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From the Managing Editor

Welcome to the final issue of volume 21 of the *Australian Journal of Economics* for 2018. Hopefully, the 2019 volume will be delivered in a more timely manner and the editorial team are working on improving throughput from submission to publication.

This issue contains articles on several different aspects of labour market analysis. The paper by Bilal Rafi and Tala Talgaswatta demonstrates an innovative use of unpublished administrative data from the Department of Immigration and Border Protection on 457 migrant sponsoring firms linked to financial information on these firms from the Business Longitudinal Analysis Data Environment (BLADE). Danielle Venn makes an important contribution to an important policy issue – closing the gap in employment outcomes between indigenous and non-indigenous youth. James Foster and Rochelle Guttmann address another important policy issue – the slowing in the rate of growth in wages, exploring the possibility that increased job insecurity may be a contributing factor. The final paper by Tutan Ahmed suggests a novel method of carrying out labour market analysis when much of the relevant information is not available. This method is applied to predict regional skill requirements in India.

The AJLE requires considerable commitment by our editorial team, ably assisted by Kumeshini Haripersad. My thanks go to them and all those who refereed papers for the journal.

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The relative performance and characteristics of Australian firms that used the 457 temporary skilled visa program

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Abstract

The now concluded sub-class 457 temporary skilled migrant visa program was used to provide Australian businesses with a means to address short-term skill shortages. Due to micro-data limitations there has been a lack of empirical research on the program. This paper circumvents this limitation by linking unpublished data from the Department of Home Affairs, which was previously the Department of Immigration and Border Protection (DIBP) on 457 migrant sponsoring firms to financial information on these sponsoring firms from the Business Longitudinal Analysis Data Environment (BLADE). This allows for a more detailed characterisation of these firms and the identification of any performance differentials between sponsoring and non-sponsoring firms. The results reveal that relative to similar non-sponsoring firms, sponsors performed better, although it is unlikely that this performance differential was exclusively due to temporary skilled migrants.

JEL Codes: J44, J61, L25

Keywords: Temporary skilled migrants, firm performance, BLADE

Disclaimer: The views expressed in this paper are those of the authors and do not necessarily reflect those of the Australian Government or the Department of Industry, Innovation and Science. The authors would like to acknowledge the helpful comments and feedback provided by Christopher Short from the Department of Immigration and Border Protection, Abrie Swanepoel from the Department of Industry, Innovation and Science, and participants from the Asian and Australasian Society of Labour Economics (AASLE) conference 2017.

Australia has for a number of years utilised a temporary skilled migrant visa program to provide Australian businesses with access to labour with specialised skillsets that were deemed to be in short supply. These temporary migrants were sponsored by Australian employers via a sub-class 457 visa and were entitled to work and stay in Australia for up to four years. The 457 visa program was introduced in 1996 and was in effect for over 20 years. In March 2018 the federal government announced abolishment of the 457 visa program to be replaced by the new Temporary Skill Shortage (TSS) visa scheme.

The conclusion of the 457 program provided an opportunity to retrospectively analyse the program to see how firms that sponsored the temporary skilled migrants fared. An area where there is sparse empirical research. This lack of research is primarily due to a lack of publically available data. Existing data sources such as the Census of Population and Housing, the Continuous Survey of Australian Migrants (CSAM) and the Household Income and Labour Dynamics Australia (HILDA) survey do not adequately capture information on 457 migrants and specifically, the Australian businesses that sponsor and employ them.

This research paper draws on unpublished administrative data from the Department of Home Affairs – which was referred to as the Depart of Immigration and Border Protection (DIBP) at the time of analysis – on 457 migrant sponsoring employers to financial information from tax data on these sponsoring businesses from the Business Longitudinal Analysis Data Environment (BLADE).[1] Doing so results in a longitudinal data set that allows for the comparison of aspects of business performance such as turnover, employment, wage per employee and labour productivity. This allows for a comparison of the performance of 457 migrant sponsoring businesses with otherwise similar businesses that did not sponsor 457 migrants. This paper aims to inform policy and the wider discourse on migration policy via this retrospective analysis, it also demonstrates the viability of using administrative data when data from more traditional sources is unavailable.

This paper begins by providing an overview of the 457 program, and its evolution over the years. This is followed by an outline of the data linking methodology. Salient recent statistical characteristics of the 457 sponsoring businesses relative to all industry benchmarks are presented next. This is followed by the results from the quasi-experimental matching estimation which establishes a synthetic counterfactual to assess performance differentials between sponsoring and non-sponsoring firms,

1 The results of this study are based, in part, on Australian Business Register (ABR) data supplied by the Registrar to the ABS under A New Tax System (Australian Business Number) Act 1999 and tax data supplied by the ATO to the ABS under the Taxation Administration Act 1953. These require that such data is only used for the purpose of carrying out functions of the ABS. No individual information collected under the Census and Statistics Act 1905 is provided back to the Registrar or ATO for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes, and is not related to the ability of the data to support the ABR or ATO's core operational requirements. Legislative requirements to ensure privacy and secrecy of this data have been followed. Only people authorised under the Australian Bureau of Statistics Act 1975 have been allowed to view data about any particular firm in conducting these analyses. In accordance with the Census and Statistics Act 1905, results have been confidentialised to ensure that they are not likely to enable identification of a particular person or organisation.

followed by a brief discussion and some concluding remarks. The terms 'firm' and 'business' and their plurals are used as synonyms throughout this paper.

The 457 program

Prior to discussion of the data and results some context is provided. This section draws on the work of Campbell and Tham (2013) who provided a comprehensive overview of the 457 program, as well as Larsen (2013) and DIBP (2017). As pointed out in Campbell and Tham (2013) the genesis of the 457 program can be traced back to the 1995 inquiry report into the Temporary Entry of Business People and Highly Skilled Specialists (Parliament of Australia, 1994). The report which is often referred to as the 'Roach Report' — named after Neville Roach, the chair of the inquiry — recommended a streamlining of migration procedures particularly those related to temporary skilled migration in order to address skills shortages and maintain the international competitiveness of Australian businesses. The incoming Coalition government adopted the recommendations of the Roach Report and introduced the 457 visa program in 1996.

The reliance by firms on temporary skilled migrants is not an intrinsically Australian phenomena, other advanced economies have also made use of schemes to source skilled labour from overseas. For example, the most notable of these is the H1-B visa in the United States which has been a mainstay of the US higher education, software development and IT industries. The United Kingdom has also made use of tiered work permit programs, Canadian employers can also temporarily sponsor foreign workers as part of the global talent stream. While the mechanics of each of these visas and programs varies according to the context of each country, their motivations were similar to the 457 program in Australia, requiring an eligible employer to sponsor a migrant worker based on a set criteria.

Given its twenty year history the 457 visa program went through a number of notable revisions that were implemented in response to evolving labour market trends and economic conditions. A comprehensive review or discussion of the evolution of the 457 program is beyond the scope of this paper. However, the salient features and notable legislative changes to the program, as well as recent summary statistics from the program are presented in this section.

Despite revisions over the last twenty years the core aspects of the program remained broadly the same. The 457 program was an uncapped, demand (employer) driven program. To make use of the program Australian businesses had to register with the immigration department and be approved and maintain their status as a sponsoring business. They could then lodge applications to sponsor overseas workers with skillsets that were deemed to be in short supply in the Australian labour market. In the final stage of the sponsorship process the overseas worker would lodge a linked visa application to the immigration department.

Sponsoring businesses were required to demonstrate that employment of overseas workers on 457 visas would be beneficial to Australia by resulting in the creation or maintenance of employment for local workers, and/or the introduction of new or improved technologies or business skills. The program required a commitment from sponsoring employers in terms of training local employees particularly by leveraging off the skills of sponsored overseas workers to reduce the prevalence of skill shortages and reliance on migrant labour in the long run. The program also stipulated that the number of 457 sponsored workers by a business should not exceed a 'reasonable proportion' of the workforce of a sponsoring business in order to minimise crowding out of suitable local workers. Additionally sponsoring employers were obligated to offer the same broad employment and wage conditions to sponsored workers as their local workers.

457 visas could be granted for a maximum of four years with the possibility of renewal. Visa holders were able to:

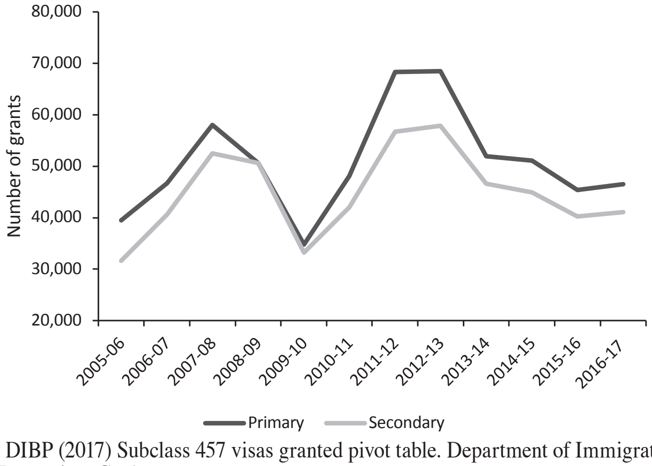
- work in Australia for an approved sponsor for the life of their visa
- bring their family to work or study in Australia
- travel in and out of Australia as often as they liked
- apply for permanent residency (PR) at a later stage as long they satisfied the pre-requisites for PR.

Additionally visa holders had to maintain their employment with their sponsor, or find employment with another approved sponsor within 60 days of ceasing employment with their initial sponsor. They were also required to obtain and maintain licences, registrations and accreditations necessary for their nominated occupation.

Notable revisions to the 457 program occurred in 2001 and 2003 which collapsed the business sponsor categories from two to one and relaxed the sponsorship requirements for regional areas. Later revisions, notably in 2007 and 2009 rolled back some of the earlier changes by strengthening the obligations of sponsoring employers in terms of compliance, particularly towards their sponsored employees. A requirement was imposed on sponsors that a nominated sponsored position for an overseas worker could not be approved unless the terms of employment and employment conditions offered to the sponsored employee were at least as favourable as those provided to local workers. The revisions also guaranteed a base rate of pay for 457 migrants that needed to be greater than an indexed temporary skilled migrant income threshold (TSMIT). The latter revisions also rolled back regional concessions and imposed English language requirements as well as introduced formal skills assessments for certain (but not all) occupations for which overseas skilled workers could be sponsored.

As shown in Figure 1, in recent years the intake of 457 migrants exhibited cyclicality, with the use of the program waning in the wake of the Global Financial Crisis (GFC) and picking up particularly during the mining boom years. Despite trending downwards since the winding down of the resources boom, in recent years, 457 visas grants have outnumbered permanent migrants by a ratio of three to one (Gregory, 2014), however when the inflows and outflows of 457 migrants (the stock) is taken into consideration, 457 migrant stocks have been stable in recent years (Short, 2017).

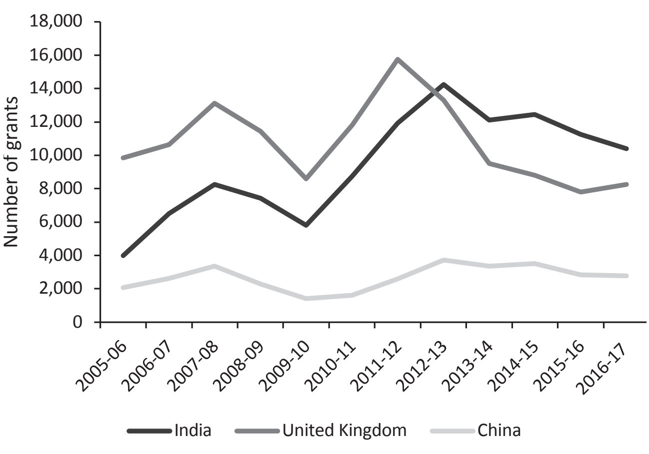
Figure 1: 457 visa grants by financial year



Source: DIBP (2017) Subclass 457 visas granted pivot table. Department of Immigration and Border Protection, Canberra

In terms of the origin of 457 sponsored migrants, the program attracted migrants from a diverse range of nationalities although as shown in Figure 2 in recent years, India, the UK and China and have been the three largest sources of temporary skilled migrants, accounting for 47 per cent of all grants in 2016-17. With temporary migrants from India surpassing those from the UK in recent years and Chinese migrants maintaining a relatively consistent trend.

Figure 2: 457 primary visa grants by financial year – top three source countries



Source: DIBP (2017) Subclass 457 visas granted pivot table. Department of Immigration and Border Protection, Canberra

All Australian industrial sectors made use of the 457 program although not to the same extent and with varying intensity of use in recent years. Table 1 reports the top ten sponsoring industries for 2016-17. Additionally 457 migrants sponsored by the Mining industry peaked in 2011-12 with approximately 6,400 primary grants (9.4 per cent of total annual 457 grants) and with the winding down in mining investment subsequently trending downwards to a relatively lower 1,000 grants in 2016-17 (2.2 per cent of total annual 457 grants).

Table 1: 457 visa primary grants by top 10 sponsoring industries, 2016-17

	Per cent of 2016-17 grants
Other Services	17.3
Professional, Scientific and Technical	13.2
Information Media and Telecommunications	12.9
Accommodation and Food Services	11.0
Health Care and Social Assistance	10.6
Construction	7.3
Education and Training	5.4
Manufacturing	4.3
Financial and Insurance Services	3.7
Retail Trade	3.5

Notes: Proportions reported relate to total primary grants across all industries in 2016-17.
Source: DIBP (2017) Subclass 457 visas granted pivot table. Department of Immigration and Border Protection, Canberra

In terms of nominated occupations, Table 2 reports the top ten occupations along with their skill level. Recent statistics from DIBP (2016) also reveal that the bulk of nominated positions were located in New South Wales (43 per cent), Victoria (25 per cent) and Western Australia (13 per cent).

Table 2: 457 primary visa grants by top 10 nominated occupations, 2016-17

	Per cent of 2016-17 grants	*ANZSCO skill level*
Software and Applications Programmers	17.3	1
General Practitioners and Resident Medical Officers	13.2	1
Cooks	12.9	3
ICT Business and Systems Analysts	11.0	1
University Lecturers and Tutors	10.6	1
Café and Restaurant Managers	7.3	2
Advertising and Marketing Professionals	5.4	1
Management and Organisation Analysts	4.3	1
Accountants	3.7	1
Chefs	3.5	2

Notes: Proportions reported relate to total primary grants across all industries in 2016-17. Smaller values of ANZSCO skill levels represent higher skills, e.g. an occupation with a skill level of 1 is considered more skill intensive and technical than an occupation with a skill level of 2 and so on. ANZSCO skill levels range from 1 to 5.
Source: DIBP (2017) Subclass 457 visas granted pivot table. Department of Immigration and Border Protection, Canberra

On 18 April 2017 the Federal Government announced the abolishment of the 457 program, which was replaced by a dual stream Temporary Skill Shortage (TSS) visa in March 2018 (DIBP, 2017). The new TSS visa is a part of reforms which strengthen the integrity and quality of temporary and permanent skilled migration. Notable new reform measures introduced via the TSS included:

- more targeted occupation lists from which occupations can be nominated
- a two year mandatory work experience requirement relevant to the nominated occupation
- limited (one) onshore visa renewal for migrants under the TSS Short-Term stream
- extension of the permanent residence (PR) eligibility period from two to three years
- removal of PR pathway for TSS Short-Term Visa holders with the pathway only available to TSS Medium-Term visa holders
- introduction of a non-discriminatory workforce test to prevent employer discrimination against suitable Australian workers
- a requirement for sponsored migrant workers to pay a contribution to the newly created Skilling Australians Fund
- Stricter English language requirements requiring a higher level of proficiency for the TSS Medium-Term stream.

These recent changes to skilled migration policy and the availability of a new source of unit record data on Australian firms provides an opportunity to conduct a preliminary analysis of performance differentials between Australian businesses that employed 457 workers and those that did not. Such an analysis at the micro level has thus far proved difficult due to a lack of unit-record data. The motivation of this research paper is to introduce a viable new source of data that can help in this regard, establish a baseline for future analysis, once the TSS matures, and introduce a compact methodology for contributing evidence on this issue that can inform subsequent debate.

Previous research on 457 migrants

There is no shortage of academic research on skilled migrants in the Australian context. However, the majority of this research considers the labour market outcomes of skilled migrants from various background and cohorts, particularly in the context of their earnings and employment outcomes relative to each other and to local workers. See for example, Chiswick and Miller (2009); Miller and Neo (2003); and Rafi (2016).

More recently, given their increasing numbers relative to other streams of skilled migration, 457 migrants have been the subject of academic research. Gregory (2014) identified the increasing importance of 457 migrants in the labour force and provided insights into the employment outcomes of 457 migrants. Notably Gregory (2014) identified the lack of suitable micro-data on 457 migrants that limits the scope of quantitative analysis on 457 migrants. Other authors have attempted to qualitatively assess and analyse issues surrounding the 457 program such as attitudes towards and perceptions of the program from the perspective of Australian employers, the migrants, and the wider community, See for example Bahn, Barratt-Pugh, and Yap (2012); and Parham, et.al. (1999). The vulnerability and precariousness of 457 migrant workers from certain backgrounds, such as Indians in the Australian labour market has also been discussed by Velayutham, (2013).

Temporary skilled migrants have also featured in economy wide impact analyses and Computable General Equilibrium (CGE) modelling such as that commissioned by the Centre for International Economics (CIE, 2013) for the New South Wales economy and the Productivity Commission (2006) as part of their reviews and reports on Australia's migrant intake and population growth. With the CIE reporting that in the absence of skilled and business migration (which includes 457 migrants) the NSW economy would be 2.3 per cent smaller in terms of its Gross State Product (GSP) and the welfare of NSW residents (proxied by real household consumption) would be lower by 3.6 per cent.

DIBP (nd.) has also contributed in this area by producing quarterly reports, and provision of detailed statistics on the 457 visa program via publically available pivot tables, and publishing findings from occasional surveys of cohorts of 457 sponsors and sponsored employees.

Despite an increasing body of qualitative and quantitative research on 457 migrants most of this research is still focused on the labour market outcomes of 457 migrants and their impact on the Australian labour market. There is comparatively limited empirical research from the perspective of sponsoring employers (the firms), primarily due to limited availability of micro level data. Given the strong reliance on the program by Australian employers, the recent development of the ABS BLADE offers an opportunity to address this gap.

Data

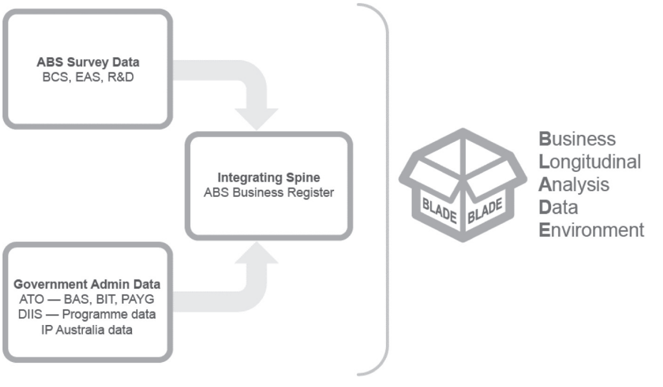
This research primarily draws on firm-level data from the ABS Business Longitudinal Analysis Data Environment (BLADE) and unpublished data from the DIBP on employers who sponsored 457 visa migrants. Figure 3 provides a graphical overview of BLADE which is best thought of as a diverse and evolving data asset that consists of a collection of interlinked data-sets.

BLADE contains administrative data on more than two million actively trading Australian businesses. It includes Australian Taxation Office (ATO) data, IP Australia data and some Department of Industry, Innovation and Science (DIIS) program data. The bulk of BLADE data items are sourced from the ATO from:

- **Business Activity Statements (BAS)** that are submitted by businesses to report their Goods and Services Tax (GST) obligations. Examples of data items included are total sales, export sales, wages & salaries, capital & non-capital purchases
- **Business Income Tax (BIT)** forms that are submitted by businesses to report taxable income or loss on one of four form types (Company, Partnership, Sole Trader, and Trust)
- **Pay as you go (PAYG)** statements provided by businesses to report personal income tax obligations of their employees. This is used to model Full-Time Equivalent (FTE) and derive employment headcounts.

