

The Dynamics of Self-Employment in Australia and the Role of the Solo Self-Employed

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Doctor of Philosophy – Business and Economics

March 2020

Faculty of Business and Economics

Melbourne Institute of Applied Economic and

Social Research

Submitted in partial fulfilment for the degree of
Doctor of Philosophy – Business and Economics
at the University of Melbourne

Abstract

A common belief held by policymakers is that the self-employed are a vital element of well-functioning economies. They promote economic growth, technological innovation and job creation. Yet, descriptive evidence across multiple industrialised economies concludes that relatively few self-employed workers create any jobs. Most self-employed workers do not hire any employees and are known as the solo self-employed. Not much is established about the role the solo self-employed have in job creation: Do they act as a more flexible form of employment and/or is solo self-employment a stepping-stone to job creation as an employer? This thesis aims to investigate the dynamics of self-employment in Australia. It uses individual-level data from the Household, Income and Labour Dynamic in Australia (HILDA) Survey from 2001 to 2016, where initial statistics support the notion of the solo self-employment stepping-stone effect. The statistics also show a declining trend in employership and solo self-employment rates and that, at most, half of the employers survive past their initial year in employership.

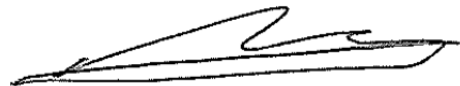
I consider three key questions regarding the Australian self-employed. The first explores the idea of solo self-employment being used as a device to reveal one's own ability to be self-employed. If true, then being solo self-employed increases the individual's probability of becoming an employer, more so than any other employment state. This assertion is empirically tested, and the results suggest that it is true. However, the results also suggest the difference, while significant, is minor when compared to the observable rates of transitions into employership. The second question investigates what the skill-based determinants of employership survival are. It is possible that high rates of employership exits are because of a mismatch between employership skill requirements and individual expectations. Using survival analysis techniques, I find experience in occupations that treat cognitive, resource management or pattern recognition skills as important determinants of employership survival. The third question examines if the declining rates of Australian self-employment represent labour market failures: are there barriers hindering entry into self-employment? I find employers and solo self-employed workers have significantly higher job satisfaction scores than wage/salary employees. I treat this as evidence for self-employment entry barriers as they should be similarly satisfied in a labour market with free entry.

Declaration

This is to certify that:

- i. The thesis comprises only my original work towards the PhD,
- ii. Due acknowledgement has been made in the text to all other material used,
- iii. the thesis is fewer than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.

This thesis uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to the DSS or the Melbourne Institute.



Michael Leith Cowling

Preface

I, Michael Leith Cowling, was supported by an Australian Government Research Training Program (RTP) Scholarship through the University of Melbourne. I also acknowledge the financial support I received from the Faculty of Business and Economics of the University of Melbourne, which in turn was linked to an Australian Research Council Discovery Project (#DP160103171).

Acknowledgements

The following is dedicated to my family. The love and support from my parents, Keith and Jenny, along with their many years of sacrifices and encouragement, helped me reach this point of my life. I also thank my sister, Misha, for tolerating my occasional worrying and critical view of myself. My family provided me with a truly privileged and supportive life. I am truly grateful for them.

While all subsequent research is my own, this thesis is also the result of the dedication of my three supervisors: Professor Mark Wooden, Dr Andrew Clarke and Professor Peter Gahan. Their patient guidance and detailed feedback have been invaluable and greatly appreciated. I also had the benefit of learning from Professor Kalvinder Shields and Professor John Haisken-Denew for teaching me various aspects of the research process, especially when it comes to engaging with other academics and confidently presenting research to any audience. I am extremely grateful to have had the opportunity to work with some of the finest academics in Australia. Thank you all for shaping me into a confident and motivated economist.

Finally, I offer my thanks to my friends in the same PhD cohort as me for their moral support. I always appreciate their willingness to discuss with me our research and listen to my concerns/doubts. I couldn't ask for a better group of friends to have met them during the program.

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List of Abbreviations

ABS	Australia Bureau of Statistics
ACCI	Australian Chamber of Commerce and Industry
ANZSIC	Australian and New Zealand Standard Industrial Classification
ANZSCO	Australian and New Zealand Standard Classification of Occupations
ASIC	Australian Securities & Investments Commission
ACT	Australian Capital Territory
AUD	Australian Dollars
CPI	Consumer Price Index
DOT	Dictionary of Occupational Titles
DOL	Department of Labor
DSS	Department of Social Services
EPL	Employment Protection Legislation
ETA	Employment and Training Administration
EU	European Union
GEM	Global Entrepreneurship Monitor
HILDA	Household, Income and Labour Dynamics in Australia
HH	Household
LFS	Labour Force Surveys
MIAESR	Melbourne Institute of Applied Economic and Social Research
NLSY	National Longitudinal Survey of Youth
NLSYM	National Longitudinal Survey of Young Men
OECD	Organisation for Economic Co-operation and Development
O*NET	Occupation Information Network
SA4	Statistical Area Level 4
SBA	Small Business Administration
UK	United Kingdom
U.S.A	United States of America
FY	Financial Year

Chapter 1

Introduction

1.1 Entrepreneurship and the Self-Employed

A common belief held by policymakers across industrialised nations is that an entrepreneur – an individual “who organizes, manages, and assumes the risks of a business or enterprise” – is a vital element of well-functioning economies (Block and Koellinger 2009). Some entrepreneurs are known to introduce technological innovation that generates new markets, spurring economic growth and job creation. Others have been credited with providing specialised goods and services ignored by the largest firms (van Praag and Versloot 2007a; Parker 2009). Entrepreneurs also create positive externalities by increasing market efficiency through competition, resulting in cheaper and/or higher quality goods and services. It is no surprise that policymakers devote much attention, resources and political capital to promote entrepreneurial activity. For example, the Australian Government set aside AU\$120 million (the financial year 2017) for the Australian Entrepreneurial Programme (Department of Industry, Innovation and Science 2018) to provide practical support – which includes funding, grants and mentoring – to small businesses. The government also passed AU\$5.2 billion (valued over 4 years) in tax cuts to further support small and medium firms (Chan 2017). Outside Australia, the US Small Business Administration was given a US\$831.8 million budget to administer several small business development and loan programmes during the 2017 financial year (US Small Business Administration 2017). Likewise, the European Commission’s 2020 Entrepreneurship Action Plan calls for measures to promote entrepreneurship by training and supporting self-employed workers (European Commission 2012). Given its policy relevance, the economic study of entrepreneurship is a thriving research field and has generated a variety of insights about how entrepreneurs and the economy interact with each other (Parker 2009). These studies analyse how economic incentives affect entrepreneurial behaviour, and how entrepreneurial behaviour affects the economy.

Before proceeding further, it is important to first define who are the entrepreneurs. In most economic studies of entrepreneurship, researchers use a definition compatible with their data. The most common definitions are small firms, business owners and the self-employed, and each of these definitions has their own advantages and drawbacks

(Parker 2009). Defining small firms as entrepreneurs has the advantage of being easily measurable, but firm size definitions are arbitrary and industry-specific. The small firm definition also ignores the characteristics of the firm's owner. Since all entrepreneurs own their own business (or businesses), it is instead more rational to use the self-employed or business owners as representatives of the entrepreneurs. A practical advantage of using the self-employed or business owner definition is that they are widely used, either at the individual-level within household surveys or at the national-level (Katz 1993). On the other hand, both measures risk failing to capture many nascent entrepreneurs – people who are engaged in creating new ventures (Wagner 2004). For example, entrepreneurs could have a wage/salary job while developing their businesses, but they are usually not measured as self-employed or as business owners in household or labour force surveys. Regardless, as I am interested in studying individual-level entrepreneurial behaviour, I equate entrepreneurship (and business ownership) with self-employment.

This thesis focuses on Australian self-employed workers because entrepreneurship remains high on the Australian political agenda, especially with the Department of Jobs and Small Business (2018) commitment to “setting the right environment for small business to grow” as they consider small businesses essential for “the creation of jobs” and economic growth (Department of Jobs and Small Business 2018, p. 1). Further, the Global Entrepreneurship Monitor (GEM) considers Australia as an entrepreneurial country as the GEM reports that Australia has an above global average perception of entrepreneurial opportunities. The GEM also reported that Australia's levels of entrepreneurial capabilities are similar to global averages. The GEM is an international study of entrepreneurship across countries. It provides an understanding of the entrepreneurial environment and the behaviour and attitudes of individuals across economies (Global Entrepreneurship Monitor 2019). The GEM highlighted that Australia outperforms most other developed economies in terms of business aspirations and prevalence of innovative start-ups (Steffans and Omarova 2018). Despite their entrepreneurial performance, most self-employment studies cover regions encompassing the US, Canada, UK and Europe. I aim to rectify this with individual-level data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey – a longitudinal household dataset with a representative sample of the Australia population covering the years 2001 to 2016.

1.2 Job Creation by the Self-Employed

A common viewpoint held by policymakers is that the self-employed are responsible for a disproportionate share of job creation (Blanchflower and Meyer 1991; Storey 2003). This view draws on evidence from several studies, starting with the Birch's report (Birch 1981). The report claims that in the US, between 1969 and 1976, small firms – those employing fewer than twenty workers – generated 66 per cent of all new US jobs.¹ Birch (1981) implied that the small-firm sector is the primary engine of job creation. Later studies would also confirm Birch's findings for the US and other countries (for an overview, see Neumark, Wall, and Zhang 2011). This view has been rebuffed by multiple studies, the most prominent one being Davis, et al. (1996). Davis et al. (1996) argued that Birch's sample suffered from misclassifying some large firms as small (large firms suffering from a temporary negative shock can appear as a small firm for a short moment). In contrast to Birch's conclusions, Davis et al. (1996) find no systematic inverse relationship between firm size and net employment growth, and that small firms are not the primary engines of job growth as initially claimed. This remains a contentious area of study with some studies supporting Birch's original claims while others conclude that small firms are no better than larger firms in creating jobs (for a review, see Haltiwanger, Jarmin, and Miranda 2013). Much of the discussion about self-employment job creation so far is framed in terms of comparisons between small and large firms.

As noted earlier, the focus on firm size ignores the role the individual self-employed worker has on job creation, especially when firm size is hypothesised to be strongly influenced by the characteristics of the self-employed owner (Barkham 1994). However, relatively few self-employed workers create any jobs. According to Parker (2009) and Congregado, Golpe, and Carmona (2010), only 20 – 30 per cent of self-employed workers in the US, the UK, Canada, and in the EU-15 hire any employees.² In Australia, the share is slightly higher with 38 per cent of self-employed workers hiring employees as of December 2016 (ABS 2019c). This has motivated studies (which I review in section 3.2) to identify the characteristics that distinguish the self-employed who hire workers (employers) from those that do not (the solo self-employed). These two types of self-employed workers are significantly different in the way they manage their businesses and the constraints they face at start-up (Cowling et al. 2004). Another research area of interest

¹ While the self-employed are the primary focus of this thesis, many small firms are owned and managed by self-employed workers, so it is appropriate to review this literature.

² The EU-15 comprises the following 15 countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom (European Commission 2014).

is the determinants of the transition from solo self-employment into employership as new businesses typically face a first-employee hiring threshold (Fairlie and Miranda 2017). Hiring the first employee involves substantial adjustment costs in managing the payroll, the payment of labour taxes, searching for and training new employees, and gaining awareness of the relevant employment legislation. Also, new firms are susceptible to asymmetric information about hidden worker types, where the newly self-employed may find it difficult to gauge the quality of available workers (Boadway and Tremblay 2005). The self-employed can instead experiment with solo self-employment first to better estimate their own entrepreneurial ability, to minimise the labour market information disadvantage and gauge if it is worthwhile to cross the first-employee hiring threshold into employership. Arguably, once this transition (from solo self-employment to employership) is made, the self-employed may be an engine for employment creation (Henley 2005).

The literature on the dynamics between solo self-employment and employership in detail is limited. Specifically, there is no consensus on whether true cross-state dependence in employership from solo self-employment exists, i.e., does being solo self-employed causally increase the individual's probability of being an employer in the future (Lechmann and Wunder 2017)? If previous solo self-employment experience has a causal effect on the probability of employership, then policy measures such as start-up grants will be effective in stimulating job creation.

There is also the possibility of “double-dividends” which refers to the act of potentially creating a job creator after lifting them out of unemployment and pushing them into self-employment (Caliendo and Kritikos 2010). Second, it is not widely understood if there is true state dependence in employership, i.e., does being an employer increase the individual's probability of being an employer in the future (Heckman and Borjas 1980; Heckman 1981; Prowse 2012)?

If so, the aforementioned policy measures will have lasting effects, even after they end. So far, Lechmann and Wunder (2017) is the only study that investigated both issues. Lechmann and Wunder (2017) findings are based on a German longitudinal household dataset and there is no indication if their conclusions are valid across borders in a different institutional setting. To further our understanding of the dynamics between solo self-employment and employership, I investigate if true (cross) state dependence in employership exists within Australian labour markets with individual-level data covering the periods 2001 – 2016 from the HILDA Survey. I hypothesise that individuals

experiment within solo self-employment first to better estimate their own entrepreneurial ability and to minimise their labour market information disadvantage.

1.3 The Skill-Based Determinants of Employership Survival

Self-employment is a volatile activity. Almost 50 per cent of all new firms that started in Australia in 2008 have been observed to shut down within 3 years (ABS 2018d). It is productive to study why some self-employed workers succeed while others failed as such findings inform policymakers about whether they should intervene to improve self-employment survival rates, or how to allocate resources more efficiently. For example, policies such as subsidies or tax concessions are counter-productive if the self-employed recipient has similar characteristics to individuals who exit self-employment after a short amount of time. This is inefficient as resources are being wasted. High rates of self-employment exits are also costly to the individual themselves as they spent time and resources on a venture that was likely to fail in a short period. In addition, other third parties such as financial intuitions and lenders are at risk in wasting their resources on ventures likely to end. Thus, self-employment survival is a key topic of economic and social importance. Yet, the literature's knowledge about appropriate government intervention in improving survival rates remains limited, especially if there is no consensus on what the optimal rate of business failure should be (Holtz-Eakin 2000). The problem is further compounded by the fact that the economics literature examining self-employment survival is small relative to the number of studies about self-employment entry (Georgellis, Sessions, and Tsitsianis 2007).

I propose that individuals exit from self-employment because of a mismatch between their entrepreneurial expectations and the skills required to be self-employed. I hypothesise that some skills are better than others in proxying for entrepreneurial ability (which is unobservable to the individual themselves). Having a good proxy allows an individual to better estimate their ability as these individuals will only set up their businesses if they have a high a priori chance of survival. Some studies suggest that the individual's beliefs about their own entrepreneurial ability are shaped by their pre-entry experiences such as education and work experience (Cressy 1999; Baptista, Karaöz, and Mendonça 2014). Hence, a common theme in the self-employment survival literature has been establishing the relationship between the individual's human capital (in the form of education and working experience) and their duration in self-employment. However, an issue with the traditional measures of human capital (i.e., education and working

experience) is that they are poor descriptors of the individual's acquired skills and abilities (Cooper, Gimeno-Gascon, and Woo 1994; Simoes, Crespo, and Moreira 2016). The literature has yet to unpack the skills or abilities acquirable from the self-employed pre-entry experiences and discuss which of those skills/abilities matter most for survival in self-employment. I attempt to measure the self-employed stock of skills by examining their previously held occupation and understanding what skills they needed to perform satisfactorily in that occupation. This thesis is the first study to unpack the skills acquirable by an individual and to investigate their influences on their duration in self-employment.

Further, there is even less discussion on the determinants of survival in solo self-employment and employership. If start-up constraints are different for both forms of self-employment then the determinants of employership survival should differ from those of solo self-employment survival (Cowling et al. 2004). I concentrate on employers as a study on the determinants of employership survival has greater implications for net job creation than a study of the determinants of solo self-employment survival.

1.4 Job Satisfaction and the Self-Employed

Over the past decade, employership and solo self-employment rates have been falling according to Figure 1-1, whereas the employment to population (EP) ratio among 20 to 64 years old individuals has been increasing over the same period (Cowling and Wooden 2018).³ Without understanding what the underlying reasons are for this continuous decline any policy to promote self-employment risks being wasteful and ineffectual. Atalay, Kim, and Whelan (2014) report evidence showing that the decline in self-employment rates is mainly because of an increase in labour force participation by women over 55 years of age – these women are less likely than other demographic groups to be self-employed.

However, according to Figure 1-2, once I restrict attention to workers aged 15 to 54 years, the downward trend among employers remain. Although the solo self-employment rate stabilised from the year 2007 onwards, the employership rates declined from about 7 per cent in 2001 to 4.5 per cent in 2016 among workers aged 15 to 54 years. There is no evidence to support the notion that demographic changes in the labour force are the only determinants of the decline in self-employment rates. This is a topic of economic

³ Among 20-64 years old, the EP ratio increased from 69.9% in January 2001 to 77.0% in March 2019. Rates are based on the original figures reported in ABS (2019a).

importance as there is a potential shortage of employers in the Australian labour market. Such a shortage can contribute to long-term negative consequences for economic growth and job opportunities (Blanchflower, Oswald, and Stutzer 2001; Koellinger and Thurik 2012).

FIGURE 1-1: TRENDS IN AUSTRALIAN SELF-EMPLOYMENT



Notes: I define self-employment rates as a proportion of employed persons who are observed to be self-employed in October. Employers are defined as owner-managers with employees. Solo self-employed workers are owner-managers without employees. They include both incorporated and unincorporated enterprises.

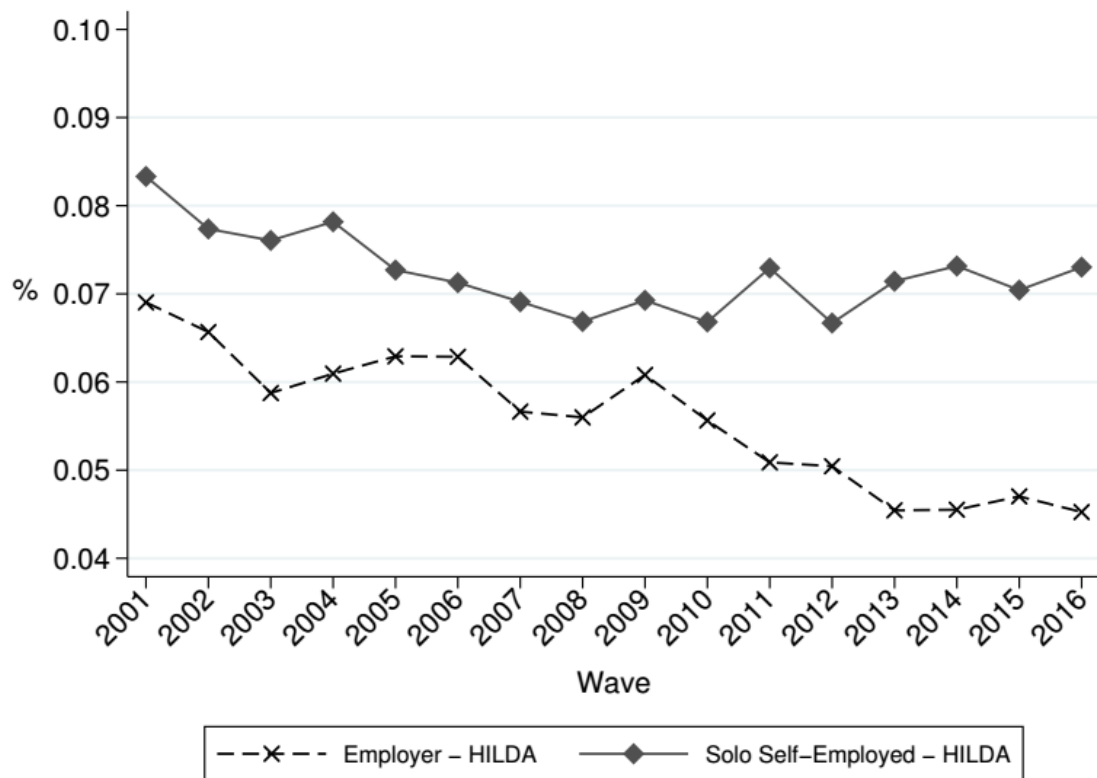
Source: Estimates come from ABS Labour Force, Australia, Detailed - Electronic Delivery, March 2019, 'Table 08. Employed Persons by Status in Employment of Main Job and Sex', time series spreadsheet, cat. no. 6291.0.55.001.

There is consistent evidence that the self-employed are more satisfied with their jobs than wage or salary employees (Hundley 2001; Benz and Frey 2004, 2008a). Tracing back to Knight (1921), the empirical evidence from the self-employment literature supports the notion that an attractive feature of self-employment is independence in the workplace, something that is referred to as a “desire to be one’s own boss” (Burke, FitzRoy, and Nolan 2000, p. 566). If individuals are likelier to be more satisfied working in self-employment than wage/salary employment, then what would explain the observed decrease in employership rates? The relationship between job satisfaction and Australian employership has yet to be thoroughly investigated by the literature. It could be that

Australian employers are less satisfied with their jobs than wage/salary employees leading to a negative trend in employership rates. An alternate hypothesis is that there are ‘market failures’ leading to insufficient employership in the Australian labour market. More specifically, there are barriers to employership entry. Aside from the start-up and hiring costs of becoming an employer, individuals are expected to overcome regulatory entry barriers. According to an inquiry by the Productivity Commission (2015), ongoing tax and employment regulatory compliance is a major business burden and risks dissuading new entrants into self-employment. The Commission also suggests new businesses are at an informational disadvantage and risk entering ‘unfair’ contracts with incumbent businesses (either as clients or as suppliers). There are also psychological barriers to entry as individuals may not fully know the benefits of working in self-employment or are risk-averse. Steffans and Omarova (2018) provide evidence that a higher than global average percentage of Australians report that a ‘fear of business failure’ is preventing them from pursuing any entrepreneurial opportunity. These ‘market imperfections’ that are hindering entry into self-employment is another common rationale for pro-entrepreneurship policies (Storey 2003).

I investigate if the declining employership rates (as shown in Figure 1-1) are caused by dissatisfaction with being an employer or by a combination of financial, regulatory or psychological barriers to employership entry. If there are barriers to entry, then it stands to reason to expect the average utility of employership to be significantly higher than the average utility of wage/salary employment. This is because an employership premium is needed to cover the costs of overcoming the entry barrier. However, the utility from an employment state is a combination of the monetary and non-pecuniary benefits associated with that state. Thus, it is insufficient to compare income from wage/salary employment with employership income. Instead, I use self-reported job satisfaction scores as a proxy for employment utility. If average job satisfaction for employership score significantly higher than for wage/salary employment, then there is evidence to suggest that there are increasing barriers to employership entry.

FIGURE 1-2: TRENDS IN AUSTRALIAN SELF-EMPLOYMENT (15–54 YEARS)



Notes: Self-employment rates are defined as the proportion of employed persons (aged 15-55 years) who are self-employed (either in solo self-employment or employership). I used responding person population weights, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24).

Source: Waves 1 to 16 of the HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

I use this opportunity to address another topic – the status of solo self-employed workers. Employers are seen as genuine entrepreneurs (individuals who are voluntarily pursuing an entrepreneurial idea in self-employment) given they are creating jobs and likely hired capital to work with their employees (Earle and Sakova 2000). In contrast, the status of solo self-employed workers is ambiguous. While some might be considered as early genuine entrepreneurs, others might be self-employed to avoid staying in unemployment. The latter, known as ‘necessity’ self-employed workers, will probably receive aid with starting up their business, but it is more productive to target businesses that offer reasonable prospects of growth and economic development (Bates 2003). The ‘necessity’ self-employed are likely to leave self-employment the moment a suitable wage or salary position is available. Any pro-entrepreneurial policy risks subsidising firms created by ‘necessity’ self-employed and diverting scarce resources away from higher quality business ventures. This thesis uses job satisfaction to investigate whether

Australian solo self-employed workers are self-employed out of necessity, an area of research that has yet to be touched by the literature.

1.5 Structure of the Thesis

Overall, this thesis includes three essays examining the dynamics, survivability and job satisfaction of the Australian self-employed workers. First, I investigate if true (cross) state dependence exists in Australia. Second, the self-employment literature has yet to discuss what specific skills, from the employer's human capital stock, increase the employer's duration in self-employment. By examining the employer's previous occupation, I unpack the skills they acquired and their relationship with employership survivability. Third, I recognise Australian employership and solo self-employment rates have dropped continuously over the past decade, but there is a lack of academic consensus on what is causing the decline. I propose there are barriers hindering self-employment entry leading to an undersupply of such individuals. To investigate this, I use self-reported measures of job satisfaction as a proxy for employment returns, and I examine the differences in job satisfaction between employers, solo self-employed workers and wage/salary employees. If there are indeed self-employment entry barriers, then we expect self-employed workers to have higher job satisfaction scores than wage/salary employees. At the same time, I investigate if the average Australian solo self-employed worker is self-employed out of necessity. While employers may be considered as genuine entrepreneurs, the status of the solo self-employed is less obvious. I use job satisfaction scores to examine if solo self-employed workers are self-employed voluntarily or are pushed into self-employed to avoid unemployment. If the latter is true, then the solo self-employed should be less satisfied than their wage/salary employee counterparts.

I structure this study as follows. Chapter 2 describes the HILDA Survey and its suitability for examining self-employed workers in Australia. The chapter also explains the method used to identify employers from solo self-employed workers and discusses why I focus on individuals between the ages of 21 and 64 years (inclusive).

Chapter 3 investigates if the true cross-state dependence in employership on solo self-employment exists in Australian labour markets. This is done by using a dynamic multinomial logit model with correlated random effects to determine if the individual's probability of being an employer this year increases if they were solo self-employed (instead of being non-employed or wage/salary employed) last year. Being solo self-employed in one year increases the probability of employership in the next, with estimates

similar to that of Lechmann and Wunder (2017) for Germany. Also, I find true state dependence in employership exists but, unlike Lechmann and Wunder (2017), males have higher persistence in employership than females.

Chapter 4 focuses on individuals who recently became employers. This chapter is the first study to match longitudinal data from Australia with an external dataset that provides information about the skills and abilities required to work a specific occupation. This allows me to identify the skills and abilities employers have likely acquired from their pre-employership entry experiences. After matching, I used factor analysis to reveal five main occupational skills: cognitive mathematics, technical specialisation, resource management and pattern recognition. Using a discrete survival analysis method in the form of a complementary log-log model, I show employers coming from occupations that consider cognitive, mathematical, or resource management as important skills have a significantly lower hazard of exiting employership at wave t (conditional on survival until wave t) than their counterparts.

Chapter 5 investigates the job satisfaction differences between employers, solo self-employed workers and wage/salary employees. I use an ordered logit model with individual fixed effects to measure the effect of being an employer or a solo self-employed worker on job satisfaction scores within the Australian labour market. The results reveal that self-employed workers, both employers and solo self-employed workers, are significantly more satisfied with their jobs than their wage/salary counterparts. I conclude that individuals are being discouraged from transitioning into self-employment.

I conclude the thesis with Chapter 6 where I summarise the main results and the thesis' contribution to the self-employment literature.

Chapter 2

The Household, Income and Labour Dynamics in Australia Survey

2.1 Introduction – HILDA Survey Data

Chapters 3, 4 and 5 rely on longitudinal data collected from individuals responding to waves 2001 to 2016 of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. I used individual-level longitudinal data to better our understanding of the transition dynamics between solo self-employment and employership, revealing the skill-based determinants of employership survivability and investigating the differences in job satisfaction between self-employed workers and wage/salary employees.

The HILDA Survey project is Australia's first and only nationally representative longitudinal household panel survey and funded by the Australian Government's Department of Families and Community Services. My primary reason for using the survey is its ability to describe the respondents' employment choice in each wave and to allow identification of individuals who are solo self-employed or in employership. I further take advantage of the longitudinal nature of the sample to examine how the individual's employment status changes over time. The survey also collects a broad array of data about the respondent's current employment situation, including their occupation title and self-reported measures of job satisfaction, which are the main variables of interest in Chapters 4 and 5, respectively. Also, the survey sample was designed to be representative of the Australian population living in private dwellings (Wooden and Watson 2007).⁴

The following section summarises the design of the HILDA Survey, its sample selection process and its collection method. Subsections 2.2.1 and 2.2.2 discuss the main variables used in this thesis and the suitability of the data for examining self-employed workers in Australia. First, I assess how well the sample represents the Australian population regarding employment status. I consider this in section 2.2.1 by comparing solo self-employment and employership rates from both the HILDA Survey and ABS

⁴ The reference population for the wave 2001 sample exclude diplomatic personnel of foreign governments, overseas residents (those who intend to stay in Australia for less than one year), members of foreign defence forces stationed in Australia, and people living in remote Australian regions with sparse populations (Watson and Wooden, 2012). Persons who live in more than one household were treated as members of the household where they spent most of their time in. Also, households were defined as "a group of people who usually reside and eat together" and were selected using a multi-stage sampling design (Wooden and Watson 2007, p. 209).

Labour Force Survey data. Section 2.2.2 assesses the quality of occupation information present within the HILDA sample. Occupation information needs to be reliable as Chapter 4 uses the employers' occupation background to infer what skills/abilities they acquired during their pre-employment entry experience. Although some respondents provided missing or insufficient occupation information, they are an insignificant minority of the HILDA Survey. Section 2.2.3 discusses and defines the common variables that I controlled for in the estimated models of Chapters 3, 4 and 5. Section 2.2.4 discusses my decision to focus on a sample comprising individuals aged between 21 and 64 years. The last sub-section, Section 2.2.5, discusses sample attrition.

2.2 HILDA Survey Design

As explained in Watson and Wooden (2002), Wooden and Watson (2007) and Summerfield et al. (2017) sample selection involves a three-stage process. At the first stage, a sample of 488 Census Collection Districts (CD) was selected from across Australia. Each CD contains about 200 to 250 households. The “frame of CDs was stratified by state, and within the five largest states in terms of population, by metropolitan and non-metropolitan regions” to ensure that the HILDA sample adequately covered the entirety of Australia (Watson and Wooden 2002, p. 6).⁵ At the second stage, within each CD, a sample of 22 to 34 dwellings was randomly selected. The actual number depended on the CD's expected response and occupancy rates (Watson and Wooden 2002, p. 8). The third stage involves selecting households within the chosen dwellings. If a dwelling contained three or fewer households, all households were sampled. For dwellings with four or more households, a random sample of three households was obtained (Watson and Wooden 2002, p. 9). A top-up sample was later introduced in wave 2011 with the same selection process. Personal interviews were then conducted with all household members aged 15 years and above.⁶ All members of households, where at least one person provided an interview in wave 2001 (or wave 2011 if they are part of the top-up sample), are tracked by the survey annually with interviews occurring between August and March.⁷

⁵ A CD is a geographic area designed for the Census of Population and Housing as the smallest unit for collection and processing (Australian Bureau of Statistics 2006). The HILDA Survey sampled CDs designed for the 1996 Census (Watson and Wooden 2002, p. 5).

⁶ Typically, interviews are administered on a face-to-face basis at the home of the respondent. If a face-to-face is impossible, telephone interviews are conducted instead. The proportion of interviews conducted by phone in wave 2001 was insignificant but increased to 9.1 per cent by wave 2016 (Summerfield et al. 2017, p. 156).

⁷ The survey also interviews any new persons that joined households which the sample members are living in. “All children born to, or adopted by, an original sample member become permanent or continuing sample members. Most other persons remain in the sample for as long as they remain living in a household with a continuing sample member” (Watson and Wooden 2012, p. 371). Members leaving a household are followed to their new household (for exceptions to this rule, see Wooden and Watson, 2007). Further, tracked sample members are not interviewed if they are in prison or living overseas.

Summerfield et al. (2017, Section 8.6) show that 13,969 persons (out of 15,127 eligible adults) from 7,682 households (out of 11,693 eligible households) were successfully interviewed for wave 2001 and, with the wave 2011 top-up sample, 4,280 eligible individuals from 2,153 households were added to the survey.⁸ According to Summerfield et al. (2017), these individuals are defined as Continuing Sample Members (CSMs) and they remain in the sample until they are out of scope (that is, those that have died, moved overseas permanently or gone to prison). The sample design accounts for most changes in household composition over time and keeps tracking CSMs (where applicable) even when their household has split, moved or both. Children born to or adopted by CSMs after wave 2001 (or after 2011 for the top-up sample), and any new household members who arrived in Australia for the first time after 2001 (or after 2011 for the top-up sample) are also sampled as CSMs. However, any other individual who joins a sampled household in wave 2002 or later (in wave 2012 or later for the top-up sample) are referred to as Temporary Sample Members (TSMs). The survey follows them until they no longer share a household with a CSM – unless the TSM has a child with a CSM.

The survey comprises two main components – the household and the individual. The household component includes the Household Form (HF) and the Household Questionnaire (HQ). The HF is “the ‘master document’ used by interviewers to determine who to interview, how to treat joiners and leavers of the household, and to record call information and non-interview reasons” (Summerfield et al. 2017, Section 2.2.1). The HQ collects information about the household and is administered to only one member of the household (Summerfield et al. 2017, Section 2.2.2). The individual component comprises either the Continuing Person Questionnaire (CPQ) or the New Person Questionnaire (NPQ) (Watson and Wooden 2012, p. 372). The CPQ is administered to every individual who responded in a previous wave whereas the NPQ is given to individuals who recently joined the household. The Person Questionnaires include topics such as the individual’s employment status (explained later in section 2.2.1), details about their current employment (e.g., their occupation and satisfaction with their job) and education. Watson and Wooden (2012, p. 372) offer a more detailed summary of the core topics included every year.

⁸ Only household members aged 15 years and over are interviewed. However, parental consent must be given before interviewing persons aged under 18 years old who are still living with their parents.

Every individual successfully interviewed is also asked to complete a self-completion questionnaire (SCQ). The questionnaire includes questions difficult to administer or are uncomfortable for respondents to answer in a face-to-face interview (Watson and Wooden 2012, p. 373). The topics covered in the SCQ include the individual's health status, lifestyle behaviour, time use, financial stress and personality traits (see Watson and Wooden 2012, p. 373, for a more exhaustive list).

2.2.1 Classifying the Main Employment Statuses

In this thesis, I identify 4 main employment statuses: **employees**, **employers**, **solo self-employed workers**, and the **non-employees** (individuals who are unemployed or not active in the labour force (NILF)).⁹ The respondent's employment status in each wave depends on their responses to three questions within the Person Questionnaires administered for that wave (if a respondent is working multiple jobs, then their employment state is based on the job they get the most pay from). These questions originated from the Labour Force Survey (LFS) component of the ABS' Monthly Population Survey (Summerfield et al. 2017, Appendix 1b; ABS 2014). For each wave, a respondent is:

- An **employee** if they responded yes to the question “[Do/did] you work for an employer for wages or salary?” or “[Do/did] you work for without pay in a family business?”.
- An **employer** if they responded yes to the question “[Do/did] you work in your own business with employees?”
- A **solo self-employed** worker if they responded yes to the question “[Do/did] you work in your own business with no employees?”
- Or a **non-employee** if they responded no to all the above questions. However, I exclude individuals who are not looking for work because of being enrolled in formal study.

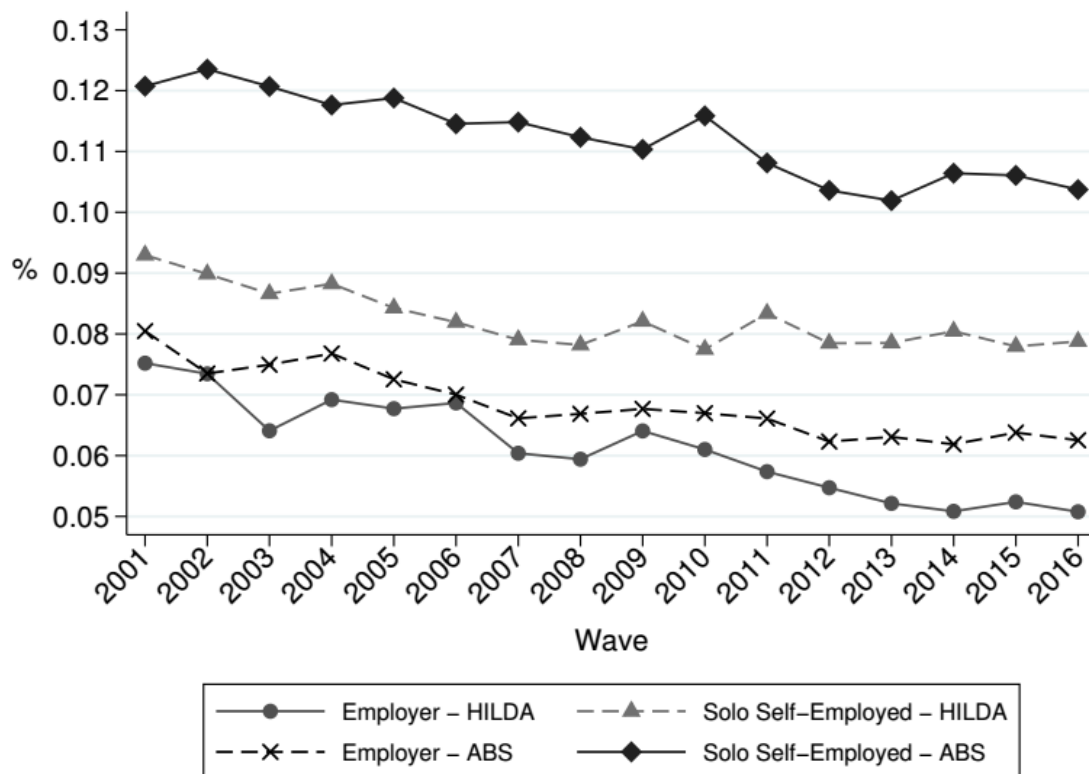
2.2.1.1 Sample Representativeness

Figure 2-1 assesses the representativeness of the employed population in the HILDA Survey sample by comparing self-employment rates based on data from the HILDA Survey and the ABS LFS (ABS 2019b) for the same years (i.e., 2001 – 2016). The ABS

⁹ An owner-manager is an individual who operates their own incorporated or unincorporated enterprise, or works as an independent professional or tradesman (ABS 2018d).

