abused unemployed workers.*

> *Fear of retribution exists.*

> *I feel uncomfortable with the complaint system because I first have to make the complaint to the person the complaint is about.*

> *Fears of retribution i.e. loss of income has a silencing effect.*

These survey results suggest there have been highly problematic effects of privatisation on access to the review of social security decisions. That survey respondents believed they would be subject to retribution shows that they believed that *jobactive* providers were unregulated and abused the state power which had been delegated to them.

Discussion

The results of this survey provide evidence that in Australia, many unemployment claimants' experiences of the *jobactive* era initiative can be conceptualised as a form of structural coercion, characterised by symbolic violence and state-perpetuated social abuse. The results showed that punitive conditionality can be understood not only as an experience that arises from the use of harsh sanctions, but also as disempowerment through lack of choice and when there is lack of reciprocity and support. The punitive nature of coercive conditionalities was expressed in the respondent comments about despair, frustration, and marginalisation.

The findings on financial penalties drew attention to ethical concerns about the harms caused by sanctions on people already experiencing financial insecurity. The serious adverse consequences of sanctions were supported by commentary that identified additional marginalising effects. These forms of marginalisation were described in respondent commentary that they had turned to illicit activity such as selling drugs, sex-work and crime as ways to survive. The respondent commentary also illustrated the 'violence' that exacerbated poverty, health issues and homelessness.

From the perspective of the political economy of labour market programs, the levels of coercion and despair illustrated in this study show how state power is abused in the enforcement of advanced capitalist commodification imperatives. In this respect the study reinforces the view that advanced capitalism differentiates social rights by the capacity to participate in the means of production, and that punitive treatment is used 'to punish those fractions of the working class who buck precarious jobs' (Wacquant, 2001: 406). This is a contradiction between choice and the commodification imperatives of neoliberal oriented welfare reform that has now existed in Australia for over 20 years.

Indeed, the punitive nature of *jobactive* era mutual obligation can be interpreted by drawing on Bourdieu's concept of symbolic violence (Bourdieu, 2000), as adapted by Peillon (1998) to describe advanced liberal welfare regimes as structures of domination (Peillon, 1998: 221). Survey findings showed that punitive conditionality had created a crisis of despair, which may be regarded as a form of structural and symbolic violence for many in the unemployment claimant population adversely affected by these coercive relations. This crisis is a matter of socio-political and historical significance because it graphically illustrates the human suffering that has accompanied neoliberal welfare reform in Australia.

In a normative sense, the findings indicate that policy makers should be concerned about the effectiveness of mutual obligation in the *jobactive* era, particularly if the overall intent of labour market programs is increasing economic integration. On indicators like job search support, attending appointments, and activities like Work for the Dole, the results showed that these requirements did not help unemployment claimants get jobs. Further, the results suggested that significant numbers of respondents indicated problems in the administration of employment services by privatised agencies, who were regarded as abusing their power. This was evident because the respondents indicated that they had been unfairly sanctioned, that they were unable to complain and would cancel unemployment payments to avoid the threats and activities they regarded as punitive. While this may lead to a reduction in unemployment claimants it provides evidence that punitive activation increases levels of marginalisation. Finally, it is important to have documented the coercion of the *jobactive* era as it informs scholarship about the form active labour market programs might take in the future.

The research findings lead to two immediate considerations in the context of the next stages of the reform process of the privatised employment services system. This reform process has led to the development of a New Employment Services model which has been trialled since 2020. In the New Employment Services which commences in July 2022, much of the administration of routine employment services requirements will occur online in the digital service stream. A new market of privatised employment services will provide a new stream of 'Enhanced Services' to fewer but harder to place job seekers.

In both streams (Digital and Enhanced services) some elements of the existing coercive conditionality policy settings will continue, including the requirement to enter into a job plan, activities like employability skills training and Work for the Dole and threat of sanction. But there will also be change, due to the increasing use of automated systems and a new model of 'points-based activation' that will replace job search targets, that will be used for the future surveillance of mutual obligation. These changes in the mutual obligation framework will provide opportunities to explore future shifts in the experience of coercion in Australian employment services.

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Agglomeration Economies and the Urban Wage Premium in Australia

Jordy Meekes [a, b, c, d, *]
a) The University of Melbourne, Melbourne Institute: Applied Economic & Social Research, and Melbourne Sustainable Society Institute, Melbourne, Australia
b) Leiden University, Department of Economics, Leiden, the Netherlands
c) IZA – Institute of Labor Economics, Bonn, Germany
d) LCC – The ARC Centre of Excellence for Children and Families over the Life Course, Australia

Abstract

This paper is the first to quantify the economic impact of urban density in Australia on individual wages, referred to as the urban wage premium. By combining Household Income and Labour Dynamics in Australia Survey microdata on 13,112 employed individuals and regional-level population data, population density effects on individual hourly wages are studied over the period 2001 to 2019. A unique feature of this paper is to apply a flow-based clustering algorithm that uses commuting flows to define spatial aggregations. The urban wage premium is estimated conditional on the specific aggregation. The Ordinary Least Squares estimate of the urban wage premium peaks at 2.7 per cent. Controlling for individual fixed effects, the estimate peaks at 1.6 per cent. This evidence suggests that wages increase by 1.6 per cent to 2.7 per cent if local density doubles.

JEL Codes: J31, R11, R12, R23
Keywords: Urban wage premium, Agglomeration, Population density, Wages, Australia, HILDA Survey

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* Corresponding author. E-mail address: jordy.meekes@unimelb.edu.au. Postal address: Melbourne Institute: Applied Economic & Social Research, The University of Melbourne, VIC 3010, Australia. Personal website: https://sites.google.com/site/jmeekes/

1. Introduction

Australia is not only one of the largest countries geographically, but also one of the most urbanised countries in the world. In 2019, 86 per cent of the 25 million people in Australia lived in urban areas, slightly higher than the 82 per cent of the population for the United States (US) and 84 per cent for the United Kingdom (UK) (World Bank, 2021). Although the population density across Australia is relatively low, because of people's tendency to live in cities the density of Australian urban areas is relatively high. Australia is also one of the Western countries with the highest relative increase in population, mostly through immigration (Moallemi and Melser, 2020), which has increased the population density in urban areas over the last decades. Interestingly, evidence on the economic effects of density for Australia is very limited. In the COVID-19 era, which has led to more serious consideration of working from home (Productivity Commission, 2021), a better understanding of the costs and benefits of spatial proximity to work and density is particularly relevant.

This study fills this gap by quantifying the economic impact of urban density on individual wages in Australia. The literature on spatial economics studies the economic effects of density on labour productivity (Ahlfeldt and Pietrostefani, 2019). The evidence base shows a positive urban density effect on wages, referred to as the urban wage premium. This result is explained by agglomeration mechanisms that affect the benefits and costs of the spatial concentration of economic activity (Duranton and Puga, 2004, 2020; Glaeser and Gottlieb, 2009). The benefits of density lead to improved matching of employers to employees, better sharing of resources and risk among companies and improved learning of knowledge by employees. The costs of density include crowding and frictions such as increased congestion in urban areas. Ultimately, the size and direction of the net density effect in Australia is an empirical question.

This paper contributes to the literature by extending the literature in an important way by analysing the role of spatial unit sizes in the estimate of the urban wage premium. Spatial unit sizes are conceptually and empirically important to consider since they approximate the geographical size of labour markets. For example, although the Statistical Area (SA) Level 3 is often used for statistical analyses to measure Australian local labour markets, the descriptive analysis points out that, perhaps surprisingly, SA3s are characterised by a population-weighted local employment of 46 per cent. That is, only one in two employed Australians live and work in the same SA3. This observation explains why it might be needed to use a higher spatial aggregation level such as the SA4, or alternative spatial aggregations that are available, to define labour markets that are self-contained in terms of place of residence and place of work.[1] In addition, previous research shows that the aggregation of spatial units into larger units is important for results of empirical analyses on wages.[2]

1 The SA4s are characterised by a local employment of 64 per cent. This containment is much lower than the US Commuting Zones, which are characterised by a local employment of 90 per cent (Fowler, Jensen, and Rhubart, 2018).

2 For example, see Burger, Van Oort, and Van der Knaap (2010) and Meekes and Hassink (2019) for the Netherlands and Briant, Combes, and Lafourcade (2010) for France.

Given Australia's geographical size and high number of spatially separate clusters of urban areas, it is a relevant country to study to what extent the geographical definition of spatial units matters for estimates of the urban wage premium.

To estimate the urban wage premium for Australia, individual microdata on workers are used from the Household Income and Labour Dynamics in Australia (HILDA) Survey over the period 2001 to 2019. The paper approximates agglomeration spillover effects by using variables that represent the population density (constructed by taking the annual estimated resident population relative to the area size in square kilometres) and area size at the spatial unit level (ABS, 2020). In the spirit of Ahlfeldt and Pietrostefani (2019), density elasticity estimates are estimated which allow for a quantitative comparison across studies. Specifically, the urban wage premium is estimated by the regression of the log of individual hourly wages on the log of population density and the log of area size, while controlling for a wide set of covariates. Several different empirical specifications are used to examine the sensitivity of the urban wage premium.

A methodological contribution of this paper is to define regional aggregations on a continuous scale and to estimate the urban wage premium conditional on the specific aggregation. Self-contained regional areas of residence and work activity are defined by using a hierarchical flow-based cluster algorithm applied on commuting flows across spatial units as a measure of relative interaction. The empirical analysis of the urban wage premium is repeated separately for various Australian Statistical Geography Standard (ASGS) structures, defined by the ABS, and a continuum of regional aggregations ranging between 2,164 disaggregated and 10 highly aggregated unique spatial units. These different sets of spatial structures are used in the multivariate panel analyses. For each specific spatial aggregation, the densities and area sizes are different holding all else constant in the regression.

Section 2 provides a background based on literature on agglomeration economies, the empirics of density effects and the modifiable areal unit problem. Section 3 describes the HILDA Survey data and the sample of analysis and provides some descriptive statistics. Section 4 presents the research method and explains the clustering algorithm that is used to return the continuum of spatial aggregations. Section 5 reports the empirical results including several robustness checks. Section 6 provides the discussion and conclusion.

2. Background

In their seminal study, Ciccone and Hall (1996) argue that density effects explain a large share of variation in labour productivity across US states. They find that a doubling of employment density increases labour productivity by 6 per cent. Glaeser and Maré (2001) document that workers in metropolitan areas earn much higher wages than workers in regional areas of the US, a finding that is commonly referred to as the 'urban wage premium'. Glaeser and Maré examined whether the urban wage premium is a wage growth or a wage level effect, concluding that it is a combination of both. That is, on average, workers not only experience an instantaneous increase in wages after becoming employed in an urban area, but they also experience higher wage growth which increases with the amount of time spent in urban areas. They find an urban wage premium of around 4 per cent to 11 per cent after including individual fixed effects, depending on the empirical specification. Based on a meta-analysis of density effects, Ahlfeldt and Pietrostefani (2019) document a mean and median effect of density on wages of 4 per cent.[3]

The theoretical benefits of micro-foundations of productivity for firms and workers in dense agglomerations are based on three mechanisms: sharing, matching and learning (Duranton and Puga, 2004). Sharing refers to improved sharing of risk and better access to resources and services, matching refers to the improved matching rate and matching quality because of a larger pool of employers and employees; and learning refers to faster learning by workers because of more knowledge spillovers and improved generation and diffusion of knowledge. For a comprehensive overview of the literature on agglomeration economies and density effects, see Duranton and Puga (2004, 2020), Glaeser and Gottlieb (2009), Ahlfeldt and Pietrostefani (2019) and Proost and Thisse (2019).

To date, research on agglomeration benefits in Australia is mainly done from the perspective of the housing market. For example, see Maclennan, Ong, and Wood (2015) for a study of the role of housing in agglomeration benefits, or Gurran *et al.* (2021) for a report on the importance of private rental housing for urban productivity. From a labour market perspective, a recent report by Leishman *et al.* (2021) provides a comprehensive overview of city population effects. For a panel of regional areas from 2011 to 2016, they find a city population size effect on regional income of about 8 per cent. Overall, however, the evidence base on agglomeration benefits for individuals in Australia is limited. A better understanding of the economic impact of urban density is important for planners and policymakers to make decisions on urban planning and to develop policy for increasing agglomeration benefits.

i. The empirics of density effects

There are several reasons why the identification of density effects is challenging. From an empirical viewpoint, Combes and Gobillon (2015) provide a comprehensive overview and discuss several confounding mechanisms for why wages could be higher in denser areas, including individual-level endogeneity and local-level endogeneity. Individual-level endogeneity is caused by sorting of more productive workers into denser areas. Importantly, Eeckhout, Pinheiro and Schmidheiny (2014) provide evidence of thick tails in dense areas. That is, dense areas attract relatively many high-skilled workers, but also low-skilled workers. Hence, the extent of sorting more productive workers into denser areas is non-random, and it depends on unobservables such as ability. The estimate of density effects could then be biased by the difference in the composition of individuals' unobserved ability across areas, with high-ability workers making location decisions that direct them to denser areas. A common

3 Ahlfeldt and Pietrostefani (2019) used 347 estimates of density elasticities of a wide range of outcomes including wages for a broad range of countries including low-income and high-income countries.

strategy to limit the individual-level endogeneity is including individual fixed effects, controlling for time-constant unobservable individual attributes.[4]

Local-level endogeneity refers to endogeneity at the spatial unit level caused by omitted aggregate variables, for example local amenities or local productivity, which may make firms and workers more likely to move to a specific area (Bond-Smith and McCann, 2020). The issue of reverse causality becomes apparent if higher population causes more positive density effects, which in turn increases population. The literature uses an instrumental variable estimator to limit the issue of omitted aggregate variables and reverse causality (for example, see Combes, Duranton, and Gobillon (2008) and Mion and Naticchioni (2009)). However, as is well known, finding a convincing instrument that satisfies the exogeneity restriction and relevance condition is difficult. One of the most commonly used instruments in analyses of the urban wage premium is based on historical values of population or population density (Graham, Melo, Jiwattanakulpaisarn, and Noland, 2010). It is argued that the exogeneity assumption holds because of changes in economic activity over a long period of time, which ensures past population does not affect current wages. In addition, it is argued that the relevance condition holds as past population is correlated to current population.

ii. The modifiable areal unit problem

In spatial economics and economic geography, empirical work focuses on the modifiable areal unit problem, which covers the issue of empirical results being sensitive to the measurement of geographic space (Openshaw and Taylor, 1979; Fotheringham and Wong, 1991). For example, in the context of this paper, the Australian geographic space could be measured in many different ways, for example using the hierarchical SA2, SA3 or SA4. The modifiable areal unit problem poses issues because of scale effects and zonation effects. The scale effects relate to the size of spatial units that may affect empirical results. The zonation effects are caused by borders of spatial units which are inherently arbitrary.

Several studies analysed the modifiable areal unit problem in the context of identifying agglomeration economies. Work by Briant, Combes, and Lafourcade (2010) using data from 1976 to 1996 for France concludes that scale effects are important but cause less issues than endogeneity issues such as model misspecification because of unobserved heterogeneity. The paper examined scale effects and zonation effects by using six different definitions of geographic space: three based on pre-defined administrative regional classifications (341 'Employment areas', 94 'Départements' and 21 'Régions') and three based on grid zoning systems (341 small squares, 91 medium squares and 22 large squares).

4 A more convincing strategy may involve a natural or quasi-experimental design that exploits exogenous variation in an aggregate agglomeration variable or individuals' location to identify causal effects of density. However, for a design exploiting exogenous regional-level variation, it can be challenging to find a valid counterfactual for 'treated' areas given that the set of observationally equivalent 'control' areas is limited. Alternatively, a structural model could be used to jointly model wages and location choices of workers and firms (for example, see Gould (2007) and Baum-Snow and Pavan (2012)).

For the Netherlands, Burger, Van Oort, and Van der Knaap (2010) found that scale effects matter for agglomeration estimates, using spatial units based on three pre-defined administrative classifications (municipality, district and region). More recent work by Meekes and Hassink (2019) is the first to estimate the urban wage premium for a continuum of regional aggregations. Using data for the Netherlands from 2006 to 2014, the authors repeatedly estimate the urban wage premium for different sets of aggregation, ranging between 398 disaggregated unique spatial units (municipalities) and 13 highly aggregated unique spatial units. The authors consider this to be representative of so-called local labour markets that are characterised by strong commuting connectivity within each labour market and weak connectivity to outside labour markets.

This paper applied the same approach used by Meekes and Hassink (2019) to estimate the urban wage premium for a continuum of regional aggregations. A key limitation of Meekes and Hassink, however, is to apply the approach to the Netherlands, which arguably has only very few local labour markets, given its land area size of 33,671 km^2. In contrast, Australia, with a land area size of 7.692 million km^2, has relatively large variation in how the country can be divided into non-overlapping spatial units while maintaining a sufficiently high number of unique spatial clusters of economic activity.

3. Data, sample and descriptive statistics

Individual microdata are used from the HILDA Survey, covering 19 waves of data over the period 2001 to 2019. The HILDA Survey is a nationally representative survey that follows households that are interviewed every year.[5] An annual panel for workers is created, pooling the waves from years 2001 to 2019 which contains 13,112 unique workers and 95,670 worker-year observations. The key dependent variable is the hourly wage, which is computed for the main job of the worker by taking the wage relative to the number of working hours. The natural logarithm of hourly wage is analysed in the empirical analysis.

i. Sample selection

Individual-year observations are included in the sample of analysis for individuals aged 21 years or older and younger than 65 years, which avoids any effects of the youth minimum wage for those under 21. Observations of workers are included in the sample if they work full-time. Full-time workers, working more than 35 hours, are selected to ensure changes in hourly wages are captured, removing any part-time wage effect on hourly wages caused by transitions between full-time employment and part-time employment. Several sample selections are implemented to limit the incidence and variation in hourly wages because of outliers. Employee-year observations are excluded if the employee works over 80 hours, earns below $200 a week or earns over $10,000 a week. In addition, the top 0.1 per cent and bottom 0.1 per cent of observations

5 Survey non-response is a main limitation of using household surveys for empirical analysis. The HILDA Survey initiated a sample top-up in 2011 to increase the representativeness of the Australian population.

of the hourly wage distribution and of the growth of hourly wages are excluded to limit error from outliers, removing 295 observations. Finally, 753 observations are excluded because of missing observations for the control variables. The sample of analysis contains 13,112 unique employed individuals and 95,760 observations.

ii. Independent variables

The empirical analysis includes a broad set of independent variables. The independent variable of interest is population density, which is computed by dividing the annual estimated resident population by the area size in square kilometres of the spatial unit (ABS, 2020). Different measurements of geographic space are used in the analysis, which affect the borders of the spatial units and the values of population density and area size. For example, the SA2, SA3, SA4; and State and Territory (hereafter: state), which are based on the ASGS structures of the ABS, are used in the empirical analysis. In addition, the empirical analysis is repeated separately for the administrative local government areas (LGAs)[6], and the sets of spatial units that are defined based on the hierarchical flow-based clustering algorithm. Spatial units coded as 'Other Territory', 'Migratory – Offshore – Shipping' or 'No usual address' are excluded from the sample of analysis. In addition, several islands and spatial units with an estimated resident population below 100 residents are excluded. This leaves a total of 2,164 SA2s and 9,711,627 commuting flows.

The individual's characteristics include zero-one indicator variables for gender (2 categories), Indigenous origin (2), being born abroad (2), age (9 categories in increments of five years), education (Year 11, Year 12, Certificates III and IV, Diploma; and Bachelor or higher educational attainment), number of household members (1, 2, 3-4; and 5 or more members), marital status (6 categories), number of own resident children (0, 1, 2; and 3 or more children), type of contract (permanent, fixed-term, casual, other; and missing contract), job occupation (8), job industry (20), the private sector (2) and year (19).

Table 1 provides summary statistics by population density quintile of individuals' residential location. The population density quintiles are defined annually at the SA2 level based on the data on estimated resident population and area sizes, which ensures the quintiles are not affected by the sample of analysis observed in the HILDA Survey. Table 1 shows that high-density areas are characterised by higher hourly wages and higher hourly wage growth. In addition, it is clear from Table 1 that the workforce in denser areas is characterised by a higher proportion of workers who are female, younger, more likely born abroad, more highly educated, and with fewer people of Indigenous origin. From the number of observations by quintile, it can be observed that the majority of the sample (51 per cent) lives in relatively dense area as part of the top two quintiles of population density.