Additionally program data from government departments such as the Department of Industry, Innovation and Science is also being integrated with BLADE. Each data-set within BLADE can be used on its own, although the true utility of BLADE is facilitating analysis on custom data-sets that draw information from a diverse array of sources such as ABS data, ATO data and data from other sources such as program data from government departments. This is facilitated by using the ABS Business Register (ABSBR) and the associated Australian Business Numbers (ABNs) as the integrating spine that allows for the linking of diverse pieces of information on the same ABN from different data-sets.

Figure 3: An overview of BLADE



Notes: BCS refers to the Business Characteristics Survey, EAS refers to the Economic Activity Survey, BAS refers to Business Activity Statement, BIT refers to Business Income Tax, and PAYG refers to Pay as you go.
Source: DIIS (2017)

The ability to integrate data with BLADE and the financial data from the ATO available within, makes BLADE particularly suited for the current research which attempts to assess the differences in performance between firms that made use of 457 visa workers and those that did not. The DIBP collects ABN information on Australian employers that sponsored 457 migrants, and this information for financial years 2005-06 to 2013-14 was shared with the ABS for linking to the ATO data available in BLADE. Due to technical challenges in integrating the tax data, at the time of estimation, ATO data within BLADE was not available for more recent financial years.

Upon linking of the DIBP and ATO data, the researchers were provided access to a custom data-set within BLADE that notably included:

- The number of 457 primary applicants sponsored by a business in a given financial year (the visa count)
- Financial variables such as annual turnover, capital and non-capital expenditure, and export sales for each business
- The annual wage bill of each business, and derived measures of employment on a full time equivalent (FTE) basis.

This resulted in a longitudinal data set that allows the performance of firms that made use of 457 workers to be tracked and analysed over time relative to firms that did not make use of the 457 program. Prior to a discussion of the insights and results generated from this linked longitudinal data-set it is worthwhile to briefly discuss the two broad cohorts of firms in BLADE.

The firms included in the ABSBR consist of non-profiled (simple) firms and profiled (complex) firms. Non-profiled firms have simple structures and conduct business under just one ABN. Profiled firms on the other hand have complex structures with multiple types of activity units (TAUs) conducting business under multiple ABNs potentially across multiple industries, markets and regions as part of an enterprise group (EG). Profiled firms are a minority of all Australian firms, although they do tend to be larger and for these firms the ABS maintains its own units structure through direct contact with businesses. This research project limits its scope to the non-profiled (simple) firms due to the difficulty of disaggregating 457 visa counts for each complex firm across its various TAUs. It is hoped that further refinements to the linked data will allow for an analysis of these complex firms. Readers interested in knowing more about BLADE are referred to Hansell and Rafi (2017) who discuss the ABS data linking methodology, salient features of BLADE as well as the current access mechanisms that are available to researchers who wish to conduct analysis using BLADE.

The next section of this paper presents descriptive statistics from the linked BLADE-DIBP data to establish some aggregate characteristics of 457 migrant sponsoring firms.

Descriptive Statistics

This section describes the 457 visa sponsoring businesses in terms of their business and financial characteristics and also compares these characteristics with other non-sponsoring Australian businesses that were similar to the 457 visa sponsoring firms. To improve the quality of the comparison the linked dataset is trimmed by:

- Only considering simple (non-profiled) businesses for both sponsoring and non-businesses. This is done to avoid the problem of misattribution that occurs with complex firms with multiple TAUs as discussed in the previous section
- Excluding businesses that did not report their wages (from which estimates of FTE are derived) as otherwise it is not possible to segregate firms by employment size cohorts. Given the complex nature of analytical issues associated with large businesses, this study focuses only on Small to Medium Sized Enterprises (SMEs) that employed less than 199 persons
- Excluding firms that, in any given financial year, had a sponsored visa count to employment (FTE) ratio of greater than one. A visa count to FTE ratio that is greater than one implies that a business sponsored more 457 migrants than its total workforce. This was the case for a very small minority of 457 sponsoring businesses in the linked BLADE-DIBP data-set. There are a number of potential reasons for this, notably, such businesses could be labour hire or contracting firms that sub-contract migrant employees or source them on behalf of other businesses. Any sponsoring business with a visa count to FTE ratio greater than one is removed from the merged data. This is unlikely to change the overall pattern of the statistics presented as such businesses were a very small minority of the data
- Finally, any firm for which there is no Industry classification is also removed from the data. Such firms were again a small minority of the linked DIBP-BLADE data-set.

Characteristics of 457 migrant sponsoring firms

It must be noted that the descriptive statistics presented below relate to the characteristics of 457 sponsoring businesses from the linked BLADE-DIBP data-set. They are not analogous to the visa grant statistics that are reported by the DIBP, and hence should not be seen as a substitute for them.

Table 3 gives the characteristics of 457 visa sponsoring firms. There was a significant increase in the number of Australian businesses that sourced specialised skills from overseas during the period 2005-06 to 2013-14 — the number of businesses that sponsored temporary skilled migrants more than doubled during this period from 4,896 to 11,988 businesses. In terms of the number of migrants sponsored, in any given financial year, almost three fourths of the sponsors hired only one temporary skilled migrant and 15 per cent of Australian businesses sponsored two temporary skilled migrants. On average, only one tenth of Australian businesses sponsored more than two temporary skilled migrants in a financial year.

Within SMEs, there was not much variation between business size and the proclivity to sponsor 457 migrants. However, micro (1-4 employees) Australian businesses increased their reliance on the 457 program in more recent years accounting for a 12 per cent increase in sponsorships between 2010-11 and 2013-14. The proportion of medium (20-199 employees) businesses decreased by 11 per cent during the same period, while the proportion of small (5-19 employees) businesses showed no significant change during that period.

One stark feature that is apparent from the statistics in Table 3 is the decline in the proportion of exporting firms involved in sponsoring 457 migrants, which decreased significantly from 28.4 per cent in 2005-06 to 16.1 per cent in 2013-14. There are a number of potential reasons for this such as, the impact of the Global Financial Crisis, changes in non-trading sectors looking to produce goods and services using more innovative methods, business reorientation to satisfy domestic demand rather than foreign demand, and or changes to consumers taste and preferences for products involving the use of specialised skilled workers.

Table 4 shows that the proportion of visa sponsoring firms also varied among industry sectors and there were significant changes in the use of 457 visa temporary skilled migrants over time. Professional, Scientific and Technical services (PST), Accommodation and food services (AFS) and manufacturing (MFG) were the top three industry sectors that were involved in sponsoring 457 visas in 2005-06. However, by 2013-14, only PST and AFS remained within the top three. In AFS, a significantly higher proportion of Australian businesses recruited overseas skilled workers in 2013-14 (21.7 per cent) compared to 2005-06 (13.4 per cent). Whereas in PST the proportion of 457 sponsoring businesses decreased from 20.5 per cent to 13.6 per cent during the same period. There was a significant decrease in manufacturing sector as well.

Table 3: Attributes of 457 migrant sponsoring businesses

Attribute		*2005-06*	*2006-07*	*2007-08*	*2008-09*	*2009-10*	*2010-11*	*2011-12*	*2012-13*	*2013-14*
Total number of sponsors		4,896	6,335	8,648	7,939	5,435	6,950	9,165	10,177	11,998
457 migrants sponsored (per cent)										
	One	70.4	70.7	69.6	72.1	77.5	72.1	66.7	64.9	74.3
	Two	15.0	14.4	15.4	14.8	12.2	14.7	16.6	18.5	15.8
	Three to four	8.3	8.7	8.8	8.0	6.3	8.0	9.9	10.7	6.7
	Five to ten	4.7	4.7	4.9	3.9	3.1	4.1	4.8	4.6	2.5
	Ten plus	1.8	1.5	1.7	1.1	0.9	1.2	2.0	1.5	0.8
Business size (per cent)										
	1-4 employees	18.7	18.9	17.9	16.2	14.7	16.1	17.2	20.2	27.9
	5-19 employees	39.7	40.6	40.0	41.2	39.9	39.9	39.1	39.0	39.4
	20-199 employees	41.7	40.5	42.1	42.6	45.4	44.0	43.6	40.8	32.7
Exporter (per cent)		28.4	25.6	24.7	24.2	25.4	24.3	21.7	18.7	16.1

Notes: Statistics relate to simple (non-profiled) businesses from the linked BLADE-DIBP dataset.
Statistics not directly comparable to official DIBP visa grant statistics.
Source: Author's calculations using the integrated BLADE dataset.

Table 4: 457 migrant sponsoring businesses by industry

Attribute	*2005-06*	*2006-07*	*2007-08*	*2008-09*	*2009-10*	*2010-11*	*2011-12*	*2012-13*	*2013-14*
Total number of sponsors	4,896	6,335	8,648	7,939	5,435	6,950	9,165	10,177	11,998
Agriculture, Forestry and Fishing	1.7	2.0	1.7	1.8	1.5	1.3	1.4	1.8	1.9
Mining	1.1	1.4	1.7	1.6	1.8	1.9	1.8	1.5	0.9
Manufacturing	10.5	11.5	11.5	11.0	8.6	8.4	8.7	8.4	7.5
Electricity, Gas, Water and Waste Services	0.3	N/A	0.3	0.3	0.2	0.3	0.3	0.3	0.2
Construction	7.7	8.4	8.7	9.3	10.0	11.5	11.6	11.0	9.5
Wholesale Trade	9.5	8.8	8.8	8.6	9.3	8.4	8.7	7.9	8.0
Retail Trade	6.4	5.7	5.9	5.2	5.1	5.0	5.8	6.8	7.0
Accommodation and Food Services	13.4	14.3	13.2	12.7	8.6	9.7	13.2	18.2	21.7
Transport, Postal and Warehousing	2.2	2.4	1.9	1.9	2.1	1.7	1.6	1.8	2.2
Information, Media and Telecommunications	1.9	1.8	2.0	2.0	2.0	1.8	1.7	1.5	1.3
Financial and Insurance Services	3.3	3.0	2.8	2.9	3.3	3.0	2.6	2.3	2.4
Rental, Hiring and Real Estate Services	1.7	1.8	1.8	1.8	1.6	1.8	2.0	1.9	2.0
Professional, Scientific and Technical Services	20.5	19.5	19.3	20.8	22.6	22.8	19.2	15.7	13.6
Administrative and Support Services	6.3	5.6	5.4	5.1	5.6	6.0	5.5	5.7	5.4
Public Administration and Safety	0.3	N/A	0.4	0.5	0.6	0.4	0.5	0.5	0.4
Education and Training	3.4	2.8	3.0	3.1	4.0	3.6	3.0	2.8	2.6
Health Care and Social Assistance	3.8	4.2	4.3	4.7	6.6	6.3	5.3	5.4	5.6
Arts and Recreation Services	1.2	1.2	1.3	1.1	1.4	1.5	1.4	1.1	1.3
Other Services	4.8	5.4	6.1	5.7	5.0	4.7	5.8	5.4	6.6

Notes: Statistics relate to simple (non-profiled) businesses from the linked BLADE-DIBP dataset.
Statistics not directly comparable to official DIBP visa grant statistics.
Source: Author's calculations using the integrated BLADE dataset.

Financial characteristics of sponsoring firms

Table 5 compares selected financial characteristics of 457 visa sponsoring businesses and non-sponsoring businesses (mean value comparison). Several financial characteristics were available in BLADE to compare the performance of 457 visa sponsoring businesses including turnover, capital expenditure, exports, wages and employment. Table 5 gives the mean values of these financial variables for the period from 2007-08 to 2013-14 and also for other Australian businesses. Table 5 indicates that on the whole 457 visa sponsoring businesses performed better than non-sponsoring Australian businesses across all indicators. On average, 457 migrants sponsoring businesses had higher turnover, employment and wages, additionally on average they generated more export revenue (albeit still modest) and recorded a higher capital spend.

Table 5: Financial attributes of 457 sponsoring businesses relative to similar non-sponsoring businesses, mean values

	Sponsoring businesses					
	Count	*Turnover ($m)*	*Capital expenditure ($m)*	*Exports ($m)*	*Wages ($m)*	*Employment*
2007-08	31,219	7.5	0.3	0.5	1.1	23.1
2008-09	32,821	7.6	0.3	0.5	1.2	22.9
2009-10	33,855	7.4	0.3	0.4	1.2	22.7
2010-11	34,535	7.9	0.3	0.5	1.3	24.5
2011-12	34,856	8.7	0.3	0.6	1.5	25.2
2012-13	35,332	8.9	0.3	0.5	1.6	25.9
2013-14	34,999	9.4	0.3	0.6	1.7	26.0
	Non-sponsoring businesses					
	Count	*Turnover ($m)*	*Capital expenditure ($m)*	*Exports ($m)*	*Wages ($m)*	*Employment*
2007-08	682,959	1.4	0.1	0.0	0.2	4.6
2008-09	682,807	1.5	0.1	0.0	0.2	4.5
2009-10	687,275	1.5	0.1	0.0	0.2	4.5
2010-11	690,146	1.6	0.1	0.1	0.3	4.6
2011-12	689,984	2.0	0.1	0.1	0.3	4.7
2012-13	691,015	1.9	0.1	0.1	0.3	4.9
2013-14	705,585	1.8	0.1	0.1	0.3	4.9

Notes: Statistics relate to simple (non-profiled) businesses from the linked BLADE-DIBP dataset. Statistics not directly comparable to official DIBP visa grant statistics.
Source: Author's calculations using the integrated BLADE dataset.

Two financial characteristics (mean turnover and mean employment) were also compared with other similar Australian businesses by business size and across industry sectors to understand these businesses characteristics further.

Table 6 reveals that, mean turnover of 457 visa sponsoring firms was always higher than other similar Australian non-sponsoring firms, even after controlling for business size. In general, the larger the firm size, the higher the mean differences in turnover between the two types of firm suggesting that 457 visa sponsoring firms perform better than similar non-sponsoring firms, although given data limitations this comparison is unable to control for other factors that may be responsible for this difference.

Table 6: Comparison of turnover by business size ($ million), mean values

Year	*Micro*		*Small*		*Medium*	
	Sponsors	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*
2007-08	1.2	0.5	3.4	2.3	17.7	15.0
2008-09	1.1	0.5	3.2	2.3	18.2	16.8
2009-10	1.1	0.5	3.1	2.3	18.3	15.6
2010-11	1.2	0.6	3.2	2.4	18.7	15.8
2011-12	1.1	0.7	3.1	2.4	19.9	23.3
2012-13	1.1	0.5	3.1	2.5	19.7	22.0
2013-14	1.1	0.5	3.3	2.8	20.5	18.6

Notes: Statistics relate to simple (non-profiled) businesses from the linked BLADE-DIBP dataset. Statistics not directly comparable to official DIBP visa grant statistics.
Source: Author's calculations using the integrated BLADE dataset.

In terms of differences in mean employment between sponsors and non-sponsors, Table 7, reveals that mean FTE employment in 457 visa sponsoring firms were always higher than non-sponsoring firms for the seven year study period irrespective of firm size indicating that on average the sponsoring firms employed more than non-sponsoring business, although the difference is modest, particularly at the micro and small business level.

Table 7: Comparison of employment (FTE) by business size, mean values

Year	*Micro*		*Small*		*Medium*	
	Sponsors	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*
2007-08	2.3	1.5	10.2	8.8	53.1	40.6
2008-09	2.3	1.5	10.2	8.7	53.0	40.6
2009-10	2.2	1.5	10.2	8.7	53.0	40.7
2010-11	2.2	1.4	10.2	8.7	53.3	41.2
2011-12	2.2	1.4	10.2	8.8	54.3	41.9
2012-13	2.3	1.4	10.1	8.8	54.3	41.9
2013-14	2.4	1.5	10.1	8.8	54.4	42.2

Notes: Statistics relate to simple (non-profiled) businesses from the linked BLADE-DIBP dataset. Statistics not directly comparable to official DIBP visa grant statistics.
Source: Author's calculations using the integrated BLADE dataset.

Industry sector performance of 457 visa sponsoring businesses are presented in Tables 8 and 9. Comparisons indicate that 457 visa sponsoring firms perform better in turnover and employment in all six key industry sectors that made relatively higher use of the 457 program. The widest difference in turnover is observed in Wholesale Trade while the widest difference in employment is observed in Manufacturing. However the difference in turnover and employment is clear to observe in other sectors as well such as PST, Construction and Retail Trade.

Table 8: Comparison of turnover for selected industries ($ million), mean values

	Manufacturing		*Construction*		*Wholesale trade*		*Retail trade*		*AFS*		*PST*	
Year	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*
2007-08	9.3	2.0	7.5	1.2	18.6	4.5	11.5	2.0	2.3	0.9	5.2	0.7
2008-09	9.3	2.0	7.7	1.2	18.9	4.6	11.6	2.0	2.3	0.9	5.4	0.8
2009-10	8.8	2.0	7.4	1.2	17.9	4.7	12.0	2.1	2.3	0.9	5.6	0.9
2010-11	9.4	2.1	7.9	1.1	19.1	5.0	11.9	2.1	2.4	0.9	6.0	0.9
2011-12	9.8	4.6	9.0	1.2	22.2	5.4	12.4	2.2	2.4	1.0	6.4	1.3
2012-13	9.8	2.3	9.2	1.2	20.8	5.4	12.9	2.3	2.5	1.0	6.7	1.3
2013-14	10.2	2.4	10.5	1.3	22.9	5.8	12.7	2.4	2.5	1.0	6.9	1.2

Notes: Statistics relate to simple (non-profiled) businesses from the linked BLADE-DIBP dataset.
Statistics not directly comparable to official DIBP visa grant statistics.
Source: Author's calculations using the integrated BLADE dataset.

Table 9: Comparison of employment (FTE) for selected industries, mean values

	Manufacturing		*Construction*		*Wholesale trade*		*Retail trade*		*AFS*		*PST*	
Year	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*	*Sponsors*	*Non-sponsors*
2007-08	30.2	7.7	21.2	3.6	26.1	6.6	21.0	4.8	15.0	4.9	22.6	3.6
2008-09	30.0	7.5	20.7	3.5	26.5	6.5	20.5	4.8	14.5	4.9	22.7	3.5
2009-10	29.4	7.4	20.5	3.5	26.0	6.5	20.9	4.8	14.3	4.9	22.3	3.4
2010-11	30.5	7.6	22.0	3.5	27.3	6.6	21.5	4.8	14.5	4.9	23.6	3.5
2011-12	31.1	7.8	24.5	3.6	28.0	6.8	22.6	4.9	14.4	5.1	25.5	3.6
2012-13	31.3	7.8	26.2	3.7	28.8	6.9	23.9	5.0	14.4	5.1	26.2	3.7
2013-14	31.2	7.9	26.4	3.8	29.0	6.9	24.0	5.2	14.3	5.2	26.1	3.8

Notes: Statistics relate to simple (non-profiled) businesses from the linked BLADE-DIBP dataset.
Statistics not directly comparable to official DIBP visa grant statistics.
Source: Author's calculations using the integrated BLADE dataset.

Establishing a counterfactual

The descriptive statistics presented in the previous section suggest that 457 sponsoring businesses were generally larger and out-performed similar non-sponsoring businesses.

As an additional robustness check to ascertain whether performance differences do in fact exist between businesses that sponsor and employ 457 migrants and those that do not, a nearest-neighbour matching estimator is used to establish a synthetic counterfactual. This is done to minimise the presence of any selection biases that might be responsible for the performance differences observed in the descriptive statistics.

This is a similar methodology to Rafi (2017) and draws upon the work of Abadie and Imbens (2002), Abadie et.al. (2004), and Caliendo and Kopeinig (2008) who discuss the theoretical underpinning and mathematical notation of matching estimators.

For an individual firm, $i = 1, \dots, N$, with all units exchangeable, let:

$\{Y_i(0), Y_i(1)\}$ denote the two possible outcomes, namely $Y_i(0)$ is the outcome when an individual firm does not sponsor a 457 migrant and $Y_i(1)$ is the outcome when it does.

The average treatment effect (ATE) can then be expressed as the difference between the two outcomes:

$$\tau = E\{Y(1) - Y(0)\}$$

However, when estimating the ATE, only one of the two outcomes is observed. Intuitively, at a given point in time, if an individual firm chooses to be a 457 migrant sponsoring firm then it cannot also be non-sponsoring firm. At a point in time, for an individual firm the two outcomes are mutually exclusive. The observed outcome can be denoted as:

$$Y_i = Y_i(W_i) = \begin{cases} Y_i(0) & if\ W_i(non - sponsor) = 0 \\ Y_i(1) & if\ W_i(sponsor) = 1 \end{cases}$$

Since only one of the two outcomes is observed we must estimate the other unobserved potential outcome for each individual firm in the sample.