LFS is the most authoritative representation of Australian solo self-employment and employership and hence can act as a benchmark to assess how well the HILDA sample represents the Australian labour market. ABS employership rates are represented by the proportion of persons who are owner-managers of incorporated or unincorporated enterprises with employees, of those who are employed. Solo self-employment rates are represented by the proportion of persons who are owner-managers of incorporated or unincorporated enterprises without employees.¹⁰

FIGURE 2-1: HILDA AND ABS SELF-EMPLOYMENT TRENDS



Notes: Self-employment rates are defined as the proportion of employed persons (aged 15-64) who are self-employed. HILDA self-employment rates are population-weighted. I used responding person population weights, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24).

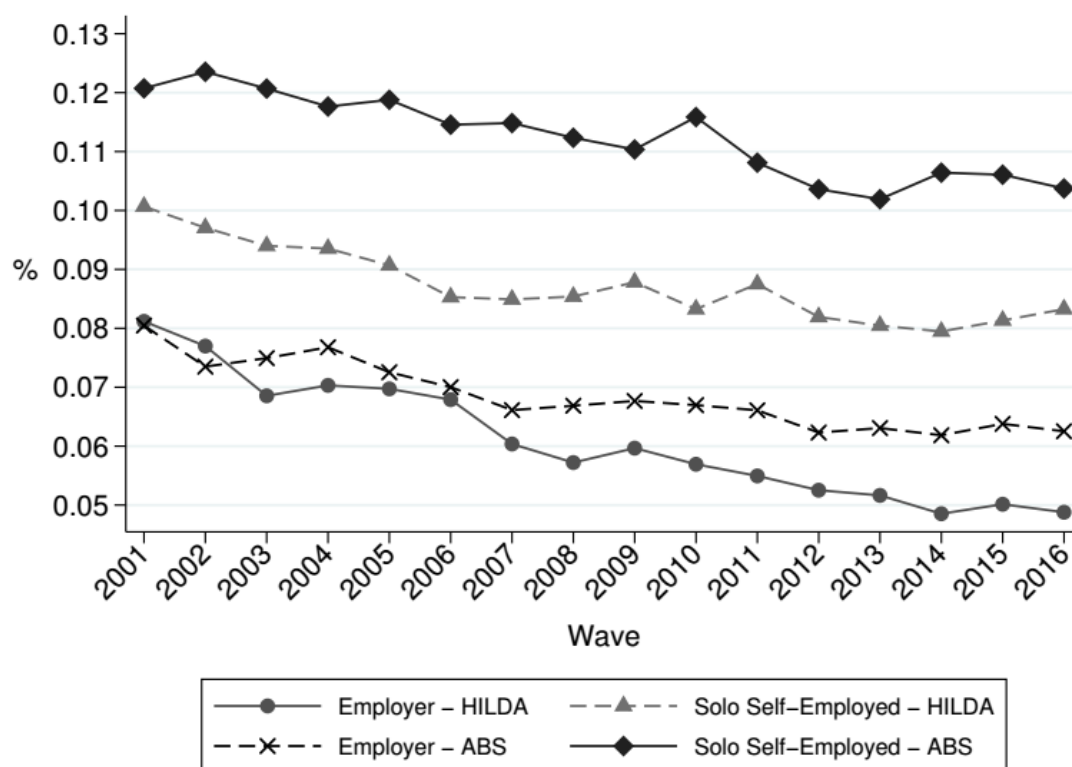
Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a) and ABS Labour Force, Australia, Detailed - Electronic Delivery, March 2019, 'Table 08. Employed Persons by Status in Employment of Main Job and Sex', time series spreadsheet, cat. no. 6291.0.55.001.

Unfortunately, in Figure 2-1, I observe a significant discrepancy between the ABS and HILDA Survey solo self-employment rates. From 2001 to 2016, the ABS solo self-employment rate is about 3 percentage points higher, on average, than the HILDA solo

¹⁰ The latest ABS definition of an owner manager of an incorporated enterprise is a "person who operates his or her own incorporated enterprise, that is, a business entity which is registered as a separate legal entity to its members or owners (also known as a limited liability company)". An owner manager of an unincorporated enterprise is a "person who operates his or her own unincorporated enterprise or engages independently in a profession or trade" (ABS 2018d).

self-employment rate. On the other hand, the ABS employership rate is about 0.7 percentage points higher, on average, than the HILDA rate, suggesting that employers are adequately sampled by the HILDA Survey.

FIGURE 2-2: UNWEIGHTED HILDA AND ABS SELF-EMPLOYMENT TRENDS



Notes: Self-employment rates are defined as the proportion of employed persons (aged 15-64) who are self-employed. HILDA self-employment rates are unweighted.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a) and ABS Labour Force, Australia, Detailed - Electronic Delivery, March 2019, 'Table 08. Employed Persons by Status in Employment of Main Job and Sex', time series spreadsheet, cat. no. 6291.0.55.001.

A plausible explanation is a difference in response rates between the two surveys. For HILDA, about 66 per cent of the households contacted responded during the initial 2001 wave and around 68 per cent of the top-up sample responded during the 2011 wave. In contrast, response rates for the ABS Labour Force Surveys appear to average above 90 per cent between the years 2005 and 2018 (ABS 2005, 2018f). Solo self-employed workers are presumably too busy to take part in the interviews for the HILDA Survey, whereas individuals are legally obliged to respond to the Labour Force Surveys (ABS 2018g). Another reason is that the HILDA Survey and ABS Labour Force Survey have different collection methodologies. The HILDA Survey administers questionnaires to every member of the household aged 15 years and over, whereas the ABS Labour Force

Survey uses the Any Responsible Adult (ARA) methodology (ABS 2018d). The ARA method has one person (the first adult with whom the interviewer contacts) in the sampled household complete the survey on behalf of other household members. This adult may misidentify the employment status of the other household members.

Despite the significant difference in solo self-employment rates, the trends (including the employership trends) are similar across HILDA and ABS data. I note that I risk underestimating the incidence of solo self-employment in Australian labour markets. As a result, in Chapter 3, I may underestimate the effect of being solo self-employed this year on the probability of employership next year, especially when HILDA solo self-employment rates are significantly lower than their ABS counterparts. In contrast, the difference between HILDA and ABS employership rates is relatively minor. However, the widening gap between HILDA and ABS employership rates after the year 2009 suggests I may also underestimate the extent of true state dependence in employership – the difference between the probability of being an employer this year conditional on being an employer last year and the probability of being an employer this year given the individual was in an alternate employment state last year. This is because the HILDA employership rate is declining faster than the ABS rate. In Chapter 5, this thesis likely overestimated the job satisfaction premium in solo self-employment and employership. If there is a shortage of solo self-employed workers and employers in Australian labour markets, then they will earn higher returns (measured by job satisfaction) than wage/salary employees. Figure 2-1 suggests the shortage is more severe within the HILDA sample than what the ABS rates suggest.

2.2.2 Occupation

Occupation data is central to the analysis undertaken in Chapter 4 where I unpack the employers' acquired skills/abilities from their previous occupation. Having the most detailed occupation information available allows me to identify the relevant skills/abilities more accurately. Thus, this study also used the HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b) to identify the employer's past occupations and the work they did before becoming an employer.¹¹ In each wave,

¹¹ There are two versions of the HILDA Survey data available: (1) The General Release version means a release of data from which more sensitive information such as names, addresses (including postcodes) and date of birth have been removed and some other information has been modified by various methods such as top coding and the application of classification codes at a more general level (including occupation and industry classifications); (2) The Restricted (also known as in-confidence unit files) Release version

respondents are asked the following question: “What kind of work do you do in this job? That is, what is your occupation called and what are the main tasks and duties you undertake in this job? Please describe fully.” These questions are based on the standard ABS design and are like the ones asked in the LFS (Summerfield et al. 2017, Appendix 1b; ABS 2014). If a respondent is working multiple jobs at the time of their interview, then they are asked about their main job (i.e., the job where they earn most of their income from).

Based on the responses, coders manually assign Australian and New Zealand Standard Classification of Occupations (ANZSCO) (ABS 2013) codes to the individual’s descriptions of their occupation.¹² ANZSCO is an ABS (and Statistics New Zealand) skill-based classification system that classifies all occupations and jobs in Australian and New Zealand labour markets.¹³ In HILDA, ANZSCO occupation variables are available at the 1-digit, 2-digit and 4-digit levels. The 4-digit level is the most disaggregated (and the most detailed) level of occupational information available within the in-confidence unit record files of the HILDA Survey data.¹⁴

Unfortunately, the survey does not always fully identify the respondent’s occupation. Some individuals don’t know their occupation, refuse to state their occupation or provide insufficient information for coders to determine their occupation. To be clear, observations where coders cannot determine the individual’s occupation at any level, are assigned the ‘unable to determine’ label. Observations where coders can determine the individual’s occupation at the 1-digit or 2-digit levels, but not at the 4-digit level, are assigned the ‘not further defined’ (n.f.d) label.¹⁵ Since Chapter 4 uses ANZSCO occupation data to describe the skills employers gained from their previous employment, individuals with ‘not stated’, ‘don’t know’ and ‘unable to determine’ occupations are dropped from the sample. They make up around 0.05 per cent of the whole sample (110 out of 235,611 observations). This is unlikely to impart bias on the results in this thesis. For the n.f.d cases, available information on occupations (at the 1-digit or 2-digit level of ANZSCO) can approximate the acquired skills for these individuals. I further explore this

means a release of data from which the names and addresses have been removed but some information such as postcodes, date of birth and other data are provided at a more detailed level than the General Release datasets (DSS 2019, p. 29).

¹² Occupations are coded manually based on the occupation title, and descriptions of job tasks and duties.

¹³ Statistics New Zealand is the public service department of New Zealand in charge of the collection of economy and population statistics in New Zealand.

¹⁴ For details on the ANZSCO structure see Appendix 7.4.

¹⁵ For example, if an individual’s occupation can be classified as ‘Manager’ at the 1-digit level but unable to be classified at the 4-digit level, then they are classified as ‘Managers – n.f.d’.

issue in Chapter 4 and Appendix 4.3. Fortunately, n.f.d. cases only make up 1.55 per cent of the original ‘employed’ sample.¹⁶

The occupation variable also suffers from measurement error. As stated earlier, coders manually enter the respondent’s ANZSCO code according to their interpretation of the respondent’s occupation description. There is a degree of subjectivity in assigning ANZSCO codes, especially when occupation titles or task descriptions are vague. Two individuals from the same occupation can be assigned two different ANZSCO codes because they each described their occupation differently and/or coders have different interpretations of the same description of job tasks and duties. Worryingly, Watson and Summerfield (2009) showed that, in wave 2006, the HILDA Survey has a 15.4 per cent rate of misclassifying occupations (at the 4-digit level) and is “double that of the ABS Labour Force Survey”. Watson and Summerfield (2009) explained that the ABS uses a combination of automatic and manual coding – around 65 per cent of occupation responses are coded automatically (with a system that is not available outside of the ABS) with an accuracy rate of over 99 per cent. Despite this weakness, the HILDA Survey remains the best source of individual-level longitudinal data to inform us of the employer’s occupational background. In addition, the measurement error appears to be random as the coding process is uncorrelated with the respondent’s characteristics or their decision to be self-employed. Thus, we should not expect the coding process to impart significant bias on any results in this thesis.

2.2.3 Control Variables

Alongside individual employment information, the HILDA Survey collects information on a wide range of aspects of individual characteristics in Australian households such as income and health. With access to a broad variety of demographic and geographic characteristics, I create a set of variables to control for in the analyses undertaken in Chapters 3, 4 and 5. As explained in the subsequent literature reviews, several studies found these variables to be associated with the decisions to be self-employed and the survivability of being self-employed.

¹⁶ This is the original HILDA sample after dropping unemployed or inactive individuals.

Determinants of Self-Employment Entry and/or Survival

Age

Age is a continuous variable measuring the respondent's age at their last birthday on June 30. I also include a squared age variable, which I divide by 100 for presentation purposes. The adjustment will only scale up the estimated coefficients. Squaring age creates a variable with large values and led to small estimates of the age squared coefficient.

Lévesque and Minniti (2006) propose there is an inverse U-shaped relationship between age and the decision to be self-employed. There are a few reasons justifying why older individuals are more prone to be self-employed but become less likely above a threshold age. Older individuals have on average a larger amount of resources that facilitate transitions into self-employment, such as human and financial capital. Second, older individuals are more likely to be self-employed because of a stronger desire for flexible employment situations (Cahill, Giandrea, and Quinn 2013). However, after reaching a certain threshold, age has a negative influence on self-employment entry because of higher risk aversion levels and less time to recover the initial investment made at entry (Hintermaier and Steinberger 2005). Thus, most empirical studies test and found that age has a nonlinear effect on self-employment duration by including both a linear and a quadratic term in the analysis (Fairlie 1999; Dunn and Holtz-Eakin 2000; Blanchflower 2004; Andersson and Hammarstedt 2010; Caliendo and Kritikos 2010).

Marital status

HILDA records the individual's responses to questions about their registered marital status and (if not married) whether they are living with their significant other. In this thesis, I constructed a dummy variable that equals to one if the respondent is married or in a de facto relationship, and zero otherwise.¹⁷ If an individual is married, then their wealth increases because of the assets owned by their spouse. This relaxes the liquidity constraints hampering the decision to enter self-employment. It also provides the self-employed with a larger contingency reserve to address any financial difficulties and delays business closure (Budig 2006). The positive influence of marital status on self-

¹⁷ A de facto relationship implies that the respondent is living together with their partner on a 'genuine' domestic basis. This is defined in Section 4AA of the Family Law Act 1975 (Family Court of Australia 2016).

employment entry has also been reported by multiple studies (Taylor 1996; Ahn 2010; Özcan 2011; Brown et al. 2011; Eliasson and Westlund 2013).

Real annual household net income

This is a continuous variable that represents the respondent's real household disposable income (after paying taxes) relating to the completed financial year preceding the date of the interview. For example, in a wave 2001 interview, income is the amount earned between July 2000 to June 2001. Household income is derived from the sum of household members' wages and/or salary, investment income, business income, private transfers, private pensions and public transfers from the Australian Government, and irregular income such as inheritances and severance payments.

A common failing of most surveys is collecting complete information because of the respondent's refusal or lack of ability to provide the requested information. Regarding income information, the HILDA Survey is no different (Watson and Starick 2011). Around 24 per cent of my HILDA sample observations have missing information about at least one component of their income. This is likely because at least one household member failed to provide details for their own individual financial income. Looking into each income component: 10 per cent of the sample had missing information about household business income; 8 per cent had missing information about their transfers from the Australian Government; 7 per cent regarding foreign pensions; 16 per cent for household investment income; 7 per cent for private pensions; 8 per cent for private transfers; 7 per cent for other regular transfers such as scholarships; 7 per cent for irregular income; and 13 per cent for the household's sum of wages and salary. Missing information about the household's wages and salary, investment income and business income are the main drivers for missing household income information. A common way of proceeding is to drop observations with missing income data (Frick and Grabka 2010), but doing so may result in biased estimates if the non-respondents have different characteristics to complete income respondents (Watson and Starick 2011).

Instead of dropping observations with missing household income, I use imputed income values made available by the HILDA Survey.¹⁸ HILDA provides data files containing both imputed and non-imputed versions of the income variables for non-

¹⁸ Hayes and Watson (2009) fully describes the income imputation process.

responding persons in responding households. The imputation steps are as follows (Hayes and Watson 2009; Summerfield et al. 2017, Appendix 2):

1. The ‘Population Carry-Over’ method is used to predict if the income of a non-respondent is zero or non-zero. The predictions are based on information from the preceding or following wave response. One of these two waves was randomly chosen with probabilities reflecting the changes in reported income between waves observed in the population.
2. The ‘Nearest Neighbour Regression’ method is then used to find the closest donor for each non-response case. For each wave, a log-linear regression model is estimated with the household variable as the dependent variable. The model is then used to predict values for the non-respondent. These values are used to identify the nearest respondent (also known as the donor) whose reported value, Y_d , will be used as the non-respondent’s imputed value. The donor (d) is chosen if their predicted value is closest to the non-respondent (i), that is $|\hat{\mu}_i - \hat{\mu}_d| \leq |\hat{\mu}_i - \hat{\mu}_p|$ for all other respondents (p) where $\hat{\mu}_i$ is the predicted mean of Y for individual i that needs to be imputed.
3. If the non-respondent received a non-zero amount from Step 1 their estimate is replaced by the donor’s values. A non-respondent with a zero amount is left alone at this stage
4. The ‘Little and Su’ imputation procedure is then run on all records. This method uses a multiplicative model of the form:

$$\hat{Y}_{ij} = Y_{dj} \left(\frac{\bar{Y}^i}{\bar{Y}^{(d)}} \right)$$

where

$$\bar{Y}^i = \frac{1}{m} \sum_j \frac{Y_{ij}}{c_j}$$

and

$$c_j = \frac{\bar{Y}_j}{\bar{Y}}$$

where

$$\bar{Y} = \frac{1}{m} \sum_j \bar{Y}_j, \text{ for each wave } j = 1, \dots, m$$

$\hat{Y}_{ij}$ represents the ‘Little and Su’ imputed values, $\bar{Y}_j$ is the sample mean of income variable Y for wave $j = 1, \dots, m$. Y_{dj} is the donor’s reported income for wave j , Y_{ij} is the

individual's i reported income for wave j - Imputed values from Step 2 are used for non-responding individuals. Zero values imputed in Step 1 are not overwritten with the calculated imputed values.

I express all income variables at December 2016 prices to remove the effects of inflation and allowing income estimates from different waves to be more comparable. I did this by using the ABS' Consumer Price Index (CPI) (ABS 2018c). Using the same process employed by Wilkins and Lass (2018), I converted income by multiplying its value by the ratio of 'the CPI for the December quarter of 2016 (110.0) to the annual CPI of the financial year ending in the wave to the value comes from'.¹⁹ For example, to convert household income measured in wave 2001 (when the annual CPI was 73.6) to December 2016 prices, the income is multiplied by 1.49 (110/73.6).²⁰ I present the full formula used to convert income into real income in Appendix 2.3.

In Chapter 3, I use lagged household income values to control for income shocks. It is hypothesised that positive income shocks have a positive impact on transitions into self-employment (Taylor 2001). Negative income shocks have the opposite effect. This is similar to a control variable used by Lechmann and Wunder (2017).

In Chapter 5, income is further adjusted based on the size and composition of the household. Since Chapter 5 investigates job satisfaction differences between wage/salary employment, solo self-employment and employership, the analysis will need to control for both disposable household income and the size of the household. A multi-person household requires a higher level of disposable income than a single-person household to achieve the same living standard. This risks influencing the individual's reported job satisfaction, especially if the respondent feels dissatisfied with what they are earning given their household size. I divide the household's income with an equivalence factor calculated by the 'modified OECD' scale which allocates 1 point to the 1st adult, 0.5 points to each additional person aged 15 years and over, and 0.3 to each child under the age of 15 (Hagenaars, Vos, and Zaldi 1994).

In every model, I use income variables that have been log-transformed. For respondents with 0 or negative income values, I assigned them a value of 1 prior to the log transformation. This affects less than 1 per cent of my working sample (1.3 per cent

¹⁹ The ABS's CPI is produced on a quarterly basis. Thus, I generate the annual CPI values by taking the averages of quarterly CPI values over the relevant financial year. For example, the CPI for 2001 will take the arithmetic average of the September 2000 CPI, the December 2000 CPI, the March 2001 CPI and the June 2001 CPI.

²⁰ The interpretation of this adjustment is that prices on average rose by 49 per cent between wave 2001 and the December quarter of 2016.

of sampled solo self-employed workers and 0.8 per cent of sampled employers). I also constructed a dummy variable to indicate which observations have imputed income values.

Housing

This is a categorical variable indicating if the respondent (or any members of their household) rent their home, own their home with a mortgage, own their home without a mortgage or living in their home rent-free (also known as “others”).²¹ I classify homeowners without a mortgage by observing their mortgage (usual) repayments per month. Monthly mortgage repayment is a derived variable that converts mortgage repayments to a monthly figure, assuming there are 4.345 (52.14/12) weeks in a month. Like the income variable, missing values have been imputed to avoid additional loss of observations for this analysis. There is a risk for the HILDA Survey (and this thesis) to misclassify respondents as homeowners with or without mortgages.

I control for the individual’s home status as their own homes act as a source of collateral for business development (Henley 2005). A homeowner is more likely to enter self-employment than a non-home owner.

Place of birth

A categorical variable indicating if the individual was born in Australia, in a majority English-speaking country or a majority non-English speaking country. According to the survey, majority English-speaking countries comprise the United Kingdom, New Zealand, Canada, Ireland and South Africa. Simoes, Crespo, and Moreira (2016), in their review of the self-employment literature, state that it is a widely accepted fact that immigrants have an above-average propensity to be self-employed. Further, I distinguish between English speaking and non-English speaking immigrants (proxied by the dominant language spoken in their home country) as host language familiarity is a known determinant of self-employment entry. Unfamiliarity with the host language can reduce job opportunities in the wage sector and push the individual into the self-employment sector (Friedberg 2000; Kanas, van Tubergen, and van der Lippe 2009).

²¹ I classify any household involved in a rent-buy scheme as a renting household.

Urban area

A dummy variable that equals one if a respondent lives in an urban area. There is empirical evidence to suggest self-employment entry behaviour differs across urban or rural areas. Studies find individuals are more likely to be self-employed in rural areas because rural labour markets typically have weaker employment opportunities than urban areas. This variable allows me to control for entries into self-employment because of necessity conditions - individuals becoming self-employed in rural areas because of a lack of sustainable employment opportunities (Moore and Mueller 2010; Ritsilä and Tervo 2002; Carrasco and Ejrnæs 2003; Tervo 2006).

Business Size

This is a categorical variable indicating the size of the individual's business. I control for the individual's business size as it has been established that there is a positive relationship between business size and business survival rates. This is a stylized fact observed by Evans (1987) and confirmed in a host of other studies (Hall 1987; Dunne, Roberts, and Samuelson 1988; Audretsch 1991; Brüderl, Preisendörfer, and Ziegler 1992; Audretsch and Mahmood 1995; Gimeno et al. 1997; Baptista, Karaöz, and Mendonça 2014). As summarised by Audretsch and Mahmood (1995), small firms suffer a cost disadvantage as they tend to produce a level of output below that of the industry's minimum efficient scale. The gap between the minimum efficient scale and the firm's output level is predicted to be positively associated with the firm's likelihood of exit.

The business size variable is constructed by looking at their responses to the interview question "Approximately how many people (including yourself) are employed [at the place at which you work/ in your business]?"²² I note that this is a question about the respondent's size of the workplace, and not necessarily about their business. Nevertheless, this is the closest available measure of business size. The business size categories are: (1) Having less than 5 employees; (2) Having 5 to 19 employees; (3) 20 to 49 employees; or (4) having 50 employees or more.

Years of work experience

This is a HILDA Survey derived continuous variable representing the cumulative number of years an individual has spent in paid employment by the time of their interview. There is a consensus that 'work experience' has a positive impact on self-employment

²² This includes all employees, part-time workers and casual workers, but not contractors.

entry (Evans and Leighton 1989; Lin, Picot, and Compton 2000; Taylor 2001; Georgellis, Sessions, and Tsitsianis 2005; Poschke 2013b) and survival (Brüderl, Preisendörfer, and Ziegler 1992; Taylor 1999; Boden and Nucci 2000; Jensen et al. 2003; Baptista, Karaöz, and Mendonça 2014; Haapanen and Tervo 2009). Individuals learn from previous experiences increasing the probability of them identifying good entrepreneurial opportunities and the knowledge pursue it successfully. However, working experience also increases the value of wage/salary employment, which can make self-employment less attractive to experienced individuals (Parker 2009; Millán, Congregado, and Román 2012; Simoes, Crespo, and Moreira 2016). This suggests that there is an inverse-U relationship between work experience and self-employment entry/survival – experience pulls individuals into self-employment, but after reaching a threshold, experience pulls individuals into wage/salary employment instead. As a result, I also included a variable that squares the values of the derived work tenure. For presentation purposes, I divide the squared values by 100.

Unemployment rate

A continuous variable measuring the unemployment rate of the major statistical region the respondent is dwelling within. There are 13 major statistical regions: Sydney, Melbourne, Brisbane, Adelaide, Perth, the rest of the six previous states, the Northern Territory and the Australian Capital Territory. This is an area-based unemployment rate variable that matches the ABS unemployment rate in October of the interview year to the dwelling's major statistical region. Higher unemployment reduces opportunities for wage/salary employment which can push individuals into self-employment (Earle and Sakova 2000; Block and Wagner 2010). High unemployment also reduces demand for products and services reducing self-employed worker's income, reducing their propensity to be self-employed.

Impairment status

This is a dummy variable that equals to 1 (and zero otherwise) if the respondent has a health condition, impairment or disability that restricts their everyday activities and is likely to persist (or has lasted) for at least 6 months. Some studies suggest there is a negative correlation between health status and self-employment (Borjas 1986; Zissimopoulos and Karoly 2007; Pagán 2008; Jones and Latreille 2011). Individuals with a long-term health condition are hypothesised to prefer self-employment over other forms

of employment because of the flexibility associated with being one's own boss (Pagán 2008; Jones and Latreille 2011). Alternatively, they may be pushed into self-employment because of discrimination against their health conditions (Simoes, Crespo, and Moreira 2016). Other studies provide evidence of an opposite relationship (Taylor 2001; Parker and Rougier 2007; Cahill, Giandrea, and Quinn 2013). They argue that poor health reduces the individual's probability of becoming self-employed because poor health diminishes the ability to work independently and coping with high levels of stress (Gorgievski 2009).

Highest level of education achievement

This is a categorical variable indicating the highest level of education achieved by the respondent at the time of their interview. I constructed five education categories: (1) dropping out before completing secondary school; (2) completing secondary school; (3) received a certificate III or IV; (4) received a diploma or advanced diploma; or a (5) degree equivalent or higher than a bachelor's (with or without honours) degree.²³ I control for education as it is a prominent positive determinant of self-employment entry and survival in the literature, although several other studies rebuffed this claim. Individuals with higher education levels are less likely to be self-employed as they may have better job opportunities in the wage sector (van der Sluis, van Praag, and Vijverberg 2008). Alternatively, highly educated individuals are better equipped to identify high-quality entrepreneurial opportunities (Simoes et al. 2016). A set of empirical studies provide evidence to suggest a positive impact of education on self-employment entry (Borjas and Bronars 1989; Bates 1995; Kim, Aldrich, and Keister 2006; Zissimopoulos, Karoly, and Gu 2010) while another provides evidence supporting the opposite conclusion (Kidd 1993; Bruce 1999; Clark and Drinkwater 2000).

Number of dependents

This is a variable counting the number of dependents under the respondent's care. A dependent is a child aged younger than 15 years and resides with the respondent. Children of the respondent's (co-resident) partner from a previous relationship are also classified as dependents of the respondent. I control for dependents as the time and resources spent on the child-rearing process may be incompatible with the parent's decision to be self-

²³ A certificate III or IV qualifies individuals to apply a broad range of specialised knowledge and skills in varied contexts to undertake skilled work (Garland 2015). Degrees higher or equivalent to receiving a bachelor (with or without honours) degree include a graduate diploma or certificate, master's degree or doctorate.

employed, which is more demanding than wage/salary jobs (Fairchild 2009). On the other hand, having children could also increase a parent's motivation to be self-employed as they increase the parents' financial concerns. They become self-employed with the expectation to increase their income, higher than what they can earn in the wage/salary employment sector (Dawson, Henley, and Latreille 2014).

Determinants of Job Satisfaction

Hours usually worked in a week

This continuous variable represents how many hours per week the respondent usually works in their main job.²⁴ As stated earlier in section 2.2.1, I am focusing on the individual's main job – the job where they earn most of their income from. Therefore, I am interested in the number of hours worked in that employment state. I assign a value of 0 for respondents who report being non-employed at the time of the interview. In Chapter 5, weekly working hours proxy for work effort in both wage/salary employment and self-employment. As work effort is commonly assumed to reduce utility (Spencer 2003) it can have a negative impact on reported job satisfaction.

Part-time employed at their main job

A dummy variable that equals to one if the individual is employed part-time, i.e., usually works less than 35 hours a week, in their main job. This is different to the definition used by the ABS in its monthly LFS, where part-time workers are persons “who usually worked less than 35 hours (in all jobs) and either did so during the reference week, or were not at work in the reference week” (ABS 2018b). I control for this variable in Chapter 5 because multiple studies have shown that part-time employment leads to a decrease in job satisfaction, especially if part-timers are doing unskilled work at lower pay than if they were employed full-time (Connolly and Gregory 2008; Manning and Petrongolo 2008).

Job tenure (in years) with current employer/business

This variable measures the years a respondent has spent with their current employer/own business and is only controlled for in Chapter 5. It has been theorised that the determinants of job satisfaction vary systematically with tenure. Long-tenured

²⁴ If a respondent's working hours vary weekly, then they are asked to answer how many hours per week do they work on average over a usual 4-week period in their main job.

workers are more satisfied with their job because their experience (as an employee or business owner) and seniority within the employer's organisation (as an employee) gives them enhanced feelings of control (Bedeian and Ferris 1992).

Only one job

This is a dummy variable indicating if the employed individual is working one job rather than working multiple jobs. Holding multiple jobs affects work-life balance, and, compared to single-job holders, multiple-job holders endure longer working hours and exert additional effort to coordinate different professional expectations (Kottwitz et al. 2017).

Industry Fixed-Effects

This categorical variable indicates the industry the respondent's main job is based in. Respondents' industries are classified into 19 different 1-digit ANZSIC 2006 codes. I assign them into 3 main groups for descriptive purposes. They are "Agriculture, forestry and fishing", "Goods-producing" and "Service" industries. "Goods-producing" includes the following industries: Mining; Manufacturing; Electricity, gas, water and waste services; and Construction. "Service" industries comprise: Wholesale trade; Retail trade; Accommodation and food services; Transport, postal and warehousing; Information media and telecommunications; Financial and insurance services; Rental, hiring and real estate services; Professional, scientific and technical Services; Administrative and support services; Public administration and safety; Education and training; Health care and social assistance; Arts and recreation services; and Other services (ABS 2012).

In Chapter 4, I control for "Agriculture, forestry and fishing", "Goods-producing" and "Service" industries as I hypothesise each industry may require a different set of skills/abilities to be successful in. In Chapter 5, I include industry fixed effects for each of the 19 industry divisions to account for varying industry conditions that can influence reported job satisfaction.

Regional Fixed Effects

A categorical variable indicating if the respondent's dwelling is located in Sydney, Melbourne, Brisbane, Adelaide, Perth, the remainder of the six previous states, Northern Territory or the Australian Capital Territory. This acts as a regional fixed effect for Chapter 3 and 5's empirical analyses. The variable captures region-specific characteristics that can influence job satisfaction or the decision to be self-employed.

2.2.4 HILDA Sample Restrictions

Given this thesis' interest in researching the individual's decision to be self-employed, I based my analyses on a population most likely to participate in the labour force. For Chapters 3, 4 and 5, I focus on individuals from what has traditionally been described as the working-age Australian population; that is individuals aged 21 to 64 years (ABS 2018f). I exclude any individuals younger than 21 from the survey as they are more likely to be in education than their senior counterparts (as of May 2016, 83 per cent of individuals aged 15 to 19 and 45 per cent of persons aged 20 to 24 years were engaged in some form of formal study (ABS 2016b)). I hypothesise workers aged 15 to 20 years are more prone than their more senior counterparts to pursue formal education by transitioning into non-employment. In contrast, I expect workers aged 21 to 64 years to be more established in the labour market, transitioning into non-employment only because of unemployment or finding income to be too low to justify any work effort.²⁵

As I am interested in analysing the individual's employment choices over time, with the assumption that the individual chooses the employment state that offers the best immediate returns, I focus my attention on a group of working-age individuals least likely to exit employment to enrol in education at any point in time.

2.2.5 Attrition

The survey uses cash incentives to encourage co-operation and respondents are provided with research materials to promote their interest in the survey (Watson and Wooden 2012; Summerfield et al. 2017).²⁶ However, as with all longitudinal surveys, the HILDA Survey is subject to sample attrition – when a person interviewed in one wave ceases to take part in the survey at a later wave. With each successive year, the HILDA Survey loses respondents, because of a failure to locate them (after they moved homes) or the withdrawal of their cooperation (Watson and Wooden 2004).

While individuals can re-join the survey following a wave (or multiple waves) of non-response(s), there is still a significant amount of attrition present in the data. From the confidentialised unit record data file of the HILDA Survey Release 16 (Department

²⁵ According to DSS (2014), the age pension (AP) eligibility for women was increasing from 60 to 65 years during the study period. If access to AP is a significant determinant of the entry into and survivorship in self-employment, then changes to AP over the years 2001 to 2016 may have important implications for decisions by older females during this period. However, Figure 3-6 shows that the female trends in self-employment are relatively steady and follows a similar trend as their male counterparts suggesting minimal influence from variations in AP eligibility requirements. Further, the empirical strategy in chapters 3 and 5 controls for year fixed effects. They should pick up any variation in outcomes that are likely caused by variation in age-pension eligibility requirements.

²⁶ Materials include annual newsletters, the HILDA annual statistical report and relevant news articles (Watson and Wooden 2012, p. 9).

of Social Services/Melbourne Institute of Applied Economic and Social Research 2017a), I calculated the (unadjusted) wave-to-wave attrition rates (the proportion of persons who did not respond in the current wave but responded during the previous wave, relative to those who responded in both current and previous waves) and I find them to range from 6.2 per cent to 14.1 per cent over the periods 2001 to 2016. Overall, from the initial sample, 55.6 per cent (based on my calculations) of people who completed interviews in wave 2001 also completed their interviews in wave 2016. From the top-up sample, only 76.7 per cent of individuals who completed their first interviews in wave 2011 also completed their interviews in wave 2016 (see Summerfield et al. 2017, Section 8.6, for a summary of the HILDA Survey response rates). Despite the high rates of attrition, the survey has information on 30,496 unique individuals comprising adults from the initial 2001 sample, from the top-up 2011 sample, household children who become eligible to be interviewed, and individuals who became members of the CSMs' households between the years 2001 to 2016.

Attrition can make the HILDA Survey less representative of the populations from which they are drawn. If the respondents who drop out of the sample differ significantly from those who remain then attrition can bias any results presented in Chapters 3 and 5 of this study.²⁷ If sample attrition is random and the characteristics associated with attrition are uncorrelated with the individual's employment decisions, then the results are not biased. Regrettably, Summerfield et al. (2017) suggest that sample attrition is non-random. Response rates are "lowest among people who were relatively young (aged between 15 and 24 years), born in a non-English speaking country, of Aboriginal or Torres Strait Islander descent, single, unemployed, or working in low-skilled occupations" (Summerfield et al. 2017, Section 8.7). The key question is whether the individual's decision to be a wage/salary employee, a non-employee, solo self-employed or an employer is correlated with future non-response. Descriptive statistics from Table 2-1 shows attrition is not uniform or random across employment states in some waves. In this table, I include likelihood ratio (LR) statistics to test, in each wave, the null hypothesis that the attrition rates in non-employment, wage/salary employment, solo self-employment or employership are equal. I observe that I reject the null hypothesis in select periods (i.e., 2002 to 2005, 2009 to 2010 and 2012 to 2016).

²⁷ Non-random attrition is not an issue in Chapter 4. Employers who exit the sample, before being observed to leave employership, are treated as right-censored observations. I define right censoring in Chapter 4.