6 The analysis based on LGAs should be interpreted more carefully because of amalgamations of LGAs over time.

Table 1
Sample means by population density quintile (proportions unless otherwise noted)

	SA2 population density year-specific quintiles				
	First quintile	*Second quintile*	*Third quintile*	*Fourth quintile*	*Fifth quintile*
Real hourly wage ($, deflated by CPI)	27.81	29.06	30.30	32.16	34.02
Log real hourly wage (log of $)	3.229	3.282	3.324	3.374	3.419
Real hourly wage growth (Average of individual year-to-year changes, %)	5.786	5.973	6.044	6.085	6.778
Density (population/km^2, based on SA2)	6.394	140.2	759.2	1,696	3,664
Log density (based on SA2)	1.147	4.715	6.559	7.421	8.114
Area size (km^2, based on SA2)	6,757	129.8	21.34	8.300	5.212
Log area size (based on SA2)	7.639	4.558	2.836	1.997	1.536
Female	0.318	0.345	0.373	0.370	0.404
Age					
21 ≤age< 25	0.086	0.093	0.095	0.088	0.090
25 ≤age< 30	0.116	0.129	0.139	0.145	0.182
30 ≤age< 35	0.110	0.125	0.125	0.132	0.164
35 ≤age< 40	0.122	0.126	0.125	0.125	0.122
40 ≤age< 45	0.134	0.139	0.138	0.130	0.115
45 ≤age< 50	0.152	0.137	0.133	0.135	0.114
50 ≤age< 55	0.135	0.122	0.120	0.119	0.100
55 ≤age< 60	0.096	0.091	0.086	0.087	0.076
60 ≤age< 65	0.049	0.039	0.038	0.040	0.036
Indigenous origin	0.023	0.026	0.019	0.013	0.012
Born abroad	0.087	0.133	0.183	0.246	0.287
Education					
Year 11	0.235	0.201	0.191	0.152	0.095
Year 12	0.117	0.133	0.142	0.149	0.140
Cert III and IV	0.354	0.331	0.293	0.231	0.170
Diploma and adv. diploma	0.095	0.108	0.111	0.112	0.100
Bachelor, grad and postgrad	0.199	0.228	0.263	0.356	0.493
Partnered	0.779	0.762	0.731	0.722	0.673
Own resident children	0.477	0.488	0.470	0.477	0.382
Type of contract					
Permanent contract	0.736	0.763	0.789	0.793	0.769
Fixed contract	0.081	0.095	0.097	0.094	0.113
Casual contract	0.086	0.067	0.061	0.050	0.048
Other contract	0.002	0.001	0.001	0.002	0.002
Missing contract	0.096	0.074	0.052	0.061	0.069
Private sector	0.729	0.745	0.738	0.729	0.753
Number of observations	9,517	16,723	20,214	22,551	26,755

Notes: Sample means for individual characteristics are provided by quintile of population density. The quintiles are defined by year at the regional level based on the SA2 spatial structure. The sample of analysis includes 95,760 individual-year observations and 13,112 unique employed individuals. The real hourly wage is expressed in 2012 dollars. For the variable hourly wage growth, which is computed for individuals with at least two consecutive waves, the total number of observations equals 74,152. The time period under observation is 2001 to 2019.

4. Methodology

To study the urban wage premium, the impact of population density on workers' hourly wage is examined. A Mincer-style empirical model is specified:

$$y_{irt} = \beta_1 \ln dens_{rt} + \beta_2 \ln area_{rt} + \delta' X_{it} + \alpha_i + D_t + \varepsilon_{irt} \quad (1)$$

The subscripts i, r and t refer to individual, spatial unit and year, respectively. y is the natural logarithm of nominal hourly wage. The model contains the variables log population density and log area size. The individual's characteristics are represented by X, which include zero-one indicator variables for gender, Indigenous origin, being born abroad, age, education, number of household members, marital status, number of own resident children, type of contract, job occupation, job industry and the private sector. α_i represents the individual fixed effects, D_t represents the calendar year fixed effects and ε_{irt} represents the idiosyncratic error term.

Identification of the impact of density comes from regional-level changes in population over time and individual-level changes in the spatial unit, where individual-level changes in the spatial unit are caused by changes in individuals' residential location. As Combes and Gobillon (2015) emphasize, agglomeration benefits exist if the impact of density or area is significantly positive. The empirical analysis focuses on estimating β_1, which represents the effect of local population density on hourly wages from increases in density or local population while controlling for local area size. A positive effect of area, holding density constant, represents the agglomeration impacts from increasing the area size and population proportionally. Note that using population size instead of population density would result in the same estimate of β_1 but a different estimate of β_2. That is, the estimated effect of the log of population density (equation (1)) or the estimated effect of the log of population size (an alternative equation) would be identical, ceteris paribus.

The coefficients in the empirical analysis are based on two sets of regressions, estimated as the effect of log population density on log hourly wage using the Ordinary Least Squares (OLS) and the Fixed Effects (FE) estimation techniques, respectively. The individual fixed effects specification is used to limit the potential of time-constant unobserved heterogeneity. The time-constant variables gender, Indigenous origin and being born abroad, are absorbed by α_i for the FE estimator. Changes in hourly wages because of business cycle effects and inflation are absorbed by the year fixed effects. The standard errors and the 95 per cent confidence intervals are computed using clustered standard errors by spatial unit, where the number of unique spatial units depends on the regional classification ranging between 2,041 (SA2s) and 8 (states) unique units.

i. A clustering algorithm to define a continuum of regional aggregations

A key identification challenge in research on regional differences is the modifiable areal unit problem, which involves the issue that empirical results and conclusions depend on the measurement of geographic space. In the context of this paper, Australia can be divided into distinct spatial units in many different ways (for example, see Watts (2013)), which may affect the estimate of the effect of local population density on hourly wages. To assess this issue, the empirical analysis is repeated to examine the role of spatial unit sizes in the estimate of the urban wage premium. That is, the urban wage premium is estimated separately for several pre-defined administrative spatial structures as well as for a continuum of regional aggregations, using different spatial unit sizes and thereby different densities and area sizes holding all else constant in the regression of individual hourly wages on population density.

The regional aggregations are defined by applying a flow-based cluster algorithm, entitled flowbca, introduced by Meekes and Hassink (2018).[7] The continuum of regional aggregations contains sets of spatial units that range from 2,164 to 10 unique spatial units, which are aggregated one-by-one using a hierarchical clustering algorithm. The regional aggregations are computed based on a starting set of commuting flows from the ABS Census of Population and Housing 2016, through TableBuilder Pro 2016 (ABS, 2016). The main input for the algorithm is relational data of 9,711,627 commuting flows from place of current residence to place of work observed at the SA2 level, as this information is not available at a finer spatial unit level. The regional-level data are linked using the SA2 identifier, which is available in the Restricted Release of the HILDA Survey. Alternative sets of regional clusters of economic activity are defined over a continuous level of regional aggregation to assess the role of regional aggregation in the estimation of the urban wage premium. After integrating the regional-level data with the individual HILDA Survey microdata, an additional 123 spatial units are excluded from the sample of analysis because of zero employed individuals in these units. In the empirical analysis, the analysis is repeated 2,155 times for all regional aggregations from 2,164 to 10 unique spatial units in increments of one defined by the algorithm.

The steps of the algorithm can be described as follows. From the starting set of commuting flows across SA2s, the algorithm selects the maximum of the single directed relative commuting flow from one source unit to a different destination unit. Relative flows are computed by taking the source unit's outgoing flow relative to the source unit's total of outgoing flows. The algorithm then aggregates the source unit to the destination unit, adding the absolute flows from the source unit and destination unit, where the core of the new spatial unit is defined as the initial destination unit's core. Following, the algorithm repeats these steps and starts again by selecting the maximum of the single directed relative commuting flow.

Figure 1A shows the maximum of the single directed relative commuting flow from one source unit to a destination unit at each iteration of the algorithm. The maximum of the single directed relative flow is defined as the highest value observed of an outgoing flow relative to the unit's total of outgoing flows. The directed flows approach is used as commuting flows are by nature directed, as they flow from one unit to another. As the algorithm starts with 2,164 unique spatial units, the relative

7 See Coelli, Maccarrone, and Borland (2021) for an application of flowbca on SA3 spatial units to define local labour markets in Australia, studying the impact of increased Chinese imports on regional labour market outcomes.

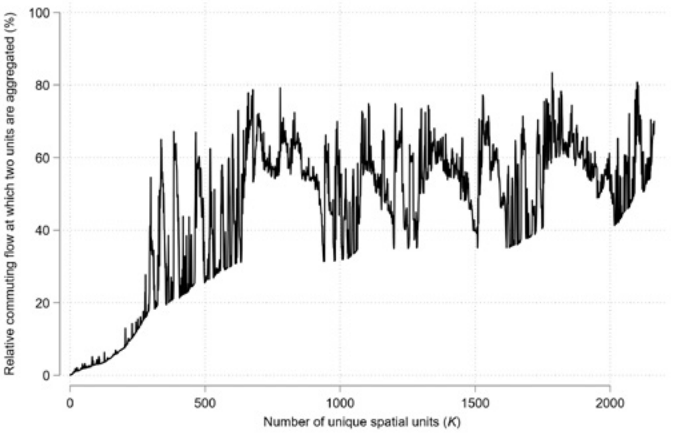
commuting flow at which two units are aggregated has a decreasing pattern given the two spatial units with the strongest commuting connectivity are aggregated first. However, Figure 1A shows a non-monotonically decreasing pattern. That is, although there is a downward trend in the maximum relative flow at which two units are aggregated, the maximum relative flow in the current iteration can be higher than that of the previous iteration. For example, after two spatial units are aggregated, another third spatial unit might have a higher relative commuting flow to the newly aggregated spatial unit that was computed by combining two units in the previous iteration.

Figure 1B shows the local employment rate by spatial structure. Local employment is defined as the number of individuals who live and work in the same spatial unit relative to the total number of employed individuals. The local employment rate is increasing if the number of unique spatial units becomes lower. For the ABS spatial structures SA3 and SA4, it is clear that local employment is relatively low, and much lower compared to the spatial units defined by using flowbca, conditional on the number of unique spatial units. This finding is important since it highlights that using SA3s, characterised by a local employment rate of 46 per cent, to define self-contained areas of residence and work activity, is not very accurate.

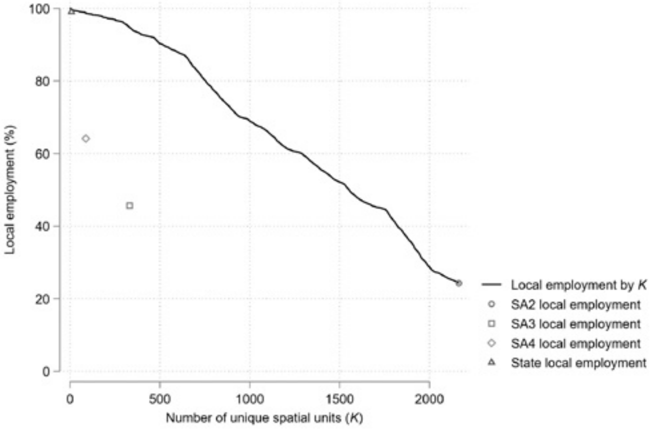
Figure 2 shows that urban areas are larger in the case of the 100 spatial units defined by flowbca than the 88 pre-defined ABS spatial structure SA4. By allowing for larger urban areas as can been observed in Figure 2, and justified by the relatively strong commuting connectivity, local employment is higher for a given number of unique spatial units, as shown by Figure 1.

Figure 1. Defining regional areas using flowbca

A) Maximum directed relative flow



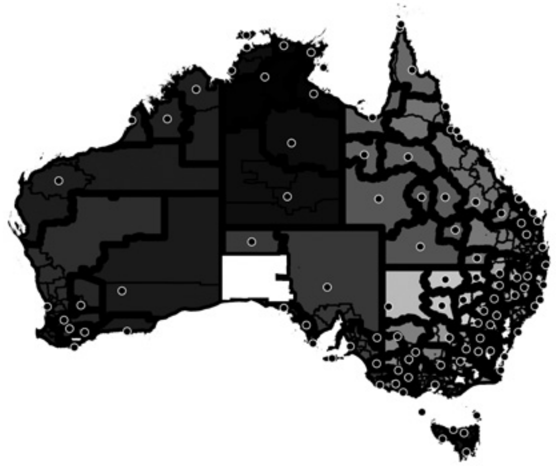
B) Local employment by spatial structure



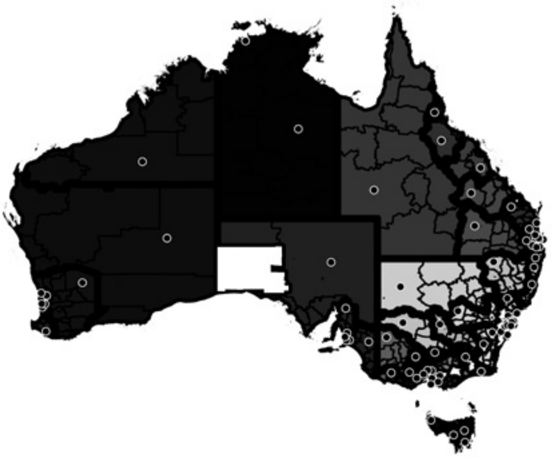
Notes: The number of unique spatial units is represented by K. The number of commuting flows used for defining spatial units equals 9,711,627, retrieved from the ABS Census of Population and Housing 2016. The process of clustering starts with 2,164 unique spatial units. In each iteration, one spatial unit is aggregated to another unit, aggregating the source unit to a destination unit characterised by the highest directed relative flow. The maximum directed relative flow is defined as the highest value observed of an outgoing flow relative to the unit's total of outgoing flows. Local employment is defined as the relative share of individuals living and working in the same spatial unit.

Figure 2. Maps of Australia: A comparison between 100 defined areas and SA4s

A) 100 spatial units defined by flowbca



B) 88 SA4 spatial units



Notes: Figure 2A shows the map of 100 spatial units defined by flowbca. Figure 2B displays the SA4 spatial units as defined by the ABS. The core of a spatial unit is visible as a black dot with a white circle. Each unique spatial unit is surrounded by a thick border and highlighted by a different shade of blue. Several islands and spatial units with an estimated resident population below 100 residents are excluded. See Figure 1 for additional notes.

5. Empirical analysis

This section documents the urban wage premium in Australia based on an empirical analysis of population density effects on hourly wages. The first part of the empirical analysis investigates the density effects based on various pre-defined regional classifications. Results are provided based on the OLS estimator and FE estimator, respectively. The second part of the analysis uses area fixed effects and the instrumental variable estimator to limit biases from local-level endogeneity. The third part of the analysis examines the role of the measurement of spatial units in estimates of the urban wage premium, estimating the population density effects on hourly wages for a continuum of regional aggregations ranging from 2,164 to 10 unique spatial units.

i. Density effects based on pre-defined regional classifications

Table 2 displays the impact of population density on hourly wages, estimated separately for five spatial structures: SA2, SA3, SA4, state and LGA. For the OLS estimator, columns (1) to (3) show how the estimate of the urban wage premium changes after including additional covariates.[8] Similar results are provided for the FE estimator in columns (4) to (6), based on regressions controlling for individual fixed effects to limit individual-level endogeneity.

Table 2 shows that for the SA2 spatial structure, the density effect on wages – the urban wage premium – equals about 1 per cent and is statistically significant at the 10 per cent significance level for the OLS estimator after including all covariates (see column (3)). For the FE estimator, the urban wage premium is also equal to about 1 per cent and is significant at the 5 per cent significance level irrespective of the set of covariates. This evidence suggests that wages increase by about 1 per cent if the population density doubles.[9]

Based on SA3s, a weakly significant positive effect of population density on hourly wages is found for the FE specification only (columns (4) and (6)). In addition, for SA4s and states, no statistically significant effects are found. Conversely, using LGAs to measure geographic space, the impact of population density on hourly wages is statistically significant for all six specifications, ranging between 0.59 per cent and 2.09 per cent (columns 5 and 1 respectively). Controlling for individual fixed effects slightly reduces the urban wage premium estimates found for LGAs, making these estimates comparable in magnitude as those obtained based on SA2s and SA3s.

Table 2 shows that the empirical evidence of positive density effects on hourly wages is mixed, as the size of the urban wage premium estimate as well as the statistical significance strongly depends on the spatial structure and the model specification. Compared to the literature (see, for example, D'Costa and Overman

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8 Tables A1 and A2 in Appendix A show the results for a sample of full-time and part-time employees together and a sample of part-time employees, respectively. Similar results are found for the sample of full-time and part-time employed workers together, whereas less significant results are found for the sample of part-time employees.

9 In the context of agglomeration economies and the urban wage premium, studies generally analyse the impact of areas becoming denser instead of areas becoming geographically larger. For completeness, Table A3 shows the estimates of the log of area size on the log of hourly wages, based on the same set of regressions as Table 2.

(2014) and Meekes and Hassink (2019)), it is surprising that the density effect on wages based on SA2s is higher after including individual fixed effects, as it controls for the endogenous sorting of more able workers to denser areas. By contrast, the estimates of the urban wage premium based on LGAs is indeed smaller for specifications that include individual fixed effects. In a meta-analysis on density effects, Ahlfeldt and Pietrostefani (2019) show that, internationally, the mean and median effect of density on wages is around 4 per cent. As such, the urban wage premium in Australia appears relatively low.

Table 2. Urban wage premium, based on pre-defined Australian spatial structures (Equation (1))

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		OLS			*FE*	
Log population density, based on:						
SA2 (2,041 unique spatial units)	0.0065	0.0083	0.0096*	0.0114***	0.0089**	0.0095**
	(0.0088)	(0.0067)	(0.0053)	(0.0043)	(0.0041)	(0.0040)
SA3 (332 unique spatial units)	0.0054	0.0070	0.0068	0.0117**	0.0083	0.0095*
	(0.0139)	(0.0105)	(0.0080)	(0.0053)	(0.0052)	(0.0049)
SA4 (88 unique spatial units)	-0.0067	-0.0041	0.0012	0.0052	0.0039	0.0058
	(0.0201)	(0.0159)	(0.0116)	(0.0093)	(0.0083)	(0.0079)
State (8 unique spatial units)	0.0034	-0.0051	0.0011	0.0004	0.0019	0.0030
	(0.0279)	(0.0226)	(0.0158)	(0.0097)	(0.0096)	(0.0097)
LGA (426 unique spatial units)	0.0209**	0.0141**	0.0118***	0.0069*	0.0059*	0.0071**
	(0.0098)	(0.0063)	(0.0041)	(0.0036)	(0.0032)	(0.0030)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	Yes	No	Yes	Yes
Occupation & industry dummies	No	No	Yes	No	No	Yes
Individual fixed effects	No	No	No	Yes	Yes	Yes

Notes: The outcome variable is log hourly wages. Each row represents a different regression for a different regional classification. Each column represents a different set of control variables and fixed effects. Standard errors, clustered by spatial unit, are in parentheses. The number of unique spatial units for each regional classification in the sample of analysis is provided in parentheses after the relevant spatial structure. ***, **, *, correspond to the significance level of 1%, 5%, 10%, respectively. The set of covariates contains the individual's characteristics, which include zero-one indicator variables for gender (1 estimated parameter), Indigenous origin (1), being born abroad (1), age (8), education (4), number of household members (3), marital status (5), number of own resident children (3), type of contract (4) and the private sector (1). The occupation and industry dummies consist of job occupation (7) and job industry (19). The time-constant variables gender, Indigenous origin and being born abroad, are absorbed by α_i for the FE estimates. The R-squared is between 0.17 and 0.46 depending on the specification. The sample of analysis contains 95,760 individual-year observations and 13,112 unique employed individuals. The time period under observation is 2001 to 2019.

ii. Density effects using area fixed effects and the instrumental variable estimator

One limitation of the benchmark results shown in the previous section is that these results could be affected by local-level endogeneity. That is, local amenities or local productivity may make a selective group of firms and workers more likely to move to a dense area, which in turn increases density, a mechanism also referred to as reverse causality. An approach to limit the potential of local-level endogeneity is to include local area fixed effects. The area fixed effects would capture time-constant unobserved heterogeneity at the area level.

However, as shown by the results in Table 3, the strategy of including area fixed effects to limit local-level endogeneity does not work well. The area fixed effects are identified based on moves across spatial units (13,312 residential relocations across SA2s among 6,675 individuals in the sample), which introduces sample selection because residential relocation is endogenous. Columns (1) and (2) show that including area fixed effects can cause large biases, and the biases are larger the less unique spatial units are used to measure geographic space. This bias, because of limited mobility, is driven by the fact that residential moves do not happen very often in the sample of analysis, especially for spatial structures at high levels of regional aggregation such as SA4s (6,700 residential relocations among 4,051 individuals) and states (1,748 residential relocations among 1,240 individuals). In these instances, area fixed effects are identified based on fewer residential relocations, which may cause the upward bias in estimates of the urban wage premium.

In addition, for models including individual fixed effects and area fixed effects, estimating density effects is challenging because of the very little within-area variation in density over time, and relocations across spatial units are used to identify both the density effect and area fixed effect. Overall, the results in columns (1) and (2) of Table 3 are consistent with the notion that including area fixed effects when studying density effects is not a promising avenue.

An alternative strategy to deal with the local-level endogeneity is to apply the instrumental variable (IV) estimator (for example, see Ciccone and Hall (1996)). The instrumental variable estimator uses local historical population as instruments for local population density and local area size. The underlying assumptions are that historical population by spatial unit is correlated to current population (relevance condition) whereas it is uncorrelated to individuals' current hourly wages and productivity (exogeneity condition). In this paper, this approach is only applied using LGAs to measure geographic space (ABS, 2019), as information on historical population is not available for the ABS spatial structures. Unfortunately, because of changes over time in the composition and existence of LGAs, the sample of analysis is reduced by over half.

Table 3. Urban wage premium, strategies to limit local-level endogeneity

	(1)	*(2)*	*(3)*	*(4)*
	Area fixed effects		*IV estimator*	
Log population density, based on:				
SA2 (2,041 unique spatial units)	-0.0255	0.0208	/	/
	(0.0182)	(0.0154)	/	/
SA3 (332 unique spatial units)	-0.0269	0.0425	/	/
	(0.0327)	(0.0419)	/	/
SA4 (88 unique spatial units)	-0.0164	0.1487**	/	/
	(0.0549)	(0.0693)	/	/
State (8 unique spatial units)	0.3801**	0.4452**	/	/
	(0.1216)	(0.1357)	/	/
LGA (426 unique spatial units)	-0.0395	0.0552	0.0244***	0.0002
	(0.0380)	(0.0434)	(0.0076)	(0.0099)
Year dummies	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Occupation & industry dummies	Yes	Yes	Yes	Yes
Individual fixed effects	No	Yes	no	Yes
Number of observations	95,760	95,760	40,242	39,604

Notes: The outcome variable is log hourly wages. Each row represents a different regression for a different regional classification. Columns (1) and (2) represent regressions including area fixed effects. Columns (3) and (4) represent regressions based on the instrumental variable estimator, which could only be applied for LGAs as information on historical population is not available for other spatial structures. The two instrumented variables are population density and area size. The three instruments are population density of 1911, population density of 1933 and population density of 1954.