If the decision to sponsor is random for individual firms with similar characteristics (often referred to as pre-treatment variables or covariates) then the average outcome of similar firms that were non-sponsors can be used to estimate the unobserved outcome for the sponsoring firms.

To ensure that the matching estimators identify and consistently estimate the treatment effects, it is assumed that:

For all x in the support of X,

W (Decision to sponsor or in general the 'treatment') is independent of ($Y(0)$, $Y(1)$) conditional on $X = x$. This is referred to as un-confoundedness or 'selection on observables'.

Additionally it is also assumed that:

$$c < \Pr(W = 1 \,|X = x) < 1 - c, \text{ for some } c > 0$$

This is referred to as the identification assumption, and states that the probability of assignment to the treatment is bounded away from 0 and 1. This assumption is also known as the overlap assumption. Essentially the overlap assumption must hold otherwise, if all businesses with similar characteristics (covariates) choose the treatment (sponsored, probability of 1) or did not receive treatment (chose not to sponsor, probability of 0), there would be no observations on similar businesses in the opposite outcome category which could be used for comparison.

The nearest neighbour matching estimator uses a scaling matrix S to determine the distance between vector covariate patterns (characteristics) to weight observations and find a close match for each individual firm from the other group (treated or untreated). Specifically, the Mahalanobis Distance, which is the inverse of the sample covariate covariance matrix is used:

$$S = \frac{(X - \bar{x}'1_n)'W(X - \bar{x}'1_n)}{\sum_i^n w_i - 1}$$

Where 1_n is an n x 1 vector of ones, $\bar{x} = (\sum_i^n w_i\, x_i) \,/ \sum_i^n w_i)$, and W is an n x 1 diagonal matrix containing frequency weights.

The following firm characteristics are used for matching:

- firm size, established via full-time equivalent employment numbers at the time of matching
- industry sector, as given by the four-digit ANZSIC for a finer comparison
- a measure of past performance, proxied by the change in turnover in the two years prior to matching.

Additionally, the matching exercise selects a very specific cohort of sponsoring businesses to control for further unobservable effects that might lead to selection bias and/or identification issues. Notably, it is possible that differences in firm performance arise not only due to the use of 457 migrant workers but also due to the timing of sponsorship. It is possible that businesses that sponsored 457 workers at different points in time had differing performance characteristics, not only relative to non-sponsoring firms but also to each other. For example, a business that sponsored 457 migrants prior to the GFC could have differing levels of performance relative to a business that made use of the program post GFC. Similarly the legislative changes to the 457 program over its many years may also have impacted on firm's decision to use 457 workers at different points in time. To control for this, the two cohort of firms to be matched are defined as:

- firms that only first made use of (sponsored) 457 migrants in 2010-11
- the pool of non-sponsoring firms for the financial year 2010-11 from which the counterfactual is drawn. Which consists of firms that have never sponsored a 457 migrant at any point prior or subsequent to 2010-11.

In this particular case each observation from the sponsoring group of firms is matched to at least three close observations with similar characteristics from the non-sponsoring group of firms based on the Mahalanobis Distance. The outcomes for the nearest neighbours are then averaged and compared against the outcome for each sponsoring firm.

Nearest neighbour matching is implemented with replacement, which means that each observation from the untreated group can potentially be used as a match more than once. This results in reduced bias in the estimator and a higher quality match although it does increase the variance of the estimates. However, this issue becomes less serious in large datasets, such as the one used for this paper.

Compared to other matching estimators such as propensity score matching, nearest neighbour matching has some advantages. By not imposing any functional form assumptions, the nearest neighbour matching estimator is more flexible relative to propensity score matching. This implies that it can be used to estimate treatment effects for a much wider class of models. However the drawback is that the nearest neighbour estimator requires much more data, and the bias in the ATE estimate starts to increase as more continuous covariates are added to the model (Huber, 2015). However, for this particular research, the advantages of the nearest neighbour matching estimator outweigh the negatives — there are a sufficiently large number of untreated non-sponsoring firms in the BLADE data to draw a counterfactual from, furthermore the continuous covariates (number of FTEs, past turnover performance) are bias adjusted when matching to overcome one of the key limitation of nearest-neighbour matching.

To assess whether there were any persistent differences in the performance of businesses sponsoring 457 visa migrant workers relative to similar non-sponsoring businesses, the three year forward change in turnover, employment (FTE), wage per FTE, and labour productivity —between 2010-11 and 2013-14 — were selected as the outcome variables in the matching estimation — with the treatment effects for these outcome variables used to assess differences in performance between sponsors and non-sponsors.

Assessing the evidence for any performance differentials

Table 10 reports the ATEs for the outcome variables for all ANZSICs as well as for certain selected ANZSICs. The results are robust to heteroscedasticity and outlier analysis was used to trim the distributions for key variables to minimise the influence of extremely small or large values. Continuous variables used for nearest neighbour matching were further bias adjusted to overcome one of the major limitations of the nearest-neighbour estimator.

In terms of basic intuition, for 457 sponsoring businesses, the ATEs for the outcome variables provide an assessment of whether change in turnover, employment, wage per FTE and labour productivity three years onwards from 2010-11 was more or less than the counterfactual (non-sponsoring businesses). The magnitude and sign of the ATE is important in assessing performance differences. A positive (greater than 0) ATE implies that for sponsoring businesses the forward change in the outcome variable was greater or higher than the counterfactual and indicative of better performance.

The results presented in Table 10 suggest a difference in turnover and employment performance of 457 sponsoring business relative to non-sponsors. However the ATEs for distinct ANZSICs exhibit more variability in terms of magnitude and statistical significance. In terms of statistical significance, evidence for additionality in performance is strongest for the forward change in turnover and employment and less so for wage per FTE and labour productivity.

Across all ANZSICs the ATE for turnover shows that the three-year forward change in turnover was on average $ 146,000 higher for the sponsoring firms relative to the non-sponsoring firms. Within ANZSICs there was marked variability with the forward change being $668,000 higher for sponsors in Wholesale Trade, $186,000 higher for sponsors in Construction and $194,000 higher for sponsors in PST. This preliminary research could not establish statistically significant evidence of differences in forward turnover performance for other key sponsors of 457 migrants such as businesses in the Accommodation and Food Services industry.

In terms of employment, the ATEs from the matching estimation also suggest a modestly better performance in terms of employment creation by 457 migrant sponsoring businesses. Prior to matching, for sponsoring businesses, their total number of FTEs is adjusted downwards by the number of 457 migrants sponsored each year. *Essentially the treatment effect for employment (FTE) for the sponsoring firms is net of the number of 457 migrants sponsored in any given financial year.* The treatment effect for FTE therefore suggests that even after controlling for the number of 457 migrants sponsored, on average across all ANZSICs the three-year forward change in employment was 1.5 FTE higher in the sponsoring businesses relative to the non-sponsoring firms. While there is some variability in the FTE forward change across key industries, in general the results in Table 10 suggest that the additional employment generated by sponsoring firms is modest relative to the non-sponsoring firms, although very statistically significant.

The evidence is considerably less statistically significant for any performance premium in terms of the forward change in wage per FTE and labour productivity. However the treatment effects for wage per FTE for Manufacturing, Retail Trade, and PST suggests that three years onwards from 2010-11, 457 sponsoring businesses in these three industries on average paid a higher wage per employee. Overall, however, the statistical evidence is tenuous to suggest that growth in wage per employee was higher in 457 industries relative to the counterfactual. One possible reason for this is likely to be the relatively rigid and regimented nature of certain aspects of the Australian labour market such as the Awards system and other forms of wage arbitration, which on average results in broadly similar cohorts of Australian businesses paying similar wages.

Similarly, the matching estimation does not find definitive statistic evidence that change in labour productivity three years onwards from 2010-11 was higher in the

457 firms relative to the counterfactual. The only sponsoring industry that returned a statistically significant results was Manufacturing where on average the forward change in labour productivity was $17,500 higher (in terms of value-added per employee) for sponsoring firms relative to the counterfactual. There are a number of possible interpretations of this result, first, that there is little difference in the labour productivity of 457 sponsoring and non-sponsoring firms, second, it is more likely that the lack of statistically significant labour productivity differentials is a consequence of measurement issues particularly for services industries and the proxy chosen to derive labour productivity from the financial data (Turnover less other non-capital expenditure per FTE). This issue requires further research and a more nuanced empirical model beyond the exploratory approach of this paper.

Table 10: Average treatment effects for 457 sponsoring firms by industry

ANZSIC	*Average Treatment effect*								*Number of firms*	
	Turnover ($)		*FTE*		*wage per FTE ($)*		*value-added per FTE ($)*		*Sponsors*	*Non-sponsors*
Manufacturing	58,000		0.85	***	5,700	**	17,500	**	194	21,260
Construction	186,000	**	2.2	***	1,860		-11,900		289	44,702
Wholesale trade	668,000	***	1.6	***	-310		30,000		192	16,625
Retail trade	233,000	**	1.6	***	2,400	**	-5,840		131	30,089
Accommodation and food services	52,400		1	***	-880		2,840		207	14,990
Professional, scientific and technical services	194,000	**	1.7	***	6,500	***	5,110		415	39,844
Administrative and support services	116,000		2.5	***	-280		-7,200		111	11,884
Health care and social assistance	90,000		0.6		-5,800		14,000		177	26,288
Other services	180,000	***	2.2	***	-900		6,240		121	22,671
All ANZSICs	146,000	***	1.5	***	2,300		3,000		2,230	312,772

Notes: *** significant at 1 per cent, ** significant at 5 per cent, * significant at 10 per cent.
FTE is a measure of employment and stands for 'Full Time Equivalent'
Source: Author's calculations using the integrated BLADE dataset.

Discussion and caveats

The descriptive statistics and the matching estimation of the preceding sections establish that there are performance differentials between firms that sponsored 457 migrants and those that did not, particularly in terms of turnover and employment performance. This is evident across a number of ANZSICs, firm size classes and time periods. It would be tempting to assert that this performance differential is exclusively due to the use of sponsored 457 migrants, however this is unlikely. The use of 457 migrants is certain to have contributed to helping preserve and grow a businesses' competitive advantage but there are other potential factors that help explain these performance differentials, notably differences in managerial ability, business age, product mix and life cycle, and the human capital and experience of existing employees (including permanent skilled migrants). Controlling for factors such as these in the analysis, particularly the matching estimation would assist in further isolating the impact of 457 migrant sponsorship on firm performance. Unfortunately, given current data limitations it is not possible to control for many of these factors as while BLADE data is rich in financial information from taxation data it is fairly limited in terms of other variables that help shed light on the labour mix, production technology, and managerial quality of a business. Future developments in terms of the development of a longitudinal linked Employer-Employee Dataset (LLEED), and the recently completed ABS Management Capability Survey will allow for any subsequent research on the impact of skilled migrants on business performance to be more definitive.

Even if performance differentials are not exclusively due to 457 migrants, the sponsorship of 457 migrants by the relatively better performing firms is an interesting research finding. The findings of this paper establish that there is a cohort of firms that is performing better relative to their peers and the recent changes to skilled temporary migration could potentially have implications — positive or negative — for this better performing cohort of firms. It is too early to assess the impact of these changes, however the policy desire to better attune skilled migration policy is likely to have maximal impact if it also aligns with the strategic aims and motivations of Australian businesses in terms of affording them labour market flexibility and access to critical skills in short supply.

In this regards this paper adds value to the academic and policy discussion by identifying a gap in the literature in terms of the assessment of the firm-level impacts of migration policies. Furthermore this paper highlights the utility of administrative data as a rich vein of information that can assist researchers in terms of quantifying and assessing these impacts. There is considerable scope to refine the current research, notably in terms of controlling for the additional factors identified above and also by broadening the scope of the research to include the larger, complex (profiled) firms within BLADE.

Conclusion

This paper provided a summary of the salient characteristics of the 457 program over the two decades of its operation. Despite its use by a variety of Australian industries and businesses there has been a lack of quantitative research on 457 migrants, employers, and industries. This is primarily due to a lack of suitable micro-data on 457 migrants and sponsoring employers. This paper partly circumvented this limitation by making use of linked administrative data, and provides a compact methodological framework for assessing research questions such as the presence and extent of performance differentials between firms that sponsored 457 migrants and those that do not. The findings of this paper suggest that 457 sponsoring firms outperform non-sponsoring firms, however it is unlikely that 457 migrants are the exclusive source of this performance premium.

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Indigenous youth employment and the school-to-work transition[1]

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Abstract

The employment gap between Indigenous and non-Indigenous youth (aged 15-29 years) increases in the years immediately following the end of compulsory schooling and continues to widen into the 20s. Indigenous youth are also more likely to work in part-time, casual and unskilled jobs than non-Indigenous youth. The situation for young Indigenous women is markedly worse than for men, even though educational participation and attainment is similar. Early labour market experiences are likely to have both immediate and ongoing effects, reducing income, wealth accumulation and impeding future labour market success. However, there are signs of improvement in the labour market situation for Indigenous youth, particularly in non-remote areas. Between 2011 and 2016, educational participation and employment increased. Growing educational attainment is likely to further improve employment rates because Indigenous youth who have completed Year 12 have far better outcomes in the labour market than early school leavers.

JEL Codes: J15, J13, J24, I24
Keywords: Labour market, youth employment, school-to-work transition, NEET

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1. Introduction

Almost 36 per cent of Aboriginal and Torres Strait Islander people are aged under 15 years, and 63 per cent are aged under 30 years (ABS 2016). Ensuring that these large cohorts of young people make successful transitions from school to work will play a vital role in improving the wellbeing of the Indigenous population in the short and long terms.

A person's first interaction with the labour market after leaving school can shape their lives for years or even decades to come. In a phenomenon known as scarring (Gregg & Tominey 2005, Bell & Blanchflower 2011, Nordström Skans 2011), time spent out of work or in poor-quality jobs contributes to low income, and impedes the development of skills and work experience that can improve future labour market outcomes.

Across the lifecourse, Indigenous people tend to have poorer labour market outcomes than non-Indigenous people (Biddle & Yap 2010). The employment gap between Indigenous and non-Indigenous young people is also large (Thapa et al. 2012, Gray et al. 2014, AIHW 2015). Young Indigenous people have higher unemployment rates (Rothman et al. 2005), and are far more likely to be disengaged simultaneously from education and work (Dusseldorp Skills Forum 2009, Nguyen 2010, OECD 2016). Indigenous status is also associated with an increased risk of long-term disengagement with the labour market (OECD 2016). Indigenous youth are more likely than non-Indigenous youth to remain out of work over time, and those that do find work are more likely to move into unemployment or out of the labour market (Hunter & Gray 2016).

It is likely that poor labour market outcomes during youth contribute to the large gap that exists between employment rates for Indigenous and non-Indigenous people at older ages.[2] Understanding the labour market situation of the young Indigenous population, as well as identifying potential barriers to engaging fully in the labour market, is therefore vital to closing the gap in employment outcomes between Indigenous and non-Indigenous Australians.

This paper provides an updated overview of the labour market situation of Indigenous youth. As well as examining the employment gap and unemployment rate, the paper looks at a commonly used measure of labour market inactivity for youth: the proportion not in employment, education or training (NEET). The characteristics of post-school jobs are also examined, including hours of work, job security and skill level. Increasing numbers of young Indigenous people are completing Year 12, so the paper examines how labour market outcomes differ by educational attainment. Finally, the paper discusses some of the consequences of poor labour market outcomes during youth.

2. Data and definitions

This paper uses data for Aboriginal and Torres Strait Islander people from the 2016 Census to examine the labour market situation of Indigenous and non-Indigenous

2 Unfortunately, data to test this hypothesis are not currently available for a sufficiently large sample of Indigenous people over a long enough time.

youth aged 15-29 years. Census data provide a very large number of observations for Indigenous youth, allowing for a detailed examination of labour market outcomes by age, gender and remoteness, as well as direct comparisons with the situation of non-Indigenous youth.

Census data are supplemented with data from the 2014-15 National Aboriginal and Torres Strait Islander Social Survey (NATSISS), to provide more detailed information on job security and work experience – data items that are not available in the census. Non-Indigenous comparisons with the NATSISS were taken from the 2014 General Social Survey Non-Indigenous sample (GSSNI), and the 2014 and 2015 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. With the exception of the HILDA Survey, all data sources were accessed using the ABS Tablebuilder tool.

Several indicators of labour market outcomes for youth are examined. The employment rate measures the proportion of the population who were employed for at least one hour in the week before the census. The unemployment rate is the ratio of unemployment (the number of people who were not employed in the week before the census but were actively looking for work in the four weeks before the census and ready to start work had they found a job) to the labour force (the sum of employed and unemployed persons). While the unemployment rate tells us something about the number of youth who cannot find work, by definition, it excludes those who are not in the labour market and tells us nothing about the activities of those who are not employed. An alternative measure – the proportion of the population who are NEET – is a broader measure of youth inactivity in the labour market.

Several characteristics of the jobs held by young people were also examined: the proportion in full-time employment (working 35 or more hours per week), the proportion in casual employment (working in a job without paid leave entitlements) and the proportion in skilled occupations (occupations with a skill level of one, two or three on the Australian and New Zealand Standard Classification of Occupations. Each of these measures refers to the situation in the main job held.[3]

While in the 2016 Census employment is defined based on working at least one hour in paid employment in the week before the census, earlier censuses also included participation in the Community Development Employment Project (CDEP) scheme as employment. The CDEP scheme was gradually wound back from 2007 (beginning in non-remote areas) and was abolished completely in 2013. Former CDEP participants who were not able to find ongoing non-CDEP work were shifted to unemployment benefits and did not qualify as employed in 2016. The change to the definition of employment will mean that comparisons with previous census data should be interpreted with caution, particularly in remote areas where CDEP participation was still relatively high in 2011.

3 The census does not include information on holding multiple jobs. The NATSISS does include data on holding multiple jobs, but the sample size is not large enough to make reliable estimates of the rates of multiple job holding for Indigenous youth by age, gender and remoteness. The overall proportion of employed Indigenous youth (aged 15–29 years) holding more than one job is 6.4% compared with 9.9% for non-Indigenous youth (2014–15 NATSISS and 2014 GSSNI sample, accessed through the Australian Bureau of Statistics TableBuilder).

Existing research suggests that important differences exist in labour market outcomes between young Indigenous men and women, those in remote and non-remote areas, and those in different age groups within the youth cohort (Dusseldorp Skills Forum 2009, Hunter & Gray 2016, OECD 2016). The paper therefore examined labour market outcomes by gender, remoteness[4] and age simultaneously to highlight heterogeneity in the labour market situation of Indigenous youth.

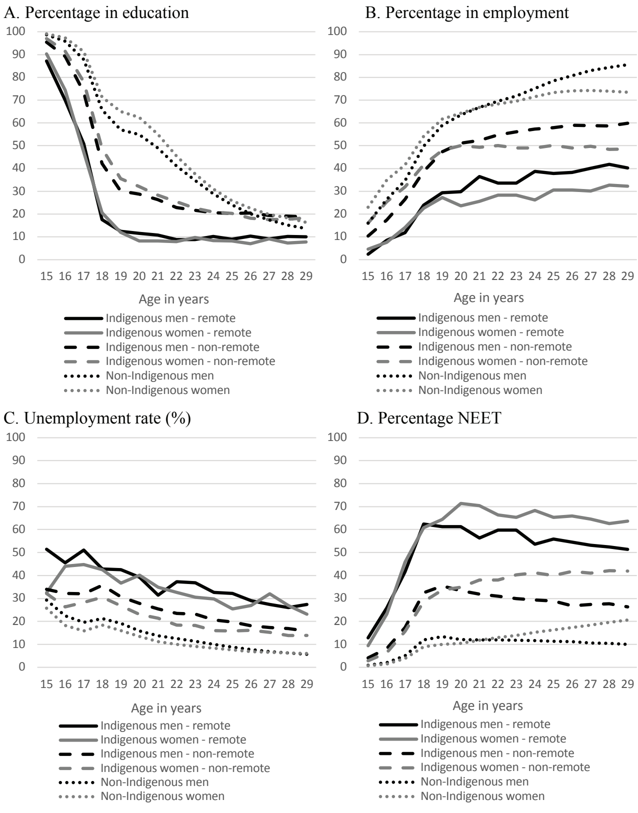
3. Results

Education and employment status

Figure 1 shows the proportion of youth who are in education, employed or NEET, as well as the unemployment rate. Indigenous youth are much less likely than non-Indigenous youth to be in education across all age groups except the late 20s. Education participation is lowest for those in remote areas, where there is little difference by gender. In non-remote areas, women tend to have higher education participation rates than men in their late teens and early 20s, although the difference is small.