TABLE 2-1: WAVE -TO-WAVE ATTRITION RATES BY EMPLOYMENT STATE

	Non-Emp.	Wage Emp.	Solo SE	Employer	LR
Panel A. Males					
2001-2002	0.157	0.136	0.142	0.146	2.45
2002-2003	0.143	0.114	0.092	0.161	13.92***
2003-2004	0.155	0.110	0.101	0.116	10.55**
2004-2005	0.116	0.082	0.086	0.073	7.32*
2005-2006	0.104	0.075	0.090	0.074	5.75
2006-2007	0.105	0.089	0.093	0.078	2.44
2007-2008	0.077	0.078	0.054	0.076	4.25
2008-2009	0.066	0.070	0.051	0.059	3.05
2009-2010	0.086	0.069	0.049	0.070	6.27*
2010-2011	0.085	0.062	0.066	0.072	4.23
2011-2012	0.096	0.076	0.073	0.064	5.30
2012-2013	0.089	0.069	0.079	0.056	6.45*
2013-2014	0.087	0.066	0.061	0.052	7.00*
2014-2015	0.112	0.063	0.067	0.067	21.20***
2015-2016	0.090	0.059	0.064	0.053	10.54**
Panel B. Females					
2001-2002	0.139	0.126	0.112	0.130	2.81
2002-2003	0.114	0.102	0.098	0.107	1.73
2003-2004	0.101	0.104	0.104	0.123	0.68
2004-2005	0.074	0.079	0.043	0.132	11.91***
2005-2006	0.071	0.077	0.078	0.033	9.61**
2006-2007	0.068	0.080	0.060	0.050	5.42
2007-2008	0.060	0.079	0.042	0.074	10.31**
2008-2009	0.052	0.056	0.037	0.057	2.16
2009-2010	0.062	0.060	0.058	0.038	2.06
2010-2011	0.061	0.050	0.030	0.041	6.60*
2011-2012	0.074	0.062	0.080	0.039	7.06*
2012-2013	0.069	0.066	0.071	0.073	0.37
2013-2014	0.064	0.062	0.064	0.082	0.96
2014-2015	0.050	0.060	0.036	0.026	10.18**
2015-2016	0.062	0.053	0.055	0.058	1.87

Notes: Author's calculations from the HILDA Survey (Release 16). Wave-to-Wave attrition rates are calculated based on the proportion of each wave respondents (aged 21-64 years) being non-responsive in the next wave. Likelihood ratio (LR) tests for the equality of the group proportions were conducted. The null hypothesis is that the attrition rates of individuals in non-employment, wage/salary employment, solo self-employment or employership are equal. Significance of the LR test statistics are represented by: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a)

I also empirically test for non-random attrition by estimating two logit models, with the dependent variable being a dummy variable that equals to one if the individual is a non-respondent during the next wave, zero otherwise. The first model contains controls only for the individual's employment choice in each wave, while the second model includes controls for individual, household and interview-level characteristics in each wave.²⁸ I also incorporate year dummies in each model to account for possible time effects. Robust standard errors are calculated to account for serial correlation in the error terms of individuals with multiple observations. Standard errors are clustered at the individual level.

TABLE 2-2: LOGIT ODDS RATIOS OF NON-RESPONSE AT $t + 1$

Non-Response at $t + 1$	(1)	(2)
<u>Employment status ($t+1$)</u>		
Wage/Salary employment	0.931* (0.027)	0.849*** (0.028)
Solo self-employment	0.869** (0.044)	0.978 (0.053)
Employer	0.840** (0.050)	1.018 (0.064)
No. of individuals	21,244	21,244
No. of observations	134,652	134,652
Pseudo R^2	0.0152	0.0729
Log-Likelihood	-32,287.98	-30,394.93

Notes: Estimates are based on a pooled sample of 21-64 years old respondents from the years 2001 to 2015. This model uses a logit model to estimate the probability a wage employee, a solo self-employed worker or an employer being a non-respondent at wave $t + 1$. Odds ratios are reported (e^β) instead of their coefficients (β). Robust standard errors of the odds ratios reported in parentheses. Robust standard errors are reported allowing for intrapersonal correlation among sampled observations. Also included, but not reported, are controls for age (specified as a quadratic), gender, marital status, English fluency, number of dependent children, country / region of birth, self-assessed health status, interview length, location (urban vs rural), SEIFA 2011 index of disadvantage, number of adults in household, number of children in household, dwelling type, home ownership, disposable household income (logged), respondent's cooperation, assisted interview, problems during the interview, respondent's understanding of the interview, other adult influence on the interview, year and regional fixed effects. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Pseudo R^2 ' values equal 1 minus the ratio of the log-likelihood of the fitted function to the log-likelihood of a function with only an intercept term (Fitzgerald, Gottschalk, and Moffitt 1998).

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a)

Table 2-2 presents the odds ratios of non-response during wave $t + 1$. The table suggests employment choice is correlated with future non-response (the full version of the table is available in the appendix as Table A2.4.1). Being employed increases the respondent's odds of responding in subsequent HILDA waves. Under specification (1),

²⁸ The controls in the 2nd specification follows closely to those included in the logistic attrition models used to create HILDA's longitudinal responding person population weights (Watson 2012).

relative to non-employment, being a wage/salary employee decreases the odds of non-response by 6.9 per cent (i.e., 0.931-1); being solo self-employed decreases the odds of non-response by 13.1 per cent (i.e., 0.869-1); and being an employer reduces the odds by 16 per cent (i.e., 0.840-1). These relative differences in the odds of non-response are significant at the 10 per cent level at least. If I include the additional control variables under specification (2), the relative odds of non-response are only significant for wage/salary employment. There appears to be no evidence of a relationship between the decision to be self-employed and staying in the survey. Regardless, as a robustness check, the analyses in Chapters 3 and 5 will account for non-random attrition. This is done by controlling for a dummy variable indicating if an individual has left the survey during the next wave.

Chapter 3

Is Solo Self-Employment a ‘Stepping-Stone’ into Employership? – The True Cross State Dependence of Employership from Solo Self-Employment

3.1 Introduction

Descriptive evidence from the ABS and HILDA Surveys (Figure 1-1) suggest that solo self-employed workers are more prevalent than employers. Table 3-1 shows that most new businesses are non-employing at the time when they started operations. Around 64 per cent and 70 per cent of new businesses in 2003 and 2017, respectively, did not hire any employees (ABS 2018a). Solo self-employment is more prevalent than employership, but there is still a limited understanding of the dynamics between solo self-employment and employership. It is not clear how the experience of being solo self-employed or an employer influences an individual’s future labour market outcomes. If solo self-employment experience has a causal effect on the probability of employership (that is, there is true cross-state dependence in employership (Lechmann and Wunder 2017)) and if earlier employership experience has a causal effect on the probability of future employership (that is, there is true state dependence in employership (Heckman and Borjas 1980; Prowse 2012)) then temporary measures to promote self-employment (e.g., onetime start-up subsidies) will have long-term effects on job creation.

True cross-state dependence in employership arises if solo self-employment experience affects the individual’s preference to be an employer in the future. Self-employment is a risky prospect since no individual can observe their entrepreneurial ability (Lucas 1978; Jovanovic 1982). Uncertain individuals can instead experiment within solo self-employment to better estimate their ability to be self-employed (Jovanovic 1982). Solo self-employment is less costly than employership for individuals to experiment with as hiring their first employees is a major threshold for any business. Employers will have to incur the fixed costs of hiring their first employees such as advertising the vacant position within the business, setting up the payroll after hiring their first employee and training the new employees. Also, amateur employers are at an information disadvantage regarding the quality of available employees (Boadway and

Tremblay 2005; Fairlie and Miranda 2017). Individuals may prefer to first enter solo self-employment and experiment before transitioning into employership.

TABLE 3-1: PERCENTAGE OF NEW BUSINESSES ENTRIES AT START OF FINANCIAL YEAR, BY EMPLOYMENT SIZE

Type of Self-Employment	2003	2016
Non-Employing	64.06%	70.66%
Employing		
1-4 employees	23.22%	26.26%
5-19 employees	9.48%	2.73%
20-199 employees	3.04%	0.34%
200+ employees	0.20%	0.02%

Sources: ABS Counts of Australian Businesses, including Entries and Exits, Jun 2003 to Jun 2006, 'Table 2.3: Survival of Entries by Main State by Employment Size Ranges', data cube: Excel spreadsheet, cat. no. 8165.0 and ABS Counts of Australian Businesses, including Entries and Exits, June 2014 to June 2018, 'Table 13: Businesses by Employment Size Range', data cube: Excel spreadsheet, cat. no. 8165.0.

Additional experience in employership will also update the individual's estimates of their entrepreneurial ability towards the actual value. Individuals with confident estimates of their abilities stay in employership as long as they can generate higher returns as an employer than in any other employment state. Otherwise, they would have exited after a brief stint in self-employment.

However, cross-state dependence and state dependence will also be observed if there is an intertemporally correlated, unobserved, individual-specific heterogeneity that influences the decisions to be an employer. These mechanisms are referred to as spurious cross-state dependence and spurious state dependence, respectively (Heckman and Borjas 1980; Prowse 2012; Lechmann and Wunder 2017). If transitions into employership from solo self-employment and persistence within employership can be fully explained by the individual's unobserved characteristics, then any policies to promote job creation via self-employment will have limited effects.

Only a limited number of studies have empirically investigated self-employment state dependence (Henley 2004; Caliendo and Uhlenborff 2008; Fitzpatrick 2017) and only one study has studied cross-state dependence in employership (Lechmann and Wunder 2017). Henley (2004), Caliendo and Uhlenborff (2008) and Fitzpatrick (2017) find evidence for state dependence in self-employment with UK, German and Australian

data, respectively. However, their estimates confound the transitions into employership with survival in employership. Lechmann and Wunder (2017) provide evidence that solo self-employment experience causally affects the probability of becoming an employer in the future in Germany. However, Lechmann and Wunder conclude that the extent of true cross-state dependence and true state dependence in employership are small – the observed transitions from solo self-employment into employership and persistency in employership are largely explained by the individual’s observed and unobserved heterogeneity. But, it is unclear if Lechmann and Wunder (2017) results are valid in a different institutional setting. As this is a topic that is still relatively new in the area of self-employment, I investigate if cross-state dependence and state dependence in employership exist within Australian labour markets – does being solo self-employed causally increase our probabilities of being an employer? And is employership a genuinely persistent state?

This chapter proceeds as follows: I first summarise (in section 3.2) the overall self-employment literature, starting with a review of the determinants of self-employment and employership, and state dependence in self-employment. Section 3.3 then summarises an employment sectoral choice model explaining the individual’s decision to be an employer as a function of their previous experience in solo self-employment. Section 3.4 describes the empirical strategy, which is a dynamic multinomial logit model with correlated random effects. Section 3.5 describes the HILDA sample used in this chapter’s analyses. Section 3.6 summarises this chapter’s main results. Section 3.7 covers a series of robustness checks to ensure the validity of the results presented in section 3.6. I conclude this chapter with section 3.8.

Using longitudinal individual-level data from Australian households, I find evidence of significant true cross-state dependence and state dependence in employership with estimates similar to that of Lechmann and Wunder (2017). The only exception is that my estimates of male true state dependence in employership are higher than those reported by Lechmann and Wunder (2017). Nevertheless, similar to Lechmann and Wunder (2017), I show that a significant proportion of the transitions into employership are explained by the individual’s unobserved heterogeneity. This conclusion is robust after controlling for non-random attrition, local unemployment, excluding workers from ‘Agriculture, Forestry & Fishing’ industries and potential household income imputation bias.

3.2 Literature Review

The decision to be self-employed is a complex process which has motivated countless studies seeking to unpack the mechanisms that encourage individuals to be self-employed. The theoretical and empirical determinants of self-employment are well documented; so much so that there is a sub-literature that provides comprehensive reviews of these studies (van Praag and Versloot 2007b; van der Sluis, van Praag, and Vijverberg 2008; Parker 2009; Simoes, Crespo, and Moreira 2016). The prominent determinants include an income gap between self-employment and wage/salary employment; the intergenerational transfer of entrepreneurship (the transfer of entrepreneurial preferences and skills from parents to their children); liquidity constraints; spousal support; education achievement; years of paid work experience; years of occupation/industry-specific work experience; risk aversion; tolerance of uncertainty; personality traits that would predispose someone to be self-employed; self-employment rates within the region; and business cycle fluctuations.

In comparison, the number of empirical studies focusing on the characteristics of employers (also referred to as job creators in the literature) is much smaller. They primarily use individual-level longitudinal data from household surveys within the US, UK and Netherlands. Among this small group of studies, there is a consensus that human capital (in the form of education, age and experience) have uniformly positive effects on the propensity of self-employed workers to hire workers (van Praag and Cramer 2001; Burke, FitzRoy, and Nolan 2000; 2002; M. Cowling, Taylor, and Mitchell 2004; Henley 2005; Fairlie and Robb 2007). One source of disagreement is between Cowling et al. (2004) and Henley (2005). Using a single wave of data from the British Household Panel Survey (BHPS), Cowling et al. (2004) find university education has no significant influence on the individual's decision to be an employer. In contrast, Henley (2005) finds that self-employed workers with university degrees are significantly more than likely to be job creators with data from waves 1991 to 1999 of the BHPS. Henley (2005) used the ordered model to investigate the relationship between the categorical firm size dependent variable and the firm's owner's characteristics. As Henley (2005) used both a superior data sample (Cowling et al. 2004 used one wave of data from the BHPS) and an econometric model which exploits the longitudinal nature of the data that accounts for individual unobserved heterogeneity (Henley 2005 used an ordered probit model with random effects whereas Cowling et al. 2004 used a probit model), his results should be preferred.

Cowling et al. (2004) also observed that employers are disproportionately men and this gender difference has been confirmed in other studies. Burke et al. (2002), with British survey data from the National Child Development Study (NCDS), show women business owners are most likely to hire workers if they run their businesses full time. They suggest part of the employership gender gap is explained by women being more likely than men to run their businesses part-time.

Wealth is also associated with employership status (Burke, FitzRoy, and Nolan 2002; Cowling et al. 2004; Henley 2005; Fairlie and Robb 2007), although wealth variables are likely to be endogenous. For example, individuals with low-risk aversion and greater financial ability are more likely to be wealthy and enter self-employment (Nykqvist 2008). Any study seeking to examine (or control for) the effects of wealth on employership must address this endogeneity issue or risk generating spurious estimates. For example, to avoid the endogenous problem with wealth, Burke et al. (2002) measure exogenous changes in wealth via windfalls (e.g., lottery wins or inheritances). Burke et al. (2002) then examine how these exogenous changes in wealth, rather than stocks of wealth, affect an individual's decision to be self-employed and their hiring decision (conditional on being self-employed). Cowling et al. (2004) proxied the wealth variable with the value of their home purchased prior to their current labour market status. Henley (2005) used a similar method to measure wealth, but they exploited time and cross-sectional variation in the local demand conditions to control for any potential endogeneity problems between financial resources and job creation. Lechmann and Wunder (2017) used lagged household disposable income values to control for income shocks that can influence the decision to be solo self-employed or enter employership. For this chapter, I use the same variable as a proxy for the individual's household wealth. Further, lagged income values are less likely to be influenced by business income shocks when the individual is self-employed.

Van Praag and Cramer 2001 (with Dutch survey data), Cowling et al. (2004) and Henley (2005) show that a self-employed person is more likely to hire if they had a self-employed parent or a parent who was a manager.

Finally, the state of the local economy and its regulations are likewise important factors. Using longitudinal household data from the European Community Household Panel (ECHP), Congregado, Millán, and Román (2010) reveal that the national unemployment rate has a strong negative effect on the likelihood of self-employed

workers becoming employers.²⁹ Millán, Millán, Román, and van Stel (2013) also used longitudinal data from the ECHP to provide evidence that the strictness of employment protection legislation (EPL) has a negative impact on transitions from solo self-employment into employership. Further, Millán et al. (2014) show that the population share of individuals with, at least, an undergraduate level degree has a positive causal effect on solo self-employed workers transitioning into employership. In addition, Millán et al. (2015) find solo self-employed workers are more likely to become employers during a period of growth than during a recession.

As reviewed above, a significant portion of the empirical research on the characteristics of employers has relied on cross-sectional or pooled-panel data to estimate static models of employership. These models estimate the individual's probability of employership based on the observed characteristics of individuals in employership, solo self-employment and wage/salary employment. These models do not control for individual-specific unobserved heterogeneity and suffer from upward-biased estimated effects of any observed characteristic on the decision to be an employer. This is because of the omitted variable bias caused by the individual's innate ability/preference to be self-employed. Although Henley (2005) controlled for unobserved heterogeneity with an ordered probit model with individual random effects, his model assumes that the individual's hiring choice is determined independently of their self-employment status in the past. Thus, the estimates reported by Henley (2005) do not distinguish between the determinants of transition into employership and those of employership survival (Evans and Leighton 1989). A series of studies using ECHP data (Congregado, Millán, and Román 2010; Millán, Millán, Román, and van Stel 2013; Millán et al. 2014; Millán et al. 2015) addressed Henley's (2005) shortcomings by explicitly modelling the relationship between transitions into employership (from solo self-employment) and the individual's observable characteristics. However, these studies do not fully exploit the longitudinal nature of the ECHP dataset to analyse (or control for) the effect of the individual's previous employment status on their probability of becoming an employer.

There are even fewer studies that analyse the dynamics of the individual's participation within self-employment over time. These studies examine periodic transitions between self-employment and wage/salaried employment and provide

²⁹ The ECHP is an 8-year longitudinal household survey covering 14 EU member states from 1994 to 2001. EU member states include Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the United Kingdom (European University Institute 2019).

conclusive evidence that state dependence in self-employment is an important determinant of self-employment, even after accounting for observed and unobserved heterogeneity. State dependence is defined as the relative probability of being in self-employment given the individual was previously in self-employment, relative to wage/salary employment. Henley (2004), using data from the first 9 waves of the BHPS, finds that self-employment, relative to wage/salary employment, increases the individual's probability of being self-employed next year by 30 percentage points. Taylor (2011) obtains similar (if not higher) estimates (between 20 and 89 percentage points) for male workers from eight countries (Britain, France, Germany, Greece, Ireland, Italy, Spain and Portugal) of waves 1994 to 2011 of the ECHP. Caliendo and Uhlenhorff (2008), with a panel sample of German workers from waves 1984-2005 of the Socio-Economic Panel (SOEP), also provide similar estimates – being self-employed last year, relative to wage employment, increases the individual's probability of currently being self-employed by 22 percentage points. Using longitudinal data from waves 2001 to 2011 of the HILDA Survey, Fitzpatrick (2017) confirms that the individual's experience in self-employment, relative to wage/salary employment, positively increases their propensity of being self-employed in the future by 26.5 percentage points. Fitzpatrick also claims that once unobserved heterogeneity and the one-year lagged self-employment choice are controlled for, the effects of several observable characteristics on the probability of self-employment are greatly diminished. For example, marital status, education level and gender were strong significant determinants of self-employment entry in a static model, but they ceased to be after controlling for lagged self-employment status and unobserved heterogeneity. However, Henley (2004), Taylor (2011), Caliendo and Uhlenhorff (2008), and Fitzpatrick (2017) did not investigate state dependence separately for solo self-employed workers and employers. Their estimates did not separate the determinants of survival in self-employment from the determinants of transitions between solo self-employment and employership. Further, Henley (2004), Taylor (2011), Caliendo and Uhlenhorff (2008), and Fitzpatrick (2017) did not examine the effect (if any) of being solo self-employed on the future decisions to be an employer.

In short, there is a lack of evidence whether solo self-employment acts as a stepping-stone to employership and if employership exhibits true state dependence. The notable exceptions are Millán, Congregado, and Román (2014b), Lechmann and Wunder (2017) and Henley (2019). Millán et al. (2014b) with longitudinal household data from the ECHP covering waves 1994 to 2001 and a competing risks hazard model show that the

probability from being solo self-employed to employership is significantly higher than the probabilities of moving to salary/wage employment or non-employment. However, they also showed that any experience in solo self-employment (represented by a dummy variable that equals to one if the individual had any prior solo self-employment experience) has no significant influence on the probability of switching into employership (from solo self-employment). In addition, the study does not show if the probability of employership is highest when the individual was in solo self-employment instead of wage/salary employment or non-employment. Henley (2019), using longitudinal UK data covering waves 2009 to 2015 from the Understanding Society Survey, used a complementary log-log model to show that the individual's length of self-employment experience (in years) has a positive influence on the probability of solo self-employed workers transitioning into employership. However, Henley (2019) does not establish if individuals are most likely to become employers if they were solo self-employed nor did they distinguish solo self-employment experience from the accumulated years of self-employment experience. Lechmann and Wunder (2017) is the only study to examine the direct relationship between the probability of employership and their immediate experience in solo self-employment.

Unlike earlier studies of self-employment state dependence, Lechmann and Wunder (2017) identify solo self-employed workers separately from employers with individual-level longitudinal data. They find state dependence in solo self-employment ranges from 7.9 to 13.3 percentage points and state dependence in employership ranges between 8.3 to 11.8 percentage points. These numbers are significantly lower than what was reported in the studies of Henley (2004), Caliendo and Uhlendorff (2008), Taylor (2011) and Fitzpatrick (2017), and highlight the importance of treating the solo self-employed workers and employers as separate groups. These comparisons show that state dependence in self-employment is partially driven by transitions between solo self-employment and employership. As a result, Lechmann and Wunder (2017) introduced the concept of cross-state dependence in employership defined as the relative change in the individual's probability of employership given they were solo self-employed instead of being wage/salary employed or non-employed during the previous period. They find that the cross-state dependence in employership ranges from 2.1 to 5.1 percentage points.

It is not clear if Lechmann and Wunder (2017) results are robust in a separate institutional setting such as Australian labour markets. According to data from the Organisation for Economic Co-operation and Development (OECD 2019), as of 2013,

Germany ranked 5th out of 34 member countries of the OECD in terms of the strictness of their employment protection legislation (EPL). The OECD uses an indicator to measure the strictness of EPL and is scaled to lie between 0 and 6, from less to more protected workers. For reference, Germany has a score of 2.68 whereas Australia has a score of 1.67 and the US has a score of 0.26. As defined by the OECD, EPL refers to regulations about hiring and firing. These regulations include training requirements and redundancy procedures. As highlighted by Millán, Millán, Román, and van Stel (2013), EPL increases the risk of hiring employees as the solo self-employed may be more cautious to take on employees. Millán, Millán, Román, and van Stel (2013) further showed that EPL is negatively related to the decision to hire employees and the decision to transition from solo self-employment to employership.

Using longitudinal household data from waves 2001 to 2016 of the HILDA Survey (similar to other longitudinal household datasets used to perform the multivariate analyses of self-employment state dependence), this chapter seeks to further develop our understanding of the transitional dynamics between solo self-employment and employership. I examine the transitional dynamics between solo self-employment and employership in a country with less strict EPL. I also ensure my estimates of true cross-state dependence and state dependence in employership are robust by controlling for non-random attrition from the HILDA, which Lechmann and Wunder (2017) did not do with the SOEP. Another shortcoming of the Lechmann and Wunder (2017) study is the lack of time-varying controls for the individual's local economic conditions. As highlighted by Congregado, Millán, and Román (2010), the unemployment rate is an important negative determinant of transitions from solo self-employment into employership. Thus, omitting controls for unemployment can potentially lead to under-estimating the extent of (cross) state dependence in employership. In this chapter, I control for state-level unemployment rates and, as a robustness check, disaggregated local unemployment rates.

3.3 Sectoral Choice Model – The Individual Choice Problem

This section explains why being solo self-employed (or as an employer) in one period will influence the individual's decision to become (or remain as) an employer during the next period. I assume individuals are continuously re-evaluating their employment decisions to choose the employment state that offers them the highest net returns when compared against a set of alternatives. Lucas (1978) introduces an observable entrepreneurial ability into the choice model and proposes that ability is positively

correlated with self-employment profits – greater ability translates into larger business profits. Thus, individuals will be self-employed if their ability is above a threshold where they are indifferent to self-employment or wage/salary employment.

Jovanovic (1982) suggests individuals have imperfect information about their innate ability to be self-employed. Individuals estimate their ability from a set of prior beliefs updated with self-employment experience. In other words, they learn how capable they are by experimenting with entrepreneurship. The Jovanovic model suggests able and/or lucky self-employed workers are more likely to survive and grow, while less able and/or unlucky individuals will shrink and exit. Frank (1988) modifies the choice model by proposing that individuals must pay fixed costs upon entry into self-employment. For clarity, such costs represent the investment associated with starting up a business. They include the costs of any physical capital (such as equipment and machinery), labour and monitoring costs for their first hired employees (i.e., the first-employee hiring threshold (Fairlie and Miranda 2017)), search and permit costs for leasing premises, contracting costs for supplies, and registration costs with the relevant governmental agencies (McKenzie and Woodruff 2006). Given the absence of the first-employee hiring threshold, solo self-employed workers have lower start-up costs than employers. If an individual is uncertain of their ability to generate revenue, they begin in solo self-employment to explore and uncover their ability before deciding to hire employees.

At the start of each year, $t = 0, 1, \dots, T$, each individual chooses the employment state with the highest net returns. They can enter the labour market as a wage/salary employee, as a solo self-employed worker, an employer, or be non-employed if employment earnings are too low.³⁰ I assume respondents are rational and each of them will take the optimal career path that maximises their utility in each year. Conditional on the individual's socioeconomic characteristics, employment utility is influenced by the financial and non-monetary aspects of the employment state. I assume there are j mutually exclusive employment states that include: (1) Non-employment; (2) Wage/salary employment; (3) Solo self-employment; or (4) Employership.³¹ For example, if $j = 3$ then the individual chooses to work as a solo self-employed worker.

Similar to Kanbur's (1979) and van Praag and Cramer (2001) specification, the individual's utility function, assuming individuals are risk-neutral in this economy, is

³⁰ An individual may remain unemployed or leave the labour force if the equilibrium profit or wage rate does not justify the disutility of work effort.

³¹ This specification does not allow for the possibility of working concurrently in more than one sector, e.g., working in solo self-employment while working part-time as a wage employee.

$$U_{i,j,t} = \pi_{i,j,t} - \alpha_i$$

$\pi_{i,j,t}$ is individual i 's income from employment state j in period t and α_i represents the person-specific work effort disutility.

The individual's labour supply problem involves choosing the employment state with the highest net utility; i.e.:

$$3-1) \quad \text{Max } U_{i,j,t} \text{ subject to } j \in [1,2,3,4]$$

Let $y_{i,j,t}$ be a dummy variable taking the value of 1 if individual i chooses state j at time t and, zero otherwise. Utility maximising behaviour implies:

$$y_{i,j,t} = \begin{cases} 1, & \text{if } U_{i,j,t} > U_{i,k,t} \text{ for all } k \neq j \\ 0, & \text{otherwise} \end{cases}$$

Individuals assess the potential income for every employment state at the beginning of each period. This is a two-stage process that is solved with backwards induction. In the second stage, the individual is self-employed and solves the optimal labour hiring problem conditional on the expectation of their entrepreneurial ability, wage rate and previous self-employment status (whether they hired any employees during the last period). Moving backwards to the first stage, conditional on their optimal hiring decision in stage two, the individual chooses to be in self-employment, wage/salary employment or non-employment.

All individuals consider the potential gains of self-employment given their beliefs about their entrepreneurial ability. Expected profit in self-employment is

$$\max_{L_t} E(\pi_{i,t} | \theta_i, L_{i,t}) = F(L_{i,t}, \theta_i) - w_t L_{i,t} - I(L_{t-1} = 0) c L_t, 0 \leq \gamma \leq 1$$

where $F(L_{i,t}, \theta_i)$ is the production function, w_t is the equilibrium wage rate in period t , $I(L_{t-1} = 0)$ is an indicator function that equals 1 if the self-employed worker has no employees from last year, and c is the combination of monetary and non-monetary fixed costs associated with hiring the first employee. Output prices are normalised to unity.

Following Kanbur's (1979) model, the production function is assumed to be of the functional form:

$$F(L_{i,t}, \theta_i) = \theta_i L_{i,t}^\gamma, \quad 0 < \gamma < 1$$

where γ is a parameter measuring the output elasticity of labour, L_t .³² With a single input of production, $\gamma < 1$ represents decreasing returns to scale of labour. The production function represents individuals organising their workforce and assumes each self-employed worker has a perfectly elastic supply of capital (this is because I have no available data about firm capital ownership and/or investment). Further, individuals do not observe their actual ability θ_i (Lucas 1978). Instead, they only observe a prior individual-specific distribution of their ability. Similar to van Praag and Cramer (2001), the individual's estimate of their ability, $\hat{\theta}_{i,t}$, is distributed log-normally:

$$3-2) \quad \log \hat{\theta}_{i,t} = \beta_j' X_{i,t} + \gamma_j' y_{i,t-1} + \epsilon_{i,t}^{se}, \quad \epsilon_{i,t}^{se} \sim N(0, \sigma_\theta^2)$$

where $X_{i,t}$ is a vector of individual characteristics (such as education) and $y_{i,t-1}$ is a vector of dummy variables indicating the individual's employment state during the previous period. $\epsilon_{i,t}^{se}$ represents an unknown level of self-employment shocks that can inform the individual's estimate of θ_i . The vector γ_j also includes the main coefficient of interest, i.e., the coefficient that picks up the 'stepping-stone' effect in which being solo self-employed changes the individual's future preferences of being an employer.

The second stage involves individuals solving the expected profit maximisation problem with respect to labour. Each year, the optimal hiring solution is as follows,

$$L_{i,t}^* = \left[\frac{\hat{\theta}_{i,t} \gamma}{w_t + cI(L_{t-1} = 0)} \right]^{\frac{1}{1-\gamma}}$$

where the solution must satisfy the condition $L_{i,t}^* > 1$. If the optimal number of hires is less than or equal to one, then the individual will hire no employees. The individual's demand for employees decreases with higher labour costs. Individuals having a higher perception of their entrepreneurial ability can increase their demand for employees. Also,

³² I assume labour input is a non-negative discrete variable.

labour costs are greater for solo self-employed workers than for existing employers because of the first employee hiring threshold, c .

Self-employed workers will hire employees if

$$3-3) \quad \hat{\theta}_{i,t} > \hat{\theta}_{i,t}^s = \frac{w_t + cI(L_{t-1}=0)}{\gamma}$$

where $\hat{\theta}_{i,t}^s$ is the estimated ability when the self-employed worker is indifferent between hiring employees or being solo self-employed.

After solving the second stage, the first stage involves individuals choosing to be self-employed, a wage employee or being a non-employee. The utility associated with wage employment is

$$U_{i,t}^{wage} = w_t - \alpha_i + \epsilon_{i,t}^{wage}$$

and the utility associated with non-employment is

$$U_{i,t}^{ne} = \epsilon_{i,t}^{ne}$$

where $\epsilon_{i,t}^{wage}$ and $\epsilon_{i,t}^{ne}$ represents the shocks specific in each employment state. For simplicity, let us consider the case individual i where $w_t > \alpha_i$. Under the assumption of risk-neutrality, the individual chooses to be self-employed (with L_t^* employees) if

$$E(\pi_{i,t} | \hat{\theta}_{i,t}, L_{i,t}^*) > w_t$$

$$\hat{\theta}_{i,t} (L_{i,t}^*)^\gamma - w_t L_{i,t}^* - I(L_{t-1} = 0) c L_{i,t}^* > w_t$$

$$3-4) \quad \hat{\theta}_{i,t} > \hat{\theta}_{i,t}^w = \frac{(w_t + w_t L_{i,t}^* + I(L_{t-1}=0) c L_{i,t}^*)}{(L_{i,t}^*)^\gamma}$$

where $\hat{\theta}_{i,t}^w$ is the estimated ability when an individual is indifferent between self-employment and wage/salary employment. Thus, an individual is an employer if their expected entrepreneurial ability is $\hat{\theta}_{i,t} \geq \hat{\theta}_{i,t}^s > \hat{\theta}_{i,t}^w$.

The labour hiring decision is complicated because θ_i is not perfectly observable but can be only estimated as $\hat{\theta}_{i,t}$ by the log-normal distribution in Equation 3-2. Even if their true ability θ_i is higher than $\hat{\theta}_{i,t}^s$ or $\hat{\theta}_{i,t}^w$, new self-employment entrants risk underestimating themselves such that $\hat{\theta}_{i,t}^s > \hat{\theta}_{i,t} > \hat{\theta}_{i,t}^w$. They lack evidence that the returns from being an employer will be enough to cover the initial hiring costs. Instead,

solo self-employed workers experiment and revise their ability expectations upwards after observing the difference between expected and actual income.³³ They will realise they are better off being an employer and are more willing to hire their first employees.³⁴ Solo self-employment is the employment state that best educates able individuals of their true ability to operate a business with employees. This informs the main hypothesis of this chapter:

H1: There is true cross-state dependence in employership conditional on solo self-employment, i.e., the probability of being an employer at time t conditional on being in solo self-employment in $t - 1$ is higher than the probability of being an employer at time t conditional on being in an alternative state in $t - 1$.

Experience with employership will further update the individual's belief in their entrepreneurial ability. Less able individuals will learn and leave employership whereas able employers are more likely to stay in employership. Thus, the probability of employership, if the individual was previously an employer, is higher than if they were in wage/salary employment or non-employment. This informs a second hypothesis:

H2: There is true state dependence in employership, i.e., the probability of being an employer at time t conditional on being an employer in $t - 1$ is higher than the probability of being an employer at time t conditional on being in an alternative state in $t - 1$.

3.4 Empirical Strategy

Equations 3-3 and 3-4 suggest the relative returns between employership, solo self-employment, or wage employment is dependent on the individual's perception of their entrepreneurial ability, $\hat{\theta}_{i,t}$. This perception is a function of their individual observed characteristics, previous employment experiences and any unobserved preferences to be self-employed (as highlighted by Equation 3-2). Adapting a Mincerian earnings specification (Mincer 1974), I present a random utility function, similar in composition to Equation 3-2, for each individual i in employment state j at year t below

$$3-5) \quad U_{i,j,t} = \beta_j' X_{i,t} + \gamma_j' y_{i,t-1} + \alpha_{i,j} + \epsilon_{i,j,t}$$

³³ This will happen when their actual income (reflective of their true entrepreneurial ability) at the end of the period is higher than expected income (reflective of the prior estimate of their entrepreneurial ability) at the beginning of the period.

³⁴ A high ability but unlucky entrepreneur can generate income lower than expected. They will either remain in solo self-employment or leave the self-employment sector.

where $U_{i,j,t}$ represents the utility of employment state j at time t , $X_{i,t}$ is a vector of individual characteristics (such as education) and $y_{i,t-1}$ is a vector of dummy variables indicating the individual's previous employment.³⁵ As stated before, the coefficient that picks up the 'stepping-stone' effect (where solo self-employment changes the individual's future preferences of being an employer) is included in the vector γ . Identification of the one-year lagged employment status coefficients requires a variety of employment states over time for each individual. $\epsilon_{i,j,t}$ represents the random error associated with employment state j at time t . Equation 3-5 further controls for individual-specific and time-invariant unobserved heterogeneity, $\alpha_{i,j}$.

The individual's exact utility of being in employment state j is unobservable, but I can identify their employment decisions each year. Based on their decision, I can infer which employment state offers the highest utility over the alternatives. With $y_{i,t}$ representing the individual's employment state at time t , $y_{i,t} = j$ if

$$U_{i,j,t} > U_{i,k,t}, \forall k \in C, j \neq k$$

where C represents the individual's employment choice set consisting of non-employment (NE, $j=1$), wage/salary employment (WE, $j=2$), solo self-employment (SSE, $j=3$) and employership (ESE, $j=4$). Thus, the probability an individual chooses to be in employment state j at time t is

$$P(y_{i,t} = j | X_{i,t}, y_{i,t-1}, \alpha_{i,j}) = P(U_{i,j,t} > U_{i,k,t}), \forall k \in C, j \neq k$$

Let us define $V_{i,j,t} = \beta'_j X_{i,t} + \gamma'_j y_{i,t-1} + \alpha_{i,j}$ so that $U_{i,j,t} = V_{i,j,t} + \epsilon_{i,j,t}$. Using this expression, the probability is further equal to

$$3-6) \quad P(y_{i,t} = j | X_{i,t}, y_{i,t-1}, \alpha_{i,j}) = P(\epsilon_{i,k,t} - \epsilon_{i,j,t} \leq V_{i,j,t} - V_{i,k,t}), \forall k \in C, j \neq k$$

I assume the error, $\epsilon_{i,j,t}$, is random with an independent standard extreme value distribution of type 1. The cumulative distribution function is defined as,

³⁵ Simoes, Crespo, and Moreira (2016) show there is a consensus that individuals with lower risk-aversion are more likely to be self-employed. It is likely that attitudes to risk are also important determinants of employership and solo self-employed. However, the most relevant variable in the HILDA Survey is a self-reported measure of financial risk that the respondent is prepared to take. This measure is not available in Waves 2005, 2007 and 2009. Further, the measure comes from a self-administered questionnaire which is associated with additional non-response. To avoid losing observations, I do not include this risk variable in my empirical model and assume that controls for the individual's unobserved heterogeneity will also capture the individual's attitude towards risk.

$$F(\epsilon_{i,j,t}) = \exp(-\exp(-\epsilon_{i,j,t}))$$

with density function being,

$$f(\epsilon_{i,j,t}) = \exp(-\epsilon_{i,j,t}) \cdot \exp(-\exp(-\epsilon_{i,j,t}))$$

For notational purposes, let $P(y_{i,t} = j | X_{i,t}, y_{i,t-1}, \alpha_{i,j}) = p_{i,j,y}$. We can estimate Equation 3-6 with an estimation of the joint conditional probability below,

$$p_{i,j,y} = \int \dots \int_{\epsilon_{i,k,t} \leq \epsilon_{i,j,t} + V_{i,j,t} - V_{i,k,t}} f(\epsilon_{i,1,t}) \dots f(\epsilon_{i,4,t}) d\epsilon_{i,1,t} \dots d\epsilon_{i,4,t}$$

which equals to,

$$p_{i,j,y} = \int_{\mathbb{R}} f(\epsilon_{i,j,t}) \cdot \prod_{j \neq k} F(\epsilon_{i,j,t} + V_{i,j,t} - V_{i,k,t}) d\epsilon_{i,j,t}$$

$$p_{i,j,y} = \int_{\mathbb{R}} \exp(-\epsilon_{i,j,t}) \cdot \exp\left(-\sum_{k=1}^4 \exp(-(\epsilon_{i,j,t} + V_{i,j,t} - V_{i,k,t}))\right) d\epsilon_{i,j,t}$$

As the integral has a closed form, the probability of choosing state j can be computed as follows:

$$p_{i,j,y} = \frac{1}{\sum_{k=1}^4 \exp(-(\epsilon_{i,j,t} + V_{i,j,t} - V_{i,k,t}))} \cdot \exp\left(-\sum_{k=1}^4 \exp(-(\epsilon_{i,j,t} + V_{i,j,t} - V_{i,k,t}))\right) \Big|_{\epsilon_{i,j,t}=-\infty}^{\infty}$$

$$p_{i,j,y} = \frac{\exp(V_{i,j,t})}{\sum_{k=1}^4 \exp(V_{i,k,t})}$$

which can be specified as,

$$3-7) \quad P(y_{i,t} = j | X_{i,t}, y_{i,t-1}, \alpha_{i,j}) = \frac{\exp(\beta_j' X_{i,t} + \gamma_j' y_{i,t-1} + \alpha_{i,j})}{\sum_{k=1}^4 \exp(\beta_k' X_{i,t} + \gamma_k' y_{i,t-1} + \alpha_{i,k})}$$

where Equation 3-7 can be estimated as a dynamic multinomial logit model with correlated random effects.