The results show that instrumenting population density and area size of LGAs between 2001 and 2019 by long-lagged population density of LGAs in 1911, 1933 and 1954 increases the density effect on wages for the OLS estimator.[10] Specifically, the effect equals 2.44 per cent (column 3 of Table 3), much higher than 1.18 per cent (column 3 of Table 2).[11] However, using the instrumental variable estimator leads to a null effect after including individual fixed effects (column 4 of Table 3). The results show that including individual fixed effects matters more for density effects

10 For column (3) of Table 3, the underidentification test suggests the model is identified, as the null hypothesis is strongly rejected (Kleibergen-Paap rk LM statistic: 17.13; p-value < 0.01). In addition, the Hansen J statistic of 1.19 indicates the model is not overidentified, as the null hypothesis is not rejected (p-value > 0.27).

11 The results in columns (3) and (4) are robust to including a different set of instruments, for example including lagged population of 1976 and 1996, as well as using different combinations of years of lagged population density. Results are available upon request. Replicating the result of column (3) of Table 2 for LGAs, using the smaller sample of 40,242 observations that was used in column (3) of Table 3, produces an estimate of 0.0155 significant at the 1 per cent significance level. This result is also available upon request.

than applying the instrumental variable estimator. As such, the results suggest that individual-level endogeneity is more important than local-level endogeneity, corroborating the empirical literature on agglomeration economies (see Combes and Gobillon (2015)).

iii. The role of spatial unit sizes in estimates of density effects

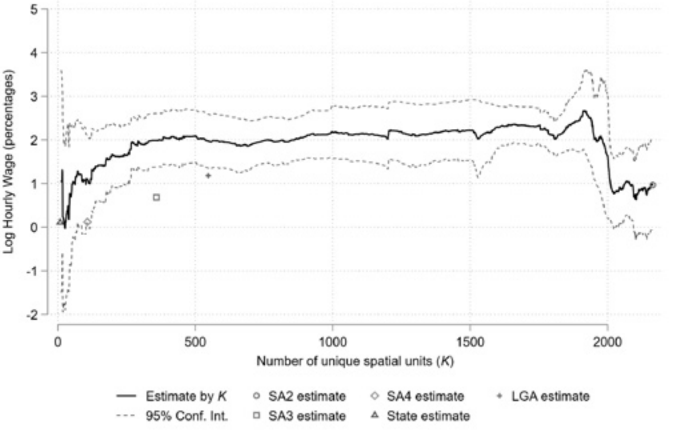
Figure 3 displays the impact of population density on hourly wages for a continuum of regional aggregations, examining the role of the measurement of spatial units in estimates of the urban wage premium. That is, it is analysed whether spatial unit sizes (scale effects) and spatial unit borders (zonation effects) matter for estimates of the impact of population density on wages. For each number of unique spatial units, K, the same regression model is estimated with the only difference being the number and thus the measurement of spatial units. The clustering algorithm that is used to aggregate spatial units is hierarchical, meaning that the building blocks for each set of spatial units are SA2s. Thus, all spatial structures are built from SA2 spatial units. To facilitate a comparison, figures 3A and 3B also contain the estimates of the urban wage premium based on the pre-defined spatial structures, as provided in columns 3 and 6 for the OLS estimator and FE estimator in Table 1, respectively.

Figure 3 shows that the OLS estimate of the urban wage premium peaks at 2.7 per cent if using around 1,900 unique spatial units, whereas the FE estimate peaks at 1.6 per cent if using around 1,750 spatial units. Importantly, it can be seen that the urban wage premium estimates are remarkably stable based on density effects estimated in the range of 1,800 to 300 unique spatial units. The scale effects of the modifiable areal unit problem in the context of Australia appear relatively small when compared to the international literature (Briant *et al*., 2010; Burger *et al*., 2010; Meekes and Hassink, 2019), where it is generally found that estimates of agglomeration externalities on wages are higher when using fewer and larger spatial units.

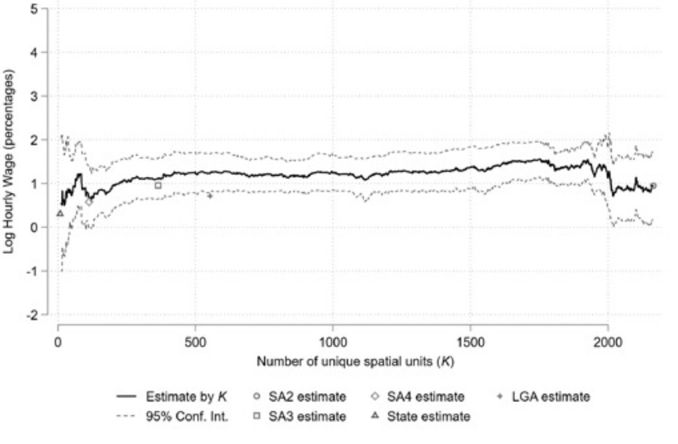
However, Figure 3 also indicates that using very few spatial units or many spatial units, outside the range between 300 and 1,800 unique units, causes less robust results. This finding can be explained by the clustering algorithm that starts with aggregating spatial units with the highest relative commuting flow, which are disproportionally located in urban areas where there are higher levels of commuting connectivity between neighbouring spatial units (see figures 2A and 2B). At a high number of unique spatial units, aggregating units with a relatively high commuting connectivity increases the estimate of the urban wage premium. Conversely, at a low number of unique units, aggregating units with a low connectively reduces the urban wage premium.

Figure 3. The Urban Wage Premium in Australia

a) OLS Urban Wage Premium



b) FE Urban Wage Premium



Notes: The coefficients are based on two sets of regressions, estimated as the effect of log population density on log hourly wage using the Ordinary Least Squares (OLS) estimator and Fixed Effects (FE) estimator. For each K, an estimate is provided based on a different regression. The 95% confidence intervals are computed using clustered standard errors by spatial unit. The number of unique spatial units is represented by K. The individual's characteristics are represented by X, which include zero-one indicator variables for gender (1), Indigenous origin (1), being born abroad (1), age (8), education (4), number of household members (3), marital status (5), number of own resident children (3), type of contract (4), job occupation (7), job industry (19) and the private sector (1). The time-constant variables gender, Indigenous origin and being born abroad, are absorbed by α_i for the FE estimates. Number of observations: 95,760. Number of individuals: 13,112. The time period under observation is 2001 to 2019.

Interestingly, the OLS estimates of the urban wage premium for the continuum of regional aggregations appear higher than those based on the ABS spatial structures (SA3 and SA4) and the administrative local government areas. This observation could be attributed to the defined regional aggregations allowing for larger urban areas, compared to the ABS spatial structures, holding the number of unique spatial units constant. For example, agglomeration benefits of a central business district do not only occur in the central business district but also in neighbouring spatial units, which are part of the same spatial unit after clustering based on commuting flows as long as this commuting interaction is relatively high. Conversely, for the ABS spatial structures, which contain more disaggregated and less self-contained urban areas (see Figure 2), there are more commuting flows across spatial units resulting in relatively high spatial autocorrelation, which may result in a measurement bias.

Consistent with this notion, Stimson, Mitchell, Rohde, and Shyy (2011) and Stimson, Flanagan, Mitchell, Shyy, and Baum (2018) use relational data of commuting flows to define regional areas with a strong commuting connectivity within each area and argue that the issue of spatial autocorrelation is more limited than is the case for using pre-defined administrative spatial structures. Thus, spatial autocorrelation may be more limited for the defined spatial units than the ABS structures if the spatial units defined by flowbca based on commuting flows are more self-contained. However, it is important to emphasise that differences in the estimate of the urban wage premium caused by zonation effects are statistically insignificant when considering the confidence intervals. In this regard, the zonation effects of the modifiable areal unit problem do not seem particularly worrying in the Australian context.

iv. Density effects excluding sparsely populated areas

Australia's geographical size is extraordinarily large. For this reason, it might be relevant to exclude spatial units that are relatively large and have relatively few residents. Table 4 shows estimates of the urban wage premium for populated areas, estimated separately for six spatial structures: SA2, SA3, SA4, state, LGA and Significant Urban Area (SUA). One approach to focus on densely populated areas is by using SUAs. The spatial structure of SUAs contains relatively few spatial units, defined by combining SA2s based on criteria related to population sizes, distances to Urban Centres and Greater Capital City Statistical Area borders (ABS, 2017).

Sparsely populated areas are excluded from the sample of analysis according to two criteria. First, observations of individuals who live in an SA2 that has at least 10,000 residents in 2016 are retained. Thus, if an SA2 has fewer than 10,000 residents in 2016, the SA2 is excluded from the sample in all years. Second, the spatial units that are not part of the 'Not in any Significant Urban Area' category are retained. Consequently, the number of unique SA2s reduces from 2,041 (see Table 2) to 877 (see Table 4). The sample used in Table 4 is not the preferred sample of analysis, as the selections introduce sample selection since more productive areas could attract more people, increasing the likelihood of satisfying the two criteria. Importantly, however, the analysis provides the opportunity to assess whether the estimates of the urban wage premium for the entire country (Table 2) are robust to excluding sparsely population areas (Table 4).

Table 4 shows that the estimates of the urban wage premium based on populated areas are higher compared to those based on the entire sample as shown in Table 2. Interestingly, for the specification including individual fixed effects, the urban wage premium is found to be about 7.4 per cent based on the Australian states and 4.5 per cent based on the SUAs. However, these high estimates of the urban wage premium are not found for the other spatial structures. Especially the estimates for the seven states are likely to be unstable because of the very few unique spatial clusters. Overall, by excluding sparsely populated areas, the estimates do not become more consistent across spatial structures neither more robust to changes in the set of covariates or the inclusion of individual fixed effects.

Table 4. Urban wage premium, based on pre-defined Australian spatial structures (Equation (1))

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		OLS			*FE*	
Log population density, based on:						
SA2 (877 unique spatial units)	0.0532**	0.0330**	0.0236*	0.0205**	0.0121	0.0125
	(0.0209)	(0.0156)	(0.0124)	(0.0086)	(0.0081)	(0.0079)
SA3 (256 unique spatial units)	0.0167	0.0139	0.0138	0.0145**	0.0094	0.0102
	(0.0189)	(0.0144)	(0.0112)	(0.0069)	(0.0067)	(0.0066)
SA4 (83 unique spatial units)	-0.0183	-0.0164	-0.0065	0.0134	0.0155*	0.0162*
	(0.0233)	(0.0176)	(0.0129)	(0.0095)	(0.0090)	(0.0087)
State (7 unique spatial units)	0.0228	0.0137	0.0170	0.0777***	0.0759***	0.0744***
	(0.0351)	(0.0268)	(0.0198)	(0.0133)	(0.0146)	(0.0143)
LGA (201 unique spatial units)	0.0136	0.0030	0.0046	0.0045	0.0030	0.0043
	(0.0166)	(0.0109)	(0.0069)	(0.0065)	(0.0058)	(0.0057)
SUA (85 unique spatial units)	0.0661***	0.0493***	0.0405***	0.0475***	0.0466***	0.0448***
	(0.0144)	(0.0121)	(0.0099)	(0.0137)	(0.0125)	(0.0122)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	Yes	No	Yes	Yes
Occupation & industry dummies	No	No	Yes	No	No	Yes
Individual fixed effects	No	No	No	Yes	Yes	Yes

Notes: The outcome variable is log hourly wages. Each row represents a different regression for a different regional classification. Each column represents a different set of control variables and fixed effects. Standard errors, clustered by spatial unit, are in parentheses. The number of unique spatial units for each regional classification in the sample of analysis is provided in parentheses after the relevant spatial structure. ***, **, *, correspond to the significance level of 1%, 5%, 10%, respectively. The set of covariates contains the individual's characteristics, which include zero-one indicator variables for gender (1 estimated parameter), Indigenous origin (1), being born abroad (1), age (8), education (4), number of household members (3), marital status (5), number of own resident children (3), type of contract (4) and the private sector (1). The occupation and industry dummies consist of job occupation (7) and job industry (19). The time-constant variables gender, Indigenous origin and being born abroad, are absorbed by α_i for the FE estimates. The sample of analysis contains 63,094 individual-year observations and 10,089 unique employed individuals. The time period under observation is 2001 to 2019.

6. Discussion and conclusion

As in many other countries, Australia has become more urbanised over time. With increased population in metropolitan areas, more people are living and working in close proximity. A relevant question is how agglomeration economies, which refer to the costs and benefits of the spatial concentration of economic activity, affect local productivity.

This paper is the first to study the economic impact of urban density in Australia on individual wages. By combining HILDA Survey microdata on 13,112 employed individuals and regional-level population data, population density effects on individual hourly wages are studied over the period 2001 to 2019. A unique feature of this paper is to apply a flow-based clustering algorithm that uses commuting flows across SA2s to define spatial units that are characterised by a strong commuting connectivity within each spatial unit. As such, population density effects are analysed over a continuum of regional aggregations, providing more variation in how geographic space could be measured in empirical analyses, as is possible with the pre-defined ABS spatial structures.

Using various empirical strategies, the body of empirical evidence in this paper suggests that the estimate of the urban wage premium in Australia ranges from 0.5 per cent to 2.7 per cent. The urban wage premium in Australia appears to be low when compared to the international evidence that shows a mean and median effect of density on wages of 4 per cent (Ahlfeldt and Pietrostefani, 2019). The question then arises: what makes Australia different compared to other countries? Two important differences are Australia's sectoral composition and Australia's extraordinarily large geographic size. Specifically, the Australian economy is characterised by a large mining sector, which causes relatively high wages for workers in several remote areas. Consequently, there exists a general compensating differential for working in these areas. In addition, the tax system provides a remote area allowance which compensates for the higher costs of living in these areas. This makes remote areas in Australia different from rural areas in other parts of the world. Importantly, after excluding sparsely populated areas, the estimated urban wage premium is 4.5 per cent based on the spatial structure Significant Urban Areas. The large estimate of the urban wage premium after excluding sparsely populated areas is, however, not robust as it is not found for the spatial structures SA2, SA3, SA4. A promising avenue for future research is to identify whether the structure of Australian cities is also important to answer the aforementioned question.

Australian cities are monocentric, as most economic activity is concentrated in central business districts. Compared to areas with multiple cores of economic activity, also referred to as polycentric cities, economic activity in monocentric cities is less spread out and moves into the same direction. As Australia is spatially large and with few urban areas in each state, most commuters move into the direction of the central business district, with relatively few moving in the opposite direction. This leads to increased road congestion, public transport crowding and urban sprawl (Infrastructure Australia, 2019), which limits the agglomeration benefits. Indeed, in the context of the COVID-19 pandemic, Hensher, Wei, Beck, and Balbontin (2021) show that the working from home environment alleviated some of the negative effects of congestion. Clearly, the benefits of agglomeration in Australia are not being sufficiently understood, and much work remains to be done to develop a better understanding of how policy development options can enhance agglomeration economies in Australia. For example, agglomeration economies may be increased by increasing positive externalities based on the sharing, matching and learning mechanisms, or by decreasing congestion and other frictions impacting the labour market.

This study has shown how agglomeration externalities can be studied in Australia using multiple data sources in a novel way. For other countries, many studies have analysed various research questions related to agglomeration externalities over the last two decades. A key topic has been the heterogeneity in agglomeration benefits among subgroups of the population, for example based on gender, educational attainment, skill, occupation and economic sector (Adamson, Clark, and Partridge, 2004; Di Addario and Patacchini, 2008; Meekes and Hassink, 2019). Other research has analysed to what extent agglomeration benefits attenuate with the distance from the core of an urban area (Rosenthal and Strange, 2008). In the context of the COVID-19 pandemic, a study on how the hybrid working environment changed the matching, sharing and learning mechanisms underlying agglomeration economies could lead to important insights. As the Productivity Commission (2021) points out, the COVID-19 pandemic and the increase in working from home has shifted economic activity from central business districts to the inner suburbs, changing the micro-foundations of agglomeration economies. These topics are well beyond the scope of this paper that documents density effects on individual wages in Australia for the first time, but suggest promising avenues for future research on Australia.

Appendix A1: Additional robustness checks

Table A1. Urban wage premium for sample of full-time and part-time employees (Equation (1))

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		OLS			*FE*	
Log population density, based on:						
SA2	0.0068	0.0094	0.0086*	0.0081**	0.0072*	0.0073**
	(0.0083)	(0.0060)	(0.0048)	(0.0039)	(0.0037)	(0.0036)
SA3	0.0070	0.0091	0.0076	0.0073	0.0049	0.0056
	(0.0125)	(0.0093)	(0.0071)	(0.0048)	(0.0047)	(0.0045)
SA4	-0.0064	-0.0027	0.0003	0.0070	0.0052	0.0051
	(0.0183)	(0.0132)	(0.0099)	(0.0081)	(0.0071)	(0.0066)
State	0.0090	0.0008	0.0045	0.0074	0.0082	0.0089
	(0.0260)	(0.0198)	(0.0148)	(0.0099)	(0.0097)	(0.0097)
LGA	0.0227**	0.0159***	0.0133***	0.0058**	0.0063**	0.0071***
	(0.0088)	(0.0051)	(0.0035)	(0.0029)	(0.0027)	(0.0025)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	Yes	No	Yes	Yes
Occupation & industry dummies	No	No	Yes	No	No	Yes
Individual fixed effects	No	No	No	Yes	Yes	Yes

Notes: The outcome variable is log hourly wages. Each row represents a different regression for a different regional classification. Each column represents a different set of control variables and fixed effects. Standard errors, clustered by spatial unit, are in parentheses. The number of unique spatial units for each regional classification in the sample of analysis is provided in parentheses after the relevant spatial structure. ***, **, *, correspond to the significance level of 1%, 5%, 10%, respectively. The set of covariates contains the individual's characteristics, which include zero-one indicator variables for gender (1 estimated parameter), Indigenous origin (1), being born abroad (1), age (8), education (4), number of household members (3), marital status (5), number of own resident children (3), type of contract (4), and the private sector (1). The occupation and industry dummies consist of job occupation (7), job industry (19) and full-time/part-time contract (1). The time-constant variables gender, Indigenous origin and being born abroad, are absorbed by α_i for the FE estimates. The sample of analysis contains 132,467 individual-year observations and 16,439 unique employed individuals. The time period under observation is 2001 to 2019.

Table A2. Urban wage premium for sample of part-time employees (Equation (1))

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		OLS			*FE*	
Log population density, based on:						
SA2	0.0076	0.0137*	0.0080	-0.0063	-0.0042	-0.0064
	(0.0104)	(0.0076)	(0.0066)	(0.0092)	(0.0091)	(0.0090)
SA3	0.0083	0.0065	0.0024	-0.0193	-0.0160	-0.0162
	(0.0112)	(0.0086)	(0.0079)	(0.0121)	(0.0120)	(0.0121)
SA4	-0.0142	-0.0127	-0.0118	0.0050	0.0039	-0.0012
	(0.0189)	(0.0130)	(0.0107)	(0.0158)	(0.0155)	(0.0152)
State	0.0221	0.0115	0.0092	0.0049	0.0082	0.0032
	(0.0168)	(0.0152)	(0.0138)	(0.0121)	(0.0133)	(0.0125)
LGA	0.0184***	0.0153***	0.0133***	0.0097	0.0138**	0.0122**
	(0.0058)	(0.0035)	(0.0029)	(0.0063)	(0.0063)	(0.0062)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	Yes	No	Yes	Yes
Occupation & industry dummies	No	No	Yes	No	No	Yes
Individual fixed effects	No	No	No	Yes	Yes	Yes

Notes: The outcome variable is log hourly wages. Each row represents a different regression for a different regional classification. Each column represents a different set of control variables and fixed effects. Standard errors, clustered by spatial unit, are in parentheses. The number of unique spatial units for each regional classification in the sample of analysis is provided in parentheses after the relevant spatial structure. ***, **, *, correspond to the significance level of 1%, 5%, 10%, respectively. The set of covariates contains the individual's characteristics, which include zero-one indicator variables for gender (1 estimated parameter), Indigenous origin (1), being born abroad (1), age (8), education (4), number of household members (3), marital status (5), number of own resident children (3), type of contract (4) and the private sector (1). The occupation and industry dummies consist of job occupation (7) and job industry (19). The time-constant variables gender, Indigenous origin and being born abroad, are absorbed by α_i for the FE estimates. The sample of analysis contains 32,647 individual-year observations and 8,492 unique employed individuals. The time period under observation is 2001 to 2019.