4 At the time of writing, remoteness indicators were not available in the 2016 Census, so this paper classifies 2016 Census Mesh Blocks, and therefore respondents, using remoteness areas based on the 2011 Census.

Figure 1. Education and labour force status, by gender, age, remoteness and Indigenous status



Notes: Education, employment and NEET rates are as a percentage of the population. Unemployment rate is as a percentage of the labour force. Education includes those in full-time and part-time study. Employment includes those who are studying and working concurrently. NEET includes those who are neither employed nor studying.
Source: 2016 Census

By contrast, there are clear gaps in the employment rate by gender as well as by Indigenous status and remoteness. Gender gaps in employment appear for Indigenous people in remote areas as early as 19, when men become more likely to be employed than women. In non-remote areas, Indigenous women in their teens have a slightly higher employment rate than men, but this situation reverses around age 20, and occurs a few years later for non-Indigenous youth. By age 20, around half of Indigenous people in non-remote areas and a quarter of those in remote areas are employed.

The unemployment rate is consistently higher for Indigenous youth, and highest in remote areas. Teenagers face the highest unemployment rate, at more than 40 per cent for Indigenous youth in remote areas, 30 per cent for Indigenous youth in non-remote areas and around 20 per cent for non-Indigenous youth. The unemployment rate for young men tends to be higher than for women for each of these groups. The unemployment rate falls with age for all groups; however, the ratio of Indigenous to non-Indigenous unemployment remains similar across the age spectrum.

An alternative measure – the proportion of the population who are NEET – shows a very different pattern of labour market disengagement by age. NEET rates increased sharply for teenagers, and then fell only slightly for men and increased slightly for women during their 20s. By their early 20s, more than 60 per cent of Indigenous women in remote areas and 45 per cent in non-remote areas are NEET, compared with around ten per cent of non-Indigenous women. NEET rates are typically lower for men, but Indigenous men are still three to five times more likely to be NEET than non-Indigenous men.

Like for employment rates, gender gaps in NEET rates open up around the time that women begin having children, which tends to be at younger ages for Indigenous than non-Indigenous women (Johnstone & Evans 2012). For example, ten per cent of 15–19-year-old Indigenous women in remote areas have had at least one child compared with 5 per cent of Indigenous women in non-remote areas and one per cent of non-Indigenous women. Likewise, 49 per cent of 20–25-year-old Indigenous women in remote areas have had at least one child compared with 27 per cent of Indigenous women in remote areas and ten per cent of non-Indigenous women.

Youth labour market outcomes vary considerably by regional location. Very few Indigenous teenagers are employed, but employment rates are highest on the coast between Rockhampton, Queensland, and the far south coast of New South Wales, in Melbourne, and in Tasmania. Employment rates increase in those areas for Indigenous 20–24-year-olds, but are also above 40 per cent across much of New South Wales, Victoria, Queensland, southern South Australia, Darwin, Perth and the South Hedland region of Western Australia.

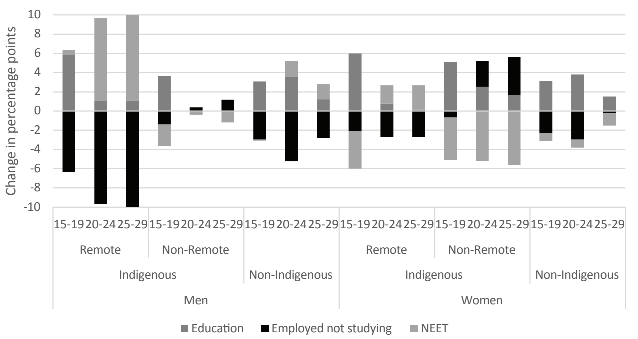
Among 15–19-year-olds, NEET rates are more than 50 per cent in Central Australia (excluding Alice Springs) and lowest in Sydney, the Australian Capital Territory, Victoria, Tasmania and southeast South Australia. However, by age 20–24 years, more than half of all youth are NEET across a wide area of the Northern Territory, Western Australia, Queensland, South Australia and western New South Wales, with particularly high NEET rates in Kununurra and northern parts of the Northern Territory. The lowest NEET rates are found in capital cities where educational opportunities are better, and where labour markets tend to be more developed (albeit with greater competition and often higher rates of discrimination). NEET rates and employment rates are typically inversely related, but some areas – notably Queensland and South Hedland in Western Australia – have relatively higher NEET rates coexisting with relatively high employment rates, highlighting the heterogeneity of youth labour market outcomes within each region. The employment and NEET situation for those aged 25–29 years is similar to that of those aged 20–24 years.

Changes in education and employment status, 2011–16

Labour market conditions for young Australians deteriorated between 2011 and 2016, with higher unemployment rates, lower employment rates and university graduates taking longer to find work (Junankar 2015, Brotherhood of St Laurence 2017, Social Research Centre 2017). As mentioned previously, this has been compounded for the Indigenous population with the demise of the CDEP scheme, particularly in remote areas.

The slowing labour market saw a general trend among non-Indigenous youth of declining employment and increased education participation as young people remained in education longer rather than enter a weak labour market (Figure 2). However, the trends for Indigenous youth were somewhat different. The proportion of Indigenous 15–19-year-olds in education increased for all groups, with the biggest increases – of around six percentage points – in remote areas. There were also increases in older youth participating in education in remote areas, and for women in non-remote areas. The increase in education participation among Indigenous youth was typically larger than for non-Indigenous youth.

Figure 2. Change in education, employment and NEET rates between 2011 and 2016



Notes: NEET = not in employment, education or training.
Source: 2016 Census

By contrast, the employment situation deteriorated for Indigenous youth in remote areas, with falls in employment particularly large for men in their 20s. This is likely to be largely due to the winding back of the CDEP scheme, so that former CDEP participants or those who would have entered CDEP after leaving school who did not find non-CDEP jobs were classified in the 2016 Census as unemployed or not in the labour force. This led to an increase in NEET rates in remote areas, although these were somewhat offset by increases in education participation.

In non-remote areas, employment fell only for the youngest Indigenous cohort (15–19-year-olds), and this appears to be due to greater numbers staying on at school or participating in post-school education. For those in their 20s, employment rose: by around one percentage point for men and three points for women. Combined, greater education participation and better employment outcomes saw NEET rates fall (often quite dramatically) across all non-remote Indigenous cohorts, with results particularly strong for women.

Employment among students

Working part-time has always been an important way for students to supplement their income and gain valuable labour market experience. On balance, the evidence has tended to show that while working long hours is associated with poorer education outcomes, working low to moderate hours is associated with improved education and labour market outcomes (Robinson 1999, Vickers et al. 2003). Around one-third of students aged 15–29 years are employed. In non-remote areas, similar proportions of Indigenous and non-Indigenous students work: around 30 per cent of men and 38 per cent of women. However, employment rates are much lower for Indigenous students in remote areas, where only around one in ten students work.

Student employment rates vary considerably by geography and the type of educational institution that students attend (Table 1). Very few Indigenous school students in remote areas work, while those in non-remote areas are less likely to work than non-Indigenous students. A similar pattern is evident for students at vocational colleges, albeit with much higher employment rates. However, among tertiary students, Indigenous employment rates are considerably higher than for non-Indigenous students. This may reflect the older average age of Indigenous university students and their greater propensity to study part-time (Crawford & Biddle 2015).

Table 1: Employment characteristics of students aged 15-29 years, by type of educational institution attending

		Men			*Women*		
		Indigenous		*Non-Indigenous*	*Indigenous*		*Non-Indigenous*
		Remote	*Non-remote*		*Remote*	*Non-remote*	
Percentage employed	School	3.3	16.5	23.8	4.2	25.4	32.9
	Vocational	53.5	58.7	63.9	44.2	45.7	51.7
	University	56.5	51.7	46.3	61.5	59.4	56.2
Percentage of employed students working 15+ hours per week	School	20.8	10.3	9.7	21.8	10.1	7.5
	Vocational	95.6	90.9	88.2	92.5	75.7	73.2
	University	75.9	60.2	55.4	87.1	58.2	52.9

Notes: Vocational includes technical and further education institutions.
Source: 2016 Census.

Of those students who work, Indigenous students in remote areas are the most likely to work more than 15 hours per week (Table 1). This is an important finding because previous literature has shown that working long hours while studying is more likely to be associated with problems completing qualifications and going onto further study (Robinson 1999, Vickers et al. 2003). While relatively few school students work long hours, employed Indigenous students in remote areas are around twice as likely to do so as those in non-remote areas. Working more than 15 hours per week is most common for vocational students, with more than 90 per cent of Indigenous vocational students who work working more than 15 hours per week, although this rate is considerably lower for Indigenous women in non-remote areas. Employed Indigenous university students are also more likely to work more than 15 hours per week than non-Indigenous students.

Characteristics of post-school jobs

In this section, the characteristics of jobs held by young people who are not currently studying is examined. Indigenous teenagers who are working have jobs with similar characteristics to those of non-Indigenous teenagers. Similar proportions of Indigenous and non-Indigenous teenagers are employed full-time, with around 60 per cent of men and 40 per cent of women in non-remote areas in full-time work (Table 2). Indigenous women aged 15–19 years in remote areas are more likely to work full-time than their non-Indigenous counterparts. Indigenous teenage workers are also equally or more likely to work in skilled occupations than non-Indigenous workers. Casual employment rates (proxied in Table 2 by jobs without paid leave entitlements) are uniformly high for teenagers, but highest for Indigenous people in non-remote areas, where 71 per cent of employed men and 63 per cent of employed women are in casual jobs. Casual employment is slightly less common for Indigenous teenagers in remote areas, but remains higher than for non-Indigenous teenagers.

Table 2. Post-school job characteristics of employed youth

		Men			*Women*		
		Indigenous		*Non-Indigenous*	*Indigenous*		*Non-Indigenous*
		Remote	*Non-remote*		*Remote*	*Non-remote*	
Percentage employed full-time	15-19 years	62.1	59.2	59.7	50.9	39.2	39.7
	20-24 years	71.8	72.3	75.6	59.4	57.7	64.4
	25-29 years	78.2	81.2	85.2	59.6	60.3	71.2
Percentage without paid leave	15-19 years	58.3	71.1	50.3	60.0	62.5	51.2
	20-24 years	35.0	43.0	34.5	35.3	41.2	31.6
	25-29 years	28.6	22.0	21.6	40.0	37.3	17.8
Percentage in skilled occupation	15-19 years	38.0	38.3	39.5	18.9	16.2	15.3
	20-24 years	41.6	43.4	52.0	28.2	28.6	40.7
	25-29 years	43.9	48.7	63.3	35.9	43.0	58.3

Notes: Excludes those currently studying. Full-time work is defined as working 35 hours or more per week. Denominator excludes those who are currently away from work. Skilled occupations include those at skill level 1, 2 or 3 of the Australian and New Zealand Standard Classification of Occupations classification.
Sources: Data on full-time and skilled employment are from the 2016 Census. Data on paid leave entitlements are from the 2014–15 NATSISS and the 2014 GSSNI.

Indigenous workers in their 20s tend to have longer hours, and more stable and skilled jobs than Indigenous teenagers. However, they also tend to be employed in jobs that are less skilled and secure than those of non-Indigenous workers, with the gap in job attributes typically larger in remote areas. By their late 20s, Indigenous people are around five to ten percentage points less likely to be working full-time than non-Indigenous people. There is little difference in casual employment rates between Indigenous men in non-remote areas aged 25–29 and non-Indigenous men of the same cohort. However, casual employment rates continue to be higher for Indigenous men in remote areas and for Indigenous women, who are more than twice as likely to work in a casual job as non-Indigenous women. Indigenous people in their 20s are also less likely to work in skilled jobs than their non-Indigenous counterparts. By their late 20s, Indigenous youth working in remote areas are around 20 percentage points less likely, and Indigenous youth in non-remote areas around 15 percentage points less likely, to work in skilled occupations than non-Indigenous youth.

These results suggest that Indigenous youth may progress more slowly than non-Indigenous youth into full-time, permanent, skilled employment as they age. However, care should be taken when interpreting the results because they are based on cross-sectional rather than longitudinal data. Educational attainment among Indigenous youth has increased rapidly (Venn and Crawford, 2018; Crawford and Venn, 2018), so younger cohorts are likely to have higher educational attainment than older cohorts, much more so for Indigenous than non-Indigenous youth. This would be reflected in a bigger Indigenous to non-Indigenous gap in job quality for older cohorts than for younger cohorts, which is what we can see in our results. It is likely that, as they age, these more highly educated youth progress more quickly to full-time, non-casual and skilled jobs than their older counterparts did. However, longitudinal analysis is needed to establish the relative importance of transitional and cohort effects.

Unfortunately, no reliable data are available on the wages or earnings of Indigenous youth.[5] However, we expect that Indigenous youth earn lower wages than their non-Indigenous counterparts because they have lower educational attainment, less work experience and are employed in lower-skilled occupations, particularly those in their mid- and late 20s. This, combined with the higher likelihood of working part-time and lower overall employment rates, suggests that Indigenous youth are also likely to have lower total earnings from paid work than non-Indigenous youth.

Do Year 12 graduates do better in the labour market?

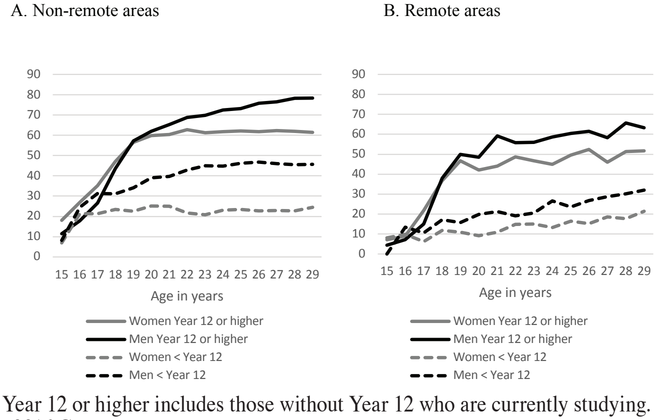
Year 12 attainment rates among Indigenous youth are increasingly rapidly. Census data show that 65 per cent of Indigenous 20–24-year-olds had completed Year 12 or

5 Data on wages and earnings are available from the HILDA Survey, but the sample of Indigenous youth is too small to provide accurate estimates. Census and NATSISS data on income do not allow for wage and salary earnings to be separated from nonlabour income, whereas other Australian Bureau of Statistics surveys of income, wages and earnings do not include Indigenous identifiers. Administrative data from the tax system have information on wages/salaries separate from other earnings but does not have an Indigenous identifier. Data from the Multi-Agency Data Integration Project (MADIP) dataset that links 2011 Census, tax and social security data may shed light on this issue, but had not been linked to the 2016 Census at the time this paper was written.

an equivalent qualification in 2016, compared with 48 per cent in 2006 (Crawford and Venn, 2018). We expect that young people who complete Year 12 have better labour market prospects than those who do not finish school, and that they make a smoother transition into the labour market after finishing their education. This section examines several key indicators of labour market status and the quality of post-school jobs for Indigenous youth by the level of educational attainment. We compared Year 12 graduates (including those who have not finished Year 12 but who are currently studying, and those who have a Certificate II–level qualification) with those who have not completed Year 12 or an equivalent qualification and who are not currently studying.

Employment rates are similar for each group while they are 15 or 16 years old, but from around the age when Year 12 is typically completed, employment rates of those with Year 12 are considerably higher than those without Year 12 (Figure 3). In their 20s, Indigenous male Year 12 graduates in non-remote areas are more than 1.5 times more likely to be employed than those without Year 12, while the ratio is more than 2.5 times for women. Indigenous Year 12 graduates in remote areas have lower employment rates than those in non-remote areas, but their employment advantage over non–Year 12 graduates is even greater: male graduates are around 2.5 times more likely to be employed than non-graduates and women more than three times.

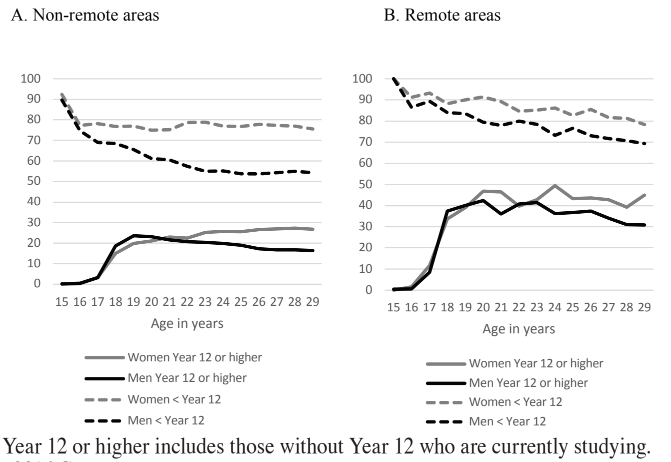
Figure 3. Percentage of Indigenous youth in employment, by gender, age and educational attainment



Notes: Year 12 or higher includes those without Year 12 who are currently studying.
Source: 2016 Census

The difference in NEET rates between those with and without Year 12 is even greater, given that Year 12 graduates are more likely to go on to further study and so may temporarily have lower employment rates while studying. The vast majority of 15–17-year-old Indigenous youth who leave school before completing Year 12 or an equivalent vocational qualification are NEET: around 90 per cent in remote areas and 80 per cent in non-remote areas (Figure 4). This suggests that very few are leaving school to pursue employment. By contrast, relatively few Year 12 graduates are NEET in the years immediately after leaving school: around 20 per cent of 18–20-year-olds in non-remote areas and 40 per cent in remote areas, with similar rates for men and women. In their 20s, early school leavers in non-remote areas are around three times more likely to be NEET than Year 12 graduates, with NEET rates of 50–60 per cent for men and just under 80 per cent for women. In remote areas, NEET rates are higher for both groups, but early school leavers are still twice as likely to be NEET as Year 12 graduates.

Figure 4. Percentage of Indigenous youth not in employment, education or training, by gender, age and educational attainment



Notes: Year 12 or higher includes those without Year 12 who are currently studying.
Source: 2016 Census

As well as having much better chances of employment, Indigenous Year 12 graduates tend to work in higher-skilled occupations and are more likely to work full-time than early school leavers (Table 3).[6] Among teenagers, the differences in post-school jobs by educational attainment are minimal, with men equally likely to work full-time whether they have finished Year 12 or not, and women equally likely to work in skilled occupations. However, among those in their 20s, Year 12 graduates are more likely to work full-time and in skilled occupations than early school leavers, and this difference tends to increase with age.

6 Because of the relatively small sample size, reliable estimates of casual employment rates (jobs without paid leave entitlement) similar to those shown in Table 2 were not available from the NATSISS.

Table 3: Post-school job characteristics of employed Indigenous youth, by highest educational attainment

		Remote		*Non-remote*	
		Year 12 or higher	*Less than Year 12*	*Year 12 or higher*	*Less than Year 12*
Percentage in full-time employment					
Men	15-19 years	41.7	30.2	38.8	38.5
	20-24 years	49.1	32.5	49.7	28.5
	25-29 years	52.0	31.6	58.1	24.4
Women	15-19 years	19.3	23.7	16.8	16.4
	20-24 years	29.6	28.9	31.7	15.9
	25-29 years	40.3	28.7	47.5	23.4
Percentage in skilled employment					
Men	15-19 years	65.6	64.5	57.8	61.7
	20-24 years	76.8	65.7	74.3	67.8
	25-29 years	84.1	72.8	83.9	74.6
Women	15-19 years	53.7	42.9	40.7	33.6
	20-24 years	64.7	46.6	60.2	46.0
	25-29 years	65.8	46.0	63.8	43.9

Notes: Excludes those currently studying.
Source: 2016 Census.

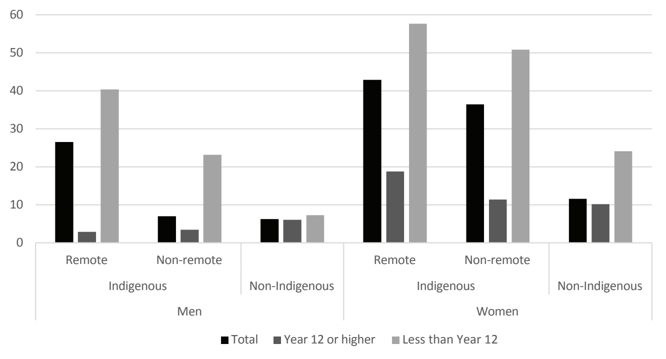
Work experience

It is important to note that NEET status is not always associated with poor outcomes. Young NEETs may be engaged in caring responsibilities, travelling, volunteering or taking time to search for a job that matches their qualifications or interests, none of which are associated, prima facie, with poor labour market outcomes. However, long or repeated NEET spells leave young people at risk of longer-term disengagement with the labour market (e.g. Lucchino & Dorsett 2013).