While it is econometrically convenient to use Equation 3-7 to model transition probabilities in a discrete mutually exclusive four-state representation of the Australian labour market, it is not without problems. There are two issues with estimating Equation 3-7 that need to be resolved before any estimation can take place. First, for most individuals in the HILDA Survey, the individual's first observed employment state is part of an unobserved sequence of life-time employment decisions. Given the dynamic structure of Equation 3-7, the individual's initially observed employment status (in the year $t=1$) depends on their unobservable previous employment choice (in year $t=0$). Treating the initial observable employment state as exogenous, in the presence of unobserved heterogeneity, will lead to an overestimation of the true cross-state dependence and state dependence in employership estimates because of inconsistent parameter estimates. This is known as the 'initial conditions' problem (Heckman 1981). Second, random effects estimation requires the assumption that $\alpha_{i,j}$ is uncorrelated with any of the individual's observables. This assumption is unrealistic. If any of the individual's covariates are correlated with the individual-employment specific unobserved heterogeneity, then estimates of Equation 3-7 will be inconsistent.

For the initial conditions problem, Heckman proposes a solution by approximating the conditional distribution of the initial employment state. This involves estimating a reduced-form model for the initially observed employment state with pre-sample data, and a random error that correlates with $\alpha_{i,j}$ but not with $\epsilon_{i,j,t}$ for $t \geq 2$. But, this process will be computationally intensive (Wooldridge 2005). Instead, Wooldridge (2005) proposes a simpler solution that performs as well as the Heckman solution (Arulampalam and Stewart 2009) and can be implemented by any standard statistical software. The Woolridge solution estimates the distribution of $\alpha_{i,j}$ conditional on the individual's initially observed employment status $y_{i,0}$ as

$$3-8) \quad \alpha_{i,j} = \delta'_{y,j} y_{i,0} + \delta'_{x,j} \bar{x}_i + v_{i,j}$$

In Equation 3-8, I model $\alpha_{i,j}$ as a function of the initially observed employment state $y_{i,0}$, a vector of individual-specific time averages of the exogenous characteristics $\bar{x}_i$, and

a new random error $v_{i,j}$. I assume $v_{i,j}$ is uncorrelated with $y_{i,0}$ and $\bar{x}_i$. By merging Equation 3-7 with Equation 3-8, the multinomial probabilistic choice model becomes:

$$3-9) \quad Prob(y_{i,t} = j | X_{i,t}, y_{i,t-1}, \alpha_{i,j}) = \frac{\exp(\beta'_j X_{i,t} + \gamma'_j y_{i,t-1} + \delta'_{y,j} y_{i,0} + \delta'_{x,j} \bar{x}_i + v_{i,j})}{\sum_{k=1}^4 \exp(\beta'_k X_{i,t} + \gamma'_k y_{i,t-1} + \delta'_{y,k} y_{i,0} + \delta'_{x,k} \bar{x}_i + v_{i,k})}$$

The solution also includes correlated random effects by introducing $\bar{x}_i$ into Equation 3-9. Mundlak (1978) argues that the vector $\bar{x}_i$ picks up any correlation between $\alpha_{i,j}$ and $x_{i,t}$, relaxing the random-effects assumption of zero correlation between observable characteristics and unobservable individual heterogeneity. I estimate Equation 3-9 with a maximum likelihood estimation of a dynamic multinomial logit model with correlated random effects. Since a latent variable ($v_{i,j}$) is in Equation 3-9, numerical integration in the form of mean-variance adaptive Gauss-Hermite quadrature is adopted to approximate the log-likelihood integral.³⁶ Rabe-Hesketh, Skrondal, and Pickles (2004) provide further details of the numerical method applied.

The main assumption in estimating Equations 3-9 is the *independence of irrelevant alternatives* (IIA); i.e., the relative odds of choosing any employment state are independent of the number and attributes of all remaining employment options. This assumption is restrictive, especially in the context of employment choices. In effect, IIA requires that each of the employment statuses be equally substitutable. However, it is likely that solo self-employment and wage/salary employment are closer substitutes than non-employment. Further, violations of the IIA assumption have been observed in real-world preference data through statistical tests and experiments in psychology (Benson, Kumar, and Tomkins 2016). I relax this assumption in Equation 3-9 by allowing $v_{i,j}$ to correlate with each other across alternate employment states (Skrondal and Rabe-Hesketh 2003).³⁷ This is done by avoiding making any assumption on the covariance relationship between $v_{i,j}$ across the alternate employment states.

First, I estimate a ‘naïve’ multinomial logit model without random effects, only controlling for the one-year lagged employment variables. Second, I estimate the naïve model with select controls for the individual’s observable characteristics and regional and year fixed effects. Third, I estimate Equation 3-9 in full; i.e., a dynamic multinomial logit

³⁶ I also estimate Equation 3-7 with 5 integration points. While more points will lead to more accurate results, it is computationally intensive. I chose 5 points to balance accuracy and convergence speed.

³⁷ I assume $v_{i,j}$ is normally distributed with 0 mean. Its variance is estimated by Equation 3-5.

model with correlated random effects ($v_{i,j}$), the observable individual-specific characteristics ($x_{i,t}$ and $\bar{x}_i$) and the one-year lagged employment choice dummy variables. These specifications are estimated separately for male and female individuals.³⁸ In addition, I calculate cluster-robust standard errors for each model to allow for intrapersonal correlation among sampled observations.

3.5 Data and Descriptive Statistics

Throughout this chapter, I use a sample of individuals aged between 21 and 64 years from the first 16 waves of the HILDA Survey to analyse the dynamics between solo self-employment and employership. As discussed in section 2.2.4, this restriction is chosen because I want to focus my analyses on a population most likely to participate in the labour force. I exclude persons aged 65 years or over because they are routinely excluded by the ABS from what they define as the working-age population (ABS 2018f). I also exclude individuals who are younger than 21 years given that persons below this age have a high propensity to be at school or studying full time. As a result, starting from an initial sample of 235,661 observations comprising 30,496 individuals, the sample size dropped to 169,974 observations comprising 23,849 individuals who are aged between 21 and 64 years. I also dropped 1,287 observations that are not looking for work because of formal study or have missing responses about their employment state.³⁹ I re-examine the self-employment trends for this subgroup of respondents. In Figure 3-1, movements in self-employment rates are similar across both restricted and unrestricted (see Figure 2-1) samples from the HILDA Survey.

The respondent's employment choice, made in wave t , is this chapter's main dependent variable. As explained in section 2.2.1, employment choices include solo self-employment, employership, wage/salary employment or non-employment. The primary explanatory variable is the individual's lagged employment choice made in wave $t - 1$. This will lead to a loss of one year (comprising 28,063 observations) with the effective period of analysis being reduced to 2002 to 2016.

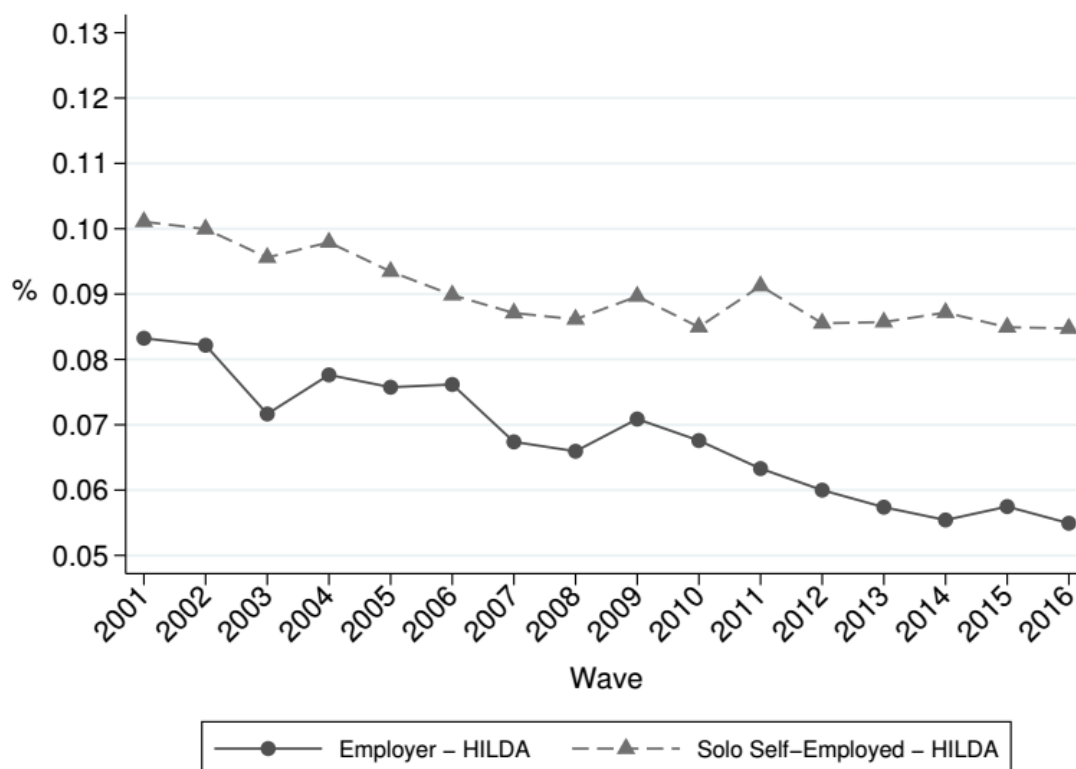
I also control for a variety of observable characteristics that have been claimed to influence the individual's decision to be an employer by earlier studies. The control variables include the respondent's age, their highest level of educational achievement,

³⁸ This study does not control for the industry sector of employed respondents. This is because industry information is unavailable for those in non-employment.

³⁹ I exclude individuals who are not looking for work because of education to avoid over-estimating true state dependence in non-employership, i.e., to avoid conflating persistency in non-employership with the individual's commitment to formal study.

their marital status, the number of dependent children under their care, their lagged real disposable household income (see sections 2.2.3 and 2.3 on how I adjusted income for price inflation), their home situation, years of working experience, their place of birth, an indicator if they are living in an urban area, impairment status and the regional unemployment rate (Section 2.2.3 defines each of the control variables mentioned here).⁴⁰ I excluded 2,977 observations comprising 392 individuals from the sample because of missing responses (except for income which relies on imputed values). Overall, my working sample comprises 138,934 observations involving 18,987 individuals across the years 2002-2016.

FIGURE 3-1: SOLO AND EMPLOYER SELF-EMPLOYMENT TRENDS



Notes: Self-employment rates are defined as the proportion of employed persons aged 21 – 64 years who are self-employed.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

⁴⁰ I use lagged income values because of the endogenous nature of household income. Higher-income proxies for greater wealth allowing the entrepreneur to meet the liquidity requirements of starting a business. However, the income variable is endogenous as individuals can accumulate wealth to prepare for self-employment. By controlling for their lagged household disposable income, I control for income shocks that may promote transitions into self-employment.

TABLE 3-2: EMPLOYMENT STATE TRANSITIONS

State at time $t - 1$	State at time t			
	Non-Emp.	Wage Emp.	Solo SE.	Employership
Panel A. Males				
Non-employment	7,737 (75.99%)	2,048 (20.11%)	343 (3.37%)	54 (0.53%)
Wage employment	2,346 (4.98%)	43,167 (91.59%)	1,138 (2.41%)	480 (1.02%)
Solo Self-Emp.	404 (5.86%)	963 (13.98%)	4,761 (69.11%)	761 (11.05%)
Employership	107 (2.07%)	415 (8.03%)	737 (14.26%)	3,910 (75.64%)
Panel B. Females				
Non-employment	18,269 (80.99%)	3,712 (16.46%)	449 (1.99%)	128 (0.57%)
Wage Employment	3,996 (8.35%)	42,792 (89.41%)	730 (1.53%)	342 (0.71%)
Solo Self-	424 (10.93%)	661 (17.03%)	2,501 (64.44%)	295 (7.60%)
Employership	174 (7.09%)	282 (11.49%)	302 (12.30%)	1,697 (69.12%)

Notes: Figures are pooled, unweighted and unbalanced. Proportions of transitions destinations are reported in parentheses. For example, 75.99 per cent of males non-employed during $t-1$ will be non-employed during wave t .

Source: Author calculations from HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

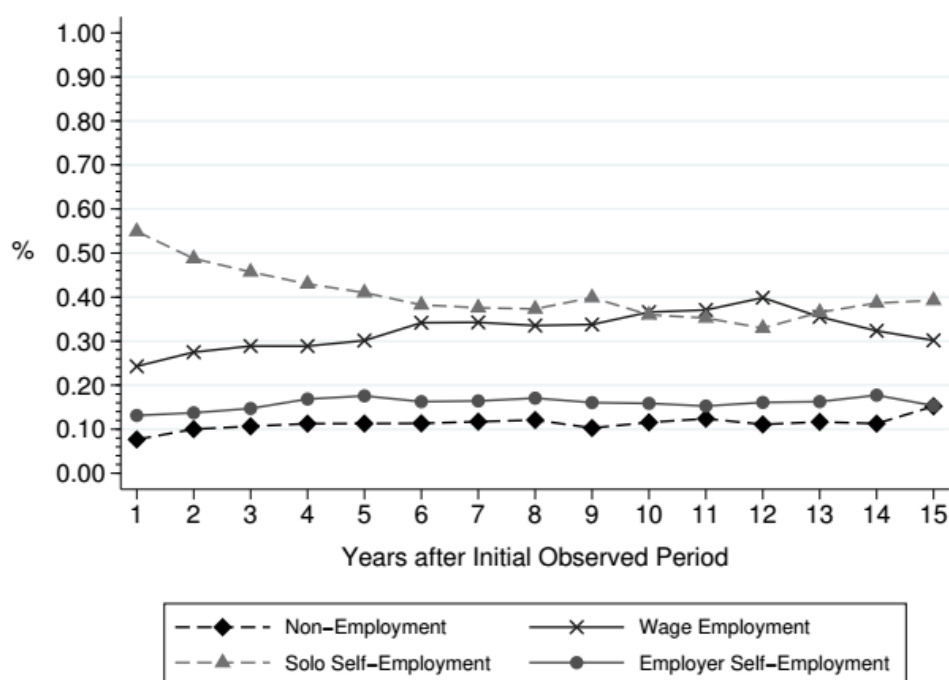
Since Table 3-2 sums up the number of transitions between employment states each year, it will include individuals who make multiple transitions between solo self-employment and employership throughout the observable period. It is thus unclear how the individual's employment status evolves over time because of their employment choices. I address these concerns by illustrating the distribution of employment choices over time conditional on being solo self-employed t years ago in Figure 3-2. We see solo self-employment is volatile with around 40 per cent (50 per cent) of males (females) transitioning out solo self-employment after one year of being solo self-employed.⁴¹ For men and women, being an employee is the most likely outcome after experiencing solo self-employment, with the effects becoming stronger over time. The probability of being an employer conditional on being solo self-employed t years ago is low but stable at around 12 per cent for men and 10 per cent for women. Although small, the values are significantly larger than if they were an employee or non-employee t years ago according

⁴¹ In the HILDA Survey, I can observe only a portion of any individual's lifetime series of labour market decisions made between the years 2001 and 2016.

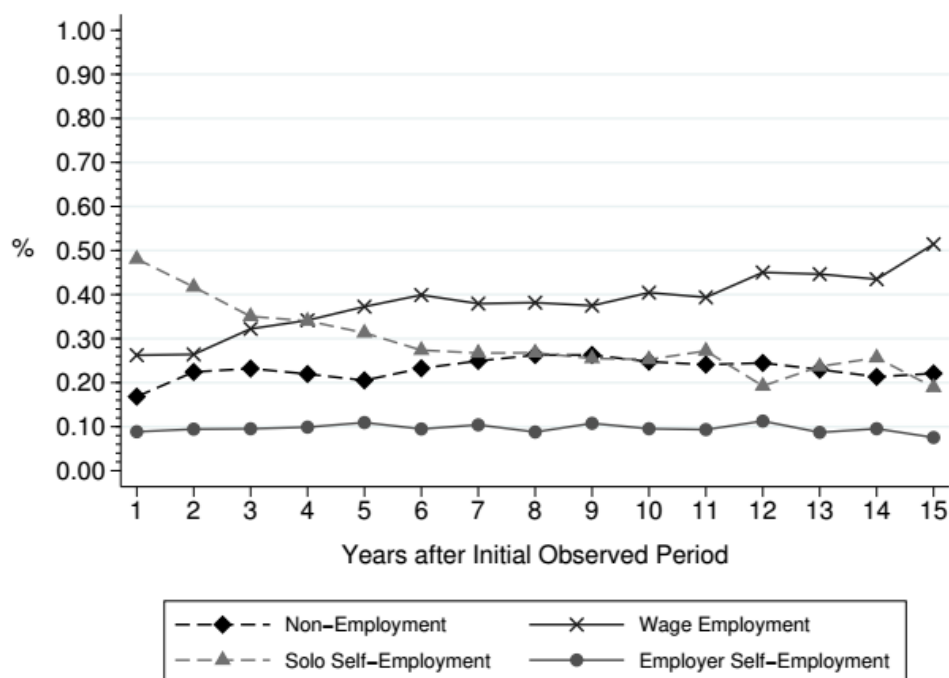
to Figure 3-3 and Figure 3-4. Figure 3-5 also shows that employership is a volatile employment state. Around 60 per cent (55 per cent) of male (female) employers are observed to transition out of employership after a year in the employment state. However, female employers appear to be less persistent than their male counterparts. Around 28 per cent of female employers stayed in employership after 15 years but 48 per cent of male employers persisted within employership.

FIGURE 3-2: OBSERVED PROBABILITIES OF LABOUR MARKET STATE CONDITIONAL ON BEING SOLO SELF-EMPLOYED IN THE PAST

(a) Males



(b) Females

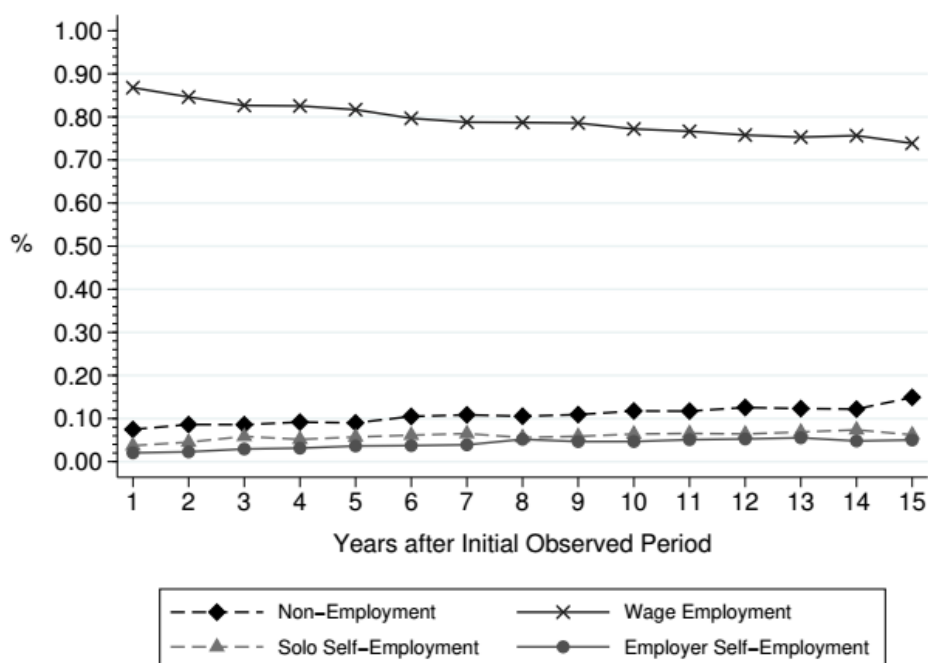


Notes: Estimates are population-weighted. I used responding person population weights, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24). I constructed Figure 3-2 by taking a subsample of respondents who entered the survey as a solo self-employed worker or made their first observed transition into solo self-employment. I then track their employment choices until their last response in the Survey. The proportion of individuals who were initially solo self-employed but chose to be an employer, non-employed or wage/salary employed t years later is derived from the group that has survived at least t consecutive years.

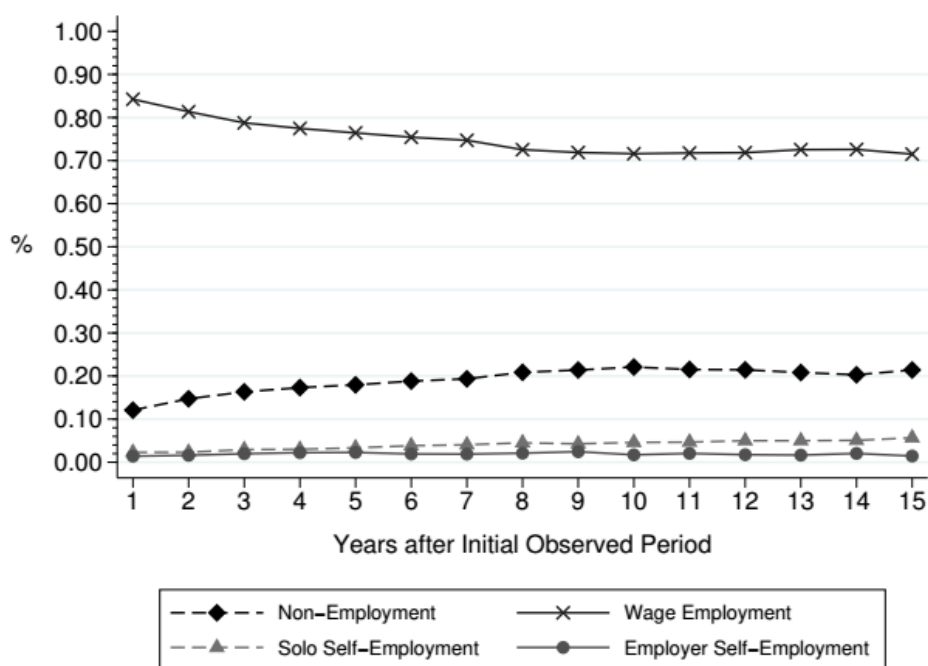
Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

FIGURE 3-3: OBSERVED PROBABILITIES OF LABOUR MARKET STATE CONDITIONAL ON BEING AN EMPLOYEE IN THE PAST

(a) Males



(b) Females

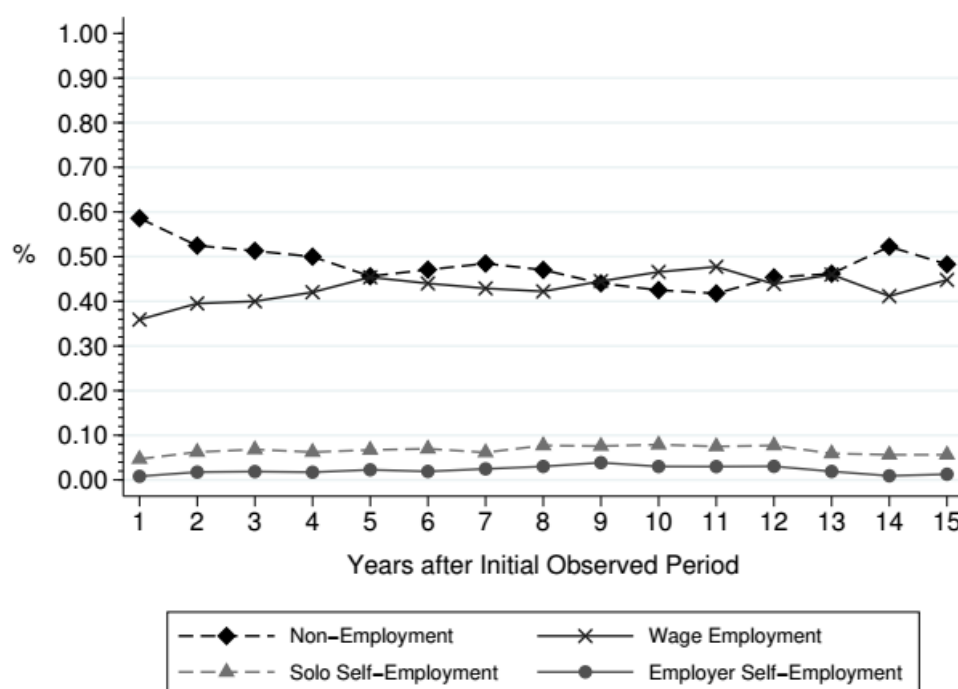


Notes: Estimates are population-weighted. I used responding person population weights, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24). I constructed Figure 3-3 by taking a subsample of respondents who entered the Survey as an employee or made their first observed transition into wage/salary employment. I then track their employment choices until their last response in the Survey. The proportion of individuals who were initially in wage/salary employment but chose to be an employer, non-employed or wage/salary employed t years later is derived from the group that has survived at least t consecutive years.

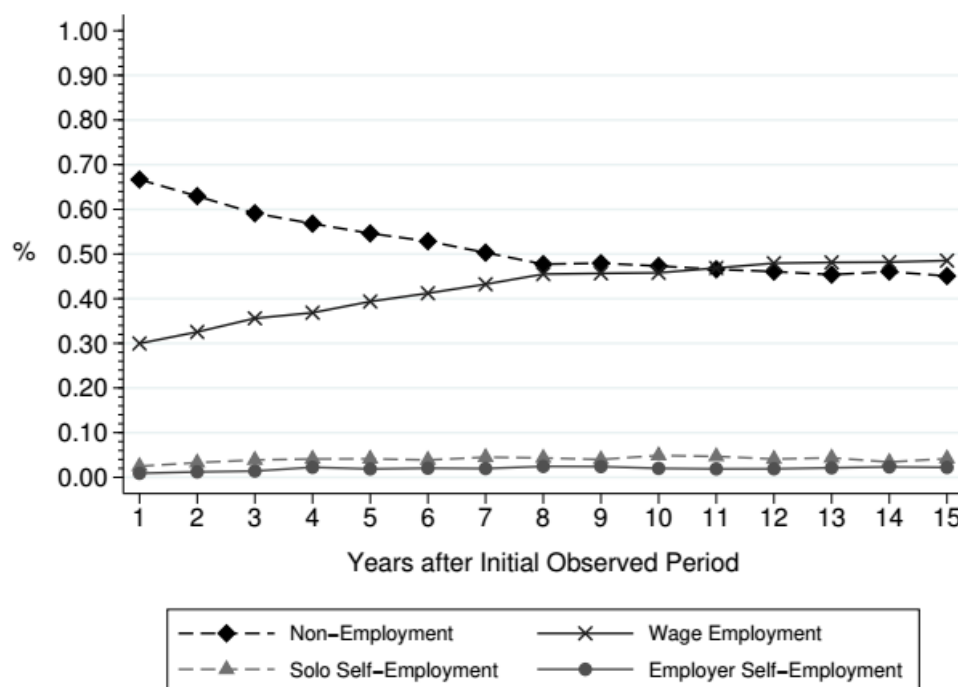
Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

FIGURE 3-4: OBSERVED PROBABILITIES OF LABOUR MARKET STATE CONDITIONAL ON BEING A NON-EMPLOYEE IN THE PAST

(a) Males



(b) Females

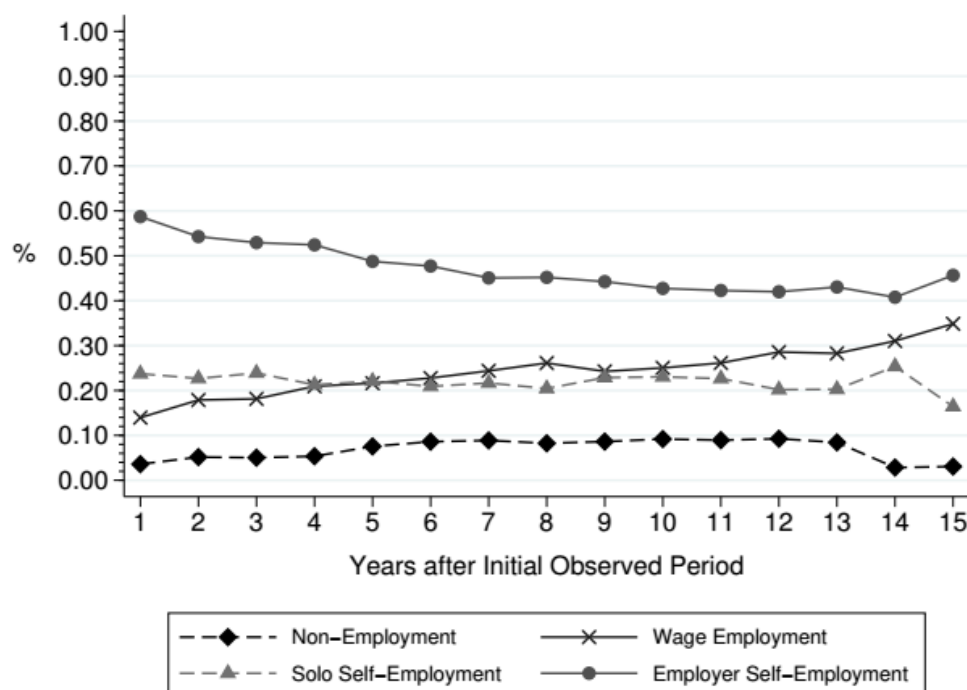


Notes: Estimates are population-weighted. I used responding person population weights, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24). I constructed Figure 3-4 by taking a subsample of respondents who entered the Survey as in non-employment or made their first observed transition into non-employment. I then track their employment choices until their last response in the Survey. The proportion of individuals who were initially in non-employment but chose to be an employer, non-employed or wage/salary employed t years later is derived from the group that has survived at least t consecutive years.

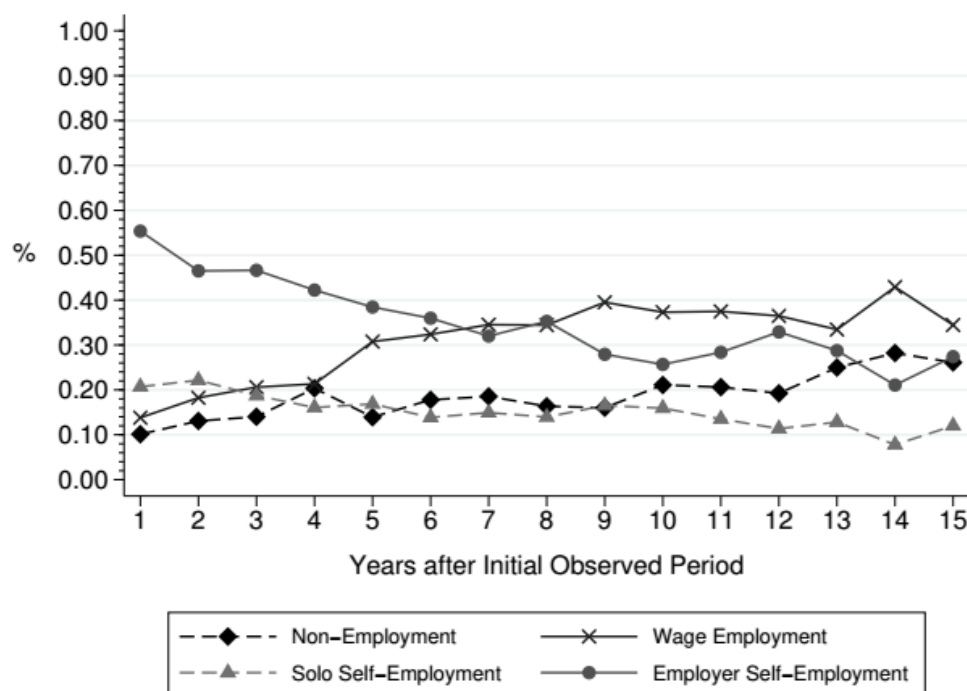
Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

FIGURE 3-5: OBSERVED PROBABILITIES OF LABOUR MARKET STATE CONDITIONAL ON BEING AN EMPLOYER IN THE PAST

(a) Males



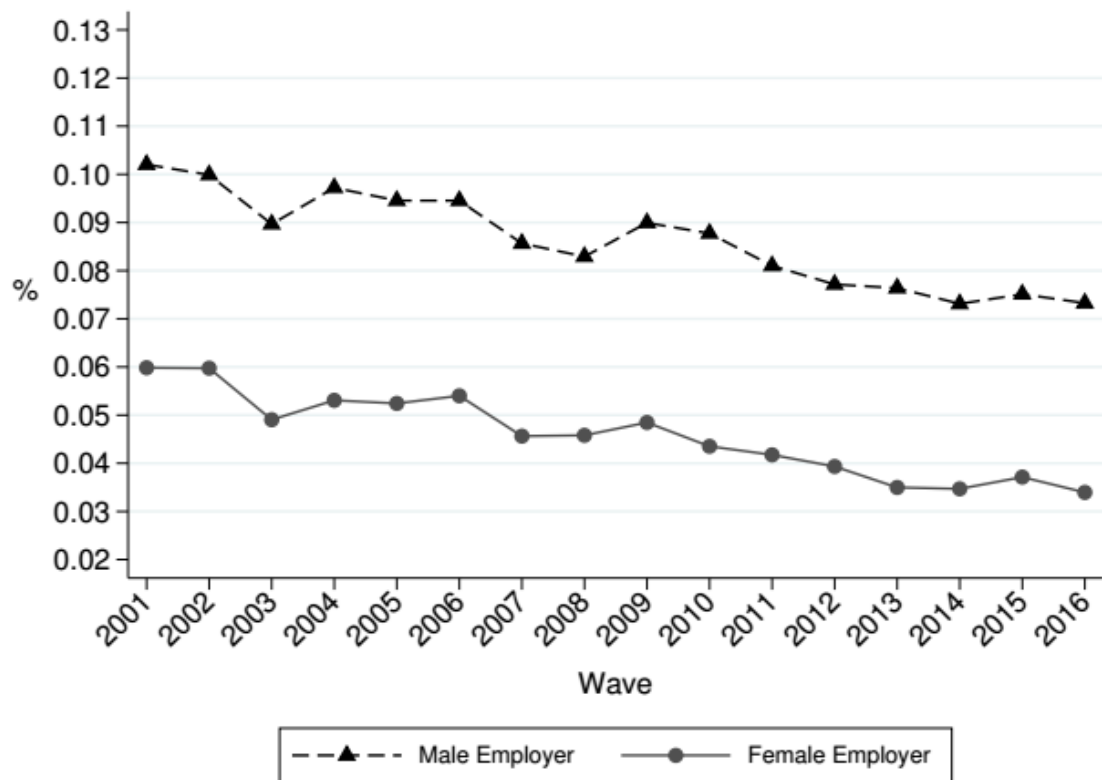
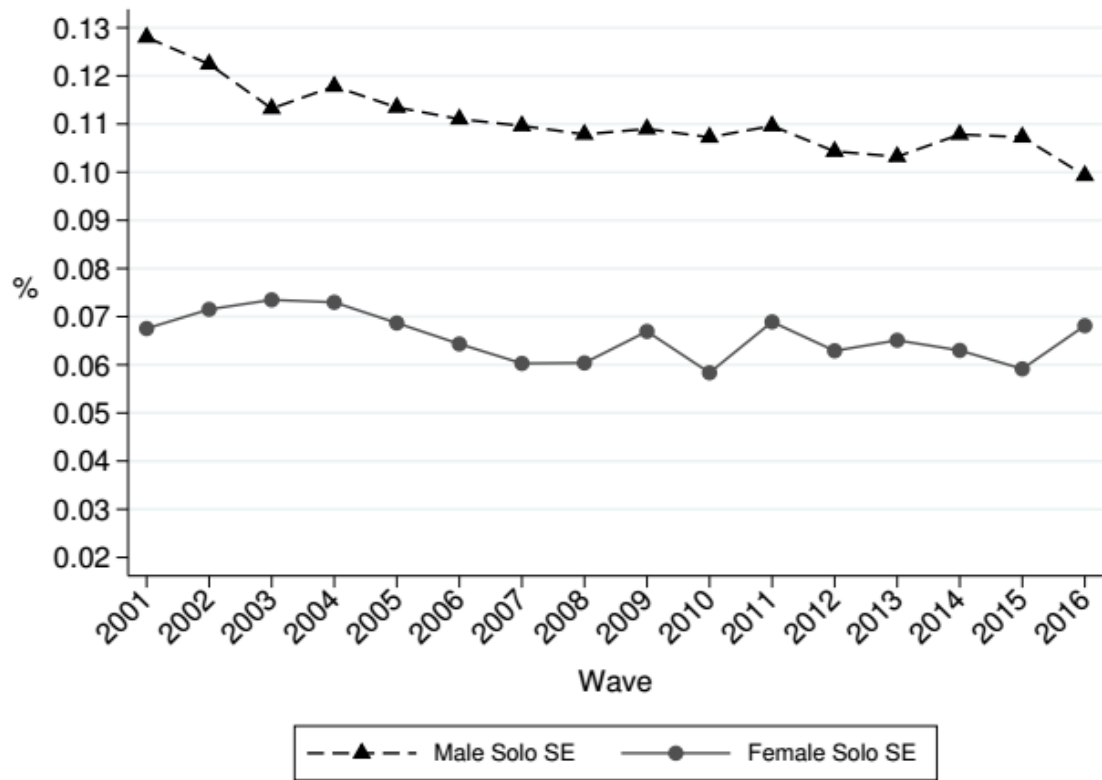
(b) Females



Notes: Estimates are population-weighted. I used responding person population weights, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24). I constructed Figure 3-4 by taking a subsample of respondents who entered the Survey in employership or made their first observed transition into employership. I then track their employment choices until their last response in the Survey. The proportion of individuals who were initially in employership but chose to be an employer, non-employed or wage/salary employed t years later is derived from the group that has survived at least t consecutive years.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

FIGURE 3-6: SELF-EMPLOYMENT TRENDS BY GENDER



Notes: Self-employment rates are defined as the proportion of employed persons who are self-employed. HILDA self-employment rates are population-weighted. I used responding person population weights, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24).