Table A3. Impact of area size on hourly wages (double-log model), based on pre-defined Australian spatial structures (Equation (1))

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		OLS			*FE*	
Log population density, based on:						
SA2 (2041 unique spatial units)	-0.0245**	-0.0137*	-0.0066	0.0038	0.0006	0.0013
	(0.0096)	(0.0072)	(0.0057)	(0.0045)	(0.0043)	(0.0042)
SA3 (332 unique spatial units)	-0.0229	-0.0113	-0.0075	0.0074	0.0035	0.0041
	(0.0145)	(0.0108)	(0.0082)	(0.0053)	(0.0051)	(0.0049)
SA4 (88 unique spatial units)	-0.0384*	-0.0258	-0.0156	-0.0016	-0.0029	-0.0016
	(0.0223)	(0.0176)	(0.0129)	(0.0100)	(0.0089)	(0.0084)
State (8 unique spatial units)	-0.0117	-0.0075	-0.0013	-0.0048	-0.0037	-0.0023
	(0.0276)	(0.0220)	(0.0149)	(0.0067)	(0.0062)	(0.0062)
LGA (426 unique spatial units)	-0.0104	-0.0073	-0.0048	0.0009	-0.0010	-0.0002
	(0.0133)	(0.0086)	(0.0057)	(0.0043)	(0.0037)	(0.0036)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	Yes	No	Yes	Yes
Occupation & industry dummies	No	No	Yes	No	No	Yes
Individual fixed effects	No	No	No	Yes	Yes	Yes

Notes: Based on the same set of regressions as Table 2. The outcome variable is log area size. Each row represents a different regression for a different regional classification. Each column represents a different set of control variables and fixed effects. Standard errors, clustered by spatial unit, are in parentheses. The number of unique spatial units for each regional classification in the sample of analysis is provided in parentheses after the relevant spatial structure. ***, **, *, correspond to the significance level of 1%, 5%, 10%, respectively. The set of covariates contains the individual's characteristics, which include zero-one indicator variables for gender (1 estimated parameter), Indigenous origin (1), being born abroad (1), age (8), education (4), number of household members (3), marital status (5), number of own resident children (3), type of contract (4) and the private sector (1). The occupation and industry dummies consist of job occupation (7) and job industry (19). The time-constant variables gender, Indigenous origin and being born abroad, are absorbed by α_i for the FE estimates. The R-squared is between 0.17 and 0.46 depending on the specification. The sample of analysis contains 95,760 individual-year observations and 13,112 unique employed individuals. The time period under observation is 2001 to 2019.

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Course non-completion and multiple qualifications: re-estimating the returns to education in Australia

Austen Peters *Bankwest Curtin Economics Centre*
Alfred M. Dockery *Bankwest Curtin Economics Centre*
Sherry Bawa *School of Accounting, Economics and Finance, Curtin University*

Abstract

Among Australian studies estimating returns to education, there is a consensus that education is a highly profitable investment. Conventional estimates of returns to education examine earnings conditional upon individuals' years of education, with years spent in education typically inferred from their highest qualification attained. However, this approach underestimates the actual time individuals may have spent in education as it ignores multiple qualifications obtained and time spent towards qualifications that were not completed. Using 2001-2019 panel data from the Household, Income and Labour Dynamics in Australia (HILDA) survey supplemented by several Australian Bureau of Statistics sources, we estimate the sensitivity of estimates of the returns to education from a standard wage equation to the inclusion of course non-completion and multiple qualifications. Taking account of these sources of mismeasurement, we estimate the wage premium associated with each additional year of education to be 5.5 per cent, as opposed to 6.5 per cent using the conventional approach, or around 15 per cent lower. These differences are similar by gender and broad age group. We find unaccounted for years spent accruing multiple qualifications to be the main source of overestimation of the returns to education, although we note the lack of individual-level data on incomplete qualifications may have mitigated against identifying a larger effect of accounting for this source of mismeasurement.

JEL Codes: I26, J24, J31
Keywords: Education, return to education, human capital theory, non-completion, multiple qualifications, Australia

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Corresponding Authors: Austen Peters, austen.peters@curtin.edu.au; Alfred Michael Dockery, m.dockery@curtin.edu.au, ORCID: 0000-0002-4517-2442; Sherry Bawa, sherry.bawa@curtin.edu.au ORCID: 0000-0002-3346-4691

1. Introduction

Estimating the returns to education for individuals and to society is of ongoing interest to researchers and policymakers (see, for example, Psacharopoulos and Patrinos, 2018). Following Human Capital Theory (HCT), two main empirical methods guide estimation of the returns to education: Mincer's (1974) human capital earnings function and Becker's (1964) internal rate of return (IRR) method. In the case of the former, the key empirical approach is to estimate wage equations, which generate an estimate of the change in earnings associated with additional years of education or with a particular qualification level, such as a bachelor's degree.

There has been significant debate around the extent to which estimates from wage equations can be taken to infer a causal effect of education on earnings. This includes theories in which education provides a signal of workers' pre-existing abilities to allocate them to jobs, rather than directly increasing their productivity as assumed in HCT (see, for example, Arrow 1973, Spence 1973). An extensive empirical literature also attempts to control for potential bias in the estimated effect of education on earnings due to unobserved characteristics, especially ability bias and selection on other factors such as family background (Bonjour *et al*. 2003; Card 1999, 2001; Li *et al*. 2012; Heckman *et al*. 2016; Wilkins 2015).

However, one aspect of returns to education estimates that appears to have been largely unchallenged is the specification of 'years of education'. The years of education undertaken by an individual is typically inferred from their highest educational qualification attained, and taken to be the number of years that specific qualification usually takes to complete. This fails to take into account individuals who do not complete their course, either due to dropout or course switching, and individuals who hold more than one qualification at the same qualification level. These sources of under-estimation of the actual years of education individuals have accrued, hereafter referred to as course non-completion and multiple qualifications, respectively, can be expected to lead to over-estimation of the returns to education. According to Australian Bureau of Statistics (ABS) data, 2.6 million individuals in 2020 had an incomplete qualification in Australia (ABS 2020c). Whilst not directly collected in major microdata sources, we also estimate multiple qualifications to be widespread in Australia.

In the Australian context, this paper analyses the sensitivity of estimates of the returns to education in standard wage equation models to the incorporation of course non-completion and multiple qualifications into the measurement of years of education. Data from various ABS sources and the Household, Income and Labour Dynamics in Australia (HILDA) survey are used to derive a measure of 'actual' years of education, which accounts for both course non-completion and multiple qualifications.[1] Results from models using this 'actual' measure of years of education are compared with those obtained using a standard 'inferred' measure based on highest level of qualification. We also test whether accounting for course non-completion and multiple qualifications has implications for inferences on differences in the returns to education by gender and age.

1 While we use the term 'actual' years of education for convenience, we fully acknowledge that this measure also has limitations.

This paper focuses on estimates of the returns to education using the earnings function approach. However, accounting for multiple qualifications and course non-completion also has implications for estimates based on the IRR approach. We show there are potentially important differences in the effect of accounting for actual years of education under the two approaches.

2. Background

Human Capital Theory, as pioneered by Schultz (1961), Becker (1964) and Mincer (1974) suggests that the human capital an individual acquires increases their labour productivity, which in turn augments their earning capacity over their lifetime. Education facilitates the growth of human capital through the development and accumulation of knowledge and skills which enhance an individual's labour productivity. However, education comes at a cost, and the concept of the return to education has become a central focus in labour economics and for policymakers (Wei 2010). Returns to education can be considered in both the private and public context; however, this paper focuses on estimates of private returns to education.

The two main approaches to estimating returns to education are the IRR and the Mincer human capital earnings function (Wei 2010). Initially devised by Becker (1964), the IRR approach is based upon the notion that, just as with traditional capital, education increases future earnings, but at an immediate cost in the present in the form of opportunity costs (foregone earnings) and direct costs (course fees, textbooks, etc.). The IRR is the discount rate which equates the present value of the future stream of benefits to the costs. If that discount rate is relatively high, say compared to a benchmark like the long-term bond rate, then investing in education in the present can be considered to be relatively profitable and individuals will opt to undertake further education (Harmon *et al*. 2003).

Mincer's human capital earnings function is a semi-logarithmic function which expresses earnings as a function of years spent in education, and takes the following form:

$$\ln Y_i = \alpha + \beta X_i + \gamma S_i + \mu_i \qquad (1)$$

Where $\ln Y_i$ represents the log of earnings for individual i and X_i represents a vector of coefficients that affect earnings, such as age, experience, disability status and Indigenous status. S_i represents years spent in education by the individual, and μ_i an error term. The parameters to be estimated include the constant term α, the vector of coefficients β, and the private rate of return to education, γ. Under this specification, γ approximates the percentage increase in earnings associated with each additional year of education.

Major challenges to the HCT approach relate to the assumed link between workers' level of education, their productivity and their wages. Alternative theories emphasise the credential role of education, whereby educational qualifications simply act as a screen or signal to employers to allocate workers to jobs. The important implication is that productivity is attached to jobs and to fixed traits of workers; education does not increase workers' productivity *per se* (Arrow 1973, Rospigliosi *et al*. 2014, Spence 1973).

A less fundamental challenge is of unobserved ability bias. If individuals with higher ability are inherently more productive workers, and also more likely to accrue higher levels of education, the effect of education on productivity and earnings will be over-estimated if this is not fully accounted for. The growing literature on returns to education has seen increasingly sophisticated econometric techniques to account for ability bias and to establish causal effects of education on earnings, such as through natural experiments (see Card 1999, 2001; Heckman *et al*. 2006; Heckman *et al*. 2016). This has included studies utilising samples of twins to control for family background and for ability in the case of identical twins (see, for example, Bonjour *et al*. 2003 and Li *et al*. 2012; and Miller *et al*.1995 for an Australian study).

Internationally, studies based on human capital earnings functions generally find education to be a profitable investment for individuals (see reviews in Dickson and Harmon 2011, Harmon *et al*. 2003, Heckman *et al*. 2006, Psacharopoulos and Patrinos 2018). This also holds for Australia, with estimates suggesting returns in the vicinity of 10 per cent higher wages per year of education (Daly *et al*. 2015; Deloitte 2017; Dockery and Miller 2012; Kler 2005; Leigh 2008; Sinning 2014; Wei 2010; Wilkins 2015), although there is evidence that returns may be declining as the number of individuals with university qualifications in Australia rises (Corliss *et al*. 2020; Productivity Commission 2019).

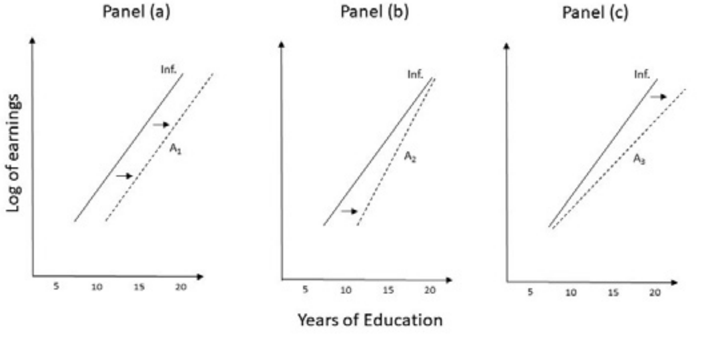
Studies to have estimated returns to education in Australia using the IRR approach similarly find education to be a profitable investment. Estimates of the return to completing a university degree typically range from between 10 to 20 per cent, with substantial variation across disciplines and over time as labour demand for graduates and non-degree holders fluctuates (see Borland *et al*. 2000; Norton 2012; Wei 2010 and a series of papers by Corliss and colleagues: Corliss *et al*. 2020, Corliss *et al*. 2013, Daly *et al*. 2015). Wei's (2010) study looked at returns to education based on each five-yearly census over a 25-year period (1981-2006), and is notable for generating estimates using both earnings functions and the IRR methods, with broadly similar results.

3. Course non-completion and multiple qualifications – theoretical expectations and some existing evidence

While the literature has paid extensive attention to potential bias in estimates of the returns to education due to ability bias or unobserved heterogeneity, very little attention has been paid to the potential bias due to mismeasurement arising from course non-completion and multiple qualifications. Our initial expectation when embarking on this study was that adding unaccounted years spent in education into the measure of years of education would lead to a roughly proportionate reduction in the estimated return to years of education. The motivation was to assess the degree of over-estimation of the returns to education, and the potential implications for decision-making by individuals and policymakers. However, in attempting to interpret our results, it became clear that the effects of this mismeasurement on estimates of the returns to education from the wage equation approach are far more nuanced.

To appreciate why, note that a wage equation of the form (1) above estimates the percentage change in wages associated with an increase in years of education, or the slope of a line of best fit to the log of earnings when plotted against years of education. This is depicted by the schedule labelled 'Inf.' (for inferred) in Figure 1. Assume all unaccounted years of education are evenly distributed across all workers. Adding these to the measure of inferred education simply leads to a rightward shift in the schedule from 'Inf' to the schedule of 'actual years' (depicted by A_1) as shown in Panel (a). It can be seen that there is no change in the slope of the earnings function with respect to years of education, and hence no change in the estimated return to an additional year of education.

Figure 1. Effects of adjusting for actual years of education



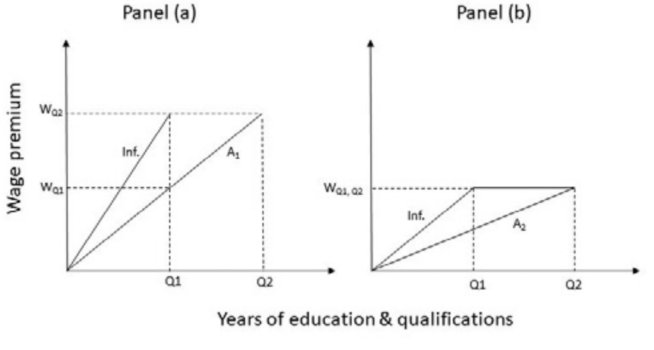
In contrast, consider the case in which unaccounted years of education are concentrated among the less educated. Relative to inferred years of education, there is lower variation for years of actual education, and a steeper education-wage gradient as shown by A_2 in Panel (b). Hence, adjusting for actual years spent in education can lead to a higher estimated rate of return. The converse, shown in Panel (c), applies if unaccounted years of education are concentrated among the more educated. Variation in measured years of education widens, reducing the education-earnings gradient.

Put another way, if the degree of mismeasurement is negatively correlated with inferred education, adjusting for actual years of education will lead to higher estimated rates of return to education. If mismeasurement is positively associated with years of inferred education, adjusting for actual years of education will reduce the estimated returns.

However, the results will also be affected by the extent to which unaccounted years of education attract a wage premium. This is illustrated using the case of multiple qualifications. Compared to the approach based on inferred years of education, a calculation based on actual years of education will necessarily reduce the return to each year of education for those with multiple qualifications. The exact nature of any bias varies depending on the returns to years of education spent attaining multiple qualifications.

This is shown in Figure 2. Panel (a) represents the case in which years spent gaining the first (Q1) and second qualification (Q2) attract exactly the same wage premium. In this case, using inferred years of education gives a higher wage gradient (Inf) for people with a second qualification, because the higher wages associated with the second qualification are attributed solely to the first qualification. Using actual years of education gives the flatter wage schedule A_1. The other extreme, in which the second qualification attracts no additional wage premium at all, is depicted in Panel (b). Again, the estimated return to years of education is higher when inferred years rather than actual years is used as the basis for calculation, but this time due only to the change in the measured number of years spent in education.

Figure 2. Estimated return to education for persons with a second qualification, based on inferred and actual years



It is difficult to say which scenario will lead to the larger divergence between estimates based on inferred and actual years of education, and the net result will depend on the values of the underlying parameters, such as the relative wage premiums, the number of additional years required to attain a second qualification, and their distributions across the population. Potentially, the case in which multiple qualifications attract a relatively high wage premium will be most sensitive to the inclusion of actual years in education, given that there is both a wage (numerator) and years (denominator) effect.

This example is related to the so-called ‘sheepskin effect’ that differentiates between wage premiums associated with years spent in education towards incomplete qualifications and those spent towards a qualification that is completed (Jaeger and Page 1996). If education has an effect on workers’ productivity, then it is argued that the time spent towards complete and incomplete qualifications should have a similar effect on productivity and wages. In contrast, if returns accrue only for years of a completed qualification, this would suggest credentialism effects, rather than productivity effects.

As in the case of multiple qualifications, these contrasting scenarios also have implications for the potential effect of controlling for time spent in non-completed qualifications. If those years offer a low return, then accounting for actual years would result in a lower estimate of the returns to education compared to an estimate using inferred years, as those additional years are ignored in the inferred measure. On the other hand, if years in completed and non-completed qualifications generate similar wage premiums, accounting for actual years may increase the estimated returns to education relative to using inferred years. This is because the higher wages associated with those years of incomplete qualifications will be assigned to unqualified persons using the inferred approach, reducing the apparent return to years spent successfully gaining qualifications.

3.1 Existing evidence

There is a substantial literature looking at rates of course attrition and its contributing factors (see, for example, Bednarz (2014) and Stromback and Mahendran (2010) for Australian apprentices and trainees; Cherastidtham *et al.* (2018), Edwards and McMillan (2015) with respect to university courses). However, these generally are not in the context of estimating returns to education. Course non-completion has also been analysed in relation to the 'sheepskin effect', with that literature typically focussing on the relative returns to course non-completers compared to completers or to those who have not commenced a course. Toutkoushian *et al.* (2013) and Zeidenberg *et al.* (2015) acknowledge that the risk of non-completion is often ignored and should be taken into account in estimating returns to education. Both those studies find a much lower return to those who attend a US college but do not complete than for those who graduate. Giani *et al.* (2020) cite mixed results in the existing literature as to the benefits of attendance at a US college without attaining a qualification. Their own study finds incomplete college does confer some future benefits in terms of employment and earnings, but non-completers do not fare as well as college graduates.

In estimating the return to education in Australia, Borland *et al.* (2000) and Daly *et al.* (2015) merely acknowledged the presence of course non-completion. Long and Shah (2008) added a 10 per cent adjustment for bias due to course non-completion in their estimation, but the study only estimated returns to vocational qualifications. Amongst the other limited literature, Marks (2007) looked at non-completion and found that having a non-completed degree was associated with a lower incidence of unemployment, but similar labour market outcomes in terms of earnings, job satisfaction and occupational status compared to those who never started a degree. Those who completed a degree fared better on all counts. Norton *et al.* (2018) report mixed subjective perceptions on the value of non-complete degrees on the part of students who drop out from university.

We have not identified any previous studies of the returns to multiple qualifications or how either of these sources of mismeasurement affect overall estimates of the returns to education.

4. Allowing for course non-completion and multiple qualifications

Most studies of the returns to education in Australia that follow the earnings function approach infer the number of years of education an individual has completed from their highest level of education attained. This omits qualifications that have not been completed, as well as multiple qualifications achieved at the same or lower qualification levels (e.g. two bachelor's degrees). As set out above, if this 'inferred' years of education is significantly lower than the actual number of years individuals spent in education, existing estimates are likely to be biased.

To assess the potential magnitude of the effect of this mismeasurement, we estimate earnings functions using data from Waves 1-19 of HILDA. Initially, the model is estimated with the measure of years of education inferred from individuals' reported highest level of qualification, as is common practice. We then draw on a range of data sources to generate more accurate measures of years spent in education, accounting for course non-completion and multiple qualifications. Finally, we compare the estimated returns to years of education when the models are estimated using 'actual years' of education instead of 'inferred years'.

HILDA is a household-based panel study that tracks and interviews Australian respondents on a yearly basis. The HILDA survey collects important economic and personal information from the respondents which provides insight into economic and personal well-being, including educational attainment, labour market experience and individual earnings (Melbourne Institute 2020). HILDA follows respondents over the course of their lifetime from the age of 15. At the time of writing, data from 19 waves were available, spanning 2001 to 2019. Since the first wave in 2001, the survey has recorded responses from around 17,000 Australians from over 7,000 households annually. A top-up sample of 2,153 households (5,477 individuals) was added in 2011 to allow new population sub-groups to be represented as well as alleviate biases from non-random attrition (Watson and Wooden 2003).

For this analysis, the sample was restricted to individuals between the age of 25-65 years who are working and earning a wage.[2] This results in an unbalanced panel, with over 125,000 observations on 18,182 individuals over the period 2001-2019.

The earnings measure is the log of real hourly wages, which we derive from the "usual hours worked per week" and the "usual weekly wages" variables within the HILDA dataset. Wages for waves 1-19 were inflated using the December quarter Consumer Price Index (CPI) in Australia (ABS 2020a) to be expressed in real 2019 dollars. Below we discuss the derivation of 'inferred' and 'actual' years of education. See Appendix A for definitions of other control variables used in the modelling.

2 The intention of the age restriction is to focus the analysis on individuals' 'prime' working years following initial investments in education. This will largely abstract from part-time jobs for people under 25 whose major labour market activity is study and people aged over 65 accepting lower wages as they transition into retirement.

4.1 Inferred years of education

HILDA asks respondents their "highest year of school completed". The years of schooling are attributed to each year level, whereby Year 12[3] is equal to 12 years of schooling, Year 11 is equal to 11 years of schooling and so on until the lowest category of "attended primary school only", which is taken as 6 years of schooling.[4] Total years of education is measured as the sum of years of schooling and years spent in post-school education and training.

The conventional ('inferred') approach to determining years spent in education by an individual is through the 'highest qualification attained'. We map individuals' highest reported post-school qualification as best as possible to years of education based on 'volume of learning' descriptors given in the Australian Qualifications Framework (AQF) as in Table 1 below (Australian Qualifications Framework Council 2013).