Analysis in this paper shows that Indigenous youth have considerably lower employment rates and higher NEET rates than non-Indigenous youth at any point in time. We are not able to measure the total time they spend disengaged from the labour market from census data. However, data on work experience taken from the NATSISS and the HILDA Survey show that, over time, accumulated labour market disadvantage during youth manifests itself in stark differences by Indigenous status in work experience for those in their 30s. Work experience is a key determinant of future success in the labour market; unpublished estimates from the 2008 NATSISS show that Indigenous people with five years of work experience have 17–18 per cent more personal income than those without work experience, which is most likely a combination of an increased probability of employment and higher wages for those that are employed.

A large proportion of Indigenous people in their 30s have very little paid work experience (Figure 5). More than 50 per cent of Indigenous women and 40 per cent of men in remote areas have less than five years of paid work experience. Fewer Indigenous men in non-remote areas have low levels of work experience, but the levels remain far higher than for the non-Indigenous population.

Figure 5. Percentage of 30–39-year-olds with less than five years of paid work experience, by highest educational attainment



Sources: Indigenous: 2014–15 NATSISS; non-Indigenous: HILDA Survey, 2014 and 2015 waves

Within the Indigenous population, differences in employment outcomes between Year 12 graduates and early school leavers generate a strikingly different pattern of work experience. By their 30s, early school leavers have considerably less paid work experience than Year 12 graduates. Around 40 per cent of Indigenous men in remote areas and more than 50 per cent of Indigenous women who have not completed Year 12 have less than five years of work experience, compared with less than five per cent of male Year 12 graduates and 11–19 per cent of female Year 12 graduates. Among Year 12 graduates, there is little difference in average work experience by Indigenous status, although women in remote areas are more likely to have less than five years of work experience.

4. Conclusion

Compared with non-Indigenous youth, Indigenous youth are less likely to be employed, studying or both. The employment gap between Indigenous and non-Indigenous youth increases in the years immediately following the end of compulsory schooling and continues to widen into the 20s. Indigenous teenagers are more likely to work in part-time, casual and unskilled jobs than people in their 20s. While the differences in working hours and skilled employment between Indigenous and non-Indigenous teenagers are small, by their late 20s the gap in job quality is much larger. Previous research suggests that their jobs are also less secure, with a greater chance of moving out of employment over time (Hunter & Gray 2016).

Within the Indigenous population, there are stark differences in labour market outcomes for young men and women. While both groups are equally likely to participate in education, employment and NEET rates diverge in the late teens for Indigenous people in remote areas and in the early 20s for those in non-remote areas. After this age, women have considerably lower employment rates and higher NEET rates than men. Women are also less likely than men to work in skilled occupations and more likely to work part-time.

These early labour market experiences are likely to have both immediate and ongoing effects. In the short term, Indigenous youth are likely to have lower and more unstable income than their non-Indigenous counterparts. In the longer term, long periods spent out of work during youth can have scarring effects on future job prospects and wages (Gregg & Tominey 2005; Bell & Blanchflower 2011). This paper has shown that Indigenous Australians in their early 30s have much less labour market experience than their non-Indigenous counterparts, with large disparities also found within the Indigenous population.

Low wages and time spent out of employment are also likely to impede an individual's ability to accumulate savings and wealth, and, ultimately, reduce retirement income. By their 30s, many Indigenous people will have such a large deficit in work experience compared with non-Indigenous people that their chances of future labour market success – and the chances that policy interventions to encourage employment will be successful – are likely to be greatly diminished. The gender differences highlighted in our results suggest that Indigenous women are likely to be worst affected, both in the short and longer terms, with some of this difference caused by greater caring responsibilities.

However, there are signs of improvement in the labour market situation for Indigenous youth. Between 2011 and 2016, large increases in educational participation among Indigenous teenagers saw NEET rates drop for Indigenous men and women in non-remote areas. NEET rates also dropped for Indigenous people in their 20s in non-remote areas (particularly women). These results are especially encouraging given the deteriorating labour market situation for young Australians during this period, particularly among those with lower levels of education. The picture in remote areas is more mixed, largely because the elimination of the CDEP scheme saw employment drop and NEET rates increase. Nevertheless, educational participation for Indigenous people in their 20s increased in remote areas.

Rapid increases in educational attainment among Indigenous youth are also likely to have a positive impact on average labour market outcomes. Indigenous youth who complete Year 12 or a higher qualification have substantially higher rates of employment, lower rates of inactivity, and are more likely to work full-time and in skilled occupations than early school leavers. Combined, these advantages mean that Indigenous Year 12 graduates in their 30s will have substantially more work experience than early school leavers of the same age, contributing to ongoing labour market advantages throughout life.

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Job security perceptions and its effect on wage growth[1]

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Abstract

A concern that low job security is constraining wage growth has been expressed in many countries. In this paper, we use Australian household panel data to analyse the drivers of self-assessed job security and its relationship with wage growth. We construct measures of industry-level trade exposure and occupation-based automation risk to assess the conjecture that technological change and globalisation are leading to fears of job loss. We find that those in jobs with a higher trade exposure or automation risk or those working on a casual or fixed-term contract feel more insecure in their job. However, regardless of one's characteristics, there has been a broad-based fall in job security in recent years that cannot be explained by the model variables. Exploiting the panel dimension of the survey, we find that heightened job insecurity has been a statistically significant but small drag on wage growth. This result is robust to various model specifications.

JEL Codes: C23, F16, J28, J31, O33

Keywords: wages, job security, automation, panel data

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1. Introduction

Workers' perceptions of their own job security may influence how hard they bargain over their wages. Several factors may contribute to these subjective assessments of job security, including labour market conditions, the type of employment contract, union membership status, as well as the potential for their work to be automated or sent offshore. Shifts in these factors could make workers feel less secure in their job and so more likely to accept smaller wage rises. The concern that low job security is constraining wage growth has been expressed across a number of advanced economies recently (Haldane 2017; Lowe 2017), as well as in the United States two decades ago (Greenspan 1997). Yet there has been little research that empirically tests this relationship.

We study perceived (or self-assessed) job security, which is a worker's subjective expectation that they will retain their job. These beliefs – whether justified or not – can influence wage bargaining behaviour. For instance, if an employee believes that their job could be moved offshore, they may accept lower wage rises to encourage their employer to keep the job onshore. It does not matter whether or not the job is eventually moved, because it is this fear of job loss, or perceived contestability of the job, that would keep wage growth contained. This is in contrast to actual (or objective) job security, which is the likelihood that a worker does hold on to their job. Actual job insecurity is typically equated with jobs that have relatively high turnover or are temporary in nature.[3] Determinants of objective job security, such as casualisation and labour market conditions, can contribute to perceptions of job security. Personal circumstances, popular narratives, expectations of the future, and domestic or international events may also play a role.

This paper documents the decline in perceptions of job security in Australia in recent years, the cyclical and structural factors that have driven it, and shows that it explains a small part of recent weak wage growth. Like many advanced economies, Australia has experienced low wage growth in recent years that is difficult to explain in a conventional Phillips curve framework. As such, the Australian experience can shed light on wage dynamics more broadly. We use data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which is a household panel survey that asks respondents about their feelings of job security and perceived likelihood of job loss. Along with questions on income, job and personal characteristics, this allows us to track whether workers who felt more secure in their job received a higher pay rise than their counterparts who were more anxious about their job security. We explore the existing literature on this topic in the next section. In Section 3 we describe the data and construction of the trade exposure and automation variables used. Next we explore the determinants of job security and its relationship to wage growth. We then perform a series of robustness checks, including accounting for selection and endogeneity effects. Section 6 concludes.

3 See de Ruyter and Burgess (2000) for an overview of the various dimensions of the job security definition.

2. Previous literature

Determinants of job security

The literature on the determinants of perceived job security in Australia is small. Some of the HILDA Statistical Reports have included a broad overview of the determinants of perceived job security, using the measure of the expected probability of losing one's job (Heady and Warren, 2008; Wilkins, 2015). Taken together they find age, tenure, education, hourly wage, occupation and industry influences job security perceptions, whereas gender and union membership do not. In addition, Borland (2002) found that perceived job-security moves pro-cyclically with the business cycle. Previous work using HILDA has found that job insecurity can be explained by regional unemployment, casual work, fixed term jobs (Milner et al. 2014) and job tenure (Green and Leeves 2013).

The international literature supports this, with job insecurity in the UK, for example, being partially explained by temporary contracts and short tenures (Green 2003). Other characteristics that are found to reduce perceived job security overseas include previous unemployment experience, regional unemployment, having a job that is manual, in the private sector, being male and being older (Böckerman 2004; de Bustillo and de Pedraza 2010; Campbell et al. 2007; Demoussis and Giannakopoulous 2007; Green, 2003; Hübler and Hübler 2006; Lurweg 2010; Näswall and de Witte 2003). All these studies examine this question with household cross-section or panel datasets. Despite globalisation and automation often being cited as drivers of job insecurity, there is little quantitative research to show this. Lurweg (2010) explores the relationship between globalisation and job security fears, finding that those in trade-exposed service industries in Germany had greater perceived and realised job insecurity. Vieitez et al. (2010) studied workers at a particular factory in Spain and showed that the types of technology used in their job influenced their perception of job security.

Job security and wages

The relationship between job security and wages can arise through either a bargaining framework model or a compensating wage differentials model. Under the bargaining model, job security influences the relative bargaining strength of employees (or unions) and employers. Greater perceived job security by employees raises their relative bargaining power, so they can demand higher wages; as such, wages and job security are complements and have a positive relationship. Bargaining models tend to be specified in terms of wage levels, but wage growth easily fits within this framework. The alternative framework sees monetary compensation (wages) and non-monetary features (such as job security) as substitutes within a total compensation package. For example, government employees may accept lower wages as a trade-off for greater job security, whereas a professional services firm may provide higher monetary compensation due to employment prospects fluctuating with the business cycle. However, this mechanism is more relevant for wage levels rather than wage growth.

Hübler and Hübler (2006) test both these theories and find support for the bargaining hypothesis. Using household-level panel data, they find that the level of job insecurity negatively affects wage levels, and the change in job security negatively affects wage growth, in Germany and the United Kingdom, although the growth effect was not robust. Also using household level data, Campbell et al. (2007) found that job insecurity lowers the rate of wage growth for men, but not women, in the United Kingdom. For the United States, Aaronson and Sullivan (1998) use regional data to augment a wage Phillips curve with average regional perceived job security and find there is a negative, but not statistically significant, relationship between wage growth and fears of job loss. The relationship between perceived job security and wage growth has not been examined in detail for Australia.[4]

Before examining the role of self-assessed job security on wage growth, it is helpful to assess whether job security is useful in predicting unemployment itself. The literature shows that perceived job security can modestly predict job loss (Dickerson and Green 2012; McGuinness et al. 2014). However, workers tend to overestimate their probability of job loss. This overestimation lends credence to the idea that expectations of potential job loss can put downward pressure on wages, independent of actual labour market conditions.

3. Data

We use the HILDA Survey from 2001 to 2016. It is a representative household panel dataset that includes several measures of self-assessed job security, as well as labour income and a vast array of personal and job characteristics.[5] As such, we can use it to track workers and measure whether their levels of job security influenced their growth in wages over the following year. We also incorporate data from the Australian Bureau of Statistics (ABS) and Frey and Osbourne (2017) to measure risks of offshoring and automation, as well as data on state-level consumer price growth from the ABS.

The HILDA survey asks all employees about job security.[6] This leaves us with 124,617 responses over 16 years across 20,882 individual employees. For the analysis on determinants of job security we take no other exclusions to our sample. Nonetheless, with missing observations for some explanatory variables in the regression, we have 100,255 observations over 18,621 individuals. The summary statistics and graphs are shown with population-weighted data, while the regressions are unweighted. For the analysis on wage growth we omit those observations where the respondent reports zero wages or hours in a year. We also exclude those that changed jobs during the year.[7] A person may change jobs for many reasons and this will impact on their measured wage

4 Examining the relationship between job security and wage *levels*, in a compensating differentials analysis, Kelly, Evans and Dawkins (1998) found that job security matters most to those on low incomes.

5 The HILDA survey tracks households and individuals on an annual basis. It incorporated a top-up sample in 2011, to account for issues relating to attrition and recent migrant arrivals. The response rates are high, around 95 per cent for previous responders and 80 per cent for new individuals. For more information see Wilkins and Lass (2018) and references within with respect to sampling methodology.

6 As such, employers, own account workers and contributing family members are excluded.

7 A job change can be a change in employer, new occupation, industry etc. We have taken a self-assessed measure of job change in this paper, but the results are robust to several definitions available using the HILDA survey.

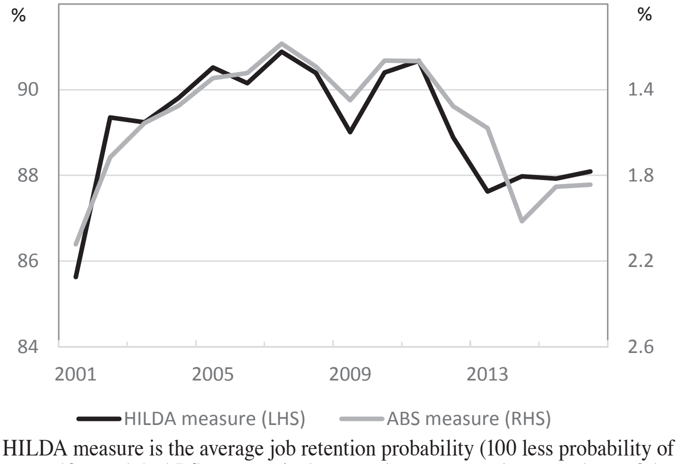
growth in ways that may or may not be related to job security concerns. In particular, we are interested in understanding how job security impacts an employee's ability to bargain for wage growth in their current job. This results in a reduction of 16 per cent of the observations. However, the robustness check in Section 5 demonstrates that it does not impact the overall conclusion. Overall, the sample for the wage regression falls to 65,864 observations, covering 13,707 employees.

Measures of subjective job security

The HILDA survey includes a range of indicators that can be used to gauge a worker's perception of their own job security. The key measure we focus on is a probability measure, which asks respondents the percentage chance of losing their job over the next 12 months. We invert this measure to frame it as the self-assessed probability of retaining one's job over the next year. That is, the probability of job retention is 100 less the stated probability of job loss. This measures perceptions of short-term job security, which should be more correlated with near-term wage outcomes, as opposed to concerns of future job loss through long-term changes in the structure of the economy.

The variable's movements closely match a measure of the probability of job retention from the Australian Bureau of Statistics (Figure 1). This gives some external validity that this measure is a sensible one to use. An alternative variable is one that measures subjective job security satisfaction. It is an ordinal measure, which asks how satisfied one is with their job security on a scale of 0–10. This ordinal job security satisfaction measure also moves closely with the probability measure and we examine its determinants in Section 5 for robustness.

Figure 1: Job security perceptions

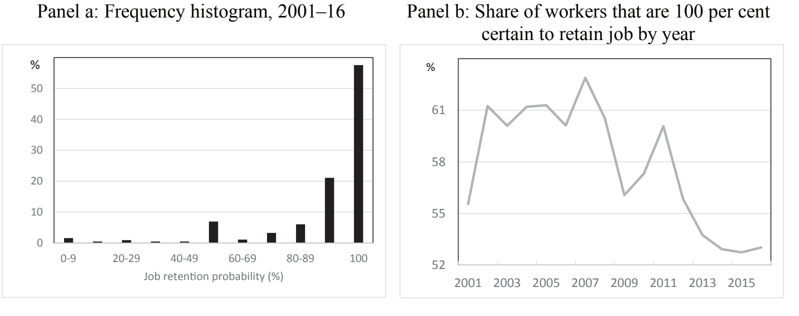


Notes: HILDA measure is the average job retention probability (100 less probability of job loss over the next 12 months). ABS measure is the annual average employment share of those expecting to leave their employer over the next 12 months due to downsizing/ closing or is a temporary worker.
Sources: ABS cat no. 6291.0.55.003, HILDA Survey Release 16.0.

While job security perceptions do not vary much, they appear to move in line with changes in overall labour market conditions. Job security is relatively low when there is ample spare capacity in the labour market or underutilisation in the economy. There was a brief spike in the unemployment rate and slowdown in growth in 2001. Low subjective job security at the time appears to reflect this. Aggregate wage growth also tends to be lower when workers felt less secure on average the year earlier. This suggests that perceived job security moves with the business cycle. As such, it is unclear whether job security can help explain movements in wage growth over and above general labour market conditions. These issues are explored in this paper.

Workers tend to have a high rate of self-assessed job security; the probability of expected job retention averages 89 per cent across the whole sample period. The variable is also highly skewed (Figure 2a). Almost 60 per cent of workers said they had a 100 per cent chance of retaining their job in the next 12 months. For those who have some uncertainty around job loss, the probability they assign to job retention is still high, with less than 4 per cent of workers expecting more than a 50 per cent chance of job loss. This highlights that only a small share of the workforce has concerns about holding on to their job over the following year.

Figure 2: Subjective probability of job retention over the next year



Sources: HILDA Survey Release 16.0.

When we model the determinants of job security, we transform this probability measure into a dummy variable. We refer to it as 'job retention certainty' and it is equal to 1 if a worker is 100 per cent sure of retaining their job over the next year, and 0 otherwise.[8] We do this for a number of reasons. First, the job security dependent variable is non-normally distributed, being bounded by 0 and 1 and highly skewed. As such, making inferences on that measure would be problematic. Second, respondents may interpret the in-between probabilities differently (say, 90 per cent probability of job retention may feel high for one person, but low for another). The bunching at round numbers suggests there is difficulty in interpreting the probabilities. Finally, much of the variation in this measure over the past decade has been in the proportion

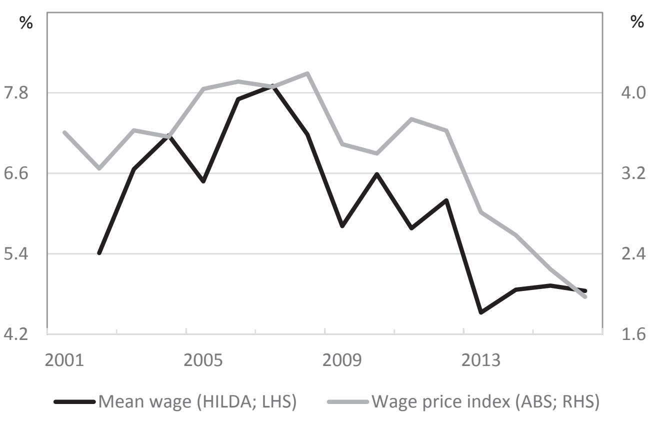
8 Sensitivity around this cut-off is examined in Section 5.

of workers that are completely certain that they will keep their job (Figure 2b). At its peak in 2007, 63 per cent of workers had absolute certainty that they would keep their job over the next year. This proportion troughed at 53 per cent in 2016. When we turn to the wage growth model, we use the raw probability variable, which goes from 0 to 1. This allows us to retain the full information from the variable. The non-normality of the distribution is no longer a concern as it is an independent variable, in this case.

Measuring wage growth

We use the HILDA data to calculate annual growth in average hourly earnings for each worker. We take weekly gross wages and salary divided by hours usually worked per week in one's main job. We omit observations where the respondent reports zero wages or hours in a year. These are log-differenced at the individual level and the highest and lowest 5 per cent of the hourly wage growth distribution for each year are winsorised, to mitigate the influence of outliers.[9] The 25th percentile, median, mean and 75th percentile of wage growth over the whole period is -6.9, 4.6, 5.7 and 18.2 per cent, respectively. Our measure tracks aggregate wage growth measured by the ABS fairly well, although it has been more stable of late (Figure 3).

Figure 3: Annual wage growth



Notes: HILDA measure is calculated as the mean of the log difference in wage per hour worked in one's main job.
Sources: ABS cat no. 6345.0, HILDA Survey Release 16.0.