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a)

Figure 3-6 shows women are less likely to be employers and solo self-employed than men, a finding consistent with earlier empirical studies of self-employment and job creation. Also, the aggregate labour mobility data (Table 3-2) suggest that solo self-employment is a ‘stepping stone’ into employership but the ‘stone’ is slightly larger for men than it is for women. Employership and solo self-employment levels, trends and dynamics are clearly different among male and female self-employed workers leading me to perform the subsequent analyses separately by gender.

Summary statistics of this chapter’s variables are presented in Table 3-3 and Table 3-4 for males and females, respectively. According to the tables, self-employed workers (both male or female employers/solo self-employed workers) are older and more experienced on average than wage/salary employees. These statistics show that higher education does not incentivise an individual to become an employer. For males, an approximately equal proportion of wage/salary employees and employers have a Bachelor’s degree (or higher) as their highest educational achievement. In contrast, the average female wage/salary employee and solo self-employed worker are better educated than the average female employer.

Employers are more likely to be married and caring for a larger number of dependents on average than those in wage/salary employment or non-employment. Male solo self-employed workers are almost as likely as employees/non-employees to be married and have fewer dependents under their care on average than their employee counterparts (but more than non-employees). In contrast, female solo self-employed workers have more dependents than their employee counterparts but less than female non-employees. Table 3-3 and Table 3-4 also show that solo self-employed workers and employers have a lesser presence in urban areas than wage/salary employees and non-employees. This likely reflects higher self-employment rates within ‘Agriculture, Forestry and Fishing’ industries which are expected to be in rural areas.⁴²

⁴² Among employed respondents residing in urban areas, less than 1 per cent have a main job in ‘Agriculture, Forestry & Fishing’ industries. Around 14% of employed individuals living in rural areas have a main job in the ‘Agriculture, Forestry & Fishing’ industry. Self-employed workers are more likely to be active in the ‘Agriculture, Forestry & Fishing’ industry than their wage/salary counterparts. Around 1.7% of the sampled wage/salary employees to be working in ‘Agriculture, Forestry & Fishing’ whereas around 11.51% (10.15%) of solo self-employed workers (employers) are active in ‘Agriculture, Forestry & Fishing’ industries.

TABLE 3-3: MALE SUMMARY STATISTICS

	Non- Employment Mean/(Std.)	Wage Employment Mean/(Std.)	Solo Self- Employment Mean/(Std.)	Employers Mean/(Std.)
<u>Lagged employment ($t-1$)</u>				
Non-employment	0.741 (0.438)	0.042 (0.199)	0.045 (0.208)	0.009 (0.093)
Wage employment	0.216 (0.412)	0.932 (0.251)	0.140 (0.347)	0.077 (0.267)
Solo Self-Employment	0.033 (0.179)	0.018 (0.133)	0.706 (0.456)	0.145 (0.352)
Employership	0.010 (0.098)	0.008 (0.089)	0.108 (0.311)	0.770 (0.421)
<u>Initial employment ($t=0$)</u>				
Non-employment	0.529 (0.499)	0.073 (0.259)	0.058 (0.234)	0.025 (0.156)
Wage employment	0.392 (0.488)	0.876 (0.330)	0.320 (0.466)	0.266 (0.442)
Solo Self-Employment	0.053 (0.224)	0.033 (0.179)	0.490 (0.500)	0.176 (0.381)
Employership	0.026 (0.159)	0.019 (0.135)	0.131 (0.338)	0.533 (0.499)
Age	48.346 (13.246)	40.374 (11.371)	46.154 (10.933)	46.079 (9.710)
Number of dependents (0-14 years old)	0.390 (0.939)	0.686 (1.024)	0.669 (1.055)	0.946 (1.182)
Impaired (0/1)	0.588 (0.492)	0.156 (0.363)	0.224 (0.417)	0.168 (0.374)
Marital status (0/1)	0.586 (0.493)	0.738 (0.440)	0.769 (0.422)	0.875 (0.331)
Disposable household income in $t-1$ (\$)	72,742.93 (74,861.91)	109,015.30 (69,591.14)	96,425.12 (79,279.44)	143,632.35 (129,421.05)
Urban area (0/1)	0.842 (0.365)	0.896 (0.305)	0.740 (0.439)	0.781 (0.414)
Regional unemployment (%)	5.378 (1.006)	5.197 (1.023)	5.196 (1.016)	5.193 (1.041)
<u>Home status (0/1)</u>				
Own a home with a mortgage(s)	0.192 (0.394)	0.466 (0.499)	0.394 (0.489)	0.462 (0.499)
Own a home w/o mortgage(s)	0.391 (0.488)	0.216 (0.411)	0.362 (0.481)	0.386 (0.487)
Renting home	0.384 (0.486)	0.295 (0.456)	0.217 (0.413)	0.134 (0.341)
Others	0.033 (0.179)	0.023 (0.151)	0.026 (0.160)	0.018 (0.133)

Highest level of education achieved (0/1)

Year 11 or lower	0.379 (0.485)	0.182 (0.385)	0.230 (0.421)	0.170 (0.376)
Year 12	0.116 (0.320)	0.140 (0.347)	0.102 (0.302)	0.120 (0.325)
Certificate	0.275 (0.446)	0.298 (0.458)	0.368 (0.482)	0.318 (0.466)
Diploma	0.084 (0.277)	0.095 (0.294)	0.103 (0.304)	0.104 (0.305)
Bachelor's degree or higher	0.147 (0.354)	0.284 (0.451)	0.197 (0.398)	0.288 (0.453)
Years of working experience	23.531 (14.181)	21.475 (11.841)	27.570 (11.577)	27.728 (10.278)

Location of birth (0/1)

Australia	0.767 (0.423)	0.796 (0.403)	0.751 (0.432)	0.750 (0.433)
English speaking	0.100 (0.300)	0.099 (0.299)	0.138 (0.345)	0.127 (0.333)
Non-English speaking Australia	0.133 (0.340)	0.105 (0.306)	0.111 (0.314)	0.124 (0.329)

No. of individuals	1,534	6,296	821	566
No. of observations	9,877	44,741	6,308	4,825

Note: The above statistics are derived from a pooled and unbalanced panel sample comprising 21-64 years old males from waves 2002 to 2016 of the HILDA Survey. Standard deviations of the means are reported in parentheses.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017 a).

TABLE 3-4: FEMALE SUMMARY STATISTICS

	Non- Employment Mean/(Std.)	Wage Employment Mean/(Std.)	Solo Self- Employment Mean/(Std.)	Employers Mean/(Std.)
<u>Lagged employment ($t-1$)</u>				
Non-employment	0.806 (0.396)	0.075 (0.263)	0.099 (0.298)	0.044 (0.204)
Wage employment	0.171 (0.377)	0.908 (0.290)	0.174 (0.379)	0.129 (0.335)
Solo Self-Employment	0.016 (0.127)	0.012 (0.110)	0.649 (0.477)	0.119 (0.324)
Employership	0.007 (0.083)	0.005 (0.073)	0.078 (0.269)	0.709 (0.454)
<u>Initial employment ($t=0$)</u>				
Non-employment	0.621 (0.485)	0.153 (0.360)	0.172 (0.377)	0.119 (0.324)
Wage employment	0.335 (0.472)	0.813 (0.390)	0.404 (0.491)	0.272 (0.445)
Solo Self-Employment	0.027 (0.163)	0.023 (0.150)	0.342 (0.474)	0.153 (0.361)
Employership	0.016 (0.127)	0.011 (0.104)	0.082 (0.274)	0.455 (0.498)
Age	45.152 (12.939)	40.997 (11.315)	45.070 (10.555)	45.584 (9.560)
Number of dependents (0-14 years old)	0.907 (1.224)	0.626 (0.954)	0.769 (1.074)	0.934 (1.163)
Impaired (0/1)	0.401 (0.490)	0.165 (0.371)	0.210 (0.407)	0.155 (0.362)
Marital status (0/1)	0.709 (0.454)	0.700 (0.458)	0.786 (0.410)	0.901 (0.299)
Disposable household income in $t-1$ (\$)	81,627.62 (79,494.05)	109,428.64 (73,175.47)	104,784.04 (100,681.00)	138,217.74 (115,026.93)
Urban area (0/1)	0.857 (0.350)	0.891 (0.312)	0.761 (0.426)	0.737 (0.441)
Regional unemployment (%)	5.270 (1.016)	5.206 (1.020)	5.191 (1.010)	5.220 (1.056)
<u>Home status (0/1)</u>				
Own a home with a mortgage(s)	0.273 (0.446)	0.469 (0.499)	0.429 (0.495)	0.432 (0.496)
Own a home w/o mortgage(s)	0.348 (0.476)	0.243 (0.429)	0.350 (0.477)	0.429 (0.495)
Renting home	0.351 (0.477)	0.267 (0.443)	0.190 (0.393)	0.124 (0.329)
Others	0.028 (0.166)	0.021 (0.142)	0.031 (0.174)	0.015 (0.120)

Highest level of education achieved (0/1)

Year 11 or lower	0.440 (0.496)	0.205 (0.404)	0.226 (0.418)	0.281 (0.450)
Year 12	0.154 (0.361)	0.143 (0.350)	0.102 (0.303)	0.167 (0.373)
Certificate	0.159 (0.365)	0.174 (0.379)	0.198 (0.399)	0.142 (0.349)
Diploma	0.083 (0.275)	0.112 (0.316)	0.142 (0.350)	0.125 (0.330)
Bachelor's degree or higher	0.165 (0.371)	0.365 (0.481)	0.332 (0.471)	0.286 (0.452)
Years of working experience	14.742 (11.569)	19.060 (10.708)	21.921 (10.407)	23.304 (9.696)

Location of birth (0/1)

Australia	0.756 (0.430)	0.802 (0.399)	0.772 (0.420)	0.790 (0.408)
English speaking	0.086 (0.281)	0.085 (0.280)	0.116 (0.320)	0.088 (0.284)
Non-English speaking Australia	0.158 (0.365)	0.113 (0.316)	0.112 (0.316)	0.122 (0.327)

No. of individuals	2,962	6,126	409	273
No. of observations	21,635	45,699	3,597	2,252

Note: The above statistics are derived from a pooled and unbalanced panel sample comprising 21-64 years old females from years 2002 to 2016 of the HILDA Survey. Standard deviations of the means are reported in parentheses.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017 a).

The HILDA Survey does not inform us about the respondent's individual and household total wealth in every wave.⁴³ Instead, I proxy for annual wealth by looking at their real household disposable income variable lagged by one year (income available to spend during the previous financial year) and their home status. Unsurprisingly, the non-employed are on average the least affluent. They have the lowest disposable household income and are more likely to rent their homes rather than owning them. Employers appear to be the wealthiest on average as they have the highest lagged real income and a larger proportion of employers own homes. In contrast, solo self-employed workers have less lagged real income on average than their wage/salary counterparts, but a greater proportion of solo self-employed workers own a home without a mortgage than wage/salary employees.

⁴³ For almost all wealth variables, information is gathered only for Waves 2002, 2006, 2010 and 2014.

3.6 Results

Table 3-5 reports the estimation results of the naïve specification of Equation 3-9, i.e., controlling for only the individual's one-year lagged employment choice and initial employment state. There is a positive and statistically significant state dependence effect for every employment state. An individual increases their probability of becoming an employer this year if they worked in solo self-employment, employership or wage/salary employment last year instead of being non-employed. I interpret the coefficient estimates as follows – the log-odds of male (female) solo self-employed workers, relative to non-employees, being employers next year, instead of non-employment, are 5.079 (4.338) times higher given all other factors in the model are held constant. In contrast, being a wage/salary employee increases the relative log-odds of employership next year by 2.923 for males and 2.406 for females. These results are qualitatively similar to Table 3-2's transition estimates which showed that new employers are more likely to come from solo self-employment rather than wage/salary employment or non-employment. We can also see that observed initial employment choices matter – being solo self-employed in wave 1 (the individual's initial observation in the HILDA Survey) increases the relative log-odds of employership by 1.595 for men and 1.226 for women. In contrast, their relative log-odds increase by 1.204 and 0.530 for men and women, respectively, if they were initially wage/salary employed. Not surprisingly, initially being an employer has the largest positive effect on the relative log-odds of employership in year t .

Table 3-6 includes the control variables as discussed earlier in section 3.5 (See A3.1.1 for the full set of results). Similar to Table 3-5, there is a positive and statistically significant state dependence effect for every employment state, but solo self-employment has the largest impact on the relative log-odds of an individual becoming an employer next year. I also observe interesting patterns between the respondent's socio-economic characteristics and their annual employment choices in Table A3.1.1. For males, age appears to have a significant non-linear effect on their probability of being employers. After calculating predicted employership probabilities, conditional on the individual's age, age has a negative effect when the individual is 23 years or older.⁴⁴ Further, this effect becomes stronger the older the male is. On the other hand, age has an inverse U-shaped relationship with the female probability of employership. Age has a positive

⁴⁴ The estimates of equation 3-9 is used to predict the probability an individual becomes an employer, conditional on their individual-specific observed and unobserved characteristics, at a given age. Sample average of the predicted probabilities being in employership in wave t at a specific age is then calculated. I find the sample average to be declining among males as they reach the age of 23 years and above.

impact on their predicted probabilities of employership among women aged between 21 to 24 years. However, among women aged 25 years and above age has an increasingly negative effect on their decision to become employers. This is consistent with the inverse U-shaped relationship between age and self-employment participation as proposed by Lévesque and Minniti (2006).

Table A3.1.1 suggests having children has no statistical effect on the male's relative log-odds of employership, but each additional child reduces the female log-odds of employership by 0.187. The difficulties of rearing children while running the business are likely greater for women than it is for men (Fairchild 2009). For men, the risks of being self-employed may balance their motivation to increase family income by running a business (Dawson et al. 2014; Simoes et al. 2016).

Table A3.1.1 also shows that work experience has a non-linear relationship with the individual's year of cumulative work experience. Calculating predicted probabilities of employership, conditional on years of work experience, I find a positive non-linear relationship between experience and the male individual's probability of employership. For males with 0 to 55 years of working experience, each additional year increases their employership probability.⁴⁵ However, the marginal increase gets smaller as the male becomes more experienced. On the other hand, females have an inverse U-shaped relationship between work experience and employership probability. Work experience has a positive effect on women with 0 to 36 years of experience. However, at 37 years and above, experience has an increasingly negative effect on the female's probability of employership. In addition, education, relative to dropping out of school, has a positive effect on the relative log-odds of employership with 'Bachelor's degree or higher' having the highest effect for both males and females. This is consistent with studies claiming that education has a positive impact on self-employment entry (Borjas and Bronars 1989; Bates 1995; Kim, Aldrich, and Keister 2006; Zissimopoulos, Karoly, and Gu 2010).

Also, in contrast to Congregado, Millán, and Román (2010) and Millán et al. (2015) findings, regional unemployment has no significant influence on the male and female relative log-odds of employership.

⁴⁵ I set a cap of 55 years because it is the maximum number of years of working experience reported by the sample.

TABLE 3-5: NAIVE MULTINOMIAL LOGIT ESTIMATIONS W/O CONTROLS

	Labour Market State at Year t					
	Male			Female		
	Wage (1)	Solo SE (2)	Employer (3)	Wage (4)	Solo SE (5)	Employer (6)
<u>Lagged Employment ($t-1$)</u>						
Wage Employment	3.852*** (0.052)	1.998*** (0.088)	2.923*** (0.170)	3.657*** (0.036)	1.807*** (0.080)	2.406*** (0.131)
Solo SE	1.989*** (0.078)	4.956*** (0.115)	5.079*** (0.177)	1.879*** (0.075)	5.193*** (0.106)	4.338*** (0.149)
Employership	2.412*** (0.125)	4.434*** (0.143)	7.707*** (0.216)	1.961*** (0.104)	3.971*** (0.131)	6.669*** (0.178)
<u>Initial Employment ($t=0$)</u>						
Wage employment	1.063*** (0.053)	0.868*** (0.097)	1.204*** (0.156)	0.878*** (0.035)	0.704*** (0.084)	0.530*** (0.129)
Solo SE	0.534*** (0.089)	1.772*** (0.118)	1.595*** (0.172)	0.454*** (0.086)	1.415*** (0.112)	1.226*** (0.164)
Employership	0.559*** (0.114)	1.439*** (0.143)	2.315*** (0.182)	0.288* (0.112)	0.993*** (0.147)	1.710*** (0.172)
No. of observations	65,751			73,183		
No. of individuals	9,217			9,770		
Log-likelihood	-29,903.61			-34,465.26		

Notes: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category of the dependent variable is non-employment. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 3-6: NAIVE MULTINOMIAL LOGIT ESTIMATIONS WITH CONTROLS

	Labour Market State at Year t					
	Male			Female		
	Wage (1)	Solo SE (2)	Employer (3)	Wage. (4)	Solo SE (5)	Employer (6)
<u>Lagged Employment ($t-1$)</u>						
Wage	3.051*** (0.054)	1.309*** (0.090)	2.037*** (0.171)	3.175*** (0.037)	1.397*** (0.081)	1.908*** (0.128)
Solo SE	1.386*** (0.086)	4.425*** (0.119)	4.423*** (0.180)	1.501*** (0.082)	4.807*** (0.108)	3.901*** (0.147)
Employer	1.618*** (0.133)	3.752*** (0.150)	6.749*** (0.219)	1.555*** (0.109)	3.568*** (0.135)	6.084*** (0.171)
<u>Initial Employment ($t=0$)</u>						
Wage	0.303*** (0.059)	0.138 (0.099)	0.227 (0.157)	0.310*** (0.039)	0.139 (0.087)	-0.019 (0.134)
Solo SE	0.078 (0.098)	1.248*** (0.124)	0.928*** (0.175)	0.111 (0.093)	1.061*** (0.116)	0.860*** (0.164)
Employer	0.061 (0.132)	0.809*** (0.156)	1.583*** (0.191)	-0.056 (0.124)	0.566*** (0.159)	1.279*** (0.179)
No. of observations	65,751			73,183		
No. of individuals	9,217			9,770		
Log-Likelihood	-27,592.56			-32,365.82		

Notes: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category of the dependent variable is non-employment. Also included, but not reported, are controls for age (specified as a quadratic), marital status, number of dependent children, impairment, country / region of birth, educational attainment, cumulative years of work experience (specified as a quadratic), home ownership, household income at $t-1$ (logged), location (urban vs rural), the regional unemployment rate, year and regional fixed effects. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 3-7: MULTINOMIAL LOGIT ESTIMATIONS WITH CORRELATED RANDOM EFFECTS

	Labour Market State at Year t					
	Male			Female		
	Wage (1)	Solo SE (2)	Employer (3)	Wage (4)	Solo SE (5)	Employer (6)
<u>Lagged employment ($t-1$)</u>						
Wage	2.267*** (0.072)	0.813*** (0.114)	1.488*** (0.203)	2.600*** (0.050)	1.145*** (0.104)	1.730*** (0.160)
Solo SE	0.948*** (0.111)	2.907*** (0.156)	3.270*** (0.225)	1.342*** (0.102)	3.366*** (0.145)	2.908*** (0.193)
Employer	1.052*** (0.166)	2.545*** (0.193)	4.731*** (0.277)	1.315*** (0.140)	2.513*** (0.184)	4.082*** (0.229)
<u>Initial employment ($t=0$)</u>						
Wage	0.870*** (0.095)	0.413** (0.147)	0.388* (0.205)	0.728*** (0.061)	0.230* (0.124)	0.035 (0.193)
Solo SE	0.332** (0.146)	3.447*** (0.234)	2.863*** (0.283)	0.172 (0.131)	3.093*** (0.212)	2.764*** (0.294)
Employer	0.178 (0.189)	2.574*** (0.266)	4.439*** (0.335)	-0.072 (0.178)	2.047*** (0.263)	4.411*** (0.360)
No. of observations	65,751			73,183		
No. of individuals	9,217			9,770		
Log-Likelihood	-26,398.78			-30,982.90		
$\text{Cov}(a_{i,Wage}, a_{i,j})$	1.572*** (0.116)	0.890*** (0.130)	1.019*** (0.172)	1.190*** (0.070)	0.433*** (0.097)	0.405*** (0.141)

$\text{Cov}(a_{i,Solo}, a_{i,j})$	3.748*** (0.322)	3.146*** (0.328)	3.259*** (0.305)	2.564*** (0.311)
$\text{Cov}(a_{i,Emp}, a_{i,j})$		4.819*** (0.463)		4.886*** (0.496)

Notes: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category of the dependent variable is non-employment. Also included, but not reported, are controls for age (specified as a quadratic), marital status, number of dependent children, impairment, country / region of birth, educational attainment, cumulative years of work experience (specified as a quadratic), home ownership, household income at $t-1$ (logged), location (urban vs rural), the regional unemployment rate, year, regional fixed effects and individual-specific time averages of the exogenous characteristics. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

Impaired individuals are shown to have lower relative log-odds of employership than non-impaired individuals, urban individuals have lower log-odds of employership than rural individuals, and married men have significantly higher relative log-odds of employership than non-married men. Lastly, a 10 per cent increase in lagged disposable household income will increase the relative log-odds of employership by 0.0472 and 0.0528 for males and females, respectively.

Table 3-7 reports the estimates of Equation 3-10; i.e., the dynamic multinomial logit model with controls for individual-specific observables and random effects (The full table is included in the appendix as Table A3.1.2). This is our main table of interest for this chapter. While solo self-employment still increases the relative log-odds of employership next year, the increase is smaller when compared to estimates from Table 3-5 and Table 3-6. This is because the full model is accounting for unobservable characteristics that correlate with the individual's decision to be an employer. The bottom three rows of Table 3-7 present the covariance matrices of the random effects for both male and female individuals. The variances of the random effects for wage/salary employment (1.572 for males and 1.190 for females) are smaller than they are for solo self-employment (3.748 for males and 3.259 for females) and employership (4.819 for males and 4.886 for females). This suggests the individual's unobserved factors (e.g., their entrepreneurial ability/preferences) are relatively more important for explaining the decision to be an employer or solo self-employed than for wage/salary employment. Also, the positive correlation between the random effects for solo self-employment and employership suggests that individuals who prefer to be solo self-employed also prefer being an employer.

I also observe that the relationship between some respondent's socio-economic characteristics and their annual employment choices changed after controlling for correlated random effects according to Table A3.1.2. Unlike in Table A3.1.1, age does not appear to have any significant effect on male decisions to be an employer, but there is still a negative quadratic relationship between age and the female relative log-odds of employership. After calculating the predicted probabilities among women aged between 21 and 25 years, an additional year of age increases their predicted probability of employership. However, among women aged 46 years and above age has a negative impact on employership predicted probabilities.

TABLE 3-8: PROBABILITY OF BEING SOLO/EMPLOYER SELF-EMPLOYED GIVEN PREVIOUS EMPLOYMENT STATE

Previous employment state in year $t-1$	Predicted Probabilities of being solo/employer self-employed in year t					
	MNL w/o controls		MNL with controls		MNL with RE	
	Solo SE (1)	Employer (2)	Solo SE (3)	Employer (4)	Solo SE (5)	Employer (6)
Panel A. Males						
Non-employment	0.041*** (0.003)	0.007*** (0.001)	0.064*** (0.005)	0.014*** (0.002)	0.095*** (0.006)	0.032*** (0.004)
Wage employment	0.024*** (0.001)	0.010*** (0.001)	0.024*** (0.001)	0.010*** (0.001)	0.053*** (0.002)	0.030*** (0.002)
Solo self-employment	0.591*** (0.011)	0.111*** (0.006)	0.567*** (0.011)	0.114*** (0.006)	0.247*** (0.011)	0.092*** (0.005)
Employer	0.156*** (0.009)	0.660*** (0.015)	0.170*** (0.009)	0.598*** (0.015)	0.156*** (0.009)	0.213*** (0.014)
Panel B. Females						
Non-employment	0.020*** (0.001)	0.005*** (0.001)	0.028*** (0.002)	0.008*** (0.001)	0.038*** (0.003)	0.016*** (0.002)
Wage employment	0.014*** (0.001)	0.007*** (0.001)	0.014*** (0.001)	0.007*** (0.001)	0.026*** (0.001)	0.018*** (0.001)
Solo self-employment	0.581*** (0.014)	0.066*** (0.005)	0.537*** (0.015)	0.062*** (0.005)	0.181*** (0.011)	0.040*** (0.003)
Employer	0.142*** (0.011)	0.549*** (0.023)	0.146*** (0.011)	0.462*** (0.023)	0.097*** (0.009)	0.098*** (0.010)

Note: Estimates above are sample averages of the predicted probabilities being in solo self-employment or employership in wave t given their employment choice in wave $t-1$. Probabilities in specifications (1) and (2) are based on estimates from Table 3-5. Specifications (3) and (4) use estimates from Table 3-6. Specifications (5) and (6) use estimates from random effects model presented in Table 3-7. Standard errors are in parentheses and are calculated using the Delta method. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

Table A3.1.2 also shows that having a ‘Bachelor’s degree or higher’ still has a positive statistically insignificant on both of the relative log-odds of male and female. These results are in stark contrast to their respective coefficients in Lechmann and Wunder (2017). Lechmann and Wunder show that education has a significant positive effect on the relative log-odds of male and female employership. A potential explanation for the difference in results is that they measure education in years whereas I use dummy variables to indicate the individual’s highest level of educational achievement. Working experience also does not affect the female relative log-odds of employership but, there is a negative and significant quadratic relationship between the male relative log-odds of employership and years of work experience. After calculating the predicted probabilities of employership, work experience has a positive influence among males with 0 to 46 years of work experience. However, among males with 47 years of experience and above, each additional year of experience reduces their probability of employership.

The overall effect of being solo self-employed on the probability of becoming an employer in the next year is difficult to interpret with log-odds. To better quantify the relative causal effect of solo self-employment last year on the probability of choosing employership, I use estimates from Table 3-7 to calculate average predicted probabilities. For each observation, I predict the probability an individual is an employer conditional on being solo self-employed, a wage/salary employee or non-employed last year. Then, I take the sample averages of the predicted probabilities and use them to calculate the extent of the true cross-state dependence and state dependence in employership.

Table 3-8 presents the average predictive probabilities of being an employer (and being solo self-employed) conditional on the previous chosen employment state. The standard errors in the parentheses are calculated with the delta method. Columns (1) and (2) use estimates from Table 3-5, columns (3) and (4) use estimates from Table 3-6, and columns (5) and (6) are based on estimates from Table 3-7. Under columns (2) and (4) of Table 3-8, we can see that the average predicted probability of being an employer next year, conditional on being solo self-employed this year, is similar to the transition rates of Table 3-2. However, under column (6), after controlling for unobserved heterogeneity, the predicted probabilities of employership conditional on being solo self-employed last year, lowered to about 9.2 per cent and 4.0 per cent for males and females, respectively. About 17.1 per cent (i.e., $1 - (9.2/11.1)$) and 39 per cent (i.e., $1 - (4.0/6.6)$) of the observed transitions from solo self-employment into employership are explained by the individual’s unobserved characteristics. Likewise, the predicted probabilities of

employership, conditional on being an employer last year, fell from 75.64 per cent and 69.12 per cent (these are the observed rates of persistence in employership from Table 3-2 for males and females, respectively) to about 21.3 per cent and 9.8 per cent for males and females, respectively, after controlling for individual heterogeneity.

Next, I calculate the extent of true cross-state dependence in employership. Following Lechmann and Wunder (2017), the empirical definition of true cross-state dependence (CSD) in employership is the difference between the probability of being an employer in year t conditional on being in solo self-employment in year $t - 1$ and the probability of being an employer in year $t - 1$ conditional on being in an alternate employment state in year $t - 1$. To be specific, the cross-state dependence in employership, compared to non-employment, NE , is defined as:

$$CSD_{NE} = P(\text{employership}_t | \text{solo self-employment}_{t-1}) \\ - P(\text{employership}_t | \text{non-employment}_{t-1})$$

and the cross-state dependence in employership, compared to wage/salary employment (WE) is defined as:

$$CSD_{WE} = P(\text{employership}_t | \text{solo self-employment}_{t-1}) \\ - P(\text{employership}_t | \text{wage/salary employment}_{t-1})$$

True cross-state dependence estimates are summarised in Table 3-9. Under column (1), being solo self-employed in wave $t - 1$, relative to being non-employed, increases the male (female) probability of being in employership by 10.4 (6) percentage points. Relative to wage employment, the employership probability is increased by 10.1 (5.9) percentage points for males (females). Column (2) shows that adding the control variables has no meaningful impact on the cross-state dependence in employership despite the significant relationships between some control variables and the individual's relative log-odds of employership. After controlling for the individual's socio-economic characteristics, solo self-employment increases the probability of employership relative to wage/salary by 10.4 (5.5) percentage points for men. Relative to non-employment, the probability increased by 10 (5.3) percentage points. Column (3) of Table 3-9 shows the true cross-state dependence of employership after controlling for individual unobserved heterogeneity. For men (women), being solo self-employed raises the probability of being

an employer next year by about 6.2 (2.3) percentage points relative to wage/salary employment. Relative to non-employment, solo self-employment increases the probability by 6.0 (2.4) percentage points. The causal effect of solo self-employment this year on the probability of employership next year is relatively small after accounting for the individual's unobserved heterogeneity.

TABLE 3-9: CROSS-STATE DEPENDENCE IN EMPLOYERSHIP

	Cross-State Dependence Estimates in Employership		
	Naïve MNL (1)	MNL with Controls (2)	MNL with RE (3)
<u>Panel A. Males</u>			
CSD_{NE}	0.104 (0.006)	0.100 (0.006)	0.060 (0.007)
CSD_{WE}	0.101 (0.006)	0.104 (0.006)	0.062 (0.006)
<u>Panel B. Females</u>			
CSD_{NE}	0.060 (0.005)	0.053 (0.005)	0.024 (0.004)
CSD_{WE}	(0.059) (0.005)	0.055 (0.005)	0.023 (0.004)

Note: Estimates above are the true cross-state dependence effect of being in solo self-employment at wave $t - 1$ relative to being in non-employment or in wage/salary employment. Probabilities estimates come from Table 3-8. Standard errors are in parentheses and are calculated using the Delta method.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

By comparing column (3) against column (1) we see that after controlling for individual heterogeneity, the cross-state dependence in employership, relative to wage/salary employment, is reduced by around 39 per cent (i.e., $(0.062-0.101)/0.101$) and 61 per cent for males and females, respectively. Cross-state dependence, relative to non-employment, fell by around 42 per cent and 60 per cent for males and females, respectively, after controlling for individual heterogeneity. In contrast, if we compare column (2), which omits controls for correlated random effects, against column (1), cross-state dependence, relative to wage/salary employment, is increased by around 3 per cent (i.e., $(0.104-0.101)/0.101$) and reduced by 7 per cent for males and females, respectively. Relative to non-employment, cross-state dependence fell by 4 per cent and 12 per cent for males and females, respectively. Unobserved characteristics such as the preference to be an employer, is a significant determinant of transitions into employership.

I then examine the persistency of the employership state by calculating the true state dependence effect in employership (TSD_{emp}). True state dependence in employership refers to the change in the probability of employership conditional on being in employership last year relative to being in an alternate employment state. In this exercise, TSD_{emp} is defined as

$$TSD_{emp} = P(\text{employership}_t | \text{employership}_{t-1}) - P(\text{employership}_t | \text{alternative state}_{t-1})$$

I take the difference between the sample average predicted probability of being an employer this year conditional on being an employer last year and the sample average probability conditional on being in any other employment state last year. Using estimates from columns (2), (4) and (6) of Table 3-8, I summarise the true state dependence estimates in Table 3-10. Similar to the cross-state dependence estimates, TSD_{emp} is drastically reduced after controlling for individual unobserved heterogeneity if we compare column (3) against column (1) of Table 3-10. According to column (3) of Table 3-10, compared to wage/salary employment, the probability of employership in wave $t - 1$ increases the probability of employership in wave t by 18.3 and 8 percentage points for males and females, respectively. Compared to non-employment, true state dependence is 18.1 and 8.2 percentage points for males and females, respectively.

By comparing estimates in column (2) with column (3) in Table 3-10, it can be said that the unobserved individual heterogeneity explains most of the observed persistence in employership. According to columns (1) and (3) of Table 3-10, state dependence is reduced by around 72 per cent (i.e. $(0.181-0.653)/0.653$ and $(0.183-0.650)/0.650$) and 85 per cent for males and females, respectively, after controlling for both observable and unobservable characteristics. In contrast, if I were to only control for observable characteristics and compare column (2) against column (1), then state dependence is reduced by around 10 per cent (i.e. $(0.584-0.653)/0.653$ and $(0.588-0.650)/0.650$) and 16 per cent for males and females, respectively. The significant drop in both CSD and TSD estimates in employership, after controlling for unobserved heterogeneity, suggest the individual's unobservable characteristics (such as their preference to be an employer) are important determinants of employership entry. I argue that individual heterogeneity

explains most of the observed male and female persistence in and transitions into employership.

TABLE 3-10: STATE DEPENDENCE IN EMPLOYERSHIP

	State Dependence Estimates of Employership		
	Naïve MNL (1)	MNL with Controls (2)	MNL with RE (3)
<u>Panel A. Males</u>			
TSD_{NE}	0.653 (0.015)	0.584 (0.015)	0.181 (0.015)
TSD_{WE}	0.650 (0.015)	0.588 (0.015)	0.183 (0.015)
<u>Panel B. Females</u>			
TSD_{NE}	0.543 (0.023)	0.454 (0.023)	0.082 (0.010)
TSD_{WE}	0.542 (0.532)	0.455 (0.023)	0.080 (0.010)

Note: Estimates above are the true state dependence effect of being in employer at wave $t - 1$ relative to being in non-employment or in wage/salary employment. Probabilities estimates come from Table 3-8. Standard errors are in parentheses and are calculated using the Delta method.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

Table 3-11 compare my results to the only other state dependence study in self-employment that distinguishes between solo self-employment and employership (Lechmann and Wunder 2017). CSD estimates are roughly the same across both studies, but Australian male true state dependence in employership estimates are much larger than their German counterparts. It is not clear what is responsible for this difference, especially since we are both using similar sources of data (we both used data from a nationally representative longitudinal household survey) and empirical strategies (we both used a dynamic multinomial logit model with correlated random effects). A potential explanation is that Australian employers are characteristically different from German employers; i.e., Australian employers are more ‘entrepreneurial’ than German employers. Evidence for this claim is reported by two GEM reports (GEM 2017a, 2017b). These reports show that the percentage of German adults aged 18 to 64 years with the intention to start a business within three years (also known as the entrepreneurial intention rate) is half the rate in Australia. Further, the reports suggest Australian start-ups are more ‘innovative’ (innovation is defined by the offering of a product or service that a few or no businesses have) than their German counterparts, and firms who innovate are more likely

to survive than firms who do not (Cosh, Hughes, and Wood 1999; Cefis and Marsili 2006; Parker 2009).