Table 1. Inferred Years of Post-School Education

Highest education level achieved	*'Inferred' years of post-school education*
PhD	8
Master's degree	5
Graduate Diploma, Graduate Certificate	4
Bachelor's degree – Honours	4
Bachelor's degree – Pass	3.5
Advanced Diploma	2
Cert III or IV	1
Cert I or II	0.5

4.2 Accounting for multiple qualifications

HILDA records the number of qualifications individuals have obtained since leaving school at each qualification level, ranging from Certificate Level I to a PhD. Where people report having multiple qualifications at any level, they will have spent more years in education than would be inferred directly from their highest qualification attained. Figure 1 shows the proportion of individuals with a qualification at a given level who hold multiple qualifications at that same level, based on the pooled HILDA data from 2001 to 2019. For both males and females, around 15 to 20 per cent of people

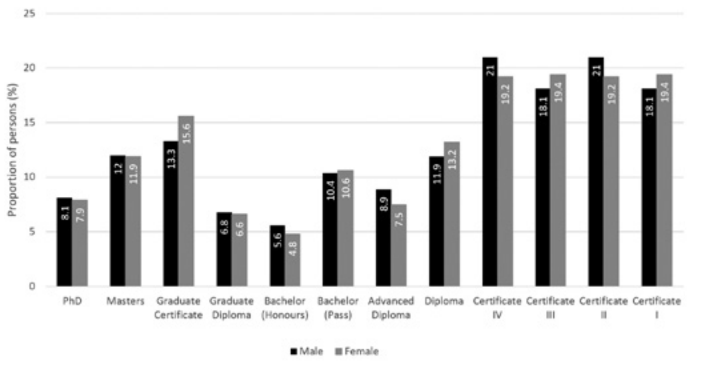
3 In the Australian education system, schooling is compulsory up to Year 10, where the vast majority of students are aged 15 to 16 years (Australian Curriculum, Assessment and Reporting Authority, 2021). Students who intend to participate in university study usually then enrol in two further years of high school study, in Year 11 and Year 12.

4 0.1% of the respondents in the sample listed their "highest year of school completed" as not finishing primary school, and were not included in the sample.

holding certificates from level I to IV have completed a second certificate at that level. Approximately 12 per cent of males and 13 per cent of females with a diploma hold multiple diplomas.

For tertiary-level education, over 10 per cent of males and females with a bachelor's (pass) degree have multiple of this qualification, but gaining multiple honours degrees is less common. Notably, 8 per cent of people with a PhD have completed multiple PhDs, requiring significant time and cost commitments.

Figure 3. Multiple qualifications by gender and qualification level, 2001-2019



To approximate how many additional years of education individuals had spent on multiple qualifications, we assume that completion of additional qualifications at a given level does not require any additional time spent on pre-requisite qualifications. For example, when an individual completes a bachelor's degree and then a master's degree, they will not complete another bachelor's degree to complete a second master's. This applies to all qualifications – allowance is only made for time spent on the incremental qualification.

Second, we assume that when studying toward a second qualification at a given level, people may get an exemption for completing some elements of the course in recognition of prior learning. This will be particularly so if the incremental qualification is in a related field to the learner's existing qualification(s) but, unfortunately, there is no way of assessing this with the HILDA data. We apply a discount of 25 per cent of the time normally taken for each additional multiple qualification. The justification behind the 25 per cent discount rate is that, although maximum recognition of prior learning credits varies by university and qualification level, as a general rule the limit is approximately a one-third (33 per cent) discount for qualifications from a bachelor's (honours) degree and up to a two-thirds (67 per cent) discount for qualifications below a bachelor's (honours) degree when studying in a related field (Curtin University 2016; Griffith University 2019; University of South Australia 2019). On this basis, we assumed that the average discount rate for an individual undertaking a multiple qualification is 50 per cent for a related field and 0 per cent for an unrelated field. Assuming an even split in the distribution between related and unrelated fields of study, yields the 25 per cent discount rate.[5] The resulting assumptions for time spent on multiple qualifications by level is shown in Table 2.

Table 2. Multiple qualifications – additional time spent in education

Qualification level	*Years to complete first qualification*	*Years to complete second and subsequent qualifications with 25% RPL discount*
PhD	4	3
Master's degree	2	1.5
Graduate Diploma, Graduate Certificate	1	0.75
Bachelor's degree – Honours	4	3
Bachelor's degree – Pass	3.5	2.625
Associate Degree	2	1.5
Advanced Diploma	2	1.5
Diploma	1	0.75
Cert III or IV	1	0.75
Cert I or II	0.5	0.375

4.3 Accounting for course non-completion

HILDA does not collect information on course non-completion or dropout. However, the ABS has microdata on course non-completion that can be separated by gender, age and level of qualification. ABS population estimates are used to assign rates of course non-completion to individuals in the HILDA dataset.

In order to measure the additional time spent in education as a result of course non-completion, two variables are created: average time spent in an incomplete qualification and average number of incomplete qualifications. Once created, the product of these yields the total years spent in incomplete courses.

Average time spent in incomplete qualifications

Additional time spent in education as a result of course non-completion is estimated from the Survey of Education and Work (ABS 2020b) and the Survey of Qualifications and Work (ABS 2020c). The latter records the level of most recent incomplete non-school qualification by current qualification level and age. Incomplete qualifications refer to qualifications the individual started, but stopped before completing all academic requirements – they do not include qualifications people are currently studying or training towards.

5 Section 5.2 discusses the sensitivity of the results to this assumption.

For people who failed to complete a qualification, we assume that they spent one-third of the typical years taken to complete that qualification (see Table 3). This is in line with the findings of Norton *et al*. (2018), who reported that over half of all bachelor's degree students in Australia dropped out of their course after completing the equivalent of one year of education, approximately one-third of the degree length.

Table 3. Additional Time Spent in a non-completed course

Qualification level of course	*Years to complete qualification with course requirements met*	*Average years spent in non-completed course (33%)*
Postgraduate Degree[a]	3	1
Graduate Diploma and Graduate Certificate	1	0.33
Bachelor's Degree[b]	3.5	1.16
Advanced Diploma and Diploma	1.5	0.5
Certificate III and IV	1	0.33
Certificate I and II	0.5	0.17

Notes: a. taken as the average of the typical time spent in a PhD (4 years) and a master's (2 years); b. taken as the average of the typical time spent in a bachelor's (pass) degree (3 years) and a bachelor's (honours) degree (4 years).

Based on the level of individuals' most recent incomplete qualification we then calculated the average number of years spent towards those unfinished qualifications using data from the Survey of Qualifications and Work. This average was calculated separately by gender and by highest existing qualification attained, on the basis that the more educated are likely to have attempted qualifications that take longer to complete. Table 4 shows this to be the case: persons holding a university level qualification are estimated to have spent almost one year in their most recent incomplete qualification, compared to around one-half of a year for those with certificate level qualifications.

Table 4. Average Time Spent in Incomplete Qualifications (Amongst Course Non-Completers)

Highest qualification attained	*Male*	*Female*
No post-school qualification	0.70	0.70
Postgraduate Degree	0.94	0.82
Graduate Diploma/Certificate	0.88	0.90
Bachelor's Degree	0.93	0.86
Advanced Diploma/Diploma	0.81	0.77
Certificate III/IV	0.56	0.60
Certificate I/II	0.54	0.54

Average number of incomplete qualifications

Having an estimate for the average time individuals spend in an incomplete qualification, we next needed an estimate of the number of incomplete qualifications people have commenced. ABS data from the Survey of Qualifications and Work on the average number of non-completed qualifications by gender and age were also incorporated into the data. Age was grouped by 10-year brackets across the age range of the sample to be included in the wage equations (25-65 years). The averages, which include individuals who did not have any incomplete qualification, are shown in Table 5.

Table 5. Average number of incomplete qualifications by age and gender

Age	*Male*	*Female*
25-34 years	0.20	0.26
35-44 years	0.22	0.27
45-54 years	0.20	0.20
55-64 years	0.16	0.19
55-64 years	0.54	0.54

Total Years Spent in Incomplete Qualifications

For each individual in the HILDA sample, we could impute a variable for their expected number of incomplete qualifications, based on the population average for their specific age and gender (Table 5). We could also impute a variable for the expected time they would have spent in each incomplete qualification, conditional upon their gender and level of highest qualification (Table 4). The final stage of calculation was to multiply these two variables to create an estimate of expected total years spent in incomplete qualifications. For example, for males aged 25-34 with a postgraduate degree as their highest qualification, each individual within this group had an additional (0.2 × 0.94) = 0.188 years added to their 'inferred' years of education.

This measure of time spent in incomplete qualifications and the measure of additional years for multiple qualifications are added to inferred years associated with an individual's highest level of qualification, to give the total 'actual' years of education measure.

5. Wage equation results

We estimate random effects panel models of the wage equation set out in equation (1) using data from waves 1 to 19 of HILDA. The random effects specification is chosen despite the Hausman test suggesting a fixed effects model. This is because a fixed effects approach would only estimate the returns to education for those individuals in the sample with a changing level of education, and these may be a small subset of the sample. Further, that subset may be biased towards a particular demographic, such as younger individuals, meaning the results are not representative of the population. Using fixed effects is particularly problematic for estimating the effects of course non-completion, since this is not observed for specific individuals in each year, but inferred based on the individual's age, gender and highest qualification. Hence variation in the variable occurs only with changes in these three parameters. Key results obtained using fixed effects are reported below as a robustness check.

The results of the random effects wage equations using the standard inferred measure of years of education and our estimate of actual years of education are reported in Table 6. All control variables have anticipated signs and are in line with existing estimates in the literature. The estimated coefficient on 'inferred' years of education is 0.0651, implying each additional year of education undertaken by an individual results, on average, in a 6.51 per cent increase in hourly wages. In comparison, the estimated coefficient on 'actual' years of education implies an increase in hourly wages of 5.52 per cent. Hence, accounting for multiple qualifications and course non-completion suggests that the return to years spent in education is a full percentage point (or 15 per cent) lower than the return to education obtained using the conventional approach.

Table 6. Random effects estimates: 'inferred' versus `actual' years of education

	Inferred years of education		*Actual years of education*	
Variable	*Estimated coefficient*	*t-statistic*	*Estimated coefficient*	*t-statistic*
Inferred years of education	0.0651***	(53.93)	-	-
Actual years of education	-	-	0.0552***	(52.69)
Age	0.0056***	(2.92)	0.0044**	(2.27)
Age^2	-0.0083***	(-3.80)	-0.0069***	(-3.20)
Experience	0.0222***	(19.72)	0.0222***	(19.65)
Experience^2	-0.0190***	(-9.13)	-0.0197***	(-9.46)
Male	0.113***	(17.30)	0.1121***	(17.06)
Disability	-0.0155***	(-4.43)	-0.0163***	(-4.66)
Indigenous	0.0452**	(2.12)	0.0363*	(1.70)
Works part-time	0.1139***	(34.30)	0.114***	(34.45)
Marital Status:				
Married	–		–	
Never married	-0.0596***	(-10.64)	-0.0607***	(-10.84)
No longer married	-0.0152***	(-4.10)	-0.0160***	(-4.31)
Employed:				
Permanent/ongoing	–		–	
Casual	-0.0107***	(-2.81)	-0.0111***	(-2.91)
Fixed-term	0.0307***	(7.94)	0.0310***	(8.00)
Union Member	0.0398***	(11.42)	0.0395***	(11.33)
Overseas born	-0.0249***	(-8.72)	-0.0176*	(-8.82)
Socioeconomic decile of neighbourhood 6-10	0.0505***	(14.3)	0.0536***	(15.19)
Language other than English spoken at home	-0.0345***	(-3.19)	-0.0349***	(-2.26)
Overseas highest qualification	-0.0309***	(-5.42)	-0.0361***	(-6.34)
Constant	2.0394***	(53.89)	2.171***	(58.66)
R-squared	0.1467		0.1419	
N	126199		126199	

Notes: t-statistics in parenthesis; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The main driver of the difference between 'inferred' and 'actual' years of education is multiple qualifications. As shown in Table 7, multiple qualifications account for nearly the entire fall in the return to education, decreasing the measure from 6.51 per cent (inferred) to 5.53 per cent, accounting for nearly all of the percentage point difference between returns for 'inferred' and 'actual' years of education. Comparatively, accounting for course non-completion alone decreases the return to education from 6.51 per cent to 6.47 per cent, a negligible 0.04 percentage point decrease.

Table 7. Disaggregation of course non-completion and multiple qualification effects

Variable	*Inferred years of education*	*Course non-completion (Actual)*	*Multiple qualifications (Actual)*
Inferred Years of Education	0.0651***		
	(53.93)		
Actual Years of Education		0.0647***	0.0553***
		(54.10)	(52.50)
Constant	2.039***	2.039***	2.179***
	(53.89)	(53.94)	(58.92)
N	126199	126199	126199

Notes: t-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

These figures for course non-completion are somewhat surprising. Multiple qualifications may have been expected to have a larger effect on the estimated returns to education due to a larger sample mean of 0.26 years compared to 0.15 years of course non-completion across the sample. While this is what we observe, the relative impact of accounting for multiple qualifications on the estimate of the returns to education is disproportionately large, and the effect of accounting for course non-completion disproportionately small.

As our results show reduced returns to education when actual years is used instead of inferred years, we anticipate that the extent of undercounting of years of education is positively correlated with inferred years, as shown in Panel (c) of Figure 1. This is confirmed by the data. Using the pooled data, the simple correlation between inferred years of education and our estimates of additional time spent in multiple- and non-completed qualifications is 0.253. However, this cannot explain the disproportionately large effect of accounting for years of multiple qualifications. Given the estimate of the returns to education is disproportionately sensitive to accounting for time in multiple qualifications compared to accounting for non-completion, we might anticipate that the former is more strongly and positively correlated with inferred education than years of non-completion. The reverse is in fact the case: the correlation between inferred years of education and additional years spent towards multiple qualifications is 0.225, but a much stronger 0.640 for course non-completion.

As demonstrated in Figure 2, the result will also be affected by the degree to which years spent gaining multiple qualifications or studying towards incomplete qualifications attract a wage premium. The disproportionate impact of accounting for multiple qualifications may indicate that years of education towards multiple qualifications at the same level attract a relatively high wage premium relative to years spent gaining the initial qualification. It is tempting to also impute that returns to incomplete and complete qualifications are closely aligned. However, these conjectures must be tempered by the fact that the effects of multiple qualifications could be estimated with greater precision, given that we have individual-specific measures of years spent in multiple qualifications through HILDA, and which are related to individual wage differentials observed in the data. In contrast, years of non-completion are applied as age-by-gender averages. The availability of individual-specific data on years spent in incomplete qualifications may have resulted in a larger impact on the estimated return to years of education.

The sensitivity to the inclusion of additional years of education on estimates for some of the other variables, as reported in Table 6, is also of interest. Allowing for multiple qualifications and course non-completion results in a lower age-earnings gradient, suggesting that age partly proxies for the accumulation of unobserved years of education in models following the conventional approach. This interpretation assumes those additional years of education have a positive association with hourly wages. Separately including years of incomplete qualifications and multiple qualifications reveals that it is mainly accounting for multiple qualifications that leads to the lower estimated coefficient for age, consistent with individuals accruing those multiple qualifications over time.

The penalty associated with being born overseas is also substantially reduced, and again this is driven entirely by the inclusion of time spent towards multiple qualifications. The mean of years spent in multiple qualifications is marginally higher for the overseas born, at 0.263, compared to 0.248 for Australian born workers. This may reflect the need for people born overseas to gain second qualifications in Australia due to limited- or non-recognition of qualifications accrued in their country of origin. Including those extra years of education would therefore be expected to increase the estimated penalty associated with being born overseas, not decrease it.

Equally, the correlation between inferred years of education and mismeasurement cannot explain why the estimated wage penalty associated with being born overseas becomes less pronounced when we account for time spent towards multiple qualifications. There is a weaker correlation between inferred education and time spent in multiple qualifications (0.165) for the overseas born, meaning accounting for that mismeasurement would result in a larger reduction in the estimated return to education for this group. With actual wages unchanged, this implies a higher estimated penalty associated with being born overseas, not a reduced penalty as the estimates imply. The explanation for these results may instead lie in the difference between Australian born and overseas born workers in terms of the relative pay-off to an initial versus a multiple qualification. If overseas born workers face a relatively low return to an initial qualification but relatively high return to multiple qualifications, then accounting for multiple qualifications will then explain some of the earnings penalty associated with being born overseas.

5.1 Effects by Gender and Age

To test for the possibility that the extent of mismeasurement in years of education varies between males and females, and between younger and older workers, wage equations were estimated separately for the sub-samples of men and women; and for persons aged 25-45 years and 46-65 years. Recall the estimates of additional years of education attributed to multiple qualifications are derived from HILDA for each individual, and additional years attributable to non-completion is differentiated by gender, age and highest qualification using ABS data. As shown in Table 8, for each group the difference in estimated returns to inferred and actual years of education is close to 1 percentage point per year, which equates to the returns to additional years of education being approximately 15 per cent lower once non-completion and multiple qualifications have been accounted for.

Table 8. Returns to Education Estimates by Gender and Age

Variable	*Male*	*Female*	*Age 25-45*	*Age 46-65*
Inferred Years of Education	0.0647***	0.0651***	0.0655***	0.0624***
	(34.63)	(39.93)	(46.55)	(31.62)
Actual Years of Education	0.0539***	0.0555***	0.0561***	0.0521***
	(33.31)	(39.36)	(45.30)	(30.24)
Difference	-0.0108	-0.0096	-0.0094	-0.0103
N	64302	61897	75803	50396

Notes: t-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.2 Sensitivity analyses

For reasons set out above, we consider the random effects specification preferable to estimation by fixed effects. Estimation by fixed effects gives a much lower overall estimate for the returns to inferred years of education of just 1.8 per cent. In line with the results above, the estimated returns to actual years of education is lower again, at 1.6 per cent, with that difference again accounted for by additional years spent accruing multiple qualifications as opposed to additional years in incomplete qualifications. In contrast to the random effects results, sensitivity of the estimates to the inclusion of actual years is observed in the fixed effects models only for males and younger workers.

To estimate the time individuals spent gaining multiple qualifications at a given level, we assumed a discount of 25 per cent from the time normally taken to complete a qualification to allow for recognition of prior learning, as explained in section 4.2. To test the sensitivity of the key findings to this assumption, we repeated the analysis using a 33 per cent discount, something we consider to be an upper bound for the average credits that students might be awarded. Compared to the estimated 6.51 per cent returns to a year of education using the inferred approach, this higher discount rate – or assumed lower time spent gaining multiple qualifications – produces an estimated 5.69 per cent wage premium per year of actual education, as opposed to our original estimate of 5.52 per cent. Ignoring years of non-completion, the estimated effect of accounting for years in multiple qualifications alone is to reduce the estimated returns to education from 6.51 per cent to 5.71 per cent (up from 5.53 per cent originally). Thus, even with this more conservative assumption, accounting for multiple qualifications still leads to a sizeable fall in the estimated returns to education, and still dominates the effect attributable to course non-completion.

Finally, we varied the assumption that individuals who fail to complete a course typically studied for one-third of the normal completion time before dropping out (see section 4.3). Even if we assume individuals remain in the course for two-thirds of the normal completion time before dropping out (i.e. twice as long as in our base case), the impact of years of course non-completion remains very modest. The overall estimate for the returns to actual years of education drops from 5.52 per cent to 5.49 per cent; while the estimate accounting for years of non-completion only drops from 6.47 per cent to 6.44 per cent. This is in line with the findings above that the estimated rates of return to education are relatively insensitive to accounting for years spent in incomplete qualifications.

7. Conclusion

Across the 2001-2019 HILDA panel, we find that accounting for the combined effect of course non-completion and multiple qualifications has a meaningful impact on the estimated returns to education in Australia. On average, the estimated increase in hourly wages associated with each additional year of education falls from 6.5 per cent to 5.5 per cent once accounting for course non-completion and multiple qualifications. If we accept the 5.5 per cent figure as a 'truer' estimate, this represents almost a full one percentage point (or 18 per cent) overestimation of the returns to education using the conventional approach. The extent of underestimation in years of education accrued, and associated over-estimation of the returns to education, seems broadly similar by gender and age.

Our exploration highlighted that the sensitivity of estimates of the returns to education to the inclusion of years of non-completion and multiple qualifications is actually quite nuanced: it does not lead to a simple reduction in the estimated rate of returns in proportion to the underestimation of time spent in education. First, the effect is dependent upon the within-sample correlation between mismeasurement and inferred years of education. If the extent of mismeasurement is distributed evenly across the sample, accounting for 'actual' years of education within the standard wage regression model will not alter the estimated returns to education, which is typically taken to be the average increase in wages associated with one additional year of education. Accounting for actual years could potentially lead to a higher estimate of the returns to education, if mismeasurement was negatively correlated with inferred education.

Second, the effects are dependent upon the relative wage premium associated with years spent in non-completed qualifications and in multiple qualifications, compared to the returns to years spent in completed and initial qualifications. Differences in these relativities may account for observed differences in earnings for groups within the labour market, such as those born overseas or from non-English speaking backgrounds.

In total, we estimate that, in any one year, the sample of workers in the HILDA survey have accrued around 2,700 combined years of education that are unaccounted for through course non-completion and multiple qualifications. While these 2,700 years are a legitimate part of the process of human capital accumulation, their associated costs have been omitted from most previous estimates of returns to education.

The key policy implication arising from these unaccounted-for years of education is that overestimating the value of post-school education can result in policy decisions that run the risk of significantly distorting markets for human capital in Australia, with the particular threat that the returns to some degree disciplines with historically low returns to education, such as humanities (Daly *et al.* 2015), may see returns further reduced, compounding the effect. Indeed, in 2021, the Commonwealth Government increased student contribution fees by up to 28 per cent for law and commerce degrees and up to 113 per cent for humanities degrees, whilst discounting fees for science, technology, engineering and mathematics (STEM) related disciplines by around 18 per cent to 42 per cent, depending on the selected course (Department of Education, Skills and Employment 2020), resulting in vulnerable degree disciplines now facing even lower returns to education.