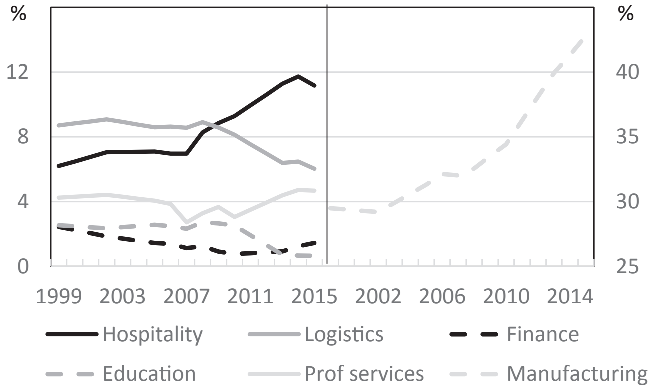
Measuring trade exposure and automation risk

Two factors that are commonly suggested to influence both actual job loss and perceptions of job security are globalisation and technological change. An industry's exposure to global trade can be measured using its import penetration ratio. These ratios are calculated as the import share of the total output supplied by an industry. It represents the foreign

9 That is, we take ln[W(i,t) – W(i,t-1)] for each year t and individual i.

share of the competition that firms in that industry face in the domestic market. Data are available from the ABS input-output tables for each industry subdivision across a range of financial years, with data for any missing years interpolated linearly. The import penetration ratio of the manufacturing industry is relatively high and has been increasing over the past decade as domestic demand for manufactured goods is increasingly met by imports (Figure 4). The hospitality and professional services industries have also faced rising import penetration, whereas trade exposure in the education industry is lower and has declined somewhat in recent years.

Figure 4: Import penetration ratios by supply industry



Notes: Selected industries; financial year; missing data are linearly interpolated.
Sources: ABS cat no. 5209.0.55.001.

Overall, the import penetration ratios of most industry subdivisions have been increasing in recent years. However, the effect of this on the aggregate labour market has been offset by stronger employment growth in industries that are less exposed to international trade. As a result of this compositional shift, the trade exposure faced by the representative worker has been little changed over the past decade, having declined over several years prior to that.

Another source of job insecurity is the risk that technology could be used to automate tasks that were previously completed by skilled workers. We capture this risk using the computerisation scores devised by Frey and Osborne (2017). These scores measure the likelihood that an occupation's tasks could be automated using current computing technology.[10] We map these scores to the Australian unit group occupations

10 A shortcoming of the Frey and Osborne (2017) approach is that the automation scores depend on the initial subjective decisions about which tasks have the potential to be automated using current technology (Borland and Coelli 2017). The method also does not allow for technology to complement labour and change the nature of an occupation. Therefore, these scores may not accurately measure the likelihood for each occupation to be automated. Nonetheless, the scores are well suited to measuring general perceptions of technological job loss, which is relevant to the topic of this article.

to capture the potential for each of these jobs to be automated. The scores are not available over time and so we cannot evaluate how job security is being affected by the pace of technological change. As expected, routine occupations are the most at risk of automation, and non-routine cognitive jobs are the least automatable (Table 1).[11] The automaton risk among non-routine manual occupations is varied, which includes service jobs, particularly in the health and hospitality industries. As is the case with industries highly exposed to global trade, occupations that have a greater potential to be automated have been decreasing as a share of total employment in recent years (Edmonds and Bradley 2015).

Table 1: Automation score by occupation type, weighted by population

Occupation type	*Median*	*25th percentile*	*75th percentile*
Routine cognitive	0.91	0.78	0.96
Routine manual	0.75	0.64	0.81
Non-routine manual	0.48	0.29	0.66
Non-routine cognitive	0.08	0.04	0.17

Sources: ABS Cat no. 1220.0, Frey and Osbourne (2017), HILDA Survey Release 16.0, author's calculations.

In the models, the trade exposure and automation variables are entered into the models linearly (quadratic terms were statistically insignificant).

Trends in job security

This section explores how economic conditions, structural factors and individual characteristics affect perceptions of job security in Australia. Perceived job security can be influenced by factors such as industry sector, occupation and work arrangements, as well as more general concerns about globalisation and automation. Figure 5 illustrates just two of these dimensions, related to the issues of offshoring and bargaining power, but we discuss the trends across additional factors too. Perceived job security is lower in industries that are more exposed to international competition.[12] The decline in perceptions of job security in recent years is a touch larger in more trade-exposed industries, but the fall has been broad based across all industry sectors. A fall in job security perceptions in business services has occurred despite strong employment growth in that sector, which suggests that labour market conditions are not the only driver of job security concerns.

11 The routine–non-routine and cognitive–manual occupation classification definitions for Australian data are described in Heath (2016).
12 An industry is classified as having high trade exposure if the import penetration ratio is above 5 per cent.

Figure 5: Job security by select job characteristics, share with job retention certainty, weighted by population

Sources: ABS cat no. 5209.0.55.001, HILDA Survey Release 16.0.

Union members and non-casual workers feel more secure in their job, relative to their non-union and casual counterparts. There is only a small difference in the job security of part-time and full-time workers. Those that are satisfied with their hours have higher job security than those wanting fewer or more hours, but concerns about job security have declined for both types of workers. Finally, those in regions with higher unemployment on average tend to have lower job security.

Despite some differences in the level of job security perceptions across various dimensions, a decline in these perceptions is apparent for almost all job characteristics, regardless of industry, occupation, contract type or union membership. The decline has also occurred across a range of personal characteristics, such as age, sex and educational attainment, as well as across most states. Overall, these patterns suggest that job and personal characteristics influence the *level* of perceived job security, but that the *decline* has been experienced across the board.

4. Job security trends, determinants and its relationship to wage growth

Determinants of job security

The descriptive analysis above suggests that a range of factors influence job security perceptions. To examine their relative importance, we estimate a random effects probit model for the job certainty dummy variable. We explore alternative panel data models and measures in Section 5. The model is estimated on an unbalanced panel of workers from 2001–2016. We include a range of job, firm and personal characteristics. The summary statistics for these independent variable and coefficient estimates are shown in Table 2.[13] We have not included interaction terms.

13 Summary statistics are shown for the wage regression sample. Concepts such as full-time/part-time and contract type used in the HILDA survey are based on definitions from the ABS (2018).

Table 2: Regression coefficient estimates – random effects models, 2002-16

	Variable Summary[a]		*Job Security*[b] *Probit model*		*Wage Growth*[c] *Linear model*	
	Mean	*S.D.*	*Coefficient estimate*	*S.E.*	*Coefficient estimate*	*S.E.*
Job security (t-1)[d]	0.92	0.17	--		1.62***	0.52
Economic Factors						
Unemployment (by region)	5.21	1.02	-0.03***	0.01	0.19	0.13
Trade exposure	0.05	0.11	-0.25***	0.07	-1.57**	0.71
Automation	0.48	0.35	-0.08***	0.03	-1.06***	0.35
State consumer price growth	2.50	0.85	--		0.61**	0.30
Industry (base: Goods production)[e]						
Business services	0.16		-0.09***	0.03	-0.38	0.30
Household services	0.38		0.16***	0.03	-1.03***	0.29
Goods distribution	0.18		0.08***	0.03	-1.12***	0.29
Other	0.11		0.08**	0.03	-0.40	0.34
Occupation (base: Non-routine cognitive)						
Routine manual	0.23		0.17***	0.03	0.19	0.31
Non-routine manual	0.15		0.09***	0.03	-0.45	0.28
Routine cognitive	0.25		0.10***	0.03	-0.40	0.31
Job Characteristics						
Lost a job in the past year	--		-0.28***	0.03	--	
Changed jobs in the past year	--		-0.09***	0.01	--	
Promoted in the past year	0.11		0.13***	0.02	3.61***	0.29
Full time	0.70		0.08***	0.02	-4.10***	0.23
Casual	0.17		-0.13***	0.02	-0.08	0.30
Temporary contract	0.08		-0.27***	0.02	0.54*	0.32
Ever work from home	0.19		0.06***	0.02	-0.85***	0.23
Number of years in a job	8.22	8.07	0.01***	0.00	-0.02*	0.01
Trade union member	0.32		0.01	0.02	0.07	0.18
Firm-type (base: private sector)						
NGO	0.09		0.10***	0.03	0.14	0.32
Public	0.30		0.19***	0.02	0.51**	0.23
Firm-size (base: small firms)						
Medium	0.32		-0.08***	0.02	0.08	0.20
Large	0.37		-0.12***	0.02	0.15	0.20
Hours preference (base: same)[f]						
Fewer	0.27		-0.09***	0.01	2.89***	0.20
More	0.12		-0.08***	0.02	-2.24***	0.30
Personal Characteristics						
Female	0.50		0.35***	0.02	-1.34***	0.17
Primary language is not English	0.08		-0.02	0.04	1.30***	0.31
Born outside of Australia	0.19		0.05	0.03	-0.58***	0.21
Outside a capital city	0.38		0.15***	0.02	-0.28	0.18
Age (base: over 55s)						
Under 25	0.14		-0.32***	0.03	6.39***	0.33
25 to 39	0.32		-0.23***	0.03	1.23***	0.23
40 to 54	0.38		-0.15***	0.02	-0.34*	0.20
Education (base: high school)						
Diploma or Certificate	0.33		-0.03	0.02	-0.04	0.17
University	0.30		-0.25***	0.03	-0.31	0.22

Continued / ….

	Variable Summary[(a)]		*Job Security*[(b)] *Probit model*		*Wage Growth*[(c)] *Linear model*	
	Mean	*S.D.*	*Coefficient estimate*	*S.E.*	*Coefficient estimate*	*S.E.*
State (base: NSW)						
Victoria	0.25		-0.02	0.02	-0.59***	0.19
Queensland	0.21		0.02	0.03	0.17	0.20
South Australia	0.09		0.15***	0.03	-0.32	0.27
Western Australia	0.09		0.35***	0.04	0.44	0.27
Tasmania	0.03		0.03	0.05	-0.62	0.38
Northern Territory	0.01		0.03	0.09	0.43	0.83
ACT	0.02		0.07	0.06	0.97**	0.49
Year (base: 2002)						
2003	0.06		-0.06**	0.03	0.69	0.63
2004	0.06		-0.04	0.03	1.14*	0.60
2005	0.06		-0.07**	0.03	1.07*	0.58
2006	0.06		-0.10***	0.03	1.68***	0.59
2007	0.06		-0.03	0.03	2.25***	0.64
2008	0.06		-0.13***	0.03	0.17	0.68
2009	0.06		-0.27***	0.03	1.55**	0.65
2010	0.06		-0.20***	0.03	0.53	0.54
2011	0.06		-0.20***	0.03	-0.14	0.54
2012	0.08		-0.36***	0.03	0.94	0.66
2013	0.08		-0.40***	0.03	-0.37	0.54
2014	0.08		-0.43***	0.03	-0.68	0.52
2015	0.08		-0.41***	0.03	-0.00	0.67
2016	0.09		-0.45***	0.03	-0.13	0.73
Constant	--		0.60***	0.03	4.30***	1.54
Pseudo log-likelihood	--		-56415.32		--	
R-squared	--		--		0.02	
Rho	--		0.48		0.02	
Individuals	13,707		18,621		13,707	
Observations	65,864		100,255		65,864	

***, ** and * show statistical significance at the 1, 5 and 10 per cent level, respectively.
Standard errors are clustered by individual.

(a) Summary statistics shown for the wage regression sample. Standard deviations are shown for continuous variables only; remaining variables are dichotomous.
(b) Dependent variable equals 1 if 100 per cent certain to retain job over next year; 0 otherwise.
(c) Those that changed jobs over the year are omitted. The dependent variable, wage growth, is calculated as the log difference of weekly gross wages and salary divided by usual weekly hours worked in one's main job. It is winsorised at the top and bottom 5 per cent of the distribution for each year.
(d) Self-assessed probability of retaining job over the next year.
(e) Business services include: professional, scientific & technical; financial & insurance; administration & support; rental, hiring & real estate; and information, media & telecommunications. Household services comprise: accommodation & food; education & training; health care & social assistance; arts & recreation; and other services. Goods-production includes: mining; construction; manufacturing; electricity, gas, water & waste. Goods-distribution comprises: transport, postal & warehousing; wholesale trade; and retail trade. Public administration and agriculture is in the 'other' category.
(f) Lagged one year in the wage growth model.

Sources: ABS cat no. 1220.0, ABS cat no. 5209.0.55.001, Frey and Osborne (2017), HILDA Survey Release 16.0, author's calculations

We include time dummies for each survey year, allowing them to capture any non-observed determinants that vary over time and are common across individuals. This can include macroeconomic, technological, legislative and international factors. However, we attempt to isolate labour market slack by exploiting regional variation in the unemployment rate, where unemployment is included for the 13 ABS major statistical regions. The regions are larger than the ideal concept for this analysis of a local labour market. Nonetheless, there remains substantial variation in unemployment over time and by region (given the resources boom and financial crisis periods are included).

The results confirm that labour market conditions are an important influence on job security. Higher unemployment modestly contributes to lower job security, where a 1 percentage point rise in the unemployment rate is associated with a 1 percentage point fall in the probability of feeling certain about job retention (Table 4, Model I, shows marginal effects for select variables). Those who would prefer more hours have a lower expectation of job retention. This suggests underemployment may weigh on feelings of job security, although those wanting to work fewer hours also had low job security.

Trade exposure and automation have the expected significant negative relationship with perceived job security. In terms of marginal effects, an industry with no exposure to international competition has job retention certainty about 3 percentage points higher than one in which imports make up around one-third of an industry's total supply (such as some of the manufacturing industries). After controlling for trade exposure and other factors, those in the goods production and business services sectors still have relatively low perceptions of job security, with those in household services having relatively high security. The average likelihood of feeling certain about job retention falls 3 percentage points when moving from an occupation with no automation risk to one that has the highest likelihood of being automated. Once automation risk is controlled for, being in a routine or manual occupation contributes to higher job security, in contrast to what is suggested by the summary statistics.

Regarding other job and personal characteristics, those that are associated with higher job security include: working full time, having a permanent position, having longer tenure, being female, being older, having less formal education and living outside a capital city.[14] The effect of union membership on job security is not statistically significant. Thus, the difference in average job security perceptions between union and non-union members can be accounted for by their job and personal characteristics. However, there are a number of surprising results. For example, those in non-routine cognitive occupations have relatively low job security and those in regional areas have higher job security. This suggests there may be some issues with the job security measure on some dimensions. Nonetheless, for the most part the results are as expected and particularly so for our key variables of interest.

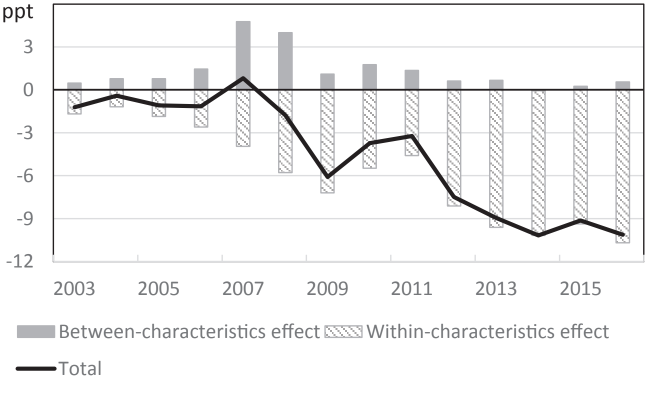
14 Some of these characteristics may be affected by selection bias. For instance, those groups with lower rates of labour market attachment – such as females and older workers – may leave the workforce if they cannot find secure employment, which would bias the results. Selection bias is examined in Section 5.

The time dummy variables are estimated to be increasingly negative in recent years. This suggests that there are aggregate factors weighing on job security that are not being captured by the other variables in the model.

Overall, the model estimates reveal the average propensity to feel secure for each personal, firm or job characteristic over time. However, these feelings of job security can and do change over time. Additionally, the changing composition of the workforce will affect aggregate job security. For instance, an increase in the share of part-time employment would be associated with more people feeling insecure, and so lower overall job security, all else being equal. A shift in the labour market to jobs that are less likely to be automated will increase the share of people feeling secure. As such, we decompose the change in job security over time into these within-characteristic and between-characteristic, or compositional, effects. By estimating the model for each year we can disentangle the roles of the within and between effects on aggregate job security. We conduct a pooled two-fold Oaxaca-Blinder decomposition for the probit model (Jann 2008). We run separate models for each year and compare the change in job security to the 2002 group.

The decline in job security has been broad based across the characteristics we examine in the model (Figure 6). This is highlighted by the persistently negative within-characteristics effect, and confirms the broad-based decline in job security shown by the trends and negative year fixed effects in the model. Compositional change had been working in the opposite direction, with employment moving towards characteristics that generally make workers feel more secure, providing a boost to aggregate job security. The drag from perceived job security within characteristics has been growing since around 2004, with the offset from compositional shifts diminishing over the post-crisis period.

Figure 6: Contributions to annual change in probability of job retention certainty, deviation from 2002



Sources: ABS cat no. 5209.0.55.001, HILDA Survey Release 16.0.

Job security and wage growth

Perceived job security is associated with higher wage growth the following year. Splitting job security into groups from low (0 per cent) to high (100 per cent secure), there is a rough positive relationship with wage growth in the following year (Table 3). A nonparametric K-sample test on the equality of medians shows the difference is statistically significant. However, the fall in wage growth in recent years has been experienced by both secure and less secure workers. And this simple correlation could be a result of a myriad of factors, including simply that higher insecurity is associated with higher unemployment, which may lead to lower wage growth.

Table 3: Median annual wage growth by lagged job security, 2002–16

Probability of Job Retention (%)	*Median Wage Growth (%)*
0–19	3.32
20–39	3.03
40–59	3.73
60–79	4.08
80–99	4.68
100	4.71
Equality of medians test	$\chi^2(5) = 19.5$; p-value=0.00

Notes: Those who changed jobs over the year are omitted.
Sources: HILDA Survey Release 16.0.

We examine this relationship by regressing annual hourly wage growth at time t on self-assessed probability of job retention at t-1. We use the full continuous probability measure of job security. The control variables included are the same as those used in the job security model above. The few differences are the: (1) inclusion of inflation – measured as growth in each capital city's consumer price index – as it should influence nominal wage growth; and (2) omission of those that changed jobs during the year. Therefore this model captures the effect of job security perceptions on wage growth over and above the many factors that can influence job security itself. Most controls in the model are included contemporaneously with the wage growth that was received in that year. However, we take the lag of job security, as our hypothesis is that one's perceptions will influence their wage negotiations in the *coming* year. Furthermore, we want to mitigate endogeneity, in that one's security perceptions are influenced by their annual pay outcomes.

We use random effects estimation, but report a suite of alternative models in Section 5. The Breusch-Pagan LM test recommends random effects over pooled OLS (χ^2= 1098.40, p-value = 0.00).

The results show that a higher perceived likelihood of job retention has a statistically significant positive relationship with wage growth over the following year (Table 1). A 1 percentage point decline in job security is associated with a 0.02 percentage point decline in wage growth. To put this into context, a 1 standard deviation fall in job security (a change of 17 percentage points) is associated with a 0.28 percentage point decline in annual wage growth (i.e. 1.62 x 0.17). However, this finding explains little of the fall in average wage growth observed in recent years. From 2010 to 2014 (the most recent peak and trough), average self-assessed job retention probability declined by only around 3 percentage points. This explains around 0.05 percentage points of the 1 percentage point fall in average wage growth over the corresponding period.

Automation risk and trade exposure are both found to significantly contribute to lower wage growth. Despite the negative relationships, these measures have not been substantially weighing on aggregate wage growth. This is because, in recent years, employment growth has been shifting away both from industries with a higher trade exposure and occupations that are more easily automated.

Several variables that capture economic and labour market conditions were statistically significant. The coefficient on inflation is significant, and subdued inflation explains a sizeable amount of the fall in average wage growth in recent years. Those who would prefer more hours have lower wage growth in the subsequent year, which suggests an additional role of underemployment in suppressing wage outcomes. Surprisingly, unemployment has a weakly positive relationship with wage growth, though it does have the expected negative effect when the time dummy variables are excluded. Another surprising result is that average wage growth has been much higher for part-time workers than full-time workers (even in the raw data). With the wage level being higher for full-time workers, this suggests some convergence in part-time wages to full-time. This result could be explored further in future work.