TABLE 3-11: COMPARING CSD AND TSD ESTIMATES

	True CSD Relative to		TSD Relative to	
	Wage (1)	Non-Emp. (2)	Wage (3)	Non-Emp. (4)
<u>Panel A. Males</u>				
Thesis	0.062	0.060	0.183	0.181
Lechmann & Wunder (2017)	0.051	0.049	0.086	0.083
<u>Panel B. Females</u>				
Thesis	0.023	0.024	0.080	0.082
Lechmann & Wunder (2017)	0.024	0.021	0.118	0.115

Note: Estimates above are sample averages of the predicted probabilities being in solo self-employment or employership in wave t given their employment choice in wave $t - 1$. Thesis' estimates come from Table 3-7.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

Both studies show that the extent of true cross-state dependence and true state dependence in employership are smaller for women than it is for men – women are less likely than men to transition into employership from solo self-employment or remain in employership. There is a clear gender gap in employership and solo self-employment. Possible explanations for this gap can be traced back to earlier studies showing women are less prone than men to be self-employed (Blanchflower 2000; Leoni and Falk 2010; Stefanovic and Stosic 2012; Verheul et al. 2012). First, this is because women tend to be more risk-averse than men (Croson and Gneezy 2009; Dohmen et al. 2011). Second, women face higher liquidity constraints than men regarding self-employment entry. Women have more limited access to finance and rely more on their resources (Carter and Shaw 2006). Third, earlier studies established that the average female stock of social capital is significantly smaller than that of their male counterpart. Male social networks are more diversified and include more professional contacts whereas female networks typically comprise family and friends (Koellinger, Minniti, and Schade 2013). Professional social networks can generate knowledge spillovers helpful in identifying business opportunities and conditions. A final plausible explanation for the gender gap in the true (cross) state dependence estimates is that women are more likely to be working part-time in self-employment. In my sample, 26 per cent of solo self-employed males are working part-time whereas 63 per cent of solo self-employed females are working part-

time.⁴⁶ According to Burket et al. (2002), individuals are most likely to be an employer if they are working full time in self-employment. In their study, they find women are less likely than men to be employers because women are more likely to be part-time self-employed. Since a majority of the sampled female solo self-employed are working part-time and only a minority of the male solo self-employed are working part-time, it stands to reason to expect male solo self-employed workers to transition into employership at higher rates than their female counterparts. Women are likely to work part-time in self-employment because of the aforementioned constraints imposed on them. They have limited resources which hinders their ability to work full-time in their business. However, I am not aware of any study that theoretically explains why the part-time solo self-employed are less likely than those working full-time to become employers. A possible explanation is that the part-time solo self-employed represent someone self-employed out of necessity, i.e., someone who's self-employed to escape unemployment (Block and Wagner 2010). Instead of establishing their business, they are solo self-employed to earn income while searching for more appropriate wage/salary employment.

Regardless, for both men and women, I show that the extent of true cross-state dependence and state dependence in employership are relatively small when compared to observed transitions into employership from solo self-employment and persistence in employership. A significant portion of transitions into employership and most of the observed persistence in employership is driven by the individual's unobserved heterogeneity.

3.7 Long-Term Impact on the Decision to be an Employer

Since Equation 3-9 controls for observed and unobserved individual heterogeneity, the predictions from Table 3-7 indicate the effect of being solo self-employed, wage/salary employed or non-employed for one year on the employership decision in subsequent years. Figure 3-7 compares the effects of different employment choices in a given year on the individual's long-term decision to be an employer. According to the figure, a temporary shift into solo self-employment has short-run effects on the employership decision. If males were solo self-employed for one year, there is a 9.5 per cent probability that he will transition into employership next year (this is the sample average predicted probability a male becomes an employer in year t given he was solo

⁴⁶ I define part-time work in Chapter 2. Also, I did not control for part-time work in my model because this variable is not available for the non-employed.

self-employed in year $t - 1$ from Table 3-8). In contrast, if he was a wage/salary employee or non-employee, the probability of employership in wave 1 is 3.0 per cent and 3.2 per cent, respectively. However, the probability the male solo self-employed worker remains in employership two years later is only 2 per cent (this is a combination of the employership probabilities from Table 3-8, i.e., $0.092 \times 0.213 = 0.02$). The probability that he is still an employer 3 years later is virtually zero and is no different than if he were to initially transition into employership from wage/salary or non-employment. For women, the probability of being an employer 3 years after transitioning into employership from solo self-employment is also virtually zero.

When compared to annual transition rates in Table 3-2, I showed that the extent of true (cross) state dependence in employership are relatively small. However, as Lechmann and Wunder (2017) suggested, these estimates may not accurately reflect the population of individuals with an intention to start a business, or those willing to accept a start-up grant. In the dynamic multinomial logit model with correlated random effects, innate individual-specific entrepreneurial preferences are captured by both the correlated random effects and their initially observed employment state (i.e., the employment state they were in when they first took part in the HILDA Survey). I use the initial employment state to proxy for the individual's entrepreneurial endowment at the start of the observation period. I assume that any individual who was initially observed to be an employer is more entrepreneurial than others and a better representative of the population who genuinely wants to start and is successful in running a business. I refer to members of this population as 'entrepreneurial' individuals. I investigate how (cross) state dependence in employership varies with individual-specific entrepreneurial preferences by calculating the sample average predicted probability of employership conditional on being an employer during their first wave of observation.⁴⁷ Table 3-12 compares the original estimates of true (cross) dependence in employership against estimates obtained after setting the initial employment state to employership. The table shows that true cross-state dependence and true state dependence in employership estimates are considerably higher for 'entrepreneurial' individuals. Among 'entrepreneurial' individuals, solo self-employment experience in a given year increases the relative probability of employership in the subsequent year by 19.8 to 20.0 and 11.5 to 13.8 percentage points for males and

⁴⁷ I get average transition probabilities as I did for Table 3-8. The main difference is that, for everyone, I predict the probability of them being an employer in year t , conditional on their employment state in year $t - 1$ with their initially observed employment state set to employership.

females, respectively, compared to only 6.0 to 6.2 and 2.3 to 2.4 percentage points for a randomly selected male and female, respectively. True state dependence in employership ranges from 45.5 to 45.7 and 33.6 to 35.9 percentage points for the ‘entrepreneurial’ male and female, respectively. In comparison, for a randomly selected male or female, the estimates range from 18.1 to 18.3 and 8.0 to 8.2 percentage points, respectively. Any pro-entrepreneurial policy, such as start-up grants, that target ‘entrepreneurial’ individuals will have more pronounced long-term effects on the decision to be an employer than targeting any randomly selected individual. This is further reinforced by Figure 3-8. Figure 3-8 shows that the probability of an ‘entrepreneurial’ male being in employership, after transitioning into employership from solo self-employment than if he were to transition from wage/salary or non-employment in wave 1. For the ‘entrepreneurial’ female, the probability of remaining in employership in wave 3, conditional on transitioning from solo self-employment in wave 1, is still higher than if she were to transition from the alternate employment states.

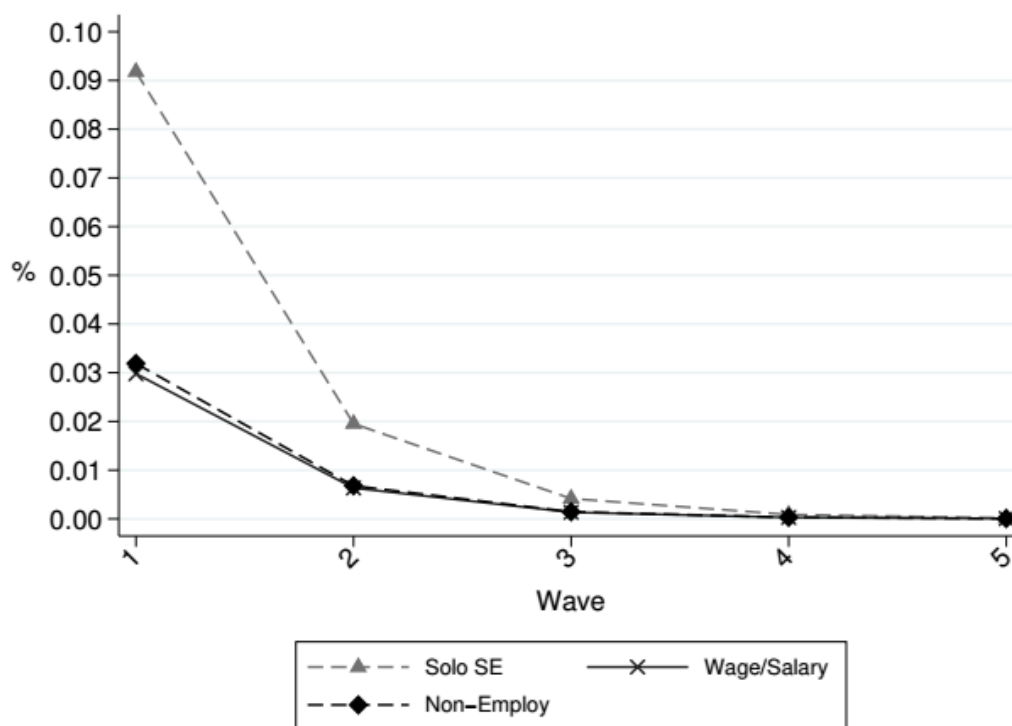
3.8 Robustness

3.8.1 Non-Random Attrition

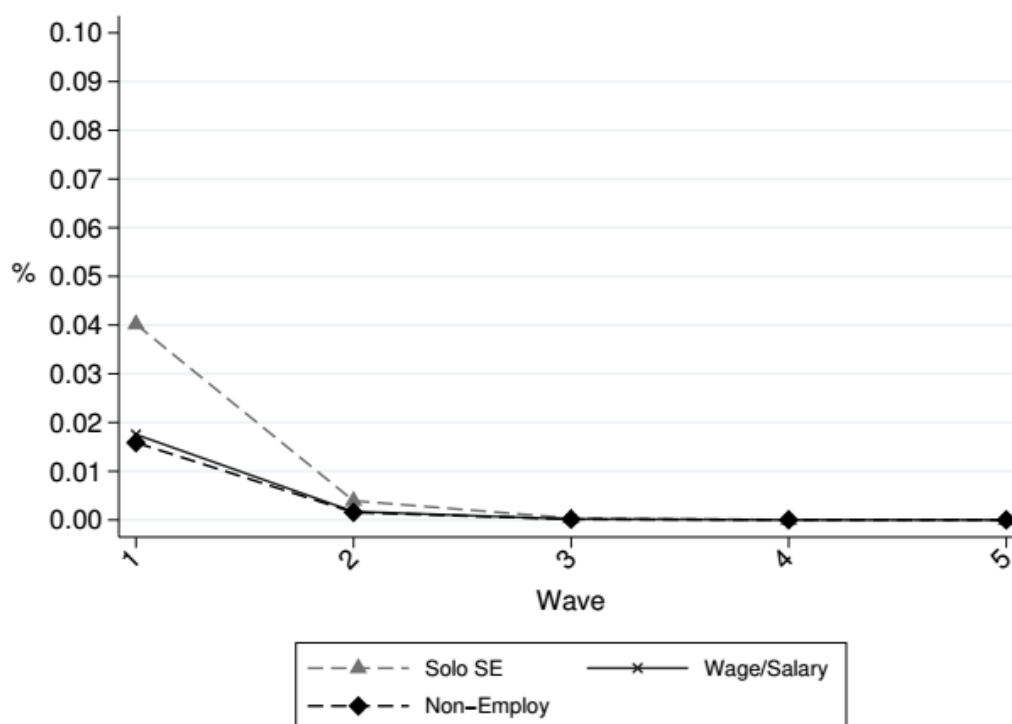
The longitudinal nature of the HILDA Survey permits this study to trace annual employment choices and study the influence of past employment experiences on future labour market decisions. Unfortunately, there is a risk that estimates in Table 3-7 are biased because of non-random attrition from the HILDA Survey. One of the most common methods used to correct for non-random attrition bias is the Heckman two-stage correction process (Heckman 1979; Wooldridge 2002). The problem with this process is identifying appropriate instrument variables that predict the individual’s decision to enter and remain in the survey but have no correlation with their employment choice. Instead, I constructed a dummy variable identifying whether an individual is a non-respondent in the next survey wave. It acts as a function of observed response behaviour that provides a simple test of (and control for) selectivity bias without the need for estimating a model specifying the attrition and response mechanism (Verbeek and Nijman 1992). I thus modify Equation 3-9 as follows:

$$3-10) \quad P(y_{i,t} = j | X_{i,t}, y_{i,t-1}, \alpha_{i,j}) = \frac{\exp(\beta'_j X_{i,t} + \gamma'_j y_{i,t-1} + \delta'_{y,j} y_{i,0} + \delta'_{x,j} \bar{x}_i + \delta'_{s,j} s_{i,t+1} + v_{i,j})}{\sum_{k=1}^4 \exp(\beta'_k X_{i,t} + \gamma'_k y_{i,t-1} + \delta'_{y,k} y_{i,0} + \delta'_{x,k} \bar{x}_i + \delta'_{s,k} s_{i,t+1} + v_{i,k})}$$

FIGURE 3-7: LABOUR MARKET DECISIONS AND THEIR LONG-TERM IMPACT ON THE DECISION TO BE AN EMPLOYER



(a) Males



(b) Females

Notes: Author's calculations using estimates from specifications (5) & (6) of Table 3-8.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

where $s_{i,t+1}$ is an indicator variable that equals 1 if individual i is a non-respondent in the next wave $t + 1$, and zero otherwise. However, including this variable will lead to another loss of one-year worth of observations (11,237 observations from the year 2016). Results from estimating Equation 3-10 are presented in Table 3-13 and show attrition is a significant concern for those who are employers. Leaving the survey (i.e., $s_{i,t+1} = 1$) in the next wave reduces the relative log-odds of the individual becoming an employer. In contrast, does not affect the relative log-odds of being a wage/salary employee or a solo self-employed worker.

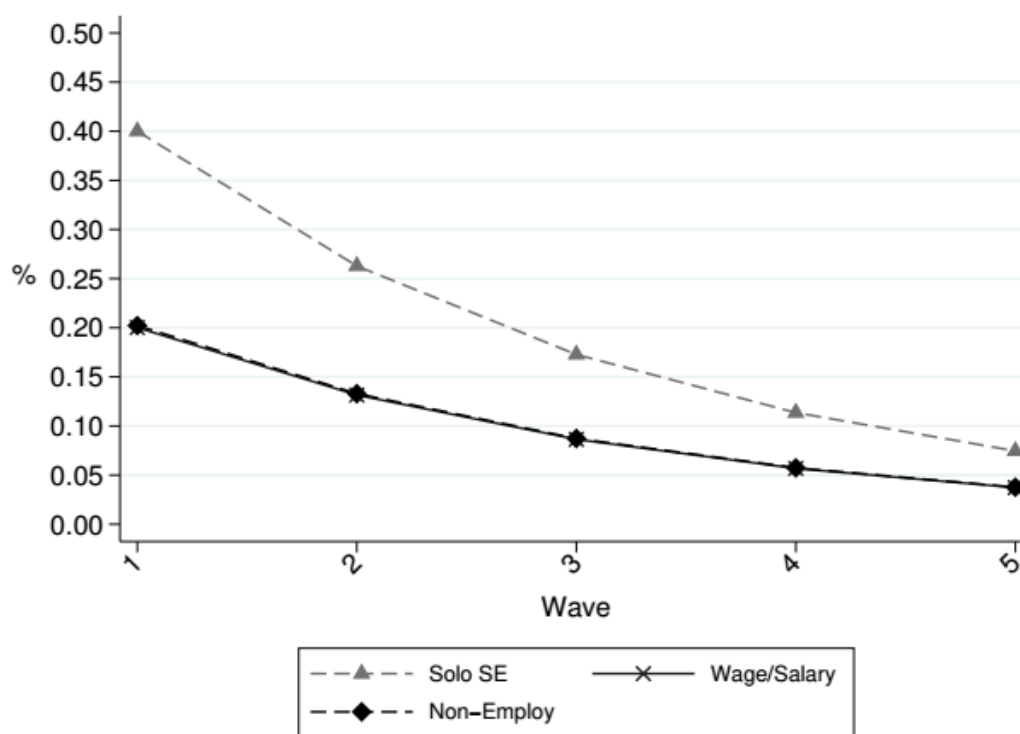
TABLE 3-12: COMPARING CSD AND TSD ESTIMATES GIVEN INITIAL EMPLOYMENT STATUS

	True CSD Relative to		True TSD Relative to	
	Wage (1)	Non-Emp. (2)	Wage (3)	Non-Emp. (4)
<u>Panel A. Males</u>				
Setting the initial employment state to employership.	0.200 (0.019)	0.198 (0.026)	0.457 (0.022)	0.455 (0.028)
Original Estimates	0.062 (0.006)	0.060 (0.007)	0.183 (0.015)	0.181 (0.015)
<u>Panel B. Females</u>				
Setting the initial employment state to employership.	0.115 (0.022)	0.138 (0.023)	0.336 (0.025)	0.359 (0.026)
Original Estimates	0.023 (0.004)	0.024 (0.004)	0.080 (0.010)	0.082 (0.010)

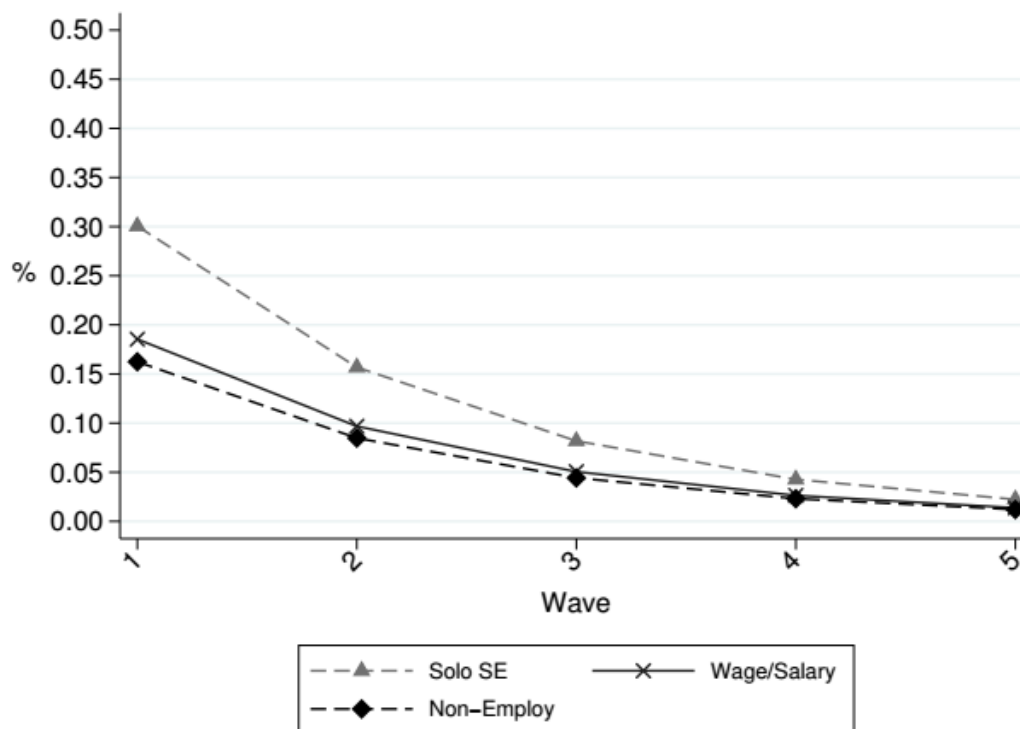
Note: Estimates above are sample averages of the predicted probabilities being in solo self-employment or employership in wave t given their employment choice in wave $t - 1$. Thesis' estimates come from Table 3-7. Standard errors are in parentheses and are calculated using the Delta method.

Source HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

FIGURE 3-8: LABOUR MARKET DECISIONS AND THEIR LONG-TERM IMPACT ON THE DECISION TO BE AN EMPLOYER – CONDITIONAL ON INITIAL EMPLOYERSHIP EXPERIENCE



(a) Males



(b) Females

Notes: Author's calculations using estimates from Table 3-14.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 3-13: MULTINOMIAL LOGIT ESTIMATIONS WITH CORRELATED RANDOM EFFECTS – CONTROLLING FOR ATTRITION

	Labour Market State at Year t					
	Male			Female		
	Wage (1)	Solo SE (2)	Employer (3)	Wage (4)	Solo SE (5)	Employer (6)
<u>Lagged employment ($t - 1$)</u>						
Wage	2.301*** (0.078)	0.876*** (0.119)	1.503*** (0.208)	2.648*** (0.053)	1.178*** (0.109)	1.800*** (0.167)
Solo-SE	1.069*** (0.118)	2.996*** (0.165)	3.373*** (0.232)	1.378*** (0.105)	3.343*** (0.154)	2.871*** (0.201)
Employer	1.098*** (0.173)	2.605*** (0.204)	4.775*** (0.289)	1.368*** (0.146)	2.490*** (0.196)	4.042*** (0.240)
<u>Initial employment ($t = 0$)</u>						
Wage	0.865*** (0.099)	0.362** (0.151)	0.277 (0.210)	0.670*** (0.062)	0.211 (0.129)	-0.013 (0.200)
Solo SE	0.251* (0.151)	3.370*** (0.242)	2.672*** (0.291)	0.162 (0.132)	3.180*** (0.223)	2.903*** (0.303)
Employer	0.089 (0.192)	2.420*** (0.271)	4.189*** (0.346)	-0.133 (0.180)	2.101*** (0.275)	4.489*** (0.370)
Attrition in wave $t+1$	-0.300*** (0.087)	-0.172 (0.132)	-0.400** (0.161)	-0.136* (0.070)	-0.178 (0.147)	-0.433** (0.197)
No. of observations	60,413			67,284		
No. of individuals	8,916			9,472		
Log-likelihood	-24,217.32			-28,471.93		
$\text{Cov}(\alpha_{i,Wage}, \alpha_{i,i})$	1.475*** (0.120)	0.732*** (0.133)	0.862*** (0.179)	1.055*** (0.071)	0.336*** (0.099)	0.269* (0.145)

$Cov(\alpha_{i,Solo}, \alpha_{i,j})$	3.440*** (0.331)	2.770*** (0.336)	3.280*** (0.329)	2.638*** (0.338)
$Cov(\alpha_{i,Emp}, \alpha_{i,j})$		4.346*** (0.478)		4.905*** (0.525)

Notes: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category of the dependent variable is non-employment. Also included, but not reported, are controls for age (specified as a quadratic), marital status, number of dependent children, impairment, country / region of birth, educational attainment, cumulative years of work experience (specified as a quadratic), home ownership, household income at $t-1$ (logged), location (urban vs rural), the regional unemployment rate, year, regional fixed effects and individual-specific time averages of the exogenous characteristics. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 3-14: PROBABILITY OF BEING SOLO/EMPLOYER SELF-EMPLOYED
GIVEN PREVIOUS EMPLOYMENT STATE – USING ESTIMATES FROM TABLE
3-13

Previous employment state	Predicted Prob. Of being self-employed at year t	
	Solo SE (1)	Employer (2)
Panel A. Males		
Non-employment	0.093*** (0.006)	0.032*** (0.004)
Wage employment	0.054*** (0.003)	0.030*** (0.002)
Solo self-employment	0.245*** (0.011)	0.095*** (0.006)
Employer	0.157*** (0.009)	0.220*** (0.015)
Panel B. Females		
Non-employment	0.038*** (0.003)	0.016*** (0.002)
Wage employment	0.026*** (0.002)	0.019*** (0.001)
Solo self-employment	0.176*** (0.011)	0.039*** (0.003)
Employer	0.094*** (0.009)	0.094*** (0.009)

Notes: Estimates above represent sample averages of the predicted probabilities being in solo self-employment/employership in wave t given their employment choice in wave $t - 1$. Specifications (1) and (2) are based on estimates from Table 3-13. Standard errors are in parentheses and are calculated using the Delta method. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

Nevertheless, controlling for non-response has a trivial impact on the extent of true cross-state dependence and true state dependence in employership. Results from Table 3-14 (which are predicted probabilities generated by estimates in Table 3-13) are approximately the same as the predicted probabilities presented in Table 3-8. Thus, we should expect minimal changes in the extent of true cross-state dependence and true state dependence in employership because of non-random attrition. Column (2) of Table 3-14 shows that, relative to wage/salary employment, true cross-state dependence amounts to 6.5 (i.e., $0.095 - 0.030$) and 2 percentage points for males and females, respectively. Relative to non-employment, true cross-state dependence is about 6.3 and 2.3 percentage points for males and females, respectively. The true state dependence in employership, relative to wage/salary employment, amounts to 19 (i.e., $0.220 - 0.030$) and 7.5 percentage

points, and, relative to non-employment, 18.8 and 7.8 percentage points for males and females, respectively. Despite controlling for non-random attrition, these estimates are very similar to the magnitudes presented under column (3) of Table 3-9.

3.8.2 Local Unemployment

The state of the individual's economy influences their decision to become self-employed and the numerous studies use unemployment as a proxy for economic conditions. Equation 3-7 includes a control for unemployment for the following regions: Sydney, Melbourne, Brisbane, Adelaide, Perth, the rest of the New South Wales state, the rest of Victoria, the rest of Queensland, the rest of South Australia, the rest of Western Australia, Northern Territory and the Australian Capital Territory. However, these unemployment rates are an abstraction of local economic conditions and assume the environment is homogeneous among individuals within each region. This assumption is unrealistic as local labour markets within a region can differ from each other. An analysis with less aggregated unemployment data could provide a different conclusion (Blalock 1971). A weakness of the general release version of the HILDA Survey is the lack of sufficiently disaggregated spatial data to construct a meaningful measure of the individual's local unemployment rate. To disaggregate regional unemployment, I extracted the respondent's ABS' SA4 location from the HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b). The ABS designed SA4 units to represent labour markets (or groups of labour markets) within each state and territory in Australia.⁴⁸ SA4 units are created to maximise the extent to which each unit contains both sets of "labour supply (where people live) and demand (where people work)" for statistical analysis (ABS 2016a). I then matched the respondent's SA4 location to the appropriate monthly SA4 unemployment rates from Table 16 of the ABS (2019b) Detailed Labour Force Surveys (unemployment rates are matched based on the time of the individual's interview).⁴⁹

I then re-estimate Equation 3-10 with the SA4 unemployment rates (and a control for non-random attrition) with estimates displayed in Table A3.2.1. Despite using a less aggregated measurement of unemployment, the average predicted probabilities in Table

⁴⁸ While SA4 units represent labour markets of the largest regional cities (e.g., Bendigo and Townsville), the units also represent aggregations of smaller labour markets. Localised labour markets are grouped based on geographical, social and economic similarities.

⁴⁹ For example, if a wave 2001 respondent is interviewed in July, I assign them the ABS SA4 unemployment rate as measured in July 2001. If a wave 2005 respondent is interviewed in January of the following year (2006), I assign them the unemployment rate as measured in January 2006.

A3.2.2 are similar to the probabilities predicted with regional aggregated unemployment rates – there are no significant qualitative or quantitative difference in the extent of true cross-state dependence and true state dependence in employership.

3.8.3 Agriculture, Forestry and Fishing Industries

Another concern is the presence of individuals working within the ‘Agriculture, Forestry & Fishing’ (agriculture for short) industries in my sample as they are structurally different from the rest of the economy. According to Table 10 of the ABS (2018a) Characteristics of Employment, agriculture industries have the highest rate of self-employment (comprising independent contractors and other business operators) at 55 per cent. Also, about 65 per cent of the agriculture workers are 40 years or older (as of November 2016) compared to 50 per cent for the rest of the economy (ABS 2019c). Last, the Productivity Commission (Productivity Commission 2005) suggests that agriculture is an industry dominated by family-operated businesses. Agriculture workers can have a downward effect on transition rates from solo self-employment to employership as agriculture solo self-employed workers appear to depend on family and/or casual workers for labour. On the other hand, around 2 per cent of employed persons, as of November 2016, were employed in agriculture industries (ABS 2019c). Even if agriculture workers are systematically different from the rest of the economy, their influence on my results is potentially small given how few they are. I confirm this by re-estimating Equation 3-10 (with controls for SA4 unemployment and non-random attrition) without agriculture workers. This will lead to an additional loss of 4,222 observations from my sample.⁵⁰ According to the results presented in Tables A3.2.3 and A3.2.4, dropping agriculture workers made no significant difference to my earlier conclusions about the relationship between past and current employment decisions.

3.8.4 Income Imputation Bias

The last concern is the inclusion of observations with imputed income values (see section 2.2.3 for a summary of the imputation process). Around 24 per cent of my sample has missing information about their household income. This could be because at least one member of the respondent’s household did not provide complete information about their income (for example, a household member may have provided their wage/salary income

⁵⁰ 900 observations were also discarded as they have missing information about their industry of work. As there is a possibility a non-trivial portion of this group could be from agriculture industries, I exclude this group from my robust sample.

but refused to declare their business income). Individuals with missing components of household income are likely to be systematically different from individuals with complete household income. Around 37.6 per cent of employers and 31.3 per cent of solo self-employed workers have imputed lagged household income, whereas it is 22.4 per cent and 21.4 per cent for wage/salary employees and non-employees, respectively. To be brief, the HILDA Survey uses a model to generate values for observations with missing income data, but model estimation is only possible for item respondents (the observations with complete income information). The household income variable likely suffers from imputation bias because it is not realistic to assume that the fitted model (the model used to predict income) will apply exactly for the item non-respondents. To account for imputation bias, I re-estimate Equation 3-10 (alongside controls for non-random attrition and SA4 unemployment rates) with a dummy variable that ‘flags’ which observation has imputed lagged household income (this variable equals one if the lagged net household income was imputed, and zero otherwise). The subsequent estimates are displayed in Tables A3.2.5 and A3.2.6. They both show that the inclusion of the imputation ‘flag’ made little difference to the extent of true cross-state dependence and true state dependence in employership.

3.9 Conclusion

This chapter studies the transitional dynamics between solo self-employment and employership in the Australian labour market. Because of information asymmetries between new firms and employees, and the first employee hiring threshold, it is costly for the self-employed to hire employees at the time of their start-up. Hiring employees is further made complicated because most individuals are uncertain about their entrepreneurial ability. This partly explains why a clear majority of self-employed workers are solo self-employed, and that the transition rate into employership is highest from solo self-employment. Individuals enter solo self-employment to experiment and learn more about their entrepreneurial ability, and to minimise information asymmetries between themselves and workers. If this is true, then there should be cross-state dependence in employership – being solo self-employed last year, instead of wage/salary employment or non-employment, increases an individual’s probability of becoming an employer this year. Further, there should also be state dependence in employership – being an employer last year, instead of wage/salary employment or non-employment, increases the individual’s probability of employership. However, (cross) state

dependence consists of true (cross) state dependence and spurious (cross) state dependence, where the latter suggests (cross) state dependence is observed because there is an intertemporally correlated, unobserved, individual-specific heterogeneity that influences the decision to be an employer. Knowledge of the extent of true cross-state dependence and state dependence in employership is important for the development and implementation of pro-entrepreneurial policies. True cross-state dependence suggests such policies will be effective in stimulating job creation – individuals who enter as solo self-employed workers will transition into employership. There is also the possibility of “double-dividends” – the effect of pulling an unemployed individual into self-employment and having them create jobs for others (Caliendo and Kritikos 2010). True state dependence in employership implies pro-entrepreneurial policies will have lasting effects, even after they end. This is a clear topic of economic importance that has yet to be researched thoroughly by the self-employment literature.

Using individual-level panel data from the HILDA Survey (Release 16), I estimated a dynamic multinomial logit model with correlated random effects to show how being in solo self-employment or employership affect the individual’s decision to be an employer in the subsequent year. I find evidence consistent with the employment sectoral choice model where individuals enter self-employment as a solo self-employed worker to learn more about their true entrepreneurial ability – there is evidence of true cross-state dependence and true state dependence in employership within the Australian labour market. However, the extent of the true cross-state dependence and true state dependence in employership are relatively small when compared to the observed rates of transition into employership and persistence within employership. This chapter shows that unobserved heterogeneity is a significant determinant of transitions into employership and a major component of persistence within employership. These conclusions are consistent with those of Lechmann and Wunder (2017) for Germany, and my estimates are robust to controlling for non-random attrition, a measure of the local unemployment rate, exclusion of the agriculture workforce and a ‘flag’ of observations with imputed lagged household income.

Policy measures that bring any random individual into self-employment will have short-run effects with limited dividends. The subsidised individual will more than likely enter self-employment as a solo self-employed worker. Even if they transitioned into employership, I showed that employership is less persistent than originally observed in Table 3-2. A significant portion of observed transitions and persistence in employership

is because of unobserved heterogeneity (such as the individual's preference to be an employer). Further, unlike what has been found in several studies within the self-employment literature, my results show that formal education, unemployment, and wealth (measured by the lagged one-year household disposable income variable) have no significant influence on the individual's decision to be an employer.

By using the initial employership status as a proxy for pro-entrepreneurial endowments (e.g., the ability to come up with a business idea), I show that the extent of true cross-state dependence and true state dependence in employership are much greater among these 'entrepreneurial' individuals. This implies that pro-entrepreneurial policies targeting the non-average 'entrepreneurial' individual will have more pronounced and long-term effects in stimulating job creation. Future research should attempt to unpack what are the elements of these entrepreneurial endowments.

I also find the relationship between solo self-employment and employership to be more spurious among women than men. True (cross) state dependence estimates are much smaller for women, even after setting their initial employment state to employership. It is not clear why this is the case, but a plausible explanation comes from Burke et al. (2002) who suggested that a higher proportion of women work part-time in self-employment and part-time self-employed workers are less likely to be employers. However, this does not explain why part-time workers are less likely to be employers and why women are more likely to be part-time self-employed, but the literature suggests women are more liquidity constrained, risk-averse, and have fewer professional connections than men. As a result, they have limited resources to fully commit to establishing their business full time.

Chapter 4

What Makes You Employer-able? Identifying the Skill Set that Increases Employership Survivability

4.1 Introduction

Self-employment is a volatile experience with many businesses shutting down a few years after opening. In Australia, around 64.5 per cent of new firms, started in 2014, remained in operation after 3 years (ABS 2018d). A failure to address employership survival could cast doubts on the effectiveness of any government programmes designed to encourage entry into self-employment, such as the Australian Entrepreneurial Programme budgeted at AU\$120 million (as of the 2017 financial year) (Department of Industry, Innovation and Science 2018). Also, self-employment exits are costly for the individuals themselves as they would have spent time and resources on a venture likely to be closed in a short period. A discussion on improving employership survivability is necessary, especially with the Australian government commitment to “setting the right environment for small business to grow” as they are essential for the creation of jobs and economic growth (Department of Jobs and Small Business 2018).

Self-employment survival is a key topic of economic importance but it received less attention than the determinants of self-employment entry in the literature. Within this limited literature, a common theme is the relationship between the individual’s human capital and their self-employment duration. Using cross-sectional or longitudinal data from sources such as business owners’ surveys, several studies used the business owner’s stock of education and work experience as measurements of their human capital. In this literature, there is a consensus that years (or level) of education is positively correlated with the individual’s duration in self-employment (Bates 1990a; Brüderl, Preisendörfer, and Ziegler 1992; Cooper et al. 1992; Boden and Nucci 2000; Lin, Picot, and Compton 2000; Haapanen and Tervo 2009; Millán, Congregado, and Román 2012), but conclusions regarding the relationship between work experience and self-employment survival have been mixed. Some studies find that paid employment increases the likelihood of self-employment survival (Brüderl et al. 1992; Carrasco 1999; Taylor 1999; Boden and Nucci 2000; Haapanen and Tervo 2009; Millán et al. 2012; Baptista, Karaöz, and Mendonça 2014), but others have found that general working experience either has a negative or no

effect on self-employment survival (van Praag 2003; Cueto and Mato 2006; Georgellis, Sessions, and Tsitsianis 2007; Oberschachtsiek 2012).

A likely reason for this lack of consensus is that general employment experience does not represent any specific preparation for managing a business or the industry that the business is set up in (Cooper et al. 1994). In response, some studies show that industry-specific experience (that is experience in the industry that the business is set up in) has uniformly positive effects on self-employment duration. Some studies also examined the relationship between managerial experience and self-employment survival but, except for Baptista et al. (2014), management experience either have no (Bates 1990a; Gimeno et al. 1997; Taylor 1999; Boden and Nucci 2000; Oberschachtsiek 2012) or negative effects on the employer's probability of survival (Cueto and Mato 2006).

A weakness of the self-employment survival literature is the treatment of the self-employed as a homogenous group. Except for Millán, Congregado, and Román (2014a; 2014b), they do not distinguish employers from solo self-employed workers. There is no reason to assume that the determinants of employership survival are the same as the determinants of solo self-employment survival, especially when they differ in terms of how they manage their businesses and the business constraints they face (Cowling et al. 2004).

I concentrate on employers as a study of the determinants of employership survival has greater implications on job creation than the determinants of solo self-employment survival. I also concentrate on the individual characteristics and not their business characteristics (e.g., their market share, gross profit margin and net worth) because it is the owner that makes the difference; the owner sets the goals and influences the newly founded firm characteristics (Chandler and Hanks 1994; Peteraf and Shanley 1997; Reuber and Fischer 1999; van Praag 2003). With this in mind, I seek to expand the literature by identifying the skills or abilities responsible for success in employership self-employment. Another weakness of the current literature is the broad measure of the individual's human capital with education and working experience variables. These variables assume that equal levels of education or experience are homogeneous across individuals, whereas the opposite is true. For example, two employers with a bachelor's degree and ten years of work experience may look similar. However, an individual with a bachelor's degree in business management and 10 years of experience as a corporate director likely learned a different set of skills, abilities, and knowledge than an individual

with a degree in chemistry with 10 years of experience as a research and development manager.