To the best of our knowledge, this is the first paper to assess how accounting for years spent in multiple qualifications and course non-completion affects estimates from wage equations of the overall returns to education in Australia. We find that the return to an additional year of education is nearly one-fifth lower than standard estimates suggest. The analysis has also highlighted important differences between the Mincerean wage equation and IRR approaches. Under the IRR approach, including those additional years spent in education would unambiguously reduce the estimated returns to education, as it would account for higher foregone earnings and direct costs that are not incorporated into the wage equation approach. As rates of participation in post-school education in Australia continue to rise appreciably, policymakers must take caution when setting student contribution fees in order to avoid disproportionately punishing disciplines which already have lower returns to education. This is also likely to have equity implications, as groups targeted for increased higher education participation, such as students from low socioeconomic backgrounds, Indigenous students and from rural and remote areas, are also more likely to drop out and face lower returns to those investments. Hence, there is a need for ongoing research following both approaches.

7.1 Limitations and further research

Perhaps the key limitation to this study is the lack of individual-level data on time spent in incomplete courses. As a result, course non-completion statistics were applied through the use of population averages from ABS data, rather than at the individual level in the HILDA panel data. If years of non-completion could be applied at the individual level, as was possible for multiple qualifications, the estimated effect of course non-completion on the returns to education may have been significantly higher. This is particularly relevant given increases in course switching and dropouts within Australian education (Cherastidtham *et al.* 2018). To the best of our knowledge, no longitudinal datasets allow identification of time spent studying towards incomplete qualifications at the individual level. A possible exception is the Longitudinal Surveys of Australian Youth, but these track individuals only to age 25, providing a very limited window to observe wage effects.

A related priority for further research is for estimates of the actual wage premiums associated with years spent towards non-completed qualifications and with multiple qualifications. This has implications both for the overall returns to years of education, and the degree to which these represent 'wastage' that can potentially be eliminated through better course matching and higher student retention. The high proportion of persons with multiple qualifications at the one level seems at odds with signaling theory (Arrow 1973, Spence 1973), which would suggest that there would be no advantage to individuals undertaking a second qualification at the same level. Further, there may be significant differences in returns to incomplete and multiple qualifications that help explain differences in wages between sub-groups within the working population, particularly migrants.

There is an ongoing need for evaluation of the returns to education in Australia using both the wage equation and IRR approaches, differentiated by field of study, to guide education funding policy and the setting of course fees. We also propose a more specific focus on estimates of the return to post-school education, given the high proportion of youth who now complete Year 12, and that course non-completion and multiple qualifications relate primarily to years of post-school education. An interesting avenue for future research is examining whether years of education have differing returns for school, university or TAFE in Australia.

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Appendix A: Variable description and means

Variable	*Description/coding*	*Sample mean*
Log hourly wage (dependent variable)	See main text	3.29
'Inferred' years of education	See main text	13.03
'Actual' years of education	See main text	13.43
Years of education – multiple qualifications	See main text	0.26
Years of education – incomplete qualifications	See main text	0.15
Male	Dummy variable equal to 1 if the respondent is male, 0 if female.	0.51
Age (& age-squared)	The age of the respondent in years (and its square/100)	42.22 (18.98)
Marital status	3 dummy variables corresponding to three marital status categories: married (the omitted category), never married or no longer married	Married 0.58; Never married 0.14; No longer married 0.28
Work experience (and work experience squared)	The amount of time spent in paid work in years (and its square/100)	21.71 (5.93)
Disability status	Dummy variable equal to 1 if the respondent has a long-term health condition, disability or impairment; 0 otherwise	0.13
Language other than English spoken	Dummy variable equal to 1 if respondent speaks another language other than English at home; 0 otherwise	0.14
Employment status	3 dummy variables corresponding to employment status: permanent (the omitted category), fixed-term or casual.	Permanent 0.75; Fixed-term 0.10; Casual 0.15.
Union membership	Dummy variable equal to if 1 if respondent is a union member; 0 otherwise	0.25
Socio-economic decile of neighbourhood	Dummy variable equal to 1 if respondent is living in area in decile 6 to 10; 0 if living in area in decile 1-5.	0.55
Part-time work	Dummy variable equal to 1 if labour force status is equal to part-time; 0 if full-time	0.27
Overseas highest qualification	Dummy variable equal to 1 if respondent completed their highest qualification overseas; 0 if completed in Australia	0.28
Overseas born	Dummy variable equal to 1 if respondent was not born in Australia; 0 otherwise	0.22

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Immigration, skills and changing urban income inequality in New Zealand

Omoniyi B. Alimi[1] *School of Accounting, Finance and Economics (SAFE), University of Waikato*
David C. Maré[2] *Motu Economic and Public Policy Research*
Jacques Poot[3] *National Institute of Demographic and Economic Analysis (NIDEA) and SAFE, University of Waikato*

Abstract

Policies have been implemented in New Zealand since the early 1990s that encourage long-term immigration of skilled workers and greater temporary immigration of unskilled workers. This paper investigates the contribution of immigration to change in income inequality of New Zealand's urban population and compares that with the contribution of the changing skill composition of the population. We apply sub-group and Shapley-value-regression decompositions of inequality to calculate contributions of eight population groups, defined by skill level and migration status, to inequality. We use microdata from six consecutive population censuses between 1986 and 2013. We find with both methodologies that: (1) more than 90 per cent of income inequality in each census can be attributed to within-group inequality; (2) the growth in the share of the population that is highly skilled and the growth in the share of foreign born in the population both had inequality-increasing effects; (3) the skill effect exceeded the migration effect. The findings suggest that changes to the level and skill composition of future immigration – triggered by the anticipated 'reset' of New Zealand immigration policies when the border re-opens after the subsiding of the COVID-19 pandemic – will impact on future income inequality. Hence our decomposition approaches ought to be revisited after the 2023 census data become available to measure early effects of any new policies.

JEL Codes: D31, F22, I26, J61
Keywords: Immigration; Skills; Income inequality decomposition; Shapley-value; New Zealand

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Disclaimer: Access to the data used in this study was provided by Statistics New Zealand under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. All frequency counts using Census data were subject to base three rounding in accordance with Statistics New Zealand's release policy for census data. The views, opinions, findings and conclusions or recommendations expressed in this paper are strictly those of the authors and do not necessarily represent, and should not be reported as, those of the organisations at which the authors are employed.

[1] (Corresponding Author) School of Accounting, Finance and Economics (SAFE), University of Waikato, Private Bag 3105, Hamilton 3240, New Zealand Email: omoniyi.alimi@waikato.ac.nz
[2] Motu Economic and Public Policy Research, PO Box 24390, Wellington 6142, New Zealand Email: dave.mare@motu.org.nz
[3] National Institute of Demographic and Economic Analysis (NIDEA) and SAFE, University of Waikato, Private Bag 3105, Hamilton 3240, New Zealand Email: jacques.poot@waikato.ac.nz
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1. Introduction

Immigration has had a major impact on the population of Aotearoa New Zealand. Among OECD countries, New Zealand has the fifth highest proportion of immigrants in the population – after Luxembourg, Switzerland, Australia, and Israel (OECD 2019). More than 27 per cent of the population is foreign born (NZPC 2021a). Policies implemented since the early 1990s encouraged greater permanent and long-term immigration of skilled workers and greater temporary migration of unskilled workers (NZPC 2021b).

New Zealand has a broad range of working-age immigration programs that enable immigrants to work, invest, or operate a business in the country. These policies allow foreign citizens to enter on a range of visas including temporary work visas, residence visas, student visas, investor and entrepreneur visas (NZPC 2021c). Bedford *et al*. (2002) provide a historical review of immigration policies in New Zealand while studies like Spoonley (2006) and Simon-Kumar (2015) provide more contemporary reviews. In the last three decades, immigrants have become an increasingly important contributor to New Zealand's workforce and have played a significant role in supporting population growth. The rise in immigration has led to a growing concern about the implications of immigration for wellbeing and welfare of the New Zealand born, as well as of immigrants themselves (Fry and Wilson, 2017). Two main areas that are often highlighted are the impact of immigration on the labour market (NZPC 2021b) and the impact on housing and public infrastructure (NZPC 2021d).

At the same time, New Zealand has witnessed growing concern about rising urban income inequality – with income inequality in large cities having increased notably since the 1980s (e.g., Alimi *et al*. 2016). There is already considerable New Zealand evidence on the impact of immigration on economic variables like wages and employment (NZPC 2021b, Tse and Maani 2017, Maani and Chen 2012, Maré and Stillman 2009). There is also evidence on the impact of immigration on the housing market (Cochrane and Poot, 2021; Hyslop *et al*. 2019), with potential implications for wealth inequality (NZPC 2021d). However, the contribution of immigration to changes in the distribution of income has, surprisingly, not been previously investigated. This paper therefore aims to quantify the effect of immigration on income inequality. Because immigration contributes to change in the skill composition of the work force, we also consider the effect of the changing skill composition of the work force on income inequality. Furthermore, because most immigrants live in urban areas, we focus on income inequality in New Zealand urban areas.

International migration may affect the distribution of income in destination countries through three channels. The first is the *compositional channel*. On average, immigrants possess characteristics that differ from the locally born and may also be rewarded differently – as has been confirmed by previous New Zealand research (Poot and Stillman 2016, Poot and Roskruge 2013, Stillman and Maré 2009). Second, the distribution of income within immigrant groups themselves can also affect the overall distribution of income in destination areas (this is the *immigrant-specific income distribution channel*). The distribution of income within the migrant community is often wider than among locals (see Card 2009 for US evidence). Furthermore, there is evidence that the effect of recent immigration on the labour market is mostly felt by earlier migrants when recent and earlier migrants act as substitutes in the labour market (Longhi *et al.* 2005). The third and final channel through which immigrants affect the income distribution of locals is the general equilibrium effect. This is one of the most actively researched areas in the labour migration literature in recent decades (see e.g. Borjas 2003, 2005, Card 1990, 2005, 2009, D'Amuri *et al.* 2010, Foged and Peri 2016, Manacorda *et al.* 2012). Evidence on the wage effects of immigration appears inconclusive, with an abundance of positive, negative and insignificant results. However, the international evidence points towards the effects being quantitatively small in most cases (Longhi *et al.* 2010). This tends to be also the conclusion of New Zealand research by Maani and Chen (2012), Maré and Stillman (2009), MBIE (2018) and Tse and Maani (2017). Generally, immigration has had small, but mostly positive, effects on the wages and employment of New Zealand born workers over the last 25 years (NZPC 2021b).

Hence, given that general equilibrium effects have been shown to be minor, we focus in this study exclusively on the composition and immigrant-specific distribution channels. We examine contributions to inequality of groups defined by skill level and migration status by two decomposition approaches: the sub-group decomposition methodology (e.g., Mookherjee and Shorrocks 1982) and the Shapley-value-regression decomposition of inequality (e.g., Fields and Yoo 2000). Both decomposition methodologies allow the examination of the contribution of a particular income determinant, or of a particular group of the population, to the level and/or change in inequality. Our research fits within the body of work that has focused on examining the contributions of various demographic, social, and economic factors to the changes in the distribution of income using decomposition procedures. For a general survey of all drivers of income inequality in developed countries, see e.g. Nolan *et al.* (2019).

We find with both decomposition methodologies that: (1) more than 90 per cent of income inequality can be attributed to within-group inequality; (2) the growth in the share of the population that is highly skilled and the growth in the share of foreign born in the population had both inequality-increasing effects between 1986 and 2013; (3) the skill effect exceeded the migration effect. Within-group contributions to inequality levels and change have generally the same sign and magnitude with the regression approach as contributions calculated with the sub-group approach. However, the two methodologies yield often opposite signs for contributions of specific groups to between-group inequality levels and change.

The rest of the paper proceeds as follows. Section 2 discusses the data. We also introduce and compare the two decomposition methodologies in this section. Section 3 describes the results. Section 4 concludes.

2. Data and Methodology

2.1 Data

The data used are from the unit records of the usually resident New Zealand population enumerated in each Census of Population and Dwelling from 1986 to 2013.[1] New Zealand Census data capture *inter alia* information on current location of residence, place of residence at the last census date, country of birth and qualifications. We use this information to first classify the population by country of birth: New Zealand or abroad. We identify international migrants in each census as people who are usually resident of New Zealand but whose country of birth is outside of New Zealand (i.e., the foreign born). We split this group by their length of stay into newly-arrived migrants (who arrived during the last five years before the census) and earlier migrants. Given information on place of residence five years ago, we can also identify a group of 'Returning New Zealand born migrants' – they are New Zealand born people who were overseas five years before the census date and were resident in New Zealand at the time of the census. We consider this group separately because we expect that their effect on the distribution of income might be different from that of New Zealanders who lived in New Zealand continuously between two censuses.[2] As well as classifying the population by duration of residence in New Zealand, we also divide each group into High Skilled and Medium/Low Skilled based on qualifications. High Skilled are those who have at minimum a Bachelor's degree qualification while all other qualifications below Bachelor's degrees are in the Medium/Low Skilled category. Altogether, we divide the total population into eight categories: (1) High Skilled Non-Migrant New Zealand Born; (2) Medium/Low Skilled Non-Migrant New Zealand Born; (3) High Skilled Returning New Zealand Born; (4) Medium/Low Skilled Returning New Zealand Born; (5) High Skilled Earlier Migrants; (6) Medium/Low Skilled Earlier Migrants; (7) High Skilled Newly-Arrived Migrants; and (8) Medium/Low Skilled Newly-Arrived Migrants.

Given our focus on the contribution of migration and skills to inequality, an ideal measure of income would be gross labour earnings, but income reported in the census refers to annual income from all sources. Hence we restrict our analysis to the population aged 25-64 who are earning positive incomes, given that for this population group income consists mostly of labour earnings.

Instead of providing a dollar amount of actual income, the census respondent selects one of a set of income bands. All income bands were converted by means of

1 New Zealand Censuses were held in 1986, 1991, 1996, 2001, 2006, 2013 and 2018. The 2018 census did not collect data about location '5-years ago' – an important variable we use to identify migrants. Furthermore, the required data on income from the 2018 census are of lower quality than data from previous censuses. Consequently, we have not included 2018 in our study.

2 Selective emigration by the New Zealand born may influence the distribution of income in New Zealand too. However, there are no data on the incomes of emigrants before they left New Zealand. Some research suggests that the propensity to emigrate is similar across all skill groups, at least in trans-Tasman migration (e.g., Bushnell and Choy, 2001). Other research shows that the New Zealand born have the highest rate, among the OECD countries, of highly skilled population living abroad (NZPC 2021b, Dumont and Lemaître 2005).

the CPI to 2013 real incomes. The top and bottom income bands are open ended.[3] The bottom income band captures those who reported a negative income. They are not included in the analysis. An important issue with the open-ended upper band is the calculation of median income in this band (about one per cent – three per cent of the population in non-metropolitan areas and two per cent – seven per cent in metropolitan areas are within this band). Pareto distributions have been fitted to the upper tail of the area-specific distributions to estimate median income of the top income groups by means of the Stata RPME command developed by von Hippel *et al*. (2016). For all other income bands, the income of the individual is assumed to be the midpoint of the income band he or she belongs to. The availability of income data in bands poses no problem for the sub-group and regression decomposition methods used in this paper, although not accounting for within-band income variation clearly leads to underestimation of actual overall inequality.

2.2 Methodology

2.2.1 Population sub-group decomposition of the level and change in inequality

Level of inequality

Our measure of inequality is the Mean Log Deviation (MLD). The MLD is a member of the family of generalised entropy indices (see Bourguignon, 1979). All entropy measures have the advantage of being additively decomposable, while the more commonly used Gini coefficient is not. Because our focus is on how changes in the population shares by migration status and skill level have affected the distribution of income, the MLD is a natural choice and fit-for-purpose index. Additionally, it has also been shown that MLD is less sensitive to uncertainty about incomes at the upper end of the distribution (Cowell and Flachaire, 2007). For a population of N persons indexed by i = 1,2,…,N and each having personal income y_i,

$$MLD = \frac{1}{N}\sum_{i=1}^{N} \ln\left(\frac{\bar{y}}{y_i}\right) = \ln(\bar{y}) - \overline{\ln(y)} \qquad (1)$$

in which the bar above a variable refers to the arithmetic average. Eq. (1) shows that MLD is the difference between the natural logarithm of mean income and the mean of the natural logarithm of individual incomes. MLD is nonnegative due to Jensen's inequality.

The overall MLD level of inequality in any year t can then be written as the weighted sum of within-group inequality and between-group inequality:

$$MLD_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \ln\left(\frac{\bar{y}_t}{y_{it}}\right) = \underbrace{\sum_{m=1}^{M} \pi_{mt} MLD_{mt}}_{Within-group\ inequality} + \underbrace{\sum_{m=1}^{M} \pi_{mt} \ln\left(\frac{1}{r_{mt}}\right)}_{\substack{Between-group\ inequality \\ or \\ Mean-group\ contribution}} \qquad (2)$$

3 For example, the top band in the 2013 census data captures everybody earning \$150,000 and over.

where:

- π_{mt} is population share of group m, i.e. $\pi_{mt} = \frac{N_{mt}}{N_t}$; and N_{mt} is the population of all those in the group m at census t. Hence the total population $N_t = \sum_{m=1}^{M} N_{mt}$;
- r_{mt} is the relative income of group m, i.e. $r_{mt} = \bar{y}_{mt}/\bar{y}_t$, where $\bar{y}_{mt} = \frac{1}{N_{mt}} \sum_{j=1}^{N_{mt}} y_{jt}$ is average income of all those in group m in census t;
- $MLD_{mt} = \frac{1}{N_{mt}} \sum_{j=1}^{N_{mt}} \ln\left(\frac{\bar{y}_{mt}}{y_{jt}}\right)$ is the MLD measure of within-group inequality.

Change in inequality

We decompose the change in inequality, as measured by MLD, by means of the approximate change decomposition introduced by Mookherjee and Shorrocks (1982).[4] The change (Δ) in overall inequality for a population of N people (indexed by i) can be decomposed into the contributions from each of M groups (indexed by m) as follows:

$$\Delta MLD \approx \underbrace{\sum_{m=1}^{M} \overline{\pi_m} \Delta MLD_m}_{C1} + \underbrace{\sum_{m=1}^{M} \overline{MLD_m} \Delta \pi_m}_{C2} + \underbrace{\sum_{m=1}^{M} (\overline{r_m} - \overline{\ln r_m}) \Delta \pi_m}_{C3'} + \underbrace{\sum_{m=1}^{M} (\overline{\pi_m r_m} - \overline{\pi_m}) \Delta \ln \bar{y}_m}_{C4'} \quad (3)$$

This decomposition identifies four components of inequality change. First, the contribution of changing within-group inequality, holding shares constant ($C1$); second, the within-group contribution of changing shares ($C2$); third, the between-group contribution due to changing shares ($C3'$); and fourth, the contribution of changing relative incomes, holding shares constant ($C4'$).

The sum of $C2$ and $C3'$ quantifies the contribution of the changing population composition to the change in income inequality. The sum of $C1$ and $C4'$ represents the contribution of change in the group-specific income distributions to the change in income inequality.

4 The approximation was introduced to give the individual components clear economic interpretation. Mookherjee and Shorrocks (1982) note that this approximation is sufficient for computational purposes (p.897). For more details, see Alimi *et al*. (2020).

2.2.2 Shapley-value regression decomposition of the level and change in inequality

Level of inequality

The regression decomposition method is an extension of Shorrocks' (1982) work on decomposition of income by additive factor components. We start with the following income generating function (IGF):

$$y_t = \sum_{m=1}^{M} \beta_{mt} d_{mt} + \sum_{j=1}^{J} \gamma_{jt} z_{jt} + \varepsilon_t, \tag{4}$$

where y_t is a $N\times1$ vector of income of individuals i (i = 1,2,…,N) at time t. The d_{mt} are a set of m dummy variable vectors denoting membership of each of the M groups (M = 8 in our application; $d_{mt} = 1$ when an individual belongs to group m and 0 otherwise), and z_{jt} are vectors of j covariates that affect income. β_{mt} and z_{jt} are sets of IGF parameters, and ε_t is a vector of random variation in income that is not related to the included variables. By construction, the d_{mt} vectors are orthogonal but the z_{jt} can be correlated with each other and with the d_{mt} vectors.

Decomposing the contributions of the m groups to income inequality is straightforward in the case where there are no correlated covariates (J=0). In this case, Shorrocks (1982) shows that the contribution to earnings inequality accounted for by group m, also referred to as the relative factor inequality weight S_{mt}, can then be calculated as:

$$S_{mt} = \frac{\hat{\beta}_{mt} * Cov(d_{mt}, y_t)}{Var(y_t)} \tag{5}$$

where $\hat{\beta}_{mt}$ are the OLS coefficients in a regression of Eq. (4) with J=0. By construction, $\hat{\beta}_{mt}$ equals average income of the members of group m. S_{mt} >0 (< 0) for groups that have an average income that is greater (less) than the overall mean. S_{mt} can be interpreted as the group-mean contribution, or the between-group contribution, of group m to overall inequality at time t. Following Shorrocks (1982), we calculate the between-group contribution of a group m to income inequality at time t by $\theta_{mt} = S_{mt} * MLD_t$.

In addition to calculating the between-group contribution of each group, we also calculate within-group contributions to the level of inequality with the regression approach. Most studies using the regression approach ignore the group-specific within-group contributions and consider these part of 'residual' inequality. We allocate this residual to the individual groups and interpret the result as providing the conditional within-group contributions:

$$Cov(\hat{\varepsilon}_t, y_t) = \sum_{m=1}^{M} Cov(\hat{\varepsilon}_{mt} d_{mt}, y_t) \tag{6}$$

We calculate these conditional within-group contribution of each migrant group both without and with accounting for age, sex and employment status. Alimi *et al*. (2020) provide technical details on similarities and differences between the regression decomposition and sub-group decomposition approaches.