5. Robustness checks

An alternative measure of job security

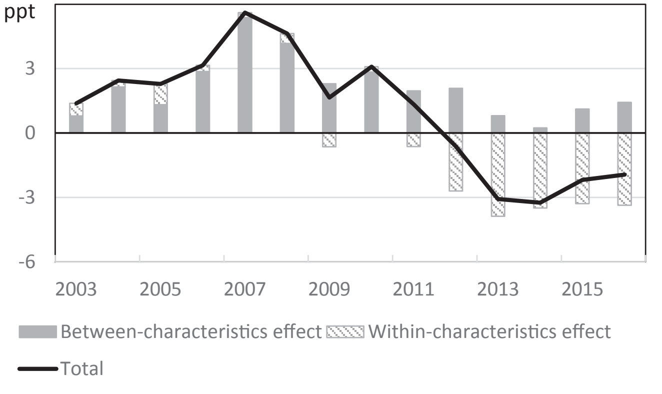
We introduced an alternative self-assessed job security measure in Section 3. It is an ordinal measure of how satisfied a worker is of their job security on a scale of 0–10. It is similarly skewed as the continuous job security measure used in the main analysis, with the vast majority of workers feeling secure. Almost a quarter of workers have the highest job security, 44 per cent chose the next two levels (i.e. 8 or 9 out of 10), close to a quarter chose the middle of the spectrum and only 8 per cent chose the bottom 5 categories. To model this variable, we divide it into three categories: high (8–10), medium (5–7) and low (0–4) job security satisfaction categories. The variable moves closely with the main job retention certainty measure and wage growth over time.

We estimated the determinants of job security satisfaction using a random effects ordered probit. The key results are similar to the main results above.[15] Unemployment, trade exposure and automation have a negative relationship with job security, although the latter is statistically insignificant. Those in routine manual roles had significantly lower perceived job security satisfaction, which is as expected but a different result to that of the job security certainty measure. Like the main model, the year dummies have substantial explanatory power. To explore the role of these unexplained aggregate economic factors further we decomposed the job security satisfaction into within- and between-characteristics factors. For ease of computation,

15 Model results are available on request.

we modelled a simple probit just for the high job security category. Compositional change appears to have had a much larger positive effect prior to 2010, with the model covariates explaining much of the rise in job security in that period (Figure 7). While compositional change continued to positively contribute to aggregate job security, the within-characteristics effect dominates in the latter part of the sample, putting substantial downward pressure on job security (similar to the job retention measure). This underlines the broad-based nature of the fall in job security in recent years.

Figure 7: Contributions to annual change in probability of high job security satisfaction, deviation from 2002



Sources: ABS cat no. 1220.0, ABS cat no. 5209.0.55.001, Frey and Osbourne (2017), HILDA Survey Release 16.0, author's calculations.

Alternative job security models

Our core results come from a random effects probit model, where variation in job security derives from differences between workers and differences over time for the same individual. Examining these various sources of variation allows us to better map the model to what is happening on aggregate in the economy. However, the effect of a particular factor on job security may be better isolated by examining within-individual changes, and so holding all fixed observed and unobserved characteristics constant.

As a fixed-effects probit model provides inconsistent estimates, we estimate a fixed effects linear probability model. For completeness, we also modelled a random effects linear probability model and a random effects model of the continuous probability variable (i.e. the data as presented in Graph 2, panel a). Finally, we re-estimate the job security random effects probit, where we define an individual as secure if they are 90 per cent certain of retaining their job (as opposed to 100 per cent). We refer to this as the 'expanded job certainty dummy'. Table 4 shows the results for key variables.

Table 4: Select determinants of job security – marginal effects

	Probit		*Linear probability model*		*Linear regression*
	(I)	*(II)*	*(III)*	*(IV)*	*(V)*
Dependent variable	Job certainty dummy	Expanded certainty dummy	Job certainty dummy	Job certainty dummy	Continuous probability
Unemployment (by region)	-0.01***	-0.01***	-0.01***	-0.01***	-0.00***
Trade exposure	-0.09***	-0.05***	-0.04*	-0.07***	-0.02**
Automation	-0.03***	-0.02***	-0.01	-0.02***	-0.01
Union member	0.00	0.01*	-0.01	0.00	0.00
Year FE	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	No	No
LL / R-Sq.	-56,415.32	-43,949.74	0.03	0.07	0.06
Rho	0.48	0.38	0.48	0.32	0.27
Individuals	18,621	18,621	18,621	18,621	18,621
Observations	100,255	100,255	100,255	100,255	100,255

Sources: ABS cat no. 1220.0, ABS cat no. 5209.0.55.001, Frey and Osbourne (2017), HILDA Survey Release 16.0, author's calculations.

The choice of cut-off for the probability of retaining one's job does not make a material difference to the results (Model II). The marginal effect of trade exposure and automation on job security is a little lower, but sign and statistical significance is the same. The coefficient on union membership becomes statistically significant at the 10 per cent level.

The signs on the coefficient estimates are largely the same for both linear probability models and the probit model (Models III and IV). However, the marginal effects in the fixed effects linear probability model are a bit smaller than in the random effects counterpart, with the former less likely to be statistically significant. Of the key variables of interest, unemployment and trade exposure remain statistically significant. Automation is not significant and, like for the job security satisfaction model, may reflect the limitation in the data in that automatability does not vary for a particular occupation over time. The regression using the continuous probability variable results in smaller marginal effects (Models V). This reflects the lower level of variability in the data.

Alternative wage growth models

Alternative models were estimated to test the robustness of the relationship between wage growth and job security. We examined a range of specifications and samples within the panel framework. We also address the issues of sample selection and endogeneity. Table 5 presents the coefficient estimates of the lagged job security probability measure on wage growth for various models.

Table 5: Regression coefficients of lagged job security on wage growth[(a)]

	Coefficient	*St. Error*	*R-squared (overall / pseudo)*	*Observations*[(b)]
Main model				
Random effects	**1.62*** **	**(0.52)**	**0.02**	**65,864**
Alternate panel structure				
Pooled OLS	1.60***	(0.51)	0.02	65,864
Fixed effects	1.82***	(0.71)	0.02	65,864
Alternate model structure				
Heckman selection	1.55***	(0.51)	--	64,730
Instrumental variables	1.26	(5.64)	0.02	65,825
Median (quantile) regression	1.75***	(0.30)	0.01	65,864
Alternate specification or sample (random effects)				
Not promoted	1.68***	(0.55)	0.02	58,924
Includes job changers	2.16***	(0.45)	0.02	78,753
Post 2009 data	2.44***	(0.66)	0.02	35,221
No time dummies	1.76***	(0.52)	0.02	65,864
No controls	1.69***	(0.52)	0.00	68,765
Job security dummy variables				
Job retention certainty	0.32*	(0.17)	0.02	65,864
High job security satisfaction	0.58	(0.43)	0.02	66,582
Medium job security satisfaction	0.46	(0.46)	0.02	66,582

(a) Standard errors are clustered by individual. *, **, *** denotes significance at the 10, 5 and 1 per cent levels, respectively.
(b) The number of individuals is 13,707 for most of the models. The number of observations is 93,152 in the selection equation.
Sources: ABS cat no. 1220.0, ABS cat no. 5209.0.55.001, Frey and Osbourne (2017), HILDA Survey Release 16.0, author's calculations.

In the random effects wage growth model, the coefficient on job security was largely unchanged when we did not control for any other factors. This was also the case when we excluded those who were promoted over the year or when we excluded the year dummy variables. The relationship between job security and wage growth was stronger when we model only the post-crisis period or when we include those who changed jobs over the year. The relationship between job security and wage growth also appears robust to outliers, as the effect was similar under a median regression. However, we find a mostly insignificant effect of job security on wage growth when we include either the dummy variable of job retention certainty (i.e. the variable used in the job security determinants regression) or the job security satisfaction dummy variables. This is in line with the results of Dickerson and Green (2012), who find that continuous probability measures of subjective job loss explain labour market outcomes better than ordinal measures.

Wages and job security are only observed for those in employment. Given a person with low perceived job security is more likely to be unemployed in the following period, their omission from the sample may lead to selection bias. In other words, the characteristics of the unemployed and those with low job security may be correlated. We estimate a Heckman selection model of wage growth to correct for the bias. To estimate the selection equation we need to include variables that will influence the probability of being employed, but be unrelated to annual wage growth. We used one's unemployment history (the number of years they have ever been unemployed), their health status (whether they have self-assessed poor or fair health and whether they have a chronic illness) and an interaction term for being female with a dependent child under five. We also included year dummies, age, education, regional unemployment rate, state, gender, having an English-speaking background, being an immigrant and living in a regional area. Despite the presence of selection effects (ρ=-0.07; χ^2=31.35; p-value =0.00), the estimate and statistical significance of job security was almost identical to the random effects model. This implies that selection bias is not a material concern in our analysis.[16]

The wage growth model may suffer from reverse causality, where the expectation of a large wage rise may make one feel more secure in their job. Alternatively, a common factor, such as the business cycle, may drive both variables (Hübler and Hübler 2006). Although job security enters the model as a lag, this does not necessarily adequately control for endogeneity (Bellemare et al. 2017). As such, we re-estimate a pooled model using instrumental variables. Our instrument is lagged subjective life satisfaction, based on a question that asks "how satisfied are you with your life (on a scale of 0–10)?". This captures how optimistic one feels about life and is expected to be correlated with one's perceptions of their job security, but unlikely to be related to wage growth in the following period.[17]

In the IV regression, we instrument lagged job security with two lagged dummy variables denoting high and medium life satisfaction (which equals 1 for those with life satisfaction of 9 or 10 or between 6 and 8, respectively). The first-stage regression F-statistic is large, so we reject the null of weak instruments (F=130.63; p-value = 0.00). We further test for instrument validity by performing the Wooldridge score test of overidentifying restrictions. We fail to reject the hypothesis of valid instruments (χ^2=0.41; p-value =0.52).

Given the instrument appears valid, we can test for endogeneity of job security with respect to wage growth. Using the Wu–Hausman test we fail to reject the null of exogeneity (F=0.01; p-value =0.91). As such, IV regression will lead to consistent but inefficient estimates, and our main random effects model is more appropriate. This is confirmed with the results of the model. The point estimate of job security on wage

16 We also estimated the job security probit model in this selection framework. The likelihood ratio test suggests selection effects are present (ρ=-0.16; χ^2=23.05; p-value =0.00). Nonetheless, most coefficient estimates of interest had similar sign and magnitude, although the effect of regional unemployment was smaller.

17 Ambrey and Fleming (2012) show personality, demographic factors and current circumstances affect life satisfaction.

growth in the IV regression is smaller to the main model result, it has an enormous standard error. As such, our main model estimates are not biased by endogeneity.

Overall, the wage growth models are robust to various specifications. In some models the results are larger and other smaller. But in each case, the overall conclusion that the role of job security on wage growth is statistically significant but small in economic terms.

6. Conclusion

This paper used household panel data to examine factors – including automation and globalisation risks – that influence workers' perceptions of their own job security. We then examined whether these job security perceptions have contributed to low wage growth in recent years. We find that perceptions of one's job security are lower for those in casual work, areas of high unemployment, jobs with a high risk of automation and industries more exposed to global trade. However, aggregate conditions not captured in our model appear to be the key driver of job security concerns. The recent decline in perceived job security has been broad based across industries, occupations, job structure and personal characteristics. As such, we cannot pinpoint any one factor that has led to the decline in perceptions of job security.

We find that greater perceived job security is associated with higher wage growth, over and above the other factors in the model, but the effect is small. A worker who is only 50 per cent sure that they will keep their job over the next year will have annual wage growth that is around 0.8 percentage points lower than a worker who is certain they will keep their job. As such, weaker job security perceptions have provided a small drag on wage growth in recent years. Furthermore, the relatively small magnitude of the fall in average job security means that the decline in aggregate wage growth is mostly explained by other factors, with the overall effect of job security being trivial. Subdued inflation contributed to more of the decline in wage growth, with most of the fall explained by aggregate factors that are not directly captured in our model.

Our strategy for identifying the effect of job security on wage growth was to use panel data to track whether those with low job security received lower wage rises the next year, controlling for a range of other factors. In theory this arises from lower job security leading to more constrained bargaining by the employee. A key limitation of our work is that wages are determined by the interaction between the firm and employees bargaining strengths, and yet we only observe the final outcome. Future work could look at surveying employees directly about their own bargaining behaviour to get at the issue directly. A more localised measure of unemployment may also improve the model, providing a more targeted and varied measure of regional unemployment.

An extension of our work would be to examine the role of self-assessed job security on hours worked. Part-time employment and underemployment have been increasing, allowing both workers and firms to adjust and bargain over hours. If workers are concerned about their job security they may not only accept lower wage rises, but also less hours, as a trade-off for stable employment.

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Employment growth/ skill requirement estimation in India: a non-traditional approach

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Abstract

There is a remarkable lack of regular labour market data in the context of a developing country such as India. Given the lack of regular labour market surveys, a lack of labour market data in the informal sector and the geographical vastness of the country, it is almost impossible to obtain labour market data regionally and regularly. Consequently, there is barely any possibility of obtaining job market forecasts. With the emphasis on skill development initiatives in India, the need for linking skill development initiatives with the labour market is felt quite prominently. Within this context, an initiative has been undertaken in India to develop a job growth and skill requirement forecasting model. It is a data-driven model to be designed with multiple sets of data such as job advertisements in websites, proxy data at the district level, and Government Survey data. Machine learning techniques will be used for prediction of job growth and skill requirement growth. This job forecasting model is likely to be cost-effective, easily replicated across districts and a tool for providing the forecasts for job growth and skill requirement growth regularly and comprehensively.

JEL Codes: J2, C81, C83, C88
Keywords: labour market, India, job forecasting, multiple data sources, Hadoop, machine learning

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1. Problem statement

A critical issue for labour market information systems in developing countries is that there is a conspicuous absence of real-time information on available job opportunities in the market for policy practitioners (let alone individuals). With the recent formation by the Government of India (GoI) of the Ministry of Skill Development and Entrepreneurship and other State Skill Development Missions, this problem has attracted the attention of policy practitioners at the union as well as at the state government level.

Skill development is a complex business, as it is not confined to the realm of training, but also intricately linked with the labour market. If there is not enough demand for a particular skill in the market, irrespective of the skill level, an individual is unlikely to obtain commensurate value in the labour market. On the other hand, there could be unmet demand in the labour market for skilled manpower. Labour market demand and skill development activity can together be considered as the 'horse and cart', whereby labour market demand acts as the horse, or the driving force for all skilling activities. Knowledge of labour market demand in a real-time manner is therefore imperative for establishing skill development programs.

Policy practitioners are dependent on national household surveys for necessary labour market information. In India, national household surveys for employment/ unemployment are conducted less frequently (once every five years). Moreover, the sample size is often too small to analyse the labour market at a disaggregated level. For example, in India, labour market research is rarely conducted at a district level because of the small sample size (whereas some districts in India have population size more than that of Belgium). Other possible datasets such as those from the Employees' Provident Fund Organisation or Employees' State Insurance Scheme have their limitations regarding coverage and access. The GoIhas recently created a taskforce to address the lack of labour market information (Financial Express Bureau, 2017).

Other institutions in India,such as the Employment Exchange which was created for meeting the labour market information gap, have not been effective in connecting labour market supply and demand (Debroy, 2008). Moreover, the problem of the labour market information gap is compounded in India by the market's heterogeneous and informal nature. The GoI's Ministry of Labour& Employment launched the National Career Service (NCS) portal;however, it has yet toprove successful (Abraham and Sasikumar, 2018). The Ministry of Skill Development and Entrepreneurship has launched the National Labour Market Information System which, too,has yet to make any impact in capturing labour market demand (Abraham and Sasikumar, 2018). However, the issue of making reliable labour market information available to policymakers (and to people, subsequently) has still yet to be addressed.

The outcome of poor coordination between skill development programs and the labour market is manifested in the extremely low placement rate from the Ministry of Skill Development and Entrepreneurship's short-term training programs (Ahmed, 2016; Makkar, 2017). The Ministry and State Skill Development Missions are facing a critical challenge to estimate labour market demand so that these entities can align their skill development activities with existing demand. While some macrolevel predictions have been made in this regard, it is difficult to translate them into an implementation plan, particularly at the district level. The World Bank, in its Skill India Mission Operation project, has identified limited sources of relevant, frequently updated and appropriately disaggregated data to signal industry demand to training suppliers as a critical problem in the skilling ecosystem. A more decentralised, demand-driven approach to skills gap analysis is proposed at the district level.

2. Proposed solution

An initiative was developed (with the initial support of the United Nations Development Programme, India, to address the problem of data discrepancy in the Indian labour market. A concerted effort was made to develop a data-driven model for job/skill requirement forecasting at the district level. This exercise was based entirely on different datasets available for the labour market –for example, job advertisement data in online media, data from different departments of the GoI's District Administration, and survey/Census data. The model, which is an outcome of this exercise, will be more cost-effective compared with traditional survey methods. Moreover, this model can be easily replicated across districts. The GoI, multilateral organisations, private training providers and job-seekers are the targeted beneficiaries of the end product of this exercise. The model is being developed with data from Nagpur district in Maharashtra.

The proposed model will predict job growth for different sub-sectors (as per National Industrial Classification (NIC)) for the various job roles in the respective sectors of a given district. It will also identify skill requirements for respective job roles. These predictions will be on a real-time basis (that is, with a reasonable time interval, for example, one to two months), on a business intelligence tool platform.

3. Model architecture

The principle of collective intelligenceis the fundamental principle for building the model. A novel aspect of this work lies in the extraction and organisation of multiple sources of labour market data for further analysis.

The labour markets in developing countries are extremely heterogeneous, which creates a restriction in labour market analysis due to the lack of available data. However, access to multiple digital datasources, data extraction and data integration technology have made it possible to obtain labour market insights in a real-time manner at regional levels.

Following are the steps which have led to the data-driven model fordeveloping employment/skill requirement forecasting.

3.1 The principle of collective intelligence

This model is based on the assumption that In an extremely heterogenous labor market, different stakeholders in different sectors and sub-sectors have authentic but limited knowledge. . Particular individuals/data sources will be the source of insights for respective sectors. However, it is unlikely that a particular individual/ data source can provide detailed insights of the entire labour market.This leads to a problem similar to that in the parable of a group of blind men and the elephant,in which everyone illustrates the elephant in their way of fragmented understanding of the totality. Whereas individual illustrations are insufficient in understanding the elephant, a comprehensive and systematic placement of these individual illustrations can provide a complete picture. A similar principle –the principle of collective intelligence – is adopted to address the labour market data intelligence problem.

As this work seeks to predict the employment forecast for an entire district as well as for different sectors of India's heterogenous labour market, comprehensive coverage of different datasets for the respective segments of the labour market is a key challenge. The following few paragraphs will explain the problem and outline the solution, with a delineation of the technology used for the necessary prediction work to follow.

3.2 Data integration framework

A critical aspect to solving the job forecasting problem is to tackle the heterogeneity of labour markets. A heterogeneous labour market has numerous sectors and sub sectors each of which has differences with the rest. It is a challenging exercise to map the data sources for each of the sub-sectors as per the NIC for a given district, and to adjust weights accordingly. Either economic Census or National Sample Survey (NSS) data for employment/unemployment can be used for this purpose. NSS data has been used because it provides more detail about types of employment along with an establishment's details. Existing research has used Labour Force Surveys (LFS) as a framework to capture online job market data (Štefánik, 2012b; Štefánik, 2012a; Jackson, 2007). LFS provide some details of the labour market –self-employment, wage employment, contractual employment, for example – which are important for building this model.

To incorporate different data sources, the NSS data framework on employment/unemployment surveys has been used. According to the NSS, there is an approximate total of 2,000 sub-sectors of the economy (and therefore corresponding labour markets). These sub-sectors are obtained using the NIC (NIC-2008).[1] Employment details for all sub-sectors are provided in the NSS data.

The prominence of economic activities in these sub-sectors vary from region to region. For example, in Nagpur (the district for this study), as per the NSS 68th round, there are 151 sectors where jobs are available. Observations from other NSS rounds (for example, 66th round, 61st round) show a repetition of these sectors regarding job availability in Nagpur. As the sample size is small, the NSS has been adopted only as the framework and not for weight assignment for employment available in different sectors.

With this framework, multiple data sources are incorporated;for example, website data and district administration data. Multiple job portal data are used for forecasting jobs/skill requirements in the formal sector, and data from different district administrations are used to measure employment generation in the informal sector

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1 The NIC is a standard developed by the GoI's Ministry of Statistics and Programme Implementation for the purpose ofclassifying different economic activities in India and maintaining a database for the same. For details, see http://mospi.nic.in/classification/national-industrial-classification.

through suitable proxies. The paragraphs below explain the different data sources available for this exercise.