I argue that a mismatch between entrepreneurial expectations and the skills required to run a business causes the high rate of business closures across developed economies. Entrepreneurial ability is an unobservable random variable that is positively correlated with self-employment income. Hence, individuals are more likely to remain in self-employment if they correctly believed they have high entrepreneurial ability (Lucas 1978; Jovanovic 1982; Frank 1988). Individuals who overestimate their ability are more likely to exit self-employment after a brief experience in running their business. Some studies suggest that the individual's pre-entry experiences inform their prior beliefs about their entrepreneurial ability which shapes their success in self-employment (Cressy 1999; Van Praag and Cramer 2001; Baptista et al. 2014). Thus, I hypothesise that individuals can acquire skills/abilities from their pre-entry experiences which act as better proxies of their entrepreneurial ability than the traditional measures of human capital in the form of education and years of work experience. I identify the employer's skill/ability set by using the Occupational Information Network (O*NET) to examine the job skill requirements from their previous occupation. O*NET is a product of a large scale research project sponsored by the U.S. Department of Labor's (DOL) Employment and Training Administration (ETA) (Peterson et al. 2001) and is a comprehensive database for collecting (through standardised surveys), organising and describing data on job characteristics and worker attributes. From O*NET, I identified 5 skill/ability groups associated with each occupation, and, for each occupation, evaluate the relative importance of each skill/ability.

The rest of this chapter proceeds as follows: Section 4.2 reviews previous analyses examining the empirical determinants of self-employment survival. Section 4.3 summarises an occupation choice model explaining how the individual's prior experiences influence their survivability in employership. Section 4.4 describes the sample extracted from the HILDA Survey and presents the occupation factors derived from O*NET's measurements of each occupation's skill and ability requirements. I also present my sample's descriptive statistics in this section. Section 4.5 presents my empirical strategy. The empirical strategy involves estimating a discrete-time proportional hazards model with a complementary log-log (cloglog) link to reveal the relationship between the relative importance of each skill from the employer's previous occupation and the employer's probability of exit from employership. The results are

displayed in section 4.6 with the associated robustness checks in section 4.7. Section 4.8 concludes with a summary of the main results. The employers' general human capital, as represented by their level of formal educational achievement and years of working experience, have no significant effect on employership exit. Instead, it is the skills/abilities they acquired from their previous employment that matters for employership survival. Specifically, I find general cognitive, resource management and pattern recognition skills have notable impacts on reducing the likelihood of employership exit, especially after controlling for the employer's education and working experience.

4.2 Literature Review

Evans and Leighton (1989) and Bates (1990a) are the first influential studies to examine the determinants of self-employment duration and departure at the individual level, although the determinants of self-employment longevity received more attention from Bates (1990). Evans and Leighton (1989) focused on a US sample of men between the ages of 14 and 24 who were surveyed in the National Longitudinal Survey of Young Men (NLSYM) twelve times between 1966 and 1981. They estimated the self-employment hazard rates (the probability an individual exits self-employment in a given year, conditional on survival up to that year) with the Kaplan-Meier procedure and show that hazard rates decrease with duration in self-employment, falling from 10 per cent during the beginning to zero by the eleventh year in self-employment. Evans and Leighton (1989) findings are consistent with the conclusions of the Jovanovic (1982) model; individuals are more likely to stay self-employed the longer they are in self-employment. They also attempted to control for individual characteristics such as education, wage experience, previous job tenure, and marital status, but they find none of them to have substantive or statistically significant effects on self-employment hazard rates.⁵¹

As the title of his article suggests, Bates (1990a) focused on revealing the relationship between the individual's human capital and self-employment duration. Bates' (1990a) study relied on a cross-sectional sample of US non-minority business owners (those who started their businesses between 1976 and 1982) from the 1982 Characteristics of Business Owners (CBO) survey (see Bates 1990b for a description of the CBO database). Using logit models to predict the business owner's probability of exit (represented by a

⁵¹ Evans and Leighton (1989) claim to have used parametric hazard formulations but, to the best of my knowledge, they do not fully describe the specifics of the hazard models employed.

dummy variable that equals to one if the business ceased operations, and zero otherwise) by the end of 1986, Bates (1990a) provided the initial evidence that education background is a major determinant of business survival; relative to business owners having less than four years of high school education, high school graduates and those with at least one year of college education are more likely to see their businesses survive to 1986. In contrast, management working experience (measured as a dummy variable that equals to one if they had worked in a managerial capacity prior to owning the business in 1982, and zero otherwise) has no significant effect on business longevity. However, Bates (1990a) estimates were likely biased upwards as they used a binary choice model to predict the probability of business closure, i.e., they assume businesses that didn't close in 1996 are survivors when, in fact, they have only been observed not yet to fail. This is known as 'right censoring', a feature that should be incorporated explicitly in the model (Parker 2009).

Improving on Bates (1990a) empirical analysis, Brüderl, Preisendörfer, and Ziegler (1992) use event history analysis to examine the relationship between self-employment spell length and human capital endowment. Brüderl et al. (1992) draw upon data from the "Munich Founder Study" which surveyed business owners who had registered a new business in Germany during the years 1985 – 1986. Brüderl et al. (1992) find education (measured by a categorical variable representing distinct groups of schooling years completed), general work experience (represented by a categorical variable) and industry-specific experience (measured by a dummy variable that equals one if the firm founder has any prior experience in the firm's industry) have strong positive effects on small business longevity.

Subsequent studies confirmed Brüderl et al. (1992) and Bates (1990a) conclusions about the influence of education on self-employment survival. With a 3-year longitudinal sample of US business owners, Cooper et al. (1994), with a multinomial logit model, find formal education (a dummy variable that equals one if the business owner had at least a bachelor's degree, and zero otherwise) to have positive effects on self-employment survivability. Boden and Nucci (2000), using a sample of male and female business owners from the 1982 (for businesses started/acquired between 1980 and 1982) and 1987 (for businesses started/acquired between 1985 and 1987) CBO business surveys, reported similar results after estimating a series of binary probit models. Lin et al. (2000), with longitudinal Canadian survey data for the years 1993 and 1994, estimated a binary logit model to find that higher levels of education (measured by a categorical variable) are

positively associated with self-employment duration. Haapanen and Tervo (2009), with a pooled sample of self-employed workers from Finnish census data (covering the years 1988 to 2001), estimated a discrete hazard model with a cloglog link to find education (measured by categorical variables) positively correlated with self-employment duration. Millán et al. (2012), with a panel of households in the EU-15 countries covering the years 1994 to 2001, estimated both discrete single risk and competing risks models to confirm the positive relationship between education and the probability of survival in self-employment. We should prefer Millán et al. (2012) findings as they used hazard estimation techniques to model self-employment duration and controlled for individual unobserved heterogeneity. One source of potential disagreement comes from Taylor (1999) with British household panel data from waves 1991 to 1995 of the BHPS. With a Cox proportional hazard model, Taylor (1999) finds that education has no substantive influence on self-employment duration. However, after splitting the sample by gender (with waves 1991 to 1998 of the BHPS), Georgellis, Sessions, and Tsitsianis (2007) find that higher education and A-level qualifications reduced female self-employment hazard rates by 36 and 39 per cent, respectively.

In contrast to education, there is less of a consensus on the impact of general working experience on self-employment duration. Contradicting Brüderl, et al. (1992) results, van Praag (2003), with US longitudinal data of white males (for homogeneity reasons) from waves 1979 to 1989 of the National Longitudinal Survey of Youth (NLSY), estimated a set of single risk and competing risks discrete hazard models with a cloglog link to find that general working experience (measured by years in paid employment) has a negative effect on self-employment survival. They argue that work experience increases the probability that an individual will receive an employment offer that compares favourably to self-employment. Similarly, Cueto and Mato (2006) with cross-sectional Spanish survey data used continuous proportional hazard models to find that labour experience negatively influences self-employment survival. A source of disagreement comes from Carrasco (1999). Drawing upon Spanish household panel data from waves 1985 to 1994 of the Continuous Family Expenditure Survey (Encuesta Continua de Presupuestos Familiares (ECPF)), Carrasco (1999) showed that general paid work experience increased the probability of survival in self-employment. However, she noted that her data set has a serious limitation: the longest self-employment spell she could observe is 2 years. Oberschachtsiek (2012), with German survey data, used competing risks hazard models to show that overall paid employment experience (represented by a dummy variable) has

no statistically significant effect on the probability of exits from self-employment. Another source of disagreement comes Millán et al. (2012) who all showed that general work experience increased the probability of self-employment survival. A likely explanation is how the reviewed studies constructed the experience variable. Van Praag (2003) was the only cited study (in this paragraph) to use a continuous ‘years of working experience’ variable, whereas the rest used a dummy variable to indicate if the individual was in wage/salary employment just before they transitioned into self-employment. This has the potential of overstating the effect of wage/salary employment experience on self-employment survival. As an example, a year of experience in wage/salary employment is treated the same as 10 years of experience in wage/salary employment.

Another weakness with the general work experience variable is that it is a broad summary of the skills, knowledge and experiences the individual gained throughout their career. As a result, the variable is a weak descriptor of the acquired skills, preparation or knowledge specific to running a business (Cooper et al. 1994), and a weak proxy of the skills useful for self-employment performance (Simoes et al. 2016). In response, few studies (including Bates 1990a) explore how specific experience, in the form of managerial experience and industry-specific experience (that is, experience in the same industry their firm is in), influence the hazard rates of self-employment exits. Among this very limited literature, managerial experience has no positive influence on self-employment survival (Gimeno et al. 1997; Boden and Nucci 2000; Oberschachtsiek 2012) or increases the probability of exits from self-employment (Cueto and Mato 2006). In contrast, van Praag (2003), Gimeno et al. (1997) and Oberschachtsiek (2012) find evidence supporting Brüderl et al. (1992) conclusions that industry-specific experience improves self-employment survivability. Nevertheless, these ‘specific’ variables do not inform us or identify the skill/ability set important for self-employment survival. Occupations vary in the skills/abilities required to perform satisfactorily in their duties. This requires defining and measuring occupation attributes, and I am not aware of any study in the self-employment survival literature that has done so. To accomplish this task, I use descriptors from O*NET to measure the skill set of each employer identified in the HILDA Survey.

The studies reviewed so far consider self-employment as a homogenous group despite its heterogeneous nature. These groups of self-employed workers differ from each other in terms of their motivation to be self-employed and/or the management constraints they face. There are no strong reasons to assume that the determinants of survival will be

the same for each of these distinct groups of self-employed workers. Block and Sandner (2009), with German longitudinal household data from waves 1990 to 2003 of the GSOEP, separated individuals who entered self-employment out of necessity (i.e., to avoid unemployment) from those who became self-employed to pursue a business opportunity. After estimating a cloglog hazard model with random effects, Block and Sandner (2009) find individuals who became self-employed out of necessity are significantly more likely to exit than those who entered self-employment to pursue an opportunity. Using a longitudinal Portuguese employer-employee dataset covering the period 1986 to 2005, Baptista et al. (2014) show that education (represented by a categorical variable), industry and managerial experience (measured by the number of years working within the start-up's industry prior to founding and the number of years spent working as a manager, respectively) are significant positive determinants of survival for opportunity-based self-employed workers. In contrast, education and industry-specific experience have no substantive impacts on survival among necessity-based self-employed workers, and managerial experience increases the probability of exit from necessity self-employment. Millán et al. (2014a, 2014b), with longitudinal household data from the ECHP covering waves 1994 to 2001, show that education has no significant relationship with solo self-employment hazard rates, but tertiary education significantly reduces the employership hazard. Millán et al. (2014b) show previous experience in wage/salary employment significantly decreases exits from solo self-employment into inactivity whereas there is no such relationship for employers. Following Millán et al. (2014a, 2014b), I continue the trend of separating employers from solo self-employed workers. I also contribute to the self-employment survival literature by examining the employer's previous occupation, identifying the skills gained from that occupation and, most critically, identifying which of those skills are important for self-employment success.

4.3 Theory

The concept of human capital is implicit in almost every empirical study of the newly self-employed survivability. A basic argument is that greater human capital increases the productivity of the self-employed, which results in higher profits and improves their chances of survival in self-employment (Brüderl et al. 1992). Alternatively, human capital can influence survival in self-employment by predicting how well the individual will perform in self-employment. To elaborate, I assume every individual has an unobservable

endowment of entrepreneurial ability, which can only be estimated by a set of prior beliefs (Jovanovic 1982). A large stock of human capital increases the accuracy of the individual's prior beliefs, which results in higher self-employment survivability via selection effects – individuals will only enter self-employment if they believe that they have a high priori chance of survival (Cressy 1999).

Human capital can be split into two knowledge bases that inform the individual priors of their entrepreneurial ability. The first is the individual's general human capital background, i.e., their level of education and years of working experience. These variables serve as proxies for life experiences and access to knowledge networks advantageous to identifying business opportunities and conditions (Cooper et al. 1994). The second is the individual's specific human capital that represents their knowledge of how to manage a business or knowledge specific to the industry the business is operating in. Each element (either general or specific) has different effects on the individual's prior beliefs, with some being better proxies of entrepreneurial ability than others. For example, managerial experience is a better predictor of entrepreneurial ability than just graduating from secondary school. If the individual can precisely estimate their true ability, then they will be less prone to exiting self-employment in the short run because they would otherwise have avoided self-employment if they were of low ability. In addition, a high ability individual, who can precisely observe their own ability, is less prone to exiting self-employment because of temporary negative exogenous income shocks. These are macroeconomic shocks that are independent of the individual's ability but individuals with dispersed priors will mistakenly associate the shocks with their profit-generating capabilities. For example, an uncertain self-employed worker will use negative income shocks as evidence that they have low levels of ability.

I formalise the above theory with the following model. In each period $t = 0, 1, \dots, T$, starting after the individual's first entry into employership and continuing to retirement/exit at period T , the employer chooses to either remain or withdraw out of employership.⁵² I assume individuals are risk neutral and choose the optimal career path that maximises their utility in each period t . An employer prefers to continue if their expected income, $E(\pi_{i,t})$, in period t is greater than the expected income, $E(W_j[H_{i,t}])$, from any other employment state j ⁵³:-

⁵² I note that employers can close and start-up multiple companies during their entrepreneurial spell.

⁵³ I assume that there is a single unique exit state j outside employership. This set-up, however, can be generalised to multiple exit states including salaried/wage employment, solo self-employment or non-employment.

$$E(\pi_{i,t}(\theta_i, L_{i,t})) > E(W_j[H_{i,t}])$$

where $H_{i,t}$ represents the vector of the individual's human capital. Employers have two elements of production: the individual's entrepreneurial ability (θ_i) and the number of employees hired at the place of business ($L_{i,t}$). Their expected profit in each period is:-

$$E(\pi_{i,t}) = E(\hat{\theta}_{i,t})L_{i,t}^\gamma - c(L_{i,t}), \quad 0 \leq \gamma \leq 1, \quad L_{i,t} \geq 1$$

where $\hat{\theta}_{i,t}$ is the individual's estimate of their true entrepreneurial ability θ_i . $\hat{\theta}_{i,t}$ is assumed to be distributed lognormally

$$\log \hat{\theta}_{i,t} = \beta' X_{i,t} + \gamma' H_{i,t} + \epsilon_{i,t}^{se}, \quad \epsilon_{i,t}^{se} \sim N(0, \sigma_\theta^2)$$

where $X_{i,t}$ is a vector of individual characteristics (such as marital status) and $H_{i,t}$ is a vector of the individual's human capital variables. $H_{i,t}$ includes the individuals' years of paid work experience, the highest level of education achieved, and the skills/abilities acquired from their previous employment. $\epsilon_{i,t}^{se}$ represents an unknown level of self-employment shocks that can inform the individual's estimate of θ_i . If employers are early in their spell, they use their human capital stock $H_{i,t}$ (alongside other observed variables) to infer their entrepreneurial ability. Individuals enter employership as long as their perceived entrepreneurial ability, $\hat{\theta}_{i,t}$, is higher than a threshold ability, θ_i^{EMP} , where they are indifferent between being an employer or being in an alternate employment state

$$E(\pi_{i,t}(\hat{\theta}_{i,t}, L_{i,t})) > E(\pi_{i,t}(\theta_i^{EMP}, L_{i,t})) = E(W_j(H_{i,t}))$$

There is a possibility for individuals to overestimate their ability to be self-employed. Consider an individual A with actual ability θ_i^A such that

$$E(\pi_{i,t}(\theta_i^A, L_{i,t})) \leq E(W_j(H_{i,t}))$$

This individual would be better off being solo self-employed, wage/salary employed or even non-employed relative to employership. However, without accurate proxies of their entrepreneurial ability, individuals risk overestimating their ability such that $\hat{\theta}_{i,t} >$

$\theta_i^{EMP} > \theta_i^A$. After an initial experience in employership, the individual will compare their actual revenue with their initial predicted revenue:-

$$R_{i,t} - E(R_{i,t}) = (\theta_i^A - E(\hat{\theta}_{i,t})) L_{i,t}^\gamma < 0$$

Judging from the negative differences between actual and expected revenue, the overconfident employer will re-estimate their entrepreneurial ability downwards such that an alternate employment state is the more optimal choice.

I hypothesise that elements from $H_{i,t}$ have varying capabilities in proxying for the individual's entrepreneurial ability. Individuals who enter employership with accurate proxies of their entrepreneurial ability are less likely to exit. They self-selected themselves into an employment state where they correctly believed it to be their most optimal choice. Thus, I examine if education, general work experience or the individual's skill set reduces the employer's probability of exit from employership.

4.4 Data

4.4.1 Employers from the HILDA Survey

Data from the HILDA Survey in-confidence unit record files (Release 16) covering 16 waves spanning from 2001 to 2016 are used to examine the influence of the employer's prior employment background and education on their employership survivability. I construct the sample as follows: First, from these files, I identify individuals aged 21 to 64 years who identified themselves as an employer between 2001 and 2016. Second, I extract only individuals who transitioned into employership at least once between 2001 and 2016. I drop all other individuals including those who entered the survey initially as employers.⁵⁴ Third, I drop all observations from periods where the sampled individuals have yet to transition into employership. Fourth, I classify the employers as 'exiters' or right-censored cases.⁵⁵ Employers are exiters if they are observed to change their employment status from employership in wave t to solo self-employment, wage/salary

⁵⁴ I drop individuals who entered the HILDA Survey as an employer because I cannot determine their spell length accurately. While the survey records how long these employers managed their business before being interviewed, they do not differentiate the time spent as solo self-employed or as an employer. I also recognise the fact that some individuals may have been employers before their first survey interview. As before, I cannot determine when that spell started and/or ended leaving me to treat all employership spells in my sample as first-time cases.

⁵⁵ An employer is right-censored if they survived until wave 2016 or attrited from the HILDA Survey sample. This includes any employer who is 'missing' for one wave but came back in the following waves. Any employer with only one observed wave of employership are dropped from the sample (they would be dropped by the empirical model anyway).

employment or non-employment in wave $t + 1$.⁵⁶ I drop their observations in wave $t + 2$ and beyond. Some employers have multiple employership spells (they leave and later re-enter employership) but I focus on single spell analysis by examining the determinants of the first exit out of employership. My sample is a panel comprising spells starting from the first observed entry into employership until the employer's first observed exit into non-employment, wage/salary employment or solo self-employment, or last observation within the survey.

The main dependent variable for this analysis is a duration variable representing the time the individual is an employer until they exit or is right-censored.⁵⁷ The main explanatory variables are their total years of paid work experience (just before entry into employership), the highest level of education they achieved (prior entry into employership), and the skills/abilities gained from their previous employment.

To measure acquired skills/abilities I first observe the individual's occupation title, described by the 4-digit level ANZSCO variable, in the wave just before their observed entry into employership.⁵⁸ While an individual may have a long and diverse occupational background, I focus on their most recent occupation, just before they became employers, as skills depreciate (or even become obsolete) over time because of insufficient use (De Grip and Van Loo 2002). Then I use O*NET to determine the skills/abilities the employer's gained from that occupation.

4.4.2 O*NET

I use O*NET to measure the skill set of each employer identified in the HILDA Survey. The O*NET program was created to replace the Dictionary of Occupational Titles (DOT) in 1998. The DOT was a United States government reference publication that measures the job skill requirements and characteristics for each occupation (Handel 2016). A major advantage of using O*NET over DOT is the former's use of a common framework describing job skill/ability requirements and worker attributes across occupations. DOT measurements are very job-specific making it hard to compare

⁵⁶ Recall employment status indicates the individual's form of employment where they get most of their pay from. There is a possibility that exiters are actually still in employership if they are working multiple jobs. It is just that employership is no longer their highest earning employment state. As we cannot observe all their employment statuses at the time of exit, I assume they completely left employership.

⁵⁷ I stress failure doesn't mean employers exit due to involuntary factors, e.g., bankruptcy. Some employer exit as they believe it is more optimal to be solo self-employed, work for a wage or be non-employed. Failure in this chapter refers to both involuntary and voluntary employership exits.

⁵⁸ 4-digit ANZSCO classifications are also known as unit groups, of which describes are 358 distinct occupations (ABS 2013). See Section 4.9 for an overview of the ANZSCO classification structure. Also, if the respondent is working multiple jobs at the time of the interview, they are asked about the occupation of their main job – that is, the job they get the most pay from each week.

skill/ability requirements across occupations in different industries (Mariani 2001). Further, Miller et al. (1980) found the DOT over-represented blue-collar manufacturing jobs, and most ratings were not re-evaluated since the 1950s making them obsolete for modern times. Peterson et al. (2001) claim that the O*NET avoided the overrepresentation of blue-collar manufacturing jobs and offers a better overview of the increasing cognitive demands of modern employment.

Occupation-specific skills/abilities are identified and measured with information from the O*NET program. At the heart of the program is the O*NET Content Model that organises information on many occupation characteristics into six domains: (1) Worker Characteristics; (2) Worker Requirements; (3) Experience Requirements; (4) Occupational Requirements; (5) Workforce Characteristics; and (6) Occupation-Specific Information. These domains investigate several aspects of work ranging from descriptions of the worker to the requirements of work (DOL ETA 2019d).

While the Content Model defines the information structure for a single occupation, the O*NET-SOC taxonomy defines the set of occupations available in US labour markets (DOL ETA 2019a). Based on the Standard Occupation Classification (SOC), the taxonomy includes about 974 occupations which have (or scheduled to have) data collected from workers and occupation experts.⁵⁹ The taxonomy is periodically revised to ensure that it accurately represents modern labour markets (the last revision was in 2010). These revisions include “the addition of 153 new and emerging (N&E) occupations they identified within 17 in-demand industry clusters” (The National Center for O*NET Development 2009, p. 3).

Information for the O*NET Content Model is collected using a two-stage design in which seven standardised surveys (a summary of the surveys’ content is available in Table 4-1) are sent to a representative sample of U.S. job incumbents selected by a two-stage design (DOL ETA 2019b). First, the program uses data from the U.S. Bureau of Labor Statistics to identify industries that significantly use the occupations identified by the O*NET-SOC taxonomy. They then identify a random sample of businesses within those industries. Second, they select a random sample of workers in those occupations within those businesses and provide the workers with a subset (not all) of the surveys to complete; this is done to reduce respondent burden. An eighth survey, with questions too abstract for workers to answer, is assigned to occupation experts (Handel 2016).

⁵⁹ The SOC is a US statistical classification of occupational categories within US labour markets.

Responses are then “averaged across respondents on the assumption that any within-occupation variation represents measurement error” (Handel 2016, p. 160).

TABLE 4-1: O*NET SURVEYS AND CONTENT

Survey	Main Content
Education/ training	Required education, related work experience, training.
Knowledge	Various specific functional and academic areas (e.g., physics, marketing, design, clerical, food production, construction).
Skills	Reading, writing, math, science, critical thinking, learning, resource management, communication, social relations, technology.
Abilities	Writing, math, general cognitive abilities, perceptual, sensory-motor, dexterity, physical coordination, speed, strength.
Work activities	Various activities (e.g., information processing, making decisions, thinking creatively, inspecting equipment, scheduling work)
Work context	Working conditions (e.g., public speaking, teamwork, conflict resolution, working outdoors, physical strains, exposure to heat, noise and chemicals, job autonomy).
Workstyle	Personal characteristics (e.g., leadership, persistence, cooperation, adaptability).

Source: Reproduced from Handel (2016, p. 162)

From the framework, I focus on identifying the cognitive abilities, basic skills and cross-functional skills associated with each occupation in the O*NET database. Cognitive abilities influence the acquisition and application of knowledge in problem-solving. Basic skills include developed capacities facilitating learning or acquisition of knowledge. Cross-functional skills are capacities that facilitate the performance of activities across jobs. I focus on extracting 35 skills and 21 cognitive abilities from O*NET. Each skill/ability have varying degrees of importance across occupations. I list these skills and abilities in Appendix 4.1. The O*NET surveys include two separate questions about the Importance and Level of a skill or ability for the targeted occupation. The Importance rating measures the degree of importance a skill/ability is to the occupation and ranges from “Not Important” (1) to “Extremely Important” (5). The Level rating summarises the level of skill/ability proficiency needed for the occupation and is collected on a 0 to 7 scale (DOL ETA 2019c). Handel (2016) finds the mean correlation across 809 occupations for each O*NET descriptor (including the 56 skills and abilities descriptors) to be 0.92, where the median is 0.94. Given the redundancy of including both ratings, I

extract only Importance ratings for the chosen 56 skills/abilities from the O*NET database. The ratings come from version 22.1 of the O*NET database (Department of Labor Employment and Training Administration / National Center for O*NET Development 2017). To simplify interpretation, ratings are standardised to a scale ranging from 0 to 100 using the following conversion equation: -

$$S = \frac{R - 1}{4} \times 100$$

where S is the standardised score and R is the Importance rating.⁶⁰

4.4.3 Factor Analysis

Having 56 variables to represent the skills/abilities associated with the employer's most recent employment spell is unwieldy and will cause multicollinearity issues in any subsequent modelling. I use exploratory factor analysis to compress 56 skills/abilities from the 966 O*NET occupations to a smaller set of latent factors that share a common variance. In short, I find common factors that linearly reconstruct the original occupation variables:

$$4-1) \quad X_{ij} = F_{i1}b_{i1} + F_{i2}b_{i2} + \dots + F_{ip}b_{ip} + e_{ij}$$

where X_{ij} is the importance rating of the j th trait from the i th occupation, F_{ik} is the i th observation on the k th common factor and e_{ij} is a residual but is known as the j th trait unique factor (which do not overlap between observed skills/abilities), and b_{ik} represent a set of linear coefficients called factor loadings. Factor loadings represent the relationship of each skill/ability variable to the underlying factor and give us an impression of how much the variable contributed to that factor. Factor loadings are similar to weights in multiple regression analysis, and b_{ik} represents the correlation strength between the k th factor and the j th skill/ability variable.

Factor analysis suggests that there are 5 factors that explain 90 per cent of the total variance in Importance ratings across all the 56 skills/abilities. I present the results in Table 4-2. This table shows that the 1st factor explains 44.2 per cent of the observed importance ratings total variance, the 2nd factor explains 19.6 per cent, the 3rd factor

⁶⁰ The equation for the conversion of original ratings to standardised scores is provided by O*NET (DOL ETA 2019c).

explains 12.8 per cent, the 4th factor explains 8.0 per cent and the 5th factor explains just 5.4 per cent.

TABLE 4-2: FACTOR ANALYSIS CORRELATION

	Variance	Proportion	Eigenvalue
Factor 1	20.667	0.442	25.938
Factor 2	9.177	0.196	9.103
Factor 3	5.959	0.128	3.359
Factor 4	3.730	0.080	2.060
Factor 5	2.521	0.054	1.592
No. of observations	967		

Notes: Factors are analysed using the PFA method and rotated using the Varimax orthogonal method.

Source: O*NET Release 22.1 (Department of Labor Employment and Training Administration / National Center for O*NET Development 2017).

TABLE 4-3: ROTATED FACTOR LOADINGS (PATTERN MATRIX) AND UNIQUE VARIANCES

Traits	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Unique
Active Learning	0.870		0.234			0.153
Active Listening	0.816	-0.397				0.142
Complex Problem Solving	0.836		0.348			0.157
Coordination	0.587			0.587	0.218	0.238
Critical Thinking	0.865		0.306			0.141
Equipment Maintenance	-0.217	0.886				0.146
Equipment Selection		0.903				0.143
Installation		0.652				0.531
Instructing	0.781			0.257		0.309
Judgment and Decision	0.809		0.287	0.234		0.197
Learning Strategies	0.812					0.286
Management of Financial Resources	0.250		0.456	0.705		0.230
Management of Material Resources	0.249		0.359	0.728		0.242
Management of Personnel Resources	0.618			0.585		0.247
Mathematics	0.308		0.851			0.162
Monitoring	0.682			0.293	0.299	0.358
Negotiation	0.602	-0.326		0.529		0.235
Operation and Control		0.864			0.291	0.136
Operation Monitoring	-0.318	0.801			0.277	0.175
Operations Analysis	0.513		0.399		-0.310	0.447

Persuasion	0.659	-0.343		0.479		0.213
Programming	0.380		0.610			0.438
Quality Control Analysis		0.839				0.245
Reading Comprehension	0.823	-0.295	0.320			0.133
Repairing		0.888				0.151
Science	0.594		0.380			0.443
Service Orientation	0.523	-0.397		0.336		0.387
Social Perceptiveness	0.647	-0.390	-0.228	0.336		0.229
Speaking	0.791	-0.441				0.146
Systems Analysis	0.760		0.456	0.242		0.150
Systems Evaluation	0.777		0.415	0.266		0.147
Technology Design	0.367	0.407	0.458		-0.252	0.412
Time Management	0.632			0.488		0.334
Troubleshooting		0.927				
Writing	0.828	-0.328	0.246			
Category Flexibility	0.611		0.493			0.353
Deductive Reasoning	0.851		0.345			
Flexibility of Closure	0.480	0.395	0.376		0.457	0.264
Fluency of Ideas	0.777		0.294	0.309		
Inductive Reasoning	0.859		0.308			
Information Ordering	0.636		0.484		0.207	0.299
Mathematical Reasoning	0.377		0.844			
Memory	0.706		0.212			0.421
Number Facility	0.311		0.829			
Oral Comprehension	0.792	-0.387				
Oral Expression	0.799	-0.440				
Originality	0.746		0.241	0.324		0.248
Perceptual Speed		0.531	0.347		0.599	0.221
Problem Sensitivity	0.735				0.359	0.250
Selective Attention	0.343	0.271			0.523	0.524
Spatial Orientation	-0.272	0.532			0.310	0.505
Speed of Closure	0.581	0.228	0.292		0.424	0.336
Time Sharing	0.401			0.260	0.577	0.387
Visualization		0.703	0.270			0.384
Written Comprehension	0.812	-0.314	0.300			
Written Expression	0.828	-0.339	0.223			

Notes: Rotated factor loadings of cognitive abilities, basic skills and cross-functional skills importance ratings. Factor loadings < |0.2| are suppressed.

Source: O*NET Release 22.1 (Department of Labor Employment and Training Administration / National Center for O*NET Development 2017).

Table 4-3 reports the pattern matrix and presents the factor loadings associated with each occupation trait. For example, “Active Learning” is highly and positively correlated with Factor 1 relative to Factors 2, 3, 4 and 5. The column labelled “Unique” calculates the proportion of a characteristic’s variance that is ‘unique’ to itself. The more ‘unique’ a variable is, the less relevant it is in the factor model. For example, 15.3 per cent of the variance in “Active Learning” is not shared with other variables in the overall factor model. I suppress items with factor loadings less than the absolute value of 0.2 (for clarity) but a full version of Table 4-3 is available in the appendix as Table A4.5.1.

A typical limitation of factor analysis is the naming of factors. This is problematic as factor names may not accurately reflect all the variables within the factor. Nevertheless, I name the factors to the best of my ability based on the traits highly correlated with each factor. For example, general cognitive abilities and learning specific skills, such as Active Learning and Critical Thinking, load heavily onto **Factor 1**. It is then appropriate to name this as a “General Cognitive” factor, which I also call “Cognitive” for short. Technical skills such as Troubleshooting and Repairing load heavily onto **Factor 2**, suggesting this should be named the “Technical Specialisation” factor. **Factor 3** is named the “Mathematics” factor because math-related traits heavily load onto this factor. Only three items load onto each of **Factor 4** and **Factor 5**. Since the items “Coordination”, “Management of Financial Resources” and “Management of Material Resources” are heavily associated with **Factor 4**, the Factor is renamed “Resource Management”. **Factor 5** is the “Pattern Recognition” factor as it includes “Perceptual Speed”, “Selective Attention” and “Time Sharing”.⁶¹

I then develop an index of cognitive, technical specialisation, mathematics, resource management and pattern recognition factor scores for each O*NET occupation using the Bartlett method. This method produces unbiased scores that are correlated only with their factor (Tabachnick and Fidell 2013). The coefficients estimated by the Bartlett method are in Table Table A4.5.2 and are used to predict factor scores for each occupation. Bartlett factor scores are numerical valued and indicate an occupation’s relative spacing or standing on a latent factor. The scores also are standardised to have means of zero (DiStefano, Zhu, and Mîndrilă 2009).

⁶¹ See Section 4.9 of the factors and their associated skills/abilities.

4.4.4 Matching O*NET Occupation Factors with HILDA 4-digit ANZSCO variables

O*NET aggregated over 12,000 occupation titles to less than 1000 occupation units using a modified SOC System (National Research Council 2010). This system is systematically different from the 4-digit level ANZSCO variable available within the HILDA Survey. Making use of O*NET information in the context of the Australian labour market is a challenge for this thesis. I overcame this challenge by using the “Job Outlook” website to match ANZSCO occupations to the most relevant O*NET occupation. “Job Outlook” is an initiative of the Australian Government’s Department of Jobs and Small Business (now known as the Department of Employment, Skills, Small and Family Business) to provide information about Australian careers. The website includes an O*NET profile of skills, knowledge and abilities for every 4-digit level ANZSCO occupation. “Job Outlook” provides a standardised method to match 4-digit ANZSCO occupations to the most relevant O*NET occupations (Department of Employment, Skills, Small and Family Business 2018).

In addition, the arbitrary scale of measurement for the derived skill variables encourages me to convert the values into percentiles. For each 4-digit level ANZSCO occupation, I am interested to see how a skill ranks in importance when compared to the rest of the employed population. To accomplish this, I re-scale each skill variable so it becomes a percentile score representing the relative importance of the skill among all Australian workers between the years 2001 and 2016. For example, an occupation with a transformed cognitive score of 0.10 indicates that 10 per cent of Australian workers are in an occupation that does not treat general cognitive as the most important skill. This is similar to an approach adopted by Peri and Sparber (2009), and the standardisation of skill values between zero and one facilitates a more intuitive interpretation of their effects on employership survival. I weight these percentile scores with occupation counts from the ABS 2011 Census (ABS 2011). I assume the 2011 census is collectively representative of the Australian workforce between the years 2001 and 2016.

Table 4-4 briefly describes how different occupations rank in their use of cognitive, mathematics, technical specialisation, resource management and pattern recognition skills. For brevity, as there are 384 4-digit level ANZSCO occupations in my sample, the table focuses on the top five occupations for each of the skill variables. As we might expect, manager-related occupations (i.e., directors and managers) are the top five occupations for the resource management skill. Except for chefs, we can see that these manager occupations also have relatively high cognitive percentile scores. In contrast, the

top five occupations for the cognitive skill (i.e., psychologists counsellors, psychiatrists, barristers and solicitors) have relatively low resource management scores. The manager occupations (including chefs) also have relatively high scores in the mathematics skill, whereas the top five occupations for the mathematics skill have significantly lower scores for resource management. Table 4-4 also highlights that we cannot assume that management experience is homogenous; research and development (R&D) managers consider cognitive and mathematics, but not resource management, as important skills for their occupation. In contrast, the other managerial occupations (i.e., directors and managers) consider all three skill groups to be important.

4.4.5 HILDA Descriptive Statistics

I also observe and control for a variety of individual-level and firm-level characteristics. They include age, sex, marital status, the number of dependents (individuals younger than 15 years old) under their care, real disposable annual household income prior to entry into employership,⁶² the size of their business,⁶³ and the employer's state-level unemployment rate.⁶⁴ The full definitions of these control variables are available in section 2.2.3. I drop any employers with missing information and employers with only one observation before they are 'right-censored'. Overall, I have a working sample of 3,367 observations from 1,007 employers with around 48 per cent of employers transitioning into employership from solo self-employment, 47 per cent of employers transitioning from wage/salary employment, and about 6 per cent of employers transitioning from non-employment.

I begin my analysis by using non-parametric survival analysis techniques to compute the employers' survival rates. The Kaplan-Meier estimator is the simplest way of computing survival over time and involves computing probabilities of failure at a certain point in time. Successive probabilities are then multiplied by any earlier computed probabilities to obtain the final estimate (Kaplan and Meier 1958).⁶⁵

⁶² This variable measures the individual's disposable household income in the wave just before they became an employer. I control for this variable as it acts as a proxy for the individual's liquidity constraints as higher-income suggests higher liquidity reserves to absorb any negative business income shocks.

⁶³ Business size is measured at the end of the employer's spell. If the employer exited, then it represents the size of their business in the wave just before they exit. If they are right-censored, the variable indicates the size of their business in their last observation.

⁶⁴ The unemployment rate is the value measured at the end of the employer's spell, similar to the business size variable. Initial analyses use unemployment rates as defined in Section 2.2.3.

⁶⁵ Kaplan-Meier estimators assume that censoring is unrelated to entry circumstances – Survival probabilities are assumed to be the same for employers who enter early or late in the survey, and the events happened at the times specified (Bland and Altman 2004).