Change in inequality

The between-group contribution of group m to *change* in inequality between time t and t+1 is given by Eq. (7) below. Unlike the contribution of each factor to the level of inequality, S_{mt}, the contribution of each factor to change in inequality, δ_m, is here dependent on the choice of inequality measure (Fields and Yoo 2000).

$$\delta_m = \theta_{m,t+1} - \theta_{mt} = S_{m,t+1} * MLD_{t+1} - S_{m,t} * MLD_t \tag{7}$$

One of the advantages of the regression decomposition framework is the possibility of accounting for multiple explanatory variables (z_{jt}). In contrast, the sub-group decomposition approach quickly becomes unwieldy if we account for multiple explanatory factors. For example, accounting for sex and migration and skills status in our research together means there would be 16 groups (eight migration and skills status categories times two genders). However, the regression decomposition framework has limitations too (Wan 2002, 2004). Most notably, the standard Fields and Yoo (2000) approach with multiple explanatory variables relies on the assumption of uncorrelated explanatory variables (Israeli, 2007), in which case the between-group contribution of each variable to overall inequality is simply the increase in R^2 when that variable is added to the regression. When correlated covariates are included, the marginal contribution of a particular variable on the R^2 of the regression is not unique, since the increase in R^2 is dependent on the order in which factors are included in the regression.[5]

Subsequent studies have therefore adopted a Shapley-value regression decomposition approach.[6] This approach calculates the marginal effect of each explanatory variable in all possible orderings of these variables. The contribution of each explanatory variable to income inequality is then calculated as the average of its marginal effects in all possible orderings. With J explanatory variables, the total number of possible orderings is $J!$.

We use the Shapley-value regression decomposition approach to examine the contribution of each migrant and skills group (m) to the level of inequality when accounting for age, sex, and employment status. For our Shapley regressions, we treat the group dummy variables (d_{mt}) as a block and they are entered into the regressions together.

Of the other variables, age is included as an integer. There are three employment status dummies (part-time, unemployment, and not in the labour force;

5 The standard Fields and Yoo (2000) approach captures the contribution of each variable as if it were added last.

6 This approach has its origins in Shorrocks (1999), later published in Shorrocks (2013), and has been used in empirical studies such as those of Wan (2004) and Gunatilaka and Chotikapanich (2009).

with full-time employed as the omitted group). To ensure that we can account for the conditional contribution of each group, we run our regressions without an intercept because dummy variables are included for all migrant and skill groups.

3. Results

3.1 Trends and patterns in income inequality by migration status and skill level

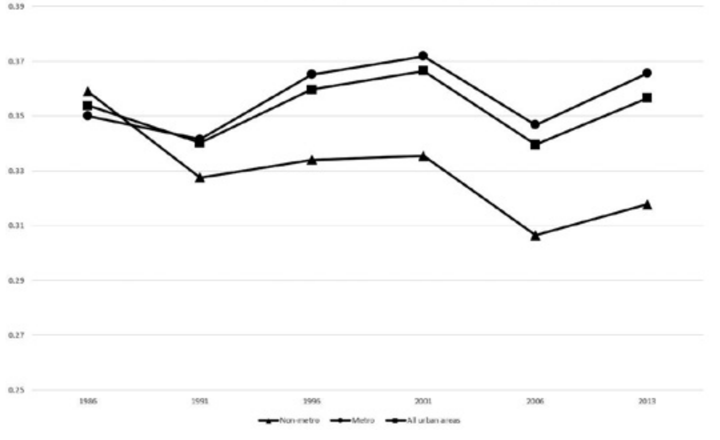
Real income of New Zealand's urban population aged between 25 and 64 in receipt of positive income increased by about half between 1986 and 2013, which implies real income growth of about 1.5 per cent per year. In 1986, average income of immigrants was about 3 per cent higher than of the New Zealand born, but by 2013 immigrants earned on average about 7 per cent less than the New Zealand born. One of the drivers of this shift has been huge growth in temporary migration, attracting relatively lower skilled workers. This reflects growth in low-paid temporary worker migration in the agriculture, caring and tourism sectors, leading to a downward trend in the relative mean incomes for immigrants in all main and secondary urban areas (NZPC 2021b, MBIE 2018, McLeod and Maré 2013).

Figure 1 shows MLD inequality by type of urban area for all censuses between 1986 and 2013 (for the population who are aged between 25 and 64 and residing in urban areas). For all urban areas combined, MLD income inequality dropped from 0.3538 in 1986 to 0.3402 in 1991. This was a period of substantial economic deregulation and reform in New Zealand that affected private and public sectors (e.g., Evans *et al.* 1996) and may have increased density at the lower end of the real wage distribution. Additionally, the 1986-1991 period heralded a change in New Zealand's immigration policy away from recruiting from traditional source countries (United Kingdom, Western Europe and Pacific Islands) to global recruitment, particularly of skilled workers.[7] A sharp reduction in social security payments and extensive liberalisation of labour contracting regulations in 1991 contributed to an increase in the MLD measure of inequality to 0.3596 in 1996 before peaking at 0.3664 in 2001. Subsequently, MLD inequality declined again sharply (to 0.3395 in 2006) before increasing to 0.3565 in 2013. The period between 2001 and 2006 was characterised by high economic growth and increasing labour force participation and hours worked. Overall, inequality of the urban population aged between 25 and 64 rose by only 0.0027 MLD points between 1986 and 2013, which is less than 1 per cent.

These macro fluctuations mask large differences between metropolitan and non-metropolitan areas. Inequality rose in metropolitan areas between 1986 and 2013 by 4 per cent while it fell in non-metropolitan areas by 11 per cent. In this paper we focus on the roles of immigration and skills at the national urban level and we do not consider the distinction between metropolitan and non-metropolitan income inequality trends here any further (but see e.g. Alimi *et al.* 2018 on that issue).

7 It should be noted that migration from and to Australia falls outside immigration policy. Under the so-called Trans-Tasman Travel Agreement (TTTA) Australians and New Zealand citizens have the right to live and work indefinitely in each other's country.

Figure 1. New Zealand income inequality from 1986 to 2013 by type of urban area



Notes: Inequality is measured by Mean Log Deviation (MLD) of reported gross income of individuals, obtained from census microdata. The population is restricted to residents of main and secondary urban areas who are aged 25 to 64 and in receipt of positive income. The metro areas are the six largest urban areas in terms of population (Auckland, Christchurch, Wellington, Hamilton, Tauranga and Dunedin).

Table 1 reports within-group income inequality, group relative income and the population share for each of the six censuses between 1986 and 2013. The share of High Skilled Earlier Migrants and High Skilled Newly Arrived Migrants in the population increased by 7.8 and 2.4 percentage points respectively between 1986 and 2013. Given strong population growth over these 27 years, it can be easily calculated that the corresponding increase in the size of these groups was even more dramatic: the High Skilled Earlier Migrants group in 2013 was about eight times as large as in 1986 and the High Skilled Newly Arrived Migrants group was about seven times as large. In contrast, the share of the Medium/Low Skilled Earlier Migrants in the population declined from 17.6 per cent to 17.0 per cent (this still equates to a 33 per cent increase in the size of this group). The share of Medium/Low Skilled Newly Arrived Migrants increased from 2.2 per cent to 3.3 per cent (equivalent to a roughly doubling of the number). The number of Medium and Low Skilled Returning New Zealand born Migrants in 2013 declined by about 24 per cent relative to the 1986 size of this group (with the population share declining from 2.5 per cent to 1.4 per cent). The number of High Skilled Returning New Zealand born increased by 219 per cent (a population share increase from 0.5 per cent to 1.1 per cent), reflecting an increasing level of cross-border mobility of New Zealand young professionals.

Table 1. Income inequality (Mean Log Deviation), relative mean income and population share by migration/skill group, 1986-2013

		HS Non-Migrant NZ-born	*M/LS Non-Migrant NZ-born*	*HS Returning NZ-born*	*M/LS Returning NZ-born*	*HS Earlier Migrants*	*M/LS Earlier Migrants*	*HS Newly Arrived Migrants*	*M/LS Newly Arrived Migrants*	*Total*
1986	MLD	0.3094	0.3466	0.3454	0.3353	0.3191	0.3075	0.4286	0.4164	0.3538
	Rel.inc.	1.70	0.94	1.54	0.96	1.66	0.95	1.56	0.91	1.00
	Pop. share	5.6%	69.5%	0.5%	2.5%	1.6%	17.6%	0.6%	2.2%	100.0%
1991	MLD	0.3127	0.3190	0.3543	0.3130	0.3223	0.3090	0.3843	0.3767	0.3402
	Rel.inc.	1.77	0.93	1.67	0.95	1.72	0.90	1.53	0.86	1.00
	Pop. share	6.4%	69.1%	0.5%	2.1%	1.9%	16.2%	1.0%	2.9%	100.0%
1996	MLD	0.3354	0.3195	0.3499	0.2997	0.3632	0.3333	0.6172	0.499	0.3596
	Rel.inc.	1.77	0.92	1.65	0.92	1.66	0.87	1.09	0.75	1.00
	Pop. share	7.7%	66.1%	0.6%	2.4%	2.5%	15.7%	1.8%	3.1%	100.0%
2001	MLD	0.3251	0.3215	0.3574	0.3308	0.3797	0.3544	0.5085	0.4798	0.3664
	Rel.inc.	1.66	0.91	1.59	0.92	1.51	0.84	1.14	0.72	1.00
	Pop. share	10.3%	62.9%	0.7%	1.7%	3.7%	14.9%	2.2%	3.6%	100.0%
2006	MLD	0.2997	0.2983	0.3261	0.3008	0.3509	0.338	0.4144	0.3926	0.3395
	Rel.inc.	1.51	0.91	1.50	0.95	1.33	0.81	1.06	0.75	1.00
	Pop. share	12.5%	55.7%	1.2%	2.0%	5.7%	14.9%	3.5%	4.6%	100.0%
2013	MLD	0.3248	0.3093	0.3701	0.3504	0.3465	0.3462	0.4393	0.4299	0.3565
	Rel.inc.	1.46	0.89	1.44	0.91	1.26	0.78	1.05	0.71	1.00
	Pop. share	15.3%	49.4%	1.1%	1.4%	9.4%	17.0%	3.0%	3.3%	100.0%
1986-2013 Population share change (%pts)		9.7%	-20.1%	0.7%	-1.1%	7.8%	-0.6%	2.4%	1.2%	0.0%
1986-2013 Population change (%)		277%	-2%	219%	-24%	694%	33%	641%	112%	38%
1986-2013 change in MLD points		0.0154	-0.0373	0.0247	0.0151	0.0274	0.0387	0.0107	0.0135	0.0027

Notes: Derived from census microdata on reported gross income of respondents aged 25 to 64 in main and secondary urban areas. HS NZ-born and M/LS NZ-born represent High Skilled and Medium/Low Skilled New Zealand born respectively; HS Ret. NZ-born and M/LS Ret. NZ-born represent High Skilled and Medium/Low Skilled Returning New Zealand born; HS Earlier and LS Earlier represent High Skilled and Medium/Low Skilled Earlier migrants; HS (High skilled) are defined as those with a Bachelor's degree or higher and M/LS (Medium/Low skilled) are those with other qualifications below a Bachelor's degree or no qualifications. Newly Arrived are those who arrived in the last inter-censal period. Earlier migrant are arrivals prior to the last inter-censal period. MLD is calculated as in Eq. (1). Rel.inc. refers to relative income, which is defined as the ratio of the average income of the population sub-group over the average income of the national urban population. Pop. share refers to the share of group in the urban population. The data refer to the population in all urban areas combined.

The relative changes are important. Evidence from the US has shown that the impact of immigration is most likely felt by earlier migrants who are close substitutes for recent arrivals in the labour market (see, e.g., LaLonde and Topel 1991; Cortés 2008). The growth in the number and share of migrants at various skill levels has implications for the distribution of income of migrant groups but also for the overall distribution of income.

Table 1 also presents the within-group inequality of each population group between 1986 and 2013. Over this quarter century, the income distribution has had a large increase in density at the upper tail of the distribution, leading to a sharp increase in average income. At the same time, group-average income declined relative to the overall mean for all eight groups considered due to higher income growth for high income groups – as can be seen in Table 1. We find that inequality is, in each year, highest among newly arrived immigrants, regardless of skill level. The much lower inequality among earlier migrants suggests a process of economic integration in terms of a narrowing of the income distribution by duration of stay.

At the level of disaggregation used in Table 1, inequality increased between 1986 and 2013 for all groups, except the Medium/Low Skilled New Zealand born. Note that this is the largest population sub-group, although its population share declined from 69.5 per cent to 49.4 per cent. The decline in income inequality within this group could have been driven by increases in the real minimum wage over this period (see e.g., Maloney and Pacheco, 2012).

3.2 Decomposition of the level of inequality – Results

3.2.1 Sub-group decomposition of the level of Inequality

Given the differences between immigrants and New Zealand born and the likely diversity between and within immigrant/skill groups, we decompose MLD inequality into 'within' and 'between' components, using Eq. (2), and examine the contribution of each group to overall inequality in each census year. The results are shown in Table 2.

Table 2. Sub-group decomposition of urban income inequality (MLD) from 1986 to 2013

	1986	*1991*	*1996*	*2001*	*2006*	*2013*
Between-group contributions						
HS Non-Migr. NZ-born	-0.0296	-0.0363	-0.0443	-0.0519	-0.0518	-0.0582
M/LS Non-Migr. NZ-born	0.0456	0.0518	0.0538	0.0611	0.0524	0.0570
HS Ret. NZ-born	-0.0022	-0.0024	-0.0031	-0.0031	-0.0049	-0.0042
M/LS Ret. NZ-born	0.0010	0.0011	0.0020	0.0014	0.0010	0.0014
HS Earlier Migrants	-0.0083	-0.0101	-0.0124	-0.0153	-0.0162	-0.0215
M/LS Earlier Migrants	0.0089	0.0162	0.0215	0.0259	0.0315	0.0413
HS Newly Arrived Migrants	-0.0025	-0.0041	-0.0016	-0.0029	-0.0020	-0.0015
M/LS Newly Arrived Migrant	0.0020	0.0044	0.0091	0.0121	0.0134	0.0115
Sum of Between	0.0149	0.0206	0.0250	0.0273	0.0234	0.0258
Proportion Between	4%	6%	7%	7%	7%	7%
Within-group contributions						
HS Non-Migr. NZ-born	0.0173	0.0199	0.0260	0.0334	0.0374	0.0497
M/LS Non-Migr. NZ-born	0.2410	0.2205	0.2113	0.2022	0.1661	0.1527
HS Ret. NZ-born	0.0017	0.0017	0.0022	0.0024	0.0039	0.0042
M/LS Ret. NZ-born	0.0083	0.0065	0.0073	0.0058	0.0060	0.0048
HS Earlier Migrants	0.0052	0.0060	0.0089	0.0140	0.0199	0.0327
M/LS Earlier Migrants	0.0540	0.0502	0.0523	0.0528	0.0503	0.0588
HS Newly Arrived Migrants	0.0024	0.0037	0.0109	0.0111	0.0143	0.0133
M/LS Newly Arrived Migrant	0.0090	0.0110	0.0157	0.0175	0.0181	0.0143
Sum of Within	0.3389	0.3195	0.3346	0.3392	0.3160	0.3305
Proportion Within	96%	94%	93%	93%	93%	93%
Total MLD inequality	0.3538	0.3401	0.3596	0.3665	0.3394	0.3563

Notes: Results are the between-group and within-group contributions to overall inequality (as measured by Mean Log Deviation) for the migration and skills status categories in all urban areas combined in each census from 1986 to 2013, using Eq. (2). For definitions of the groups, see the notes below Table 1.

Table 2 shows that between-group inequality accounted for only 4 per cent of MLD inequality in 1986. This share increases to 7 per cent by 1996 and remains constant thereafter until 2013. Between-migrant/skill group inequality calculated here is higher than the between-age group inequality reported by Alimi *et al*. (2018), indicating bigger differences in average income across migrant and skill groups than age groups.

Table 2 also clearly shows that the between-group contribution of high skilled workers to inequality is negative, irrespective of migration status. This perhaps counterintuitive result is due to the average income of groups of high skilled workers exceeding overall average income, thereby leading to a negative contribution to overall MLD (see Eq. (2)). The 1986-1996 increase in between-group inequality is due to the increasingly negative contributions of the high skilled being offset by even faster growing positive contributions of the low and medium skilled.

Decomposing the level of MLD into the sum of between-group and within-group contributions shows that most of the change in inequality is driven by what is happening within each group, with big differences between the time trends in the within-group contributions across sub groups. In Section 3.3, we employ change-decomposition procedures to provide a decomposition of overall inequality change between 1986 and 2013 and to understand the role of changes within each migrant/skill group.

3.2.2 Regression decomposition of the level of Inequality

We start with comparing the results of the regression approach to decomposing the variance in personal income (Eqs. (4) and (5)) with those of the sub-group decomposition of MLD (Eq. (2)). The results are presented in Table 3.

Table 3. Comparison of between- and within-group contributions to the level of urban income inequality (MLD) with the regression and sub-group decomposition approaches

	Regression decomposition of inequality level						*Sub-group decomposition of inequality level*					
	1986	*1991*	*1996*	*2001*	*2006*	*2013*	*1986*	*1991*	*1996*	*2001*	*2006*	*2013*
Between-group contribution												
HS Non Migr. NZ-born	12%	14%	13%	14%	14%	14%	-8%	-11%	-12%	-14%	-15%	-16%
M/LS Non Migr. NZ-born	-7%	-7%	-6%	-6%	-7%	-7%	13%	15%	15%	17%	15%	16%
HS Ret. NZ-born	1%	1%	1%	1%	1%	1%	-1%	-1%	-1%	-1%	-1%	-1%
M/LS Ret. NZ-born	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%
HS Earlier Migrants	3%	4%	3%	4%	4%	4%	-2%	-3%	-3%	-4%	-5%	-6%
M/LS Earlier Migrants	-1%	-2%	-2%	-2%	-3%	-4%	3%	5%	6%	7%	9%	12%
HS Newly Arrived Migrants	1%	1%	0%	0%	0%	0%	-1%	-1%	0%	-1%	-1%	0%
M/LS Newly Arrived Migrants	0%	-1%	-1%	-1%	-1%	-1%	1%	1%	3%	3%	4%	3%
Overall between-inequality	**7%**	**9%**	**8%**	**9%**	**8%**	**8%**	**4%**	**6%**	**7%**	**7%**	**7%**	**7%**
Within-group contributions												
HS Non Migr. NZ-born	12%	13%	18%	20%	21%	26%	5%	6%	7%	9%	11%	14%
M/LS Non Migr. NZ-born	58%	54%	49%	46%	42%	35%	68%	65%	59%	55%	49%	43%
HS Ret. NZ-born	1%	1%	1%	1%	2%	2%	0%	0%	1%	1%	1%	1%
M/LS Ret. NZ-born	2%	2%	2%	1%	2%	1%	2%	2%	2%	2%	2%	1%
HS Earlier Migrants	3%	4%	5%	7%	9%	13%	1%	2%	2%	4%	6%	9%
M/LS Earlier Migrants	13%	12%	11%	10%	10%	10%	15%	15%	15%	14%	15%	17%
HS Newly Arrived Migrants	1%	2%	3%	3%	4%	4%	1%	1%	3%	3%	4%	4%
M/LS Newly Arrived Migrants	2%	2%	3%	3%	3%	2%	3%	3%	4%	5%	5%	4%
Overall within-inequality	**93%**	**91%**	**92%**	**91%**	**92%**	**92%**	**96%**	**94%**	**93%**	**93%**	**93%**	**93%**

Notes: Results are the between- and within-group contributions in all main and secondary urban areas combined, as obtained with the regression and sub-group decomposition approaches. The sub-group decomposition contributions are the 'percentage of total inequality' equivalents of the contributions reported in Table 2. The regression approach contributions are calculated as described in Section 2.2.2. For definitions of the groups, see the notes below Table 1.

We find that the overall between-group contributions in the regression method contribute less than 10 per cent to the overall level of urban income inequality in New Zealand. Hence that is very similar to what we found above with the sub-group decomposition of the MLD. Both methods show also a notable increase in the share of overall between-group inequality from 1986 to 1991, followed by a roughly stationary share.

Although the overall between- and within-group inequality contributions (expressed in percentages) from both approaches are directly comparable, the signs of the individual between-group contributions from the sub-group approach are opposite to those obtained in the regression approach. The main reason is that the two approaches use different measures of inequality (MLD versus Variance). With the regression approach, groups with higher mean income than the overall mean will have a positive by-group contribution (because the covariance in Eq. (5) is then positive) while with the MLD, these groups have a negative between-group contribution (as noted earlier).

Table 3 shows that the within-group contributions of each group are very similar across the two methods. The population shares play an important role here. The Medium/Low Skilled Non-Migrant New Zealand born group makes the largest within-group contribution, but also represents the largest group share of the population (see Table 1). The group shares act explicitly as weights in the formula for sub-group decomposition (see Eq.(2)) and do so implicitly in the calculation of the covariances in Eq. (6).

3.3 Decomposition of the change in inequality – Results

3.3.1 Decomposition of inequality change by sub-groups

Table 4 presents the group contributions to the change in MLD of urban income inequality between 1986 and 2013. Recall from Eq. (3) in Section 2.2.1 that the calculated components of change $C3'$ and $C4'$ are approximations. The calculated total change is therefore not exactly equal to the total 1986-2013 change in the MLD. However, the approximation is quite close relative to the magnitude of the individual contributions. The sign of the sum of $C1$ to $C4'$ determines whether a group makes an inequality-increasing or inequality-decreasing contribution to the 1986-2013 (slight) growth in inequality.