With the availability of labour market data on the internet, the ways to use these data for labour market analysis are already established (Kureková, Beblavy and Thum, 2014; Askitas and Zimmermann, 2009). A large amount of labour market data is obtained using a web crawler for job availability and skill requirement analysis (Capiluppi and Baravalle, 2010; Jackson, Goldthorpe and Mills, 2005). However, most research into these categories is focused on a single website data source. In this exercise, data from multiple websites has been used to analyse job/skill requirement growth in the formal sector.

3.3 A matrix of data source to labour market segments: core of the solution

A critical aspect to solving the labour market data intelligence problem is to tackle the heterogeneity of the labour market with mapping data sources for each of the above sub-sectors for a given district (151 sub-sectors in the case of Nagpur). However, the mapping is required to be further disaggregated to capture skill requirement and employment forecast. As per the NSS, types of employment in each sector can be further disaggregated as: self-employment, regular/ salaried, casual (government and private). For different sub-sectors, these types of employment vary to a large extent. An illustration of this disaggregation is provided in A1. All together, there are 235 cells after mapping the sub-sector and types of employment.

Post the mapping withNSS data, a major assignment was to map each cell with the relevant job roles. Neither the NSS nor Census captures this data on job roles. The nearest approximation provided by the NSS is the National Classification of Occupations (NCO).[2] To obtain the details of job roles for each economic sub-sector and for each type of employment, NCO classification was added to the above framework. However, only classification and integration of the data sources isn't enough as field level insights are necessary to finalize different job roles to be kept in each cell of NIC-Employment Type-NCO. A consultation between district employment offices, district skill development offices, relevant district departments and the academics was conducted to validate job roles in each cell. For example, the Textile/Apparel sector in Nagpur comprises the following sub-sectors:preparation of cotton fibre (13111),[3] weaving and manufacturing of wool and wool-mixture fabrics (13123), manufacturing of knitted and crocheted synthetic fabrics (13913), manufacturing of all types of textile garments and clothing accessories (14101) and custom tailoring (14105) which are prominent in Nagpur. From A1, it is clear that self-employment is the only mode of employment for custom tailoring (14105), whereas weaving and manufacturing of wool and wool-mixture fabrics (13123) have regular/salaried employment as the only mode of employment. Once the sub-sector and type of employment data as contained in A1are obtained, experts work to incorporate dominant job roles for each of these

2 The National Classification of Occupations is a set of standards created and maintained by the GoI's Ministry of Labour&Employment. For details, see: https://labour.gov.in/sites/default/files/National%20Classification%20of%20Occupations_Vol%20II-B-%202015.pdf.
3 This is the five-digit National Industrial Classification.

sectors. The matrix for the mapped datasource to labour market segment has been prepared based on capturing this local knowledge. A sample of such is provided in A2.

3.4 Formal labour market data sources

Labour market coverage of online job portals is quite limited in India. The NCS portal had only .13 million active job vacancy postings across the country as on 2nd March 2019. On the other hand, every year, as per the 66th and 68th round of the NSS survey, the addition of labour force is around 4.68 million per year (considering usual principal and subsidiary status of employment)(Shaw, 2013). Thus, around one-tenth of the labour force addition is represented by the NCS portal.[4] However, at a regional level, there are multiple job portals such as monster.com, naukri.com, indeed.com, quikr.com, olx.com and urbanclap.com, as examples, which have an extensive coverage over and above the NCS portal. For example, as at 2nd March 2019, for the Nagpur District, the number of job vacancies posted in various portals were: naukri.com= 4241,indeed.com= 815, quick.com= 3432, monsterindia.com= 326, shine.com= 1084 and olx.com= 2146, with an average job-posting duration of one to two months. However, these portals are active mostly in the urban regions. In urban-centric employment prediction, these job portals are quite important (Maksuda, Ahmed and Nomura, in publication).

Newspapers are traditionally a rich source of job advertisement data (Jackson, Goldthorpe and Mills, 2005). Government jobs and some informal sector jobs (for example, private tutor, personal assistant) are traditionally advertised in print newsmedia. With the availability of online versions of print media, these advertisements are digitally available. Examples of these websites for the Nagpur district include: Nokarisandharbha, Employment Newspaper Maharashtra and Nagpur Today. Also, there is an emerging online labour market for the informal sector (for example, maid, driver, security guard, plumber) to cater to the urban areas. Leading websites in this regard are: babajob.com and olx.com, among others. These websites provide data about job demand for the present month or coming months for the various sectors.

3.5 Informal labour market data sources

As mentioned, the labour market in India is extremely heterogeneous, and there is no direct labour market data for the informal labour market. However, it is the informal sector which is dominant in India. A suitable ‘proxy’ is to be identified from the available district administration data to map employment in the informal sector.

Fortunately, district departments recently started maintaining data in digital format, and the extent of data availability is quite vast. With the availability of various datasets at Nagpur, it was observed that data available under different headings (for example, quantity of production, manpower involved, investment, capital, types of workers, establishment details, details of the infrastructure in the establishments and asset creation) were acting as suitable proxy inputs.

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4 For Nagpur District (as at 2nd March, 2019), there were only 2 jobs posted. Link: https://www.ncs.gov.in/job-seeker/Pages/Search.aspx?OT=fheFJjl41aGWG85YSvGqng%3D%3D&OJ=sdm0Lg%2BxO9o%3D

For example, the District Employment Office (DEO) maintains details of employment data for the registered sector. By mapping NSS data to the data available with DEO, it is observed that the DEO data covers approximately the entire formal sector in Nagpur. Moreover, the District Industries Centre maintains data of the establishments at the individual level. This provides an opportunity to obtain input data which corresponds to the employment generation in the formal sector.

For different sectors/sub-sectors, there are multiple types of suitable proxies which are obtained from gleaning the district level data sources. For example, the District Transport Office provides the complete details of different types of vehicles purchased in the district (for example, auto-rickshaw, taxi, bus, jeep, station wagon, personal car).These are suitable proxies for employment generation in the future. Another example is employment generation in the animal husbandry sector. A full detail of production, employment, investment and asset creation in various sub-sectors – for example, poultry, cattle breeding –is available with the District Animal Husbandry department. Different Planning Departments maintain investment data across the departments/sectors or sub-sectors of employment. Mapping these investment and employment-growth details provides a rich source of proxy data and a basis for futuristic predictions. Similarly, for all different departments, different proxy data are being obtained, as these are helpful as a suitable proxy for employment prediction in respective sectors/sub-sectors.

Essentially, to work with the complex problem of labour market prediction, it is necessary to obtain different data sources and map them into the right place to complete the jigsaw puzzle of the labour market and facilitate the prediction of employment/skill-requirement growth with the help of necessary technologies.

3.6 Initial weight assignment for representativeness

It is essential that appropriate weights are allocated to each of these data sources, to take care of the representativeness aspect and therefore to generalise the results.[5] It is important to make a distinction between stock and flow concepts for employment data before explaining these datasets. Stock datasets could be explained as historical datasets, whereas flow datasets provide the most recent information about the labour market (say, for the past quarter). Below is an illustration of the existing datasets for stock and flow measurements. It is to be noted that the weight adjustment is calculated manually for the stock data only. Long periods of stock datasets are likely to provide a stable estimator. Following de Pedraza, Tijdens and de Bustillo (2007), weight is to be allocated applying the post-stratification method (for example, location-based, industry detail-based) to internet data and proxy data for different formal and informal sectors. Manual adjustment of the weights using the flow data would likely cause large fluctuations with little variation. Hence, no manual adjustment of weights is done for flow data. Moreover, a neural network is applied for the prediction exercise, and an essential attribute of neural net is a dynamic weight adjustment with several iterations. This is explained further in the following sections.

5 Neural Net adjusts the consequent weights which are discussed in the following sections.

Table 1: Employment Data Stock and Flow Measurement

	Online Job Market	*Administrative*	*Government Census/ Survey*
Stock	Data repository for job posting/ company registered for a few years (to be accessed after agreement with Job Board Company)	I. Repository of the establishments registered/vacancies posted by District Industrial Centre/ District Employment Office 1. II. Other proxy dataset for informal sector jobs	I. Economic Census (for the details of all establishments) 2. II. National Sample Survey for the adjustment of labour force in different employment type/ industry
Flow	Job posting for last quarter (obtained through web-scraping)	Both of the above sources to be obtained regularly from District Administration	None

3.7 Employment prediction to skill prediction

Many types of research have focused on obtaining the details of skill requirement along with employment requirement details with their predictions (Lenaerts, Beblavy and Fabo, 2016; Capiluppi and Baravalle, 2010; Kureková, Beblavy and Thum, 2014). With web crawling techniques, these research studies have gleaned vacancy data from different websites such as Burning Glass,Monster,EURES, among othersThe crawling technique provides a way to obtain the details of skill requirement specifications along with the specific employment requirement details. However, these details are restricted to individual websites, which are limited to an analysis of a specific segment of the labour market. The complexity level is higher in this present context, as skill requirement details are obtained from multiple websites as well as from proxy datasets. The data de-duplication method (explained below) addresses the complexity that arises from the usage of multiple website data. To specify the skill requirement corresponding to each type of employment in different sub-sectors, field-level data are also incorporated in the form of expert opinions. The details obtained are used as an input to the respective cell for skill details. This can be illustrated as follows. From previous examples of the textile sector, the growth of job roles in this sector is obtained from the NIC-Employment Type-NCO table. For necessary updates, district officials – business experts in this domain – are further consulted, and it is observed that sales and technician jobs in this sector are prominently growing in Nagpur. Thus, local knowledge is being incorporated into this collective intelligence gathering process.

3.8 Data extraction for formal sector labour market: crawling websites

Post the identification of these websites for obtaining job details for different sectors,a web crawler was developed to obtain data automatically with a certain periodicity from the websites as mentioned above. Following Capiluppi and Baravalle (2010), the 'web spider', a data extractor module, and an entity recognizer component was developed. The purpose of the web spider is to download vacancies, whereas the data extractor module is responsible for processing and categorizing raw data. Once extracted, the data was fragmented and parsed into smaller segments.The task of the crawler is to extract the most relevant keywords which appear in the job description. Examples of keywords include 'experience', 'education', 'salary', 'sector', 'work location' and 'date of the job advertisement'. Data crawling also identifies sectors for which job advertisements are available in websites (and sectors for which they are not). Naturally, this process is dependent on the existing structure and content of the data;that is,the way the job advertisements are posted on different websites. For example, some websites provide keywords for specific skill set requirements,while others provide details of the job description and the skill requirements are to be selected from the job descriptions. However, when extracting data from multiple websites, there is a high possibility of data duplication and variation of data formats. In fact, these are key challenges for web data extraction. How to address this problem is explained in the following sections.

3.9 Aspects of de-duplication and a'way out'

There are multiple challenges while performing a crawling exercise. A key problem is to obtain a comprehensive set of job advertisement details from multiple websites where the format, structure and wording of the advertisements differ. For example, naukri.com provides keywords for necessary skill requirements whereas other websites provide job descriptions and skill requirements are to be obtained from these descriptions. However, this is not a new problem, as many commercial organizations who routinely gather large databases in business and marketing analysis face this challenge regularly. The challenge here is to identify similar advertisements/job-postings and to determine whether they indicate the same advertisement/job-posting. The Sorted Neighborhood Method (SNM) is one such method used to address this issue. The fundamental problem here is that the data provided by various sources is 'string' in nature. Here, the equality of two values cannot be identified by having some arithmetic equivalence, but rather it requires a set of equational axioms to define the equivalence (Hernández and Stolfo, 1995). The technique used here is to partition the data pooled from different websites using the crawling technology. This pooled data is partitioned into clusters whereby each cluster will have potentially matching records. As proposed by Hernándezand Stoflo (1995), instead of pairwise matching multiple datasets, given it is expensive and time-consuming, clusters are formed, and then equational axioms are followed.

In this present exercise, there are eight to ten principal data sources (websites and online news media). Approximately 10,000 advertisements were obtained over three months (June to August2017), when advertisements from different websites were pooled. Small clusters were then created, following which a series of steps was performed to establish the equivalence of strings. These steps include spell corrections, main keyword check (for example, the title of a job advertisement, company name, experience, salary) and setting an acceptance rule(based on multi-pass or single-pass SNM).

3.10 Prediction using machine learning

To date, labour market/employment growth prediction has been restricted to the realm of linear extrapolation, whereby a fixed equation set by the author is the sole knowledge base for predicting employment growth (Hughes, 1991; Wang and Liu, 2009). However, the machine learning technique has an inherent advantage over other methods, as it learns from the data to adjust necessary weights in its intervening layers of regressions so as to provide the best prediction. The Artificial Neural Network (ANN) technique has an inherent advantage of correcting the prediction mechanism based on the data inputs it receives. The specific neural net used for correcting the prediction algorithm is known as the Back Propagation technique. The programmer is not required to set an equation establishing the relationship between a set of inputs (for example, production, investment, asset generation, the existing number of employees, future investment) and output (that is, employment and skill requirement). The ANN method establishes the relationship between inputs and output variable through the creation of a set of hidden layers/derived variables. Moreover, it continues to assign weights to the hidden layers/derived variables in the process of establishing a relationship between inputs and output variable.

This multiple layer creation is important in this context of employment prediction as the set of inputs and output (employment) enjoy a complex relationship. For each cell derived in the matrix for labour market segments (as explained earlier), the ANN is to run separately to derive the prediction of employment growth for each sub-sector/cell derived (as shown in A2). The prediction models thus developed are used for predicting future employment using the existing algorithm and other future data (for example, investment data which is obtained from the Planning Departments). However, the structure of the network is to be determined (for example,the number of intermediate layers), which is crucial for this exercise. The fundamental advantage of the ANN mechanism is that it keeps on improving the algorithm for each sub-sector with the usage of more data.

These available datasets for building the model are known as training data. Once the model is built with the available training data, it is ready to make predictions using future datasets. However, there is the critical problem of ‘overfitting’, which may induce significant errors in this prediction model. To address this, the following steps are adopted.

3.11 Validation

In building the model for employment/skill forecasting, there is a critical problem called ‘overfitting’. As there are large numbers of categories of sub-sectors and employment type as derived in the matrix (see A1 and A2), a lesser number of observations is available for each category. When the training dataset is small, or the number of parameters in the model is large, there is a possibility that this model will not fit with the rest of the data, whereas it may fit with the training data quite well. This is overfitting.

To eliminate the problem of overfitting, cross-validation is used for choosing the right parameters in the model-building exercise. In the cross-validation process, a part of the training data is kept separate to run and test the model. In this model, a ‘k-fold’ cross-validation exercise is to be performed with the test dataset being partitioned into k-subsets. On the other hand, rest of the data (outside of training) is used only to see how well the model that is obtained as an outcome of training and cross-fitting is performing.

3.12 Use of Hadoop platform

A key challenge in dealing with multiple sources of data of differing formats and structures is to sort, process and analyze the data for forecasting purposes. Also, there is a high level of calculation complexity in this forecasting process that necessitates the use of Apache Hadoop cluster information architecture. Hadoop can ingest data from multiple sources and can process data received on a different schedule (for example, web data is to be received more frequently than other proxy datasets from administration). Hadoop chops the data into smaller chunks and computes it through a parallel computation process which is extremely convenient for the existing exercise. Further, giventhe complexity of multiple web crawlers, SNM execution for data de-duplication, running multiple ANN processes for employment/skill requirement prediction for different sub-sector employment types (as per the grids shown in A2) and also the cross-validation process, theHadoop platform is ideal. Moreover, it can deliver insights into employment/skill requirement growth on a real-time basis, which is a key deliverable of this project. The programming language Python has been used for this exercise.

4. The output of the exercise, replicability of the model and regional aspects

As explained at the outset, the output of the exercise is the prediction of employment and skill requirement for each of the sub-sectors and employment type combinations (as shown in A2). These predictions are provided regularly (for example, with a certain interval of a few months) for a given region (Nagpur district in this case) on a business intelligence platform. Going forward, it is expected that this model of employment/skill forecasting will also be replicated in other districts. While most of the components of the data-driven model will remain the same for different districts, a separate exercise for each district will need to develop the Data Integration Framework, to develop the Matrix for Data Sources for Labour Market Segments and to obtain separate field details. The framework may vary from district to district depending on the presence of industry and jobs in the respective district. Further, the data sources may vary for different segments of the labour market in different districts. However, the software tools and methodology for estimating employment growth/skill requirement growth will remain the same, and this will save the cost of this estimation across the districts. Finally, the major problem of lack of employment information in India can be addressed with the use of this exercise, which precisely is the purpose of this model-building.

5. Conclusion

This work is aimed at exploring the possibility of predicting job-growth forecasting with the use of multiple data sources and machine learning techniques. It has explained the process of achieving such an outcome with associated steps to develop a data-driven forecasting model. This model should be a valuable addition to the existing pursuit of obtaining labour market data in a regular manner. Considering the complexity involved with the prediction of the heterogeneous labour market in Asian, African or Latin American countries, this data-driven model may be quite helpful. There has hardly been any information on the informal labour market in India. The use of proxy data, thanks to the digitization of the district administration data repository, would facilitate unlocking this lack of data availability for the informal sector. This model is capable of covering both formal and informal segments of the labour market comprehensively. It is also capable of providing regular job growth updates quite regularly and in a relatively inexpensive way (compared with the labour market survey). Moreover, the use of machine learning technology would ensure a higher accuracy in prediction, as the model is 'self-taught' with data and not merely a prediction which uses a pre-determined algebraic formula.

Table 2: A1Sub-sector and type of employment (manufacturing sector)

		Type of employment			
NIC	*Sub-sector*	*Self-employment*	*Salaried / regular*	*Casual (Govt.)*	*Casual (Private)*
10402	Manufacture of vegetable oils and fats, excluding corn oil	0	0	0	2,628
10613	Dahl (pulses) milling	0	0	0	5,325
13111	Preparation and spinning of cotton fibre including blendedcotton	0	19,584	0	674
13123	Weaving, manufacture of wool and wool-mixture fabrics.	0	2,543	0	0
13913	Manufacture of knitted and crocheted synthetic fabrics	0	2,685	0	0
14101	Manufacture of all types of textile garments and clothing accessories	4,096	0	0	0
14105	Custom tailoring	52,234	0	0	0
16101	Sawing and planing of wood	0	10,648	0	9,572
18112	Printing of magazines and other periodicals, books and brochures	0	2,139	0	0
20238	Manufacture of 'agarbatti' and other preparations	0	0	0	2,023
24109	Manufacture of other basic iron and steel	0	1,307	0	0
24319	Manufacture of other iron and steel casting and products	0	418	0	0
25112	Manufacture of metal frameworks or skeletons for construction	312	0	0	0
25119	Manufacture of other structural metal products	792	0	0	0
25121	Manufacture of metal containers for compressed or liquefied gas	0	2,865	0	0
25933	Manufacture of hand tools such as pliers, screwdrivers, press tools	391	0	0	0
25994	Manufacture of metal household articles	0	1,114	0	0
25999	Manufacture of other fabricated metal products	318	0	0	0
26209	Manufacture of computers and peripheral equipment	0	1,711	0	0
28213	Manufacture of spraying machinery for agricultural use	0	3,583	0	0
29102	Manufacture of commercial vehicles such as vans, lorries	0	2,377	0	0
31001	Manufacture of furniture made of wood	4,608	0	0	0

Table 3: A2Industry sub-sector, employment type and job roles in textile sector (NIC employment type – NCO)

		Self-employment job roles	*Salaried/ wage employment job roles*	*Casual (Govt.)*	*Casual (Private)*
13111	Preparation and spinning of cotton fibre including blended cotton	Home-based yarn manufacturing	Spinning Shift Officer, Weaving Supervisor, Finishing	NA	Contracted out jobs for the workers
13123	Weaving, manufacture of wool and wool mixture fabrics	NA	Marketing,	NA	NA
13913	Manufacture of knitted and crocheted synthetic fabrics	Home-based knitting	Yarn Dying	NA	NA
14101	Manufacture of all types of textile garments and clothing accessories	Home-based/sub-contracted	Polyester Staple Fibre Manufacturer, Sales, Technicians	NA	NA
14105	Custom tailoring	Home-based/self entrepreneurial tailoring	Marketing, Technician	NA	NA

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