TABLE 4-4: OCCUPATIONS AND RELATIVE SKILL IMPORTANCE

Occupation	Cognitive Percentile	Technical Special. Percentile	Mathematics Percentile	Resource Manage. Percentile	Pattern Recognition Percentile
<u>Five occupations with the highest cognitive percentile scores</u>					
Psychologists	1.000	0.367	0.033	0.045	0.217
Counsellors	0.998	0.285	0.012	0.519	0.506
Psychiatrists	0.996	0.338	0.200	0.182	0.808
Barristers	0.996	0.336	0.144	0.599	0.359
Solicitors	0.995	0.336	0.143	0.598	0.364
<u>Five occupations with the highest mathematics percentile scores</u>					
Actuaries, math. & statistic.	0.588	0.249	1.000	0.007	0.514
R & D managers	0.847	0.371	1.000	0.009	0.018
Intel. and policy analysts	0.846	0.370	0.999	0.010	0.017
Chem. & materials engineers	0.766	0.822	0.997	0.545	0.324
Accountants	0.454	0.072	0.997	0.209	0.896
<u>Five occupations with the highest technical specialisation percentile scores</u>					
Aircraft maint. engineers	0.951	1.000	0.179	0.099	0.199
Motor mechanics	0.713	0.999	0.331	0.425	0.283
Refrigeration mechanics	0.678	0.990	0.612	0.484	0.248
Telecomm. trades workers	0.839	0.988	0.358	0.170	0.420
Telecomm. tech. specialists	0.839	0.987	0.356	0.171	0.418

Five occupations with the highest resource management percentile scores

Chief exec. & managing directors	0.893	0.514	0.879	1.000	0.526
Policy and planning managers	0.888	0.509	0.881	0.995	0.528
General managers & legislators	0.777	0.542	0.747	0.993	0.533
Managers nfd.	0.781	0.546	0.751	0.993	0.533
Chefs	0.472	0.750	0.765	0.989	0.726

Five occupations with the highest pattern recognition percentile scores

Air transport professionals	0.785	0.848	0.873	0.492	1.000
Train & tram drivers	0.480	0.798	0.577	0.032	0.999
Anaesthetists	0.979	0.751	0.770	0.145	0.998
Police	0.811	0.605	0.093	0.377	0.997
Automobile, Bus & Rail Drivers	0.263	0.711	0.426	0.358	0.992

Notes: Author's calculations. Percentile scores rank how important the skills or abilities are within the employed population.

Source: O*NET Release 22.1 (Department of Labor Employment and Training Administration / National Center for O*NET Development 2017), ABS 2011 Census and HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

Figure 4-1 suggests employership is a volatile employment state. Over 50 per cent of new employers leave within a year of operation but the rate of exit diminishes over time. This is consistent with the Jovanovic (1982) theory of entrepreneurial learning and survival. The longer the individual remains as an employer, the more likely they are to survive. This is known as negative duration dependence.

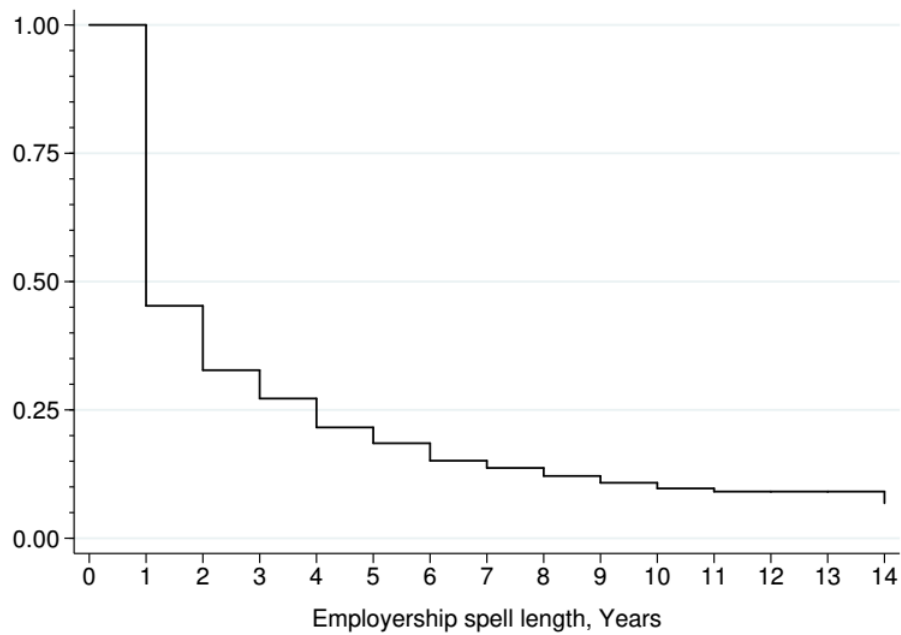
A visual inspection of Figure 4-2 suggests there are only minor differences in survivability between male and female employers. However, the comparison of the survival curves of the two groups should be based on a formal non-parametric statistical test. In this figure, I use a log-rank test of equality with a null hypothesis of no difference between the probabilities of male and female employership survival.⁶⁶ The test is a method for comparing survival times of two or more groups of subjects. It involves the calculation of observed and expected frequencies of failures in separate time intervals. The relevant test statistic is a comparison of the observed number of exits occurring in each wave with the number of employers expected to leave employership (assuming the characteristics of the two groups are the same). The p-value of the log-rank test is 0.1449 (located at the top right of Figure 4-2), suggesting that I failed to reject the null hypothesis at the 5 per cent level. There is not enough evidence to suggest males and female employers have significantly different hazard rates.

Figures 4-3 and 4-4 examine the employer's general human capital stock and their relationship with the probability of employership exit. Figure 4-3 shows that employers with, at least, a bachelor's degree (or equivalent education) have significantly higher survival probabilities than those who do not. In contrast, there is no difference between employers who completed year 12 (as their highest level of education achieved) and employers with higher or lower education achievements. Figure 4-4 also suggests work experience is a significant determinant of employership exit. Employers with above sample average years of work experience are more likely to exit employership than their less experienced counterparts.⁶⁷

⁶⁶ The test is based on the same assumptions as of the Kaplan-Meier survival curve.

⁶⁷ In my sample, the sample average years of work experience is around 19 years.

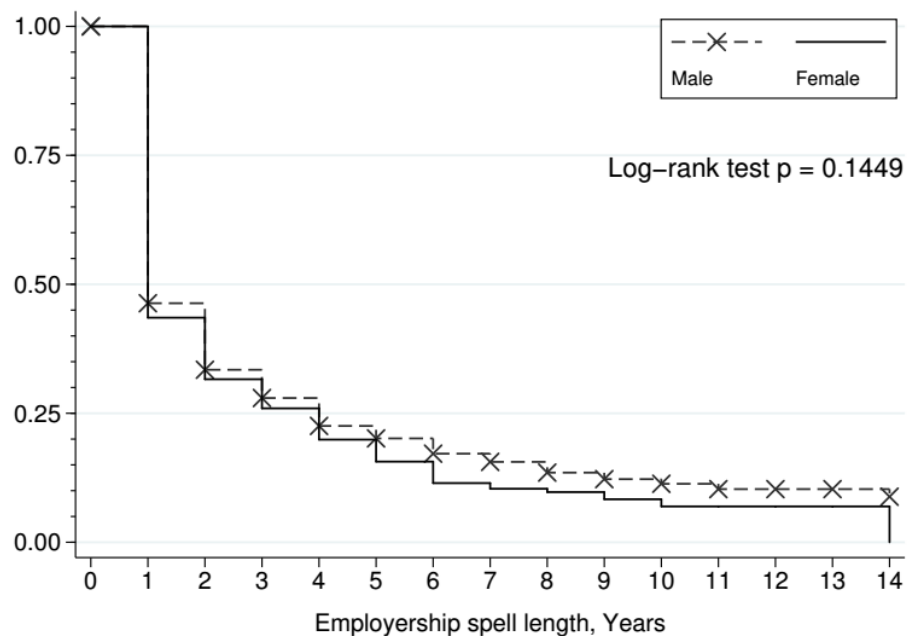
FIGURE 4-1: KAPLAN-MEIER (1958) EMPLOYERSHIP SURVIVAL FUNCTION



Notes: Kaplan-Meier estimate of the probability of an individual staying in employership in wave t conditional on being an employer in wave $t-1$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

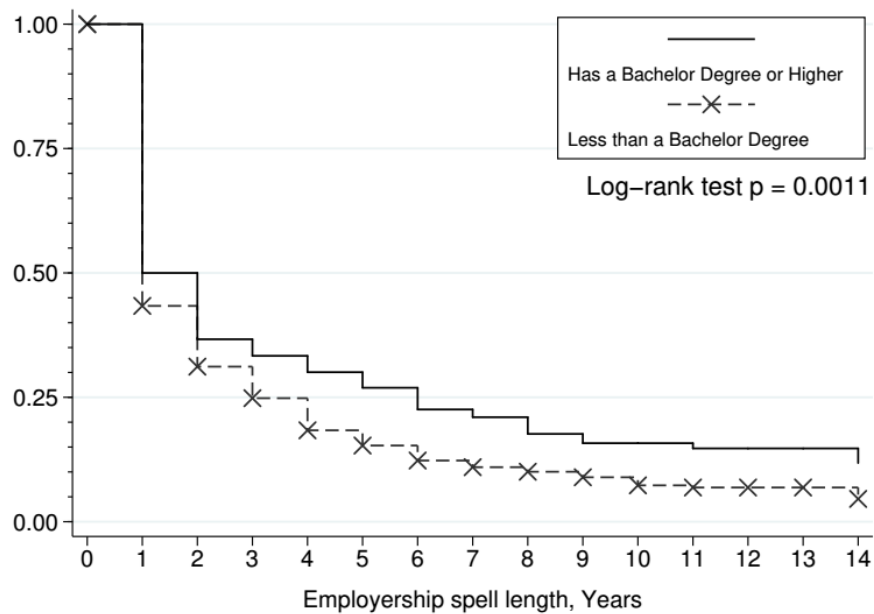
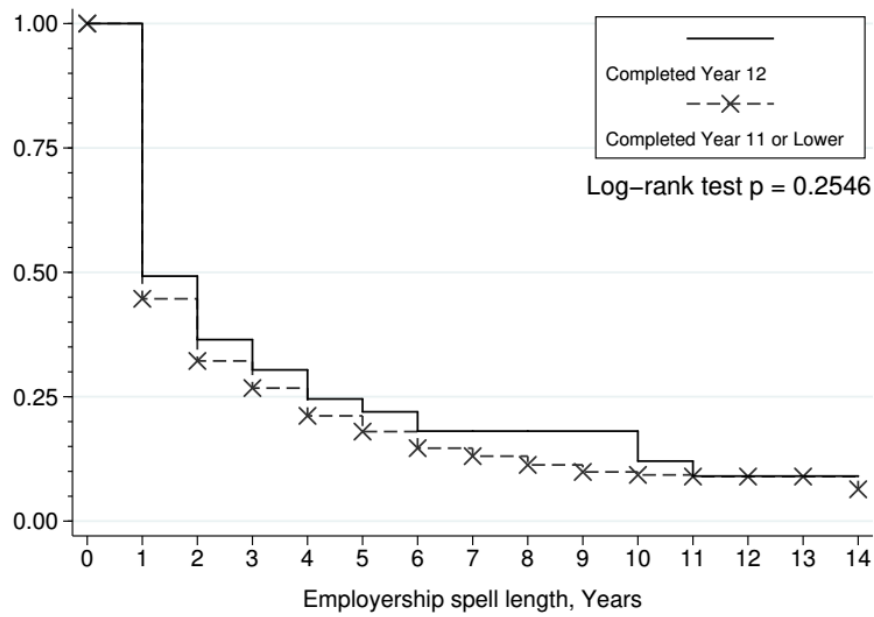
FIGURE 4-2: KAPLAN-MEIER EMPLOYERSHIP SURVIVAL FUNCTION BY GENDER



Notes: Kaplan-Meier estimates the probability of a male or female employer staying in employership in wave t conditional on being an employer in wave $t-1$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

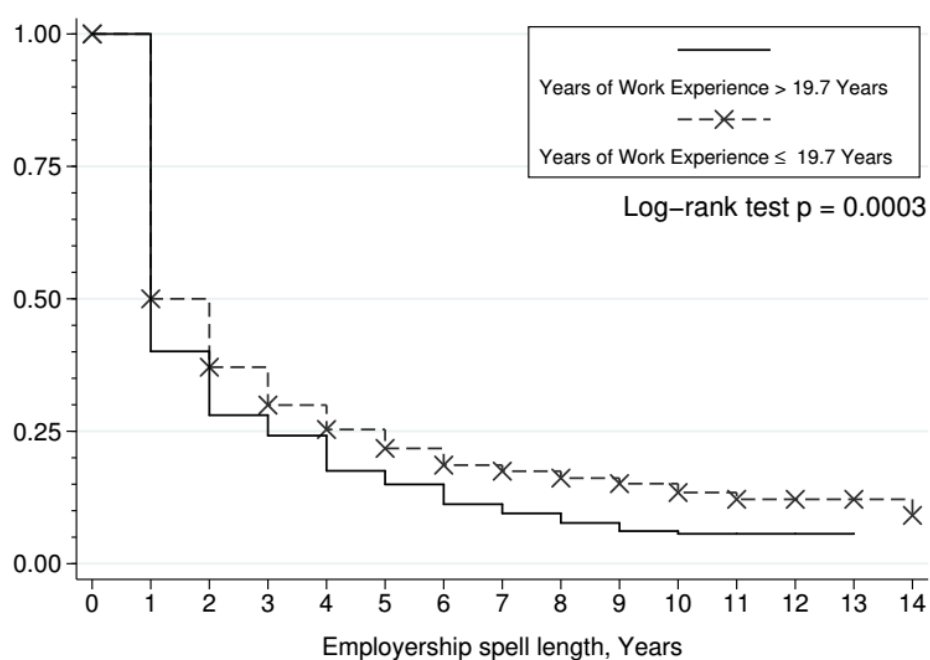
FIGURE 4-3: EMPLOYER SURVIVAL (IN YEARS) BY EDUCATION



Notes: Kaplan-Meier estimates of the probability of an individual staying in employership in wave t conditional on being been an employer in wave $t-1$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

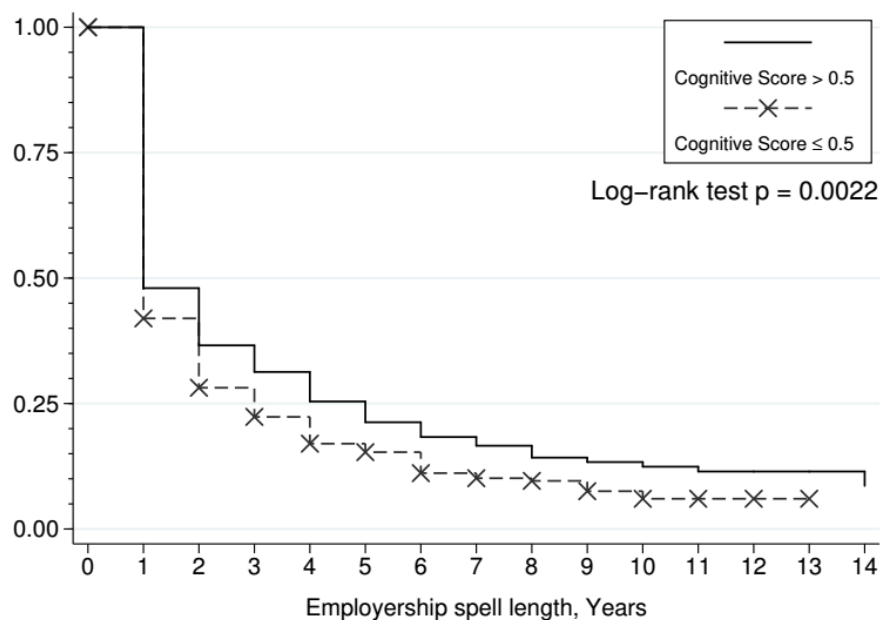
FIGURE 4-4: EMPLOYER SURVIVAL (IN YEARS) BY WORK EXPERIENCE



Notes: Kaplan-Meier estimates of the probability of an individual staying in employership in wave t conditional on being been an employer in wave $t-1$. 19.7 years of working experience is the sample average of each employer at the time of starting their employership spell.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

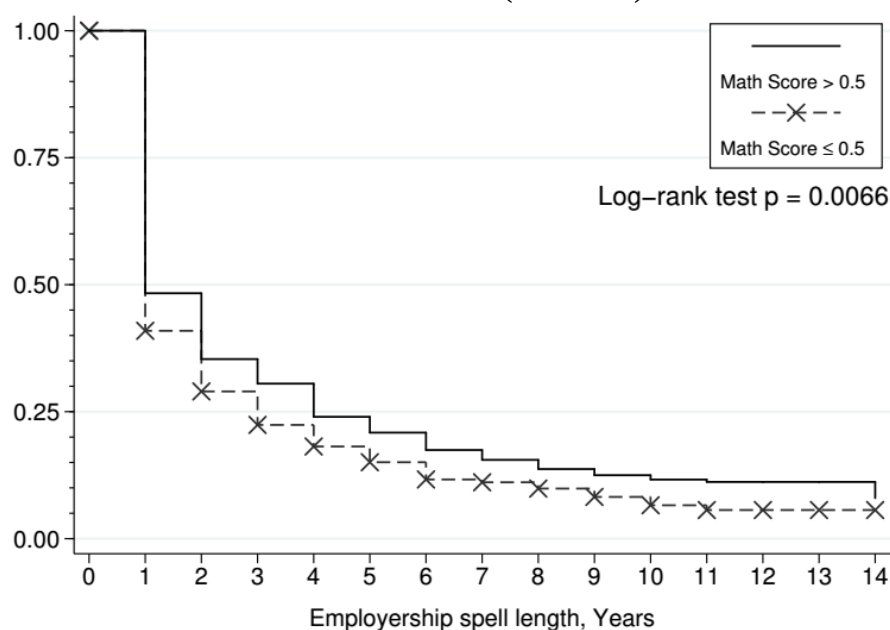
FIGURE 4-5: EMPLOYER SURVIVAL (IN YEARS) BY COGNITIVE SKILL



Notes: Kaplan-Meier estimates of the probabilities an individual staying in employership in wave t conditional on being been an employer in wave $t-1$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

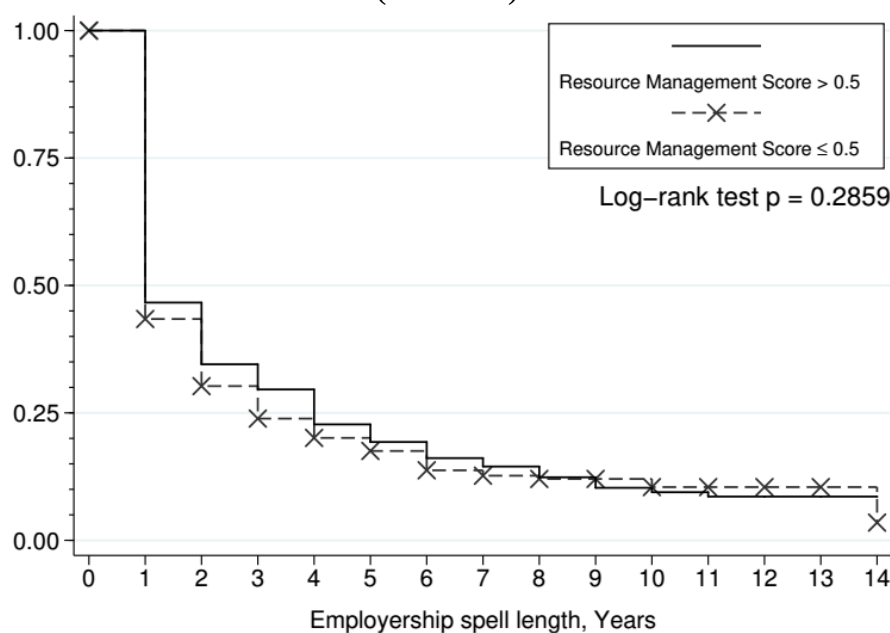
FIGURE 4-6: EMPLOYER SURVIVAL (IN YEARS) BY MATH SKILL



Notes: Kaplan-Meier estimated probabilities of an individual staying in employership in wave t conditional on being an employer in wave $t-1$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

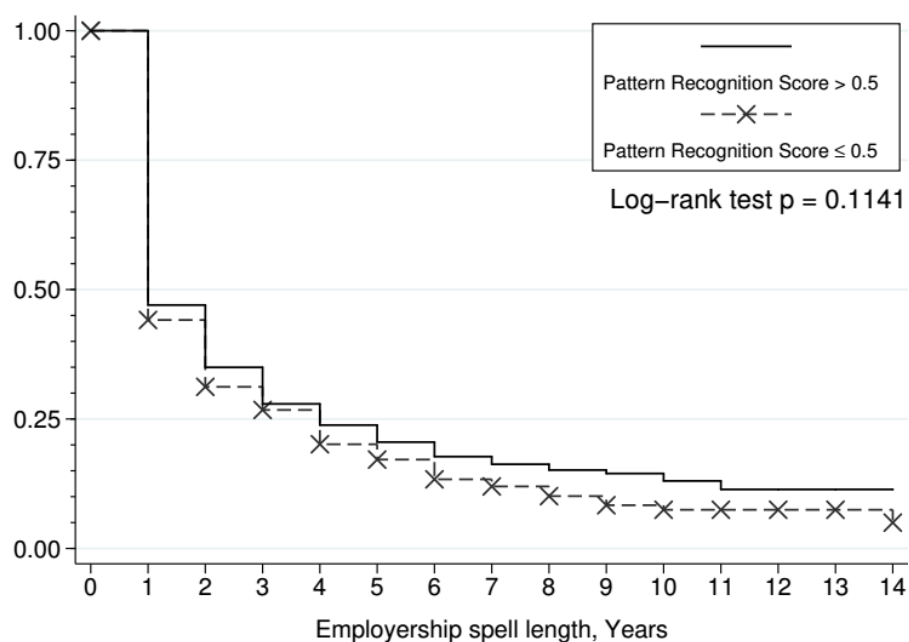
FIGURE 4-7: EMPLOYER SURVIVAL (IN YEARS) BY RESOURCE MANAGEMENT SKILL



Notes: Kaplan-Meier estimated probabilities of an individual staying in employership in wave t conditional on being an employer in wave $t-1$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

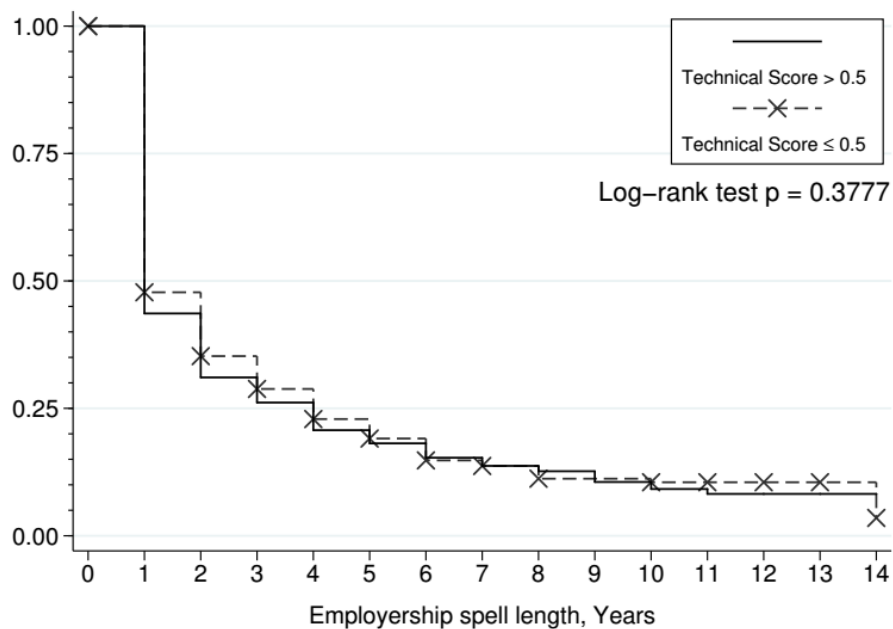
FIGURE 4-8: EMPLOYER SURVIVAL (IN YEARS) BY PATTERN RECOGNITION SKILL



Notes: Kaplan-Meier estimated probabilities of an individual staying in employership in wave t conditional on being an employer in wave $t-1$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

FIGURE 4-9: EMPLOYER SURVIVAL (IN YEARS) BY TECHNICAL SKILL



Notes: Kaplan-Meier estimated probabilities of an individual staying in employership in wave t conditional on being an employer in wave $t-1$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

TABLE 4-5: SUMMARY STATISTICS OF EMPLOYERS

	Exiting Employers Mean/(Std.)	Censored Employers Mean/(Std.)
Duration (Years)	3.967 (2.813)	8.279 (4.636)
Work experience prior entry (Years)	20.366 (10.403)	17.314 (9.272)
<u>Highest level of education achieved (%)</u>		
Year 11 or lower	0.225 (0.417)	0.132 (0.339)
Year 12	0.128 (0.334)	0.152 (0.360)
Certificate	0.281 (0.449)	0.223 (0.416)
Diploma	0.098 (0.297)	0.088 (0.283)
Bachelor's degree or higher	0.269 (0.444)	0.405 (0.491)
<u>Skills Rank</u>		
Cognitive	0.522 (0.277)	0.564 (0.260)
Technical specialisation	0.559 (0.287)	0.546 (0.276)
Mathematics	0.551 (0.299)	0.615 (0.293)
Resource management	0.561 (0.290)	0.587 (0.301)
Pattern recognition	0.431 (0.283)	0.504 (0.287)
<u>Business Size (0/1)</u>		
Less than 5 employees	0.716 (0.451)	0.421 (0.494)
5 to 19 employees	0.212 (0.409)	0.453 (0.498)
20 to 49 employees	0.045 (0.207)	0.076 (0.265)
>50 employees	0.027 (0.163)	0.050 (0.218)
Male	0.623 (0.485)	0.692 (0.462)
Age	42.839 (10.152)	41.632 (9.227)

Number of dependents (0-14 years old)	0.929 (1.171)	1.271 (1.335)
Marital status (0/1)	0.842 (0.364)	0.892 (0.311)
Gross regular income (\$)	109,000.00 (95586.71)	116,000.00 (76705.66)
Regional unemployment (%)	5.217 (1.018)	5.359 (0.842)
No. of spells	802	205
No. of observations	2,285	1,082

Note: The above statistics are derived from a pooled and unbalanced panel sample comprising 21-64 years old individuals who transitioned into employership between waves 2001 to 2016 of the HILDA Survey. Standard deviations of the means are reported in parentheses.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

Figure 4-5, Figure 4-6, Figure 4-7 and Figure 4-8 highlight the importance of the employer's skill set on employership survival. Employers who worked in occupations where cognitive, mathematics resource management, and pattern recognition skills have a percentile score of 0.5 and above are more likely to survive. In contrast, the technical specialisation skill has no significant impact on employership survival.

Table 4-5 displays the summary statistics of employers present in my working sample. The average exiter has more years of working experience than censored employers, suggesting experience is an element of human capital better rewarded outside of employership. Further, a larger proportion of censored employers have a bachelor's degree (or higher) than exiters. Both estimates are consistent with the Kaplan-Meier curves presented in Figure 4-3 and Figure 4-4. Consistent with Figures 4-5 to 4-9, censored employers rank cognitive, mathematics, pattern recognition and resource management skills more highly than exiting employers on average. Also, both censored and exiting employers previously worked in occupations that treated the technical specialisation skill almost equally.

The two employer groups again differ in areas aside from their human capital stock. The average censored employer is more likely to have larger enterprises than the average exiter. Around 72 per cent of exiting employers have a firm with less than 5 employees while roughly 58 per cent of censored employers have firms with 5 employees or more. Censored employers are likewise observed to earn more regular gross disposable household income on average than their exiting counterparts' prior entry into employership. I hypothesise that high household earnings correlate positively with

liquidity reserves that can fund the employer's business during periods of negative business income shocks.

The second issue is that employers can come from solo self-employment, an employment state that risks having little variation in acquirable skills, especially if most of the sampled solo self-employed workers are heavily involved in managerial-related duties. Fortunately, there is heterogeneity among the occupation titles reported by the solo self-employed; around 31 per cent of employers, that arrived from solo self-employment, reported they were in a management-related occupation during their time in solo self-employment. There is also considerable diversity among the management occupation titles as there are 34 different management-related occupations, ranging from finance managers to childcare centre managers; these managerial occupations require different skill sets to perform satisfactorily within those occupations. Further, around 32 per cent of employers who were solo self-employed for 12 months (or fewer) came into solo self-employment from a managerial-type occupation. Thus, I keep the originally reported occupations by the solo self-employed.

4.5 Proportional Hazard Model

The descriptive statistics above suggest education, work experience, cognitive skill, resource management skill and pattern recognition skill matter for employership survival. The flaw with using Kaplan-Meier estimates (supported by a log-rank test) is that they cannot be used to explore the effects of several human capital variables on employership survival simultaneously. In addition, the log-rank test does not adjust for the effects of several other variables that known to affect survival.

In response, I estimate the probability an employer exiting during the next wave $T + 1$, if he/she survived up to the current wave T . This probability is established as the employer's hazard rate and can be expressed by a proportional hazard (PH) specification as shown below:

$$4-2) \quad \theta(T) = \theta_0(T) \exp[\beta' X(i)]$$

$\theta_0(T)$ serves as a baseline hazard function of time T and $X(i)$ represents the employer's vector of explanatory and control characteristics.⁶⁸ The baseline hazard function describes the risk for employers with $X(i) = 0$, who serves as a reference individual, while

⁶⁸ The baseline hazard function is the hazard rate obtained when every covariate is set to 0.

$\exp[\beta'X(i)]$ represents the proportionate change in risk of exiting from employership, associated with the vector $X(i)$. The Cox model makes no assumptions on the shape of the baseline hazard function. Even though the baseline hazard is not specified, reasonably good estimates of the coefficients and hazard ratios of interest can be obtained (Kleinbaum and Klein 2012).

Data from the HILDA Survey is interval-censored where the individual's employership status can only be observed at the time of their interviews. As an example, consider the case of an individual who responded as an employer in a wave 2002 interview but later responded to be a wage/salary employee in the wave 2003 interview. We cannot observe the exact date when they left employership between the two interviews. While a Cox model can handle right-censored data, it cannot accommodate interval-censored data. Using the HILDA Survey data requires an extension to the Cox PH model consistent with a continuous-time model for interval-censored survival data.⁶⁹ I know exit times, T , will fall within the interval a_j and a_{j-1} :-

$$\theta(a_j|X(i)) = \text{Prob}(a_{j-1} < T < a_j | T_i \geq a_{j-1})$$

where $\theta(a_j|X(i))$ represents employer i hazard function at the interval boundary a_j . This represents the probability an employer will exit between a_j and a_{j-1} , given they survived up to a_{j-1} . This leads to the following model:

$$4-3) \quad \theta(a_j|X(i)) = 1 - \exp\{-\exp[\beta'X(i) + u_i + \gamma_0(j)]\}$$

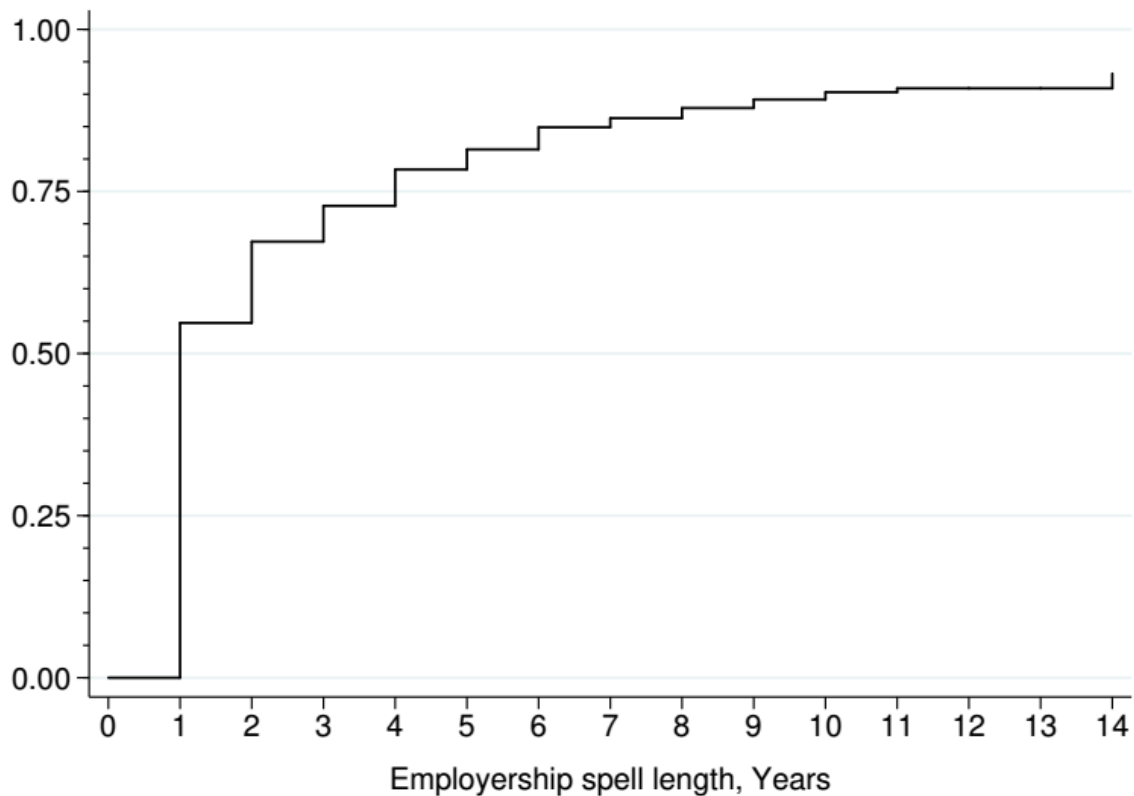
Equation 4-3 estimates a discrete-time proportional hazards model with a complementary log-log (cloglog) link (Prentice and Gloeckler 1978; Sueyoshi 1995), expressing the probability of employership exit between the beginning (a_{j-1}) and end of an interval (a_j), given the employer survives up to a_{j-1} , as a linear function of regression parameters (see Appendix 4.4 for a derivation of Equation 4-3). The cloglog model is a form of a generalised linear model with a cloglog link where its coefficients are the same as those characterising the continuous-time hazard rate $\theta(T) = \theta_0(T)\exp[\beta'X(i)]$. The coefficient β from Equation 4-3 provides the proportional effect on the hazard of absolute

⁶⁹ This means the individuals continuously makes the decision to stay in or exit employership.

changes in $X(i)$. Further, the discrete hazard model above allows me to treat the decision to continue or exit ‘employership’ as a continuous random variable observed at discrete intervals.⁷⁰

$\gamma_0(j)$ is the log difference of the integrated baseline hazard evaluated between the beginning and end of interval j . The parameter acts as a summary of the duration pattern for each interval hazard but cannot be estimated without further assumptions. I use $r \log(j)$ to describe the variation in $\gamma_0(j)$.⁷¹ The log parametric specification can be thought of as a discrete-time analogue to the continuous-time Weibull model because Figure 4-10 suggests the shape of the hazard is monotonically decreasing, i.e., $r < 0$ (Jenkins 2005).

FIGURE 4-10: EMPLOYERSHIP HAZARD FUNCTION



Notes: Kaplan-Meier estimates of the probability of an individual leaving employership in wave t conditional on being an employer in wave $t-1$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

u_i in Equation 4-3 is a disturbance term including the time-invariant and person-specific unobserved heterogeneity. Controlling for unobserved heterogeneity is important

⁷⁰ To estimate Equation 4-3, I have to throw away each employer’s first observation during their spell (Jenkins 2005). The empirical sample reduces to 2,360 observations from the descriptive sample of 3,367 observations as a result.

⁷¹ Spell duration is measured by the number of waves an individual is observed to be in employership.

because of the possibility of measurement errors in survival times and individual characteristics (Lancaster 1992), or omitting unobservable variables such as ‘entrepreneurial ability’. If I ignore unobserved heterogeneity, I risk over-estimating negative duration dependence (or under-estimating positive duration dependence) and introducing bias to the estimates of coefficient β .⁷² For example, employers with low entrepreneurial ability (group B) are expected to leave employership earlier than employers with high entrepreneurial ability (group A). As employers leave group B, the survivors of group B will have an average hazard rate similar to group A’s. As a result, the coefficient estimates are biased downwards.

To control for unobserved heterogeneity, I adopt the Heckman-Singer non-parametric procedure to characterise the distribution of u_i (Heckman and Singer 1984). The Heckman-Singer approach is a consistent nonparametric maximum-likelihood estimator of the distribution of unobserved heterogeneity. For any number of support points, the technique creates two sets of parameter estimates. The first, u_j , measures the expected contribution of unobserved heterogeneity to the individual’s hazard function. The second set of parameter estimates measures the proportion of the population, m_j , at each point of support; these proportions must amount to one.

To carry out the Heckman-Singer approach, I assume the distribution of u is approximated by two points of support, denoted by subscripts h and l . They represent two mutually-exclusive employer groups within the Australian population: the high ability (H) and low ability employers (L).⁷³ With this approximation, Equation 4-3 can be rewritten as

$$\theta^h(a_j|X) = 1 - \exp\{-\exp[(\beta_0 + u_h) + \beta'X(i) + \gamma_0(j)]\}$$

$$\theta^l(a_j|X) = 1 - \exp\{-\exp[(\beta_0 + u_l) + \