Table 4. Contributions to change in the Mean Log Deviation (MLD) index of inequality between 1986 and 2013 when using the sub-group decomposition approach

Group	*Components of change*				*Total change (approx.)*	*Composition contribution C2+C3′*	*Group-specific distribution contribution C1+C4′*	*Contribution to within-group inequality C1+C2*	*Contribution to between-group inequality C3′+C4′*
	C1	*C2*	*C3′*	*C4′*					
HS Non Migr. NZ-born	0.0016	0.0308	0.1094	0.0136	0.1554	0.1402	0.0152	0.0324	0.1230
M/LS Non Migr. NZ-born	-0.0222	-0.0660	-0.2022	-0.0170	-0.3074	-0.2682	-0.0392	-0.0882	-0.2192
HS Ret. NZ-born	0.0002	0.0023	0.0071	0.0013	0.0109	0.0095	0.0015	0.0025	0.0084
M/LS Ret. NZ-born	0.0003	-0.0038	-0.0110	-0.0004	-0.0148	-0.0148	-0.0001	-0.0035	-0.0114
HS Earlier Migrants	0.0015	0.0259	0.0851	0.0020	0.1146	0.1111	0.0035	0.0275	0.0871
M/LS Earlier Migrants	0.0067	-0.0018	-0.0057	-0.0046	-0.0055	-0.0076	0.0021	0.0049	-0.0104
HS Newly Arrived Migrants	0.0002	0.0107	0.0260	0.0000	0.0369	0.0367	0.0002	0.0109	0.0260
M/LS Newly Arrived Migrants	0.0004	0.0049	0.0120	-0.0008	0.0165	0.0169	-0.0005	0.0053	0.0112
Sum	**-0.0113**	**0.0031**	**0.0207**	**-0.0060**	**0.0066**	**0.0238**	**-0.0173**	**-0.0082**	**0.0148**

Notes: Results are the contributions to change in overall inequality (as measured by the MLD) between 1986 and 2013 in all main and secondary urban areas combined. C1 is the aggregate change in within- group inequality for given group-shares; C2 is the aggregate change in within-group inequality due to changing group shares; C3′ is aggregate change in between-group inequality due to changing group shares; C4′ is aggregate growth in group mean income for given group shares. See Eq. (3). For definitions of the groups, see the notes below Table 1.

One of the advantages of the Mookherjee and Shorrocks (1982) approach is that we can split the total change into the overall contribution of each group to within-group contributions to change ($C1$+$C2$) and between-group contributions ($C3'$+$C4'$), or alternatively into a compositional change contribution ($C2$+$C3'$) and a group-specific distribution change contribution ($C1$+$C4'$).

Focusing on the role of immigrant groups (both foreign-born and returning New Zealand born), our results show that high skilled (High Skilled Returning New Zealand born, High Skilled Earlier migrants and High Skilled Newly Arrived migrants) display inequality-increasing between- and within-group contributions. This is because for these groups, their relative group mean was above the overall mean in all periods, and between 1986 and 2013 within-group inequality increased, population share increased, and mean income increased. Of all immigrant groups, the positive contribution to growing inequality among high skilled workers is the least for the Returning New Zealand born. If we combine all immigrant groups regardless of skill (i.e., simply exclude the non-migrant New Zealand born), the 1986-2013 increase in migration has been inequality-increasing in terms of both composition and group-specific distribution contributions or, alternatively, in terms of both within-group inequality and between-group inequality.

Focusing on the skill distribution, we find that changes in the skill distribution of the workforce in New Zealand are very important for changes in the distribution of income, regardless of migration status. The total contribution to inequality from all high skilled groups i.e., High Skilled Non-Migrant New Zealand born, High Skilled Returning New Zealand born, High Skilled Earlier migrants and High Skilled Newly Arrived migrants was inequality-increasing while Medium/Low Skilled groups made inequality-reducing total contributions (except for the Medium/Low Skilled Newly Arrived).

The inequality-increasing contributions of high skilled groups occurred because relative mean income of these groups was high (greater than 1), and within-group inequality, population share, and mean incomes increased. Thus, groups at the top of the income distribution experienced greater within-group inequality and an increase in relative average income. This widens the income distribution at the top. For medium/low skilled groups, even though group-mean income increased, their relative income was low (relative mean less than 1) and their population share also fell. This led to inequality-reducing between-group contributions for these groups, except for Medium/Low Skilled Newly Arrived. The Medium/Low Skilled Newly Arrived group is different because it is the only low skilled group to experience an increase in population share; thus, their inequality-increasing contribution was driven by the composition contribution ($C2$+$C3'$).

3.2.2 Decomposition of inequality change by the regression method

Given that one of the advantages of the regression approach is the ease of accounting for multiple factors, we also report the contribution of each migration status group to inequality levels and change when we account for age, sex and employment status. We compare the results from this extended decomposition with the basic one (with migration/skill status as the only covariate of income). First we show the estimated extended income generating functions (Eq. (4)) in 1986 and 2013 in Table 5.

Table 5. Estimated income generating functions, 1986 and 2013

Variables	*1986*	*2013*
Age	216.68	511.80
	(1.92)	(3.04)
HS Non Migr. NZ-born	47687.36	64931.59
	(89.38)	(87.41)
M/LS Non Migr. NZ-born	25931.46	35174.55
	(26.94)	(50.65)
HS Ret. NZ-born	43717.12	67481.47
	(294.15)	(307.47)
M/LS Ret. NZ-born	27020.32	38806.09
	(132.64)	(280.39)
HS Earlier Migrant	46202.12	53467.48
	(162.59)	(109.46)
M/LS Earlier Migrant	24218.14	29869.02
	(51.52)	(81.81)
HS New Migrant	43998.54	47201.35
	(276.48)	(191.44)
M/LS New Migrant	23921.83	28818.69
	(141.06)	(181.38)
Fulltime employed	0	0
	[0]	[0]
Part-time employed	-4560.03	-11108.72
	(53.01)	(72.54)
Unemployed	-11502.97	-17635.42
	(118.67)	(162.33)
Not in the Labour Force	-10726.83	-16174.88
	(37.05)	(71.76)
Male	0	0
	[0]	[0]
Female	-5256.64	-5045.79
	(16.01)	(22.39)
Constant	0	0
Observations	1,029,201	1,415,343
R-squared	0.40	0.27

Notes: The coefficients are obtained by regression of the level of real income on migration status, age, sex and employment status. Standard errors in parentheses. The data are for all main and secondary urban areas combined. Age is measured as a deviation from average age; employment status and sex are defined as deviation contrasts, so that the coefficients on migrant/skill groups are evaluated at overall means of the other covariates. For definitions of the groups, see the notes below Table 1. Fulltime employed and males are reference groups. All coefficients are statistically significant at the 0.1 per cent level.

The covariates are defined in the two regressions as deviation contrasts, so that the coefficients represent differences relative to overall mean income. Categorical covariates such as employment status and sex are defined as mean-deviation contrasts and age is measured as a deviation from its mean. Using deviation contrasts for the categorical variables ensures that the conditional-between mean contributions reported are not sensitive to the choice of the excluded group (in our case, full-time employed and men) for the categorical variables.

It should be noted that the dependent variable in these regressions is the dollar value of real income and not the natural logarithm of real income. We note that the latter is commonly used in earnings regressions but the reason for using the level of income here is that the level of income is also used in the sub-group approach which we compare with the regression approach.

The income determinants in Table 5 all have the expected signs and levels. Using contrasts for the covariates means that coefficients on migrant groups are evaluated at overall means of the other covariates. The highest incomes are found among the high skilled non-migrant New Zealand born in 1986, but by 2013 their average income is exceeded by that of the high skilled returning New Zealand born, consistent with the analysis of survey data by Poot and Roskruge (2013). Income increases with age. Females have a considerably lower average income. With respect to employment status, the average income of the unemployed is the lowest. The variation in income that can be attributed to factors other than those taken into account increased notably between 1986 and 2013, with R-squared declining from 0.40 to 0.27.

Table 6 compares the regression-based decomposition with and without accounting for covariates in 1986 and in 2013. The left panel of Table 6 (basic regression) reports the results when only migrant/skill groups are considered as explanatory variables. In the right panel (extended regression), we report the between and within-group contributions when also accounting for age, sex and employment status. We treat all migration status groups as a block (as if they are one single explanatory variable) when calculating Shapley-value marginal effects. These are the average of the marginal contributions of each factor from all possible orderings. However, the within-group contributions do not depend on the order in which they are included and are calculated using the Fields and Yoo (2000) approach.

Table 6. Between and within group contributions to urban income inequality levels and change with the regression approach, with and without accounting for covariates

	Basic regression			*Extended regression*		
	1986	*2013*	*Contribution to change in MLD points* (δ_k)	*1986*	*2013*	*Contribution to change in MLD points* (δ_k)
	Between-group contribution			**Conditional between-group contribution**		
HS Non-Migr. NZ-born	11.7%	14.0%	0.0086	10.3%	12.8%	0.0094
M/LS Non-Migr. NZ-born	-7.3%	-6.5%	0.0027	-6.4%	-5.6%	0.0025
HS Ret. NZ-born	0.7%	1.0%	0.0009	0.6%	0.9%	0.0010
M/LS Ret. NZ-born	-0.2%	-0.2%	0.0000	-0.1%	-0.1%	0.0000
HS Earlier Migrants	3.2%	4.1%	0.0034	2.8%	3.7%	0.0032
M/LS Earlier Migrants	-1.5%	-3.9%	-0.0087	-1.2%	-3.3%	-0.0074
HS Newly Arrived Migrants	0.9%	0.2%	-0.0023	0.8%	0.2%	-0.0020
M/LS Newly Arrived Migrants	-0.3%	-0.9%	-0.0022	-0.3%	-0.8%	-0.0020
Overall between	**7.3%**	**7.9%**	**0.0024**	**6.4%**	**7.7%**	**0.0048**
	Within-group contribution			**Conditional within-group contribution**		
HS Non-Migr. NZ-born	12.2%	25.8%	0.0485	9.9%	21.5%	0.0416
M/LS Non-Migr. NZ-born	57.6%	34.9%	-0.0795	35.2%	25.9%	-0.0324
HS Ret. NZ-born	0.9%	2.0%	0.0037	0.7%	1.6%	0.0033
M/LS Ret. NZ-born	1.8%	1.1%	-0.0024	1.2%	0.9%	-0.0009
HS Earlier Migrants	3.5%	12.7%	0.0331	2.8%	10.6%	0.0280
M/LS Earlier Migrants	13.3%	10.1%	-0.0111	8.2%	7.5%	-0.0021
HS Newly Arrived Migrants	1.4%	3.6%	0.0080	1.1%	2.9%	0.0066
M/LS Newly Arrived Migrants	2.0%	2.0%	0.0001	1.4%	1.6%	0.0007
Overall within	**92.7%**	**92.1%**	**0.0003**	**60.4%**	**72.5%**	**0.0448**
Total	**100.0%**	**100.0%**	**0.0027**	**66.8%**	**80.2%**	**0.0496**
Covariates effect	**0.0%**	**0.0%**	**0.0000**	**33.2%**	**19.8%**	**-0.0469**
MLD levels and change	0.3538	0.3565	0.0027	0.3538	0.3565	0.0027

Notes: Results are the between- and within-group contribution of migrant/skill groups to inequality with and without accounting for age, sex and employment status in all main and secondary urban areas combined. The contributions to change in MLD between 1986 and 2013 are calculated using Eq. (6). For definitions of the groups, see the notes below Table 1.

In the basic regression, the sum of within and between-group contributions add up to total inequality. However, because in the adjusted regressions some of the overall inequality is accounted for by between-age/between-sex/between-employment status contributions, the conditional-migration/skill status group contributions do not add up to overall inequality. Hence the proportion of inequality not explained by the conditional within-group and conditional between-group contributions respectively reflects the contribution of between-group differences in other observable characteristics included in the regression.

Table 6 shows that the between-group contributions do not differ much between the basic and the extended regression. The high skilled groups contribute positively to overall between-group inequality and the medium-low skilled groups negatively. Taken together, the migrant groups (including returning New Zealanders) contribute positively to overall between-group inequality, but there is evidence that the joint contribution of the two non-migrant New Zealand born groups to between-group inequality is also positive and in fact much larger.

When we consider 1986-2013 change in inequality with the regression method (using Eq. (7)), the contributions of specific groups are again similar in magnitude and sign, both in the basic and in the extended regression. However, we see that the role of within-group inequality of age, sex and employment status groups has been declining (from 33.2 per cent in 1986 to 19.8 per cent in 2013), leading to a large negative contribution (-0.0469) of covariates to change in the MLD that mostly offsets the positive aggregate contribution of the migrant/skill groups. The overall within-migration status group contribution in the extended regression is 0.0448, which is much larger than the corresponding overall contribution in the basic regression (0.0003), and suggesting a total change of 0.0496. Again, the contribution to change from age, sex and employment status is $0.027 - 0.0496 = -0.0469$

As shown in Table 6, the between and within-group percentage contributions of migration/skill status to the level of inequality are lower in the extended regression than in the basic regression. The results imply that migration/skill groups are closer together in terms of average incomes once differences between these groups in terms of age, sex and employment status are taken into account. Even more importantly, a considerable proportion of within-group inequality among migrant/skill groups is, as expected, due to within-group inequality that can be attributed to age, sex and employment status.

Table 7 summarises the by-group decomposition of 1986-2013 inequality change from the sub-group and regression decomposition approaches. The calculations of the decomposition of inequality change by subgroup have been reproduced from Table 4, while those for the basic and extended regression decompositions have been copied from Table 6. Recall that the sub-group decomposition of change calculated with Eq. (3) is an approximate decomposition and therefore does not equal the exact change in inequality. For the regression decompositions, the extended regressions show the conditional-between and conditional-within migrant contributions of each migrant groups *after* accounting for age, sex and employment status in the regression. Here the sum of the conditional group contributions to 1986-2013 inequality change greatly exceeds the total change in inequality. That is because, as noted above, changes in the population's composition in terms of age, employment status and gender had a downward effect on 1986-2013 inequality change. Ignoring this effect in the basic regression, the sum of the group contributions to change does equal the actual MLD change in inequality in the decomposition with the basic regression.

Table 7. Comparison of the group contributions to change in urban income inequality between 1986 and 2013 with the sub-group decomposition and regression decomposition approaches

	Sub-group decomposition of inequality change (approximation)			*Basic regression decomposition of inequality change*			*Extended regression decomposition of inequality change*		
	Contribution to between-group change	*Contribution to within-group change*	*Contribution to total change (approx.)*	*Contribution to between-group change*	*Contribution to within-group change*	*Contribution to total change (approx.)*	*Contribution to between-group change*	*Contribution to within-group change*	*Contribution to total change (approx.)*
HS NZ born	0.1230	0.0324	0.1554	0.0086	0.0485	0.0571	0.0094	0.0416	0.0510
M/LS NZ born	-0.2192	-0.0882	-0.3074	0.0027	-0.0795	-0.0768	0.0025	-0.0324	-0.0299
HS Ret. NZ	0.0084	0.0025	0.0109	0.0009	0.0037	0.0046	0.0010	0.0033	0.0043
M/LS Ret. NZ	-0.0114	-0.0035	-0.0148	0.0000	-0.0024	-0.0024	0.0000	-0.0009	-0.0009
HS Earlier Migrant	0.0871	0.0275	0.1146	0.0034	0.0331	0.0365	0.0032	0.0280	0.0312
M/LS Earlier Migrant	-0.0104	0.0049	-0.0055	-0.0087	-0.0111	-0.0198	-0.0074	-0.0021	-0.0095
HS Newly Arrived Migrant	0.0260	0.0109	0.0369	-0.0023	0.0080	0.0057	-0.0020	0.0066	0.0046
M/LS Newly Arrived Migrant	0.0112	0.0053	0.0165	-0.0022	0.0001	-0.0021	-0.0020	0.0007	-0.0013
Total of all migrant/skill status group contributions	**0.0148**	**-0.0082**	**0.0066**	**0.0024**	**0.0003**	**0.0027**	**0.0048**	**0.0448**	**0.0496**
Actual 1986-2013 change in MLD			0.0027			0.0027			0.0027
All High Skilled (HS)	0.2445	0.0733	0.3178	0.0106	0.0933	0.1039	0.0116	0.0795	0.0911
All Medium/Low Skilled (M/LS)	-0.2298	-0.0815	-0.3112	-0.0082	-0.0929	-0.1011	-0.0069	-0.0347	-0.0416
All non-migrants	-0.0962	-0.0558	-0.1520	0.0113	-0.0310	-0.0197	0.0119	0.0092	0.0211
All migrants	0.1109	0.0476	0.1586	-0.0089	0.0314	0.0224	-0.0072	0.0356	0.0285

Notes: The data are obtained from all main and secondary urban areas combined. In the basic regression, the sum of within and between-migrant group contributions add up to total inequality. In the extended regression, we show the conditional-between and conditional-within migrant contributions of each migrant groups after adjusting for age, sex and employment status. Because some of the overall inequality is accounted for by the between age, sex and employment status group contributions (which has made a negative contribution to overall inequality change), the sum of the conditional-migrant group contributions to inequality change will not add up to overall inequality change. For definitions of the groups, see the notes below Table 1.

In general we find that high skilled workers have had an upward effect on the 1986-2013 increase in income inequality, irrespective of the decomposition method used. Additionally, both the between-group and within-group contributions of high skilled workers have been inequality increasing. Conversely, the total contribution of medium and low skilled workers to 1986-2013 inequality growth has been negative, irrespective of the decomposition method used (with Medium and Low Skilled Newly Arrived migrants the only exception). When considering between-group and within-group contributions to change separately, the signs for Medium and Low Skilled workers vary across decomposition methods and migration status groups.

When we combine all high skill groups in Table 7, we get a positive contribution to change of 0.3178 with the sub-group decomposition, 0.1039 with the basic regression and 0.0911 with the extended regression. Similarly adding all migrant groups (including the returning New Zealand born), we get a positive contribution to change of 0.1586 with the sub-group decomposition, 0.0224 with the basic regression and 0.0285 with the extended regression. We conclude that migration and upskilling of the labour force have both contributed to an increase in inequality in New Zealand. However, it is clear that the skill effect has been larger than the migration effect irrespective of the method used.

4. Conclusion

Using New Zealand data, we focus in this paper on the contribution of changes in population composition to changes in the distribution of personal income. Using two distinct decomposition methodologies, we contribute to the literature by examining two channels through which a group may affect the distribution of income in New Zealand, namely (i) the group size and group-relative mean income effect; and (ii) the within-group income distribution effect. We provide evidence on the role of migration and skills on the level and change in the distribution of income between 1986 and 2013 – a period of strongly growing immigration of both high skill and low skill workers, together with a general upskilling of the labour force. We find that differences across groups (between-group inequality) account for less than 10 per cent of overall inequality. Most of the observed level of inequality is due to within-group inequality.

In terms of the 1986-2013 change in inequality we find that changes in the skill distribution of the workforce in New Zealand are very important for changes in the distribution of income. The total contribution to inequality from all high skilled groups i.e., high skilled New Zealand born, high skilled returning New Zealand born, high skilled earlier migrants and high skilled newly arrived migrants was inequality increasing while changes in income of medium/low skilled groups were broadly inequality reducing.

The approach provided here could be usefully replicated in countries such as Australia and Canada, which operate skills-oriented migration policies that are similar to those in New Zealand. Additionally, the decomposition approaches may be fruitfully investigated for countries of the European Union that have experienced large-scale immigration in recent times and have high-quality disaggregated data on individual incomes.

Our findings regarding the importance of within-group inequality change have implications for ongoing policy debates about growing income inequality, equity and wellbeing in New Zealand. Since we find that changes within groups make large contributions to income inequality trends, the focus of policy should be directed at programmes that not only provide safety nets for those at the bottom end of the distribution but also address negative externalities and downward effects on wellbeing of growing inequality within groups with similar observable characteristics (e.g. Oishi *et al*. 2011).

Our findings have also implications for migration policy in New Zealand especially since COVID-19 has virtually suspended almost all forms of working age migration to New Zealand. The onset of the COVID-19 pandemic led to closure of the New Zealand border. The provisional net migration gain of only 800 people in the year ended September 2021 is consequently a huge contrast compared with the record net migration gain of 92,000 in the March 2020 year and the average net gain of 56,000 over the previous seven September years (Statistics New Zealand, 2021). While net migration will undoubtedly increase again once the border reopens, the pandemic has triggered a review of immigration policies (NZPC, 2021e).

The findings suggest that any changes to the level and skill composition of future immigration – triggered by the anticipated 'reset' of New Zealand immigration policies when the border re-opens after the subsiding of the COVID-19 pandemic – will impact on future income inequality. Hence our decomposition approaches ought to be revisited after the 2023 census data become available to measure early effects of the new policies.

However, it is important to note that our study does not provide a comprehensive examination of the role immigrants play in the New Zealand society. We have just examined the compositional and within-group migrant specific distribution effects. Any comprehensive evaluation of immigration needs to include other wider benefits and costs of immigration including the fiscal, social and cultural capital contributions as well as any macroeconomic impacts from immigration.

Immigration has historically tended to be used primarily as a tool to address skill shortages of both high skilled and low skilled workers (NZPC, 2021e). This, and a wide within-group distribution of income, has made the contributions of immigrant groups to be inequality-increasing. Of course, other high skill groups, either expatriate New Zealanders (Returning New Zealand born) or high skilled New Zealand born have also been shown to make inequality increasing contributions to the changes in the inequality trends, which highlights the role that within-skill group changes play in the changes in the distribution of income. Thus policies to address growing inequality in New Zealand should focus on avenues of support to improve the re-distribution of post-tax income within-groups (for example focusing on monopsony, gender gaps, discrimination, pay exploitation etc.), as well as providing safety nets for those at the bottom end of the distribution.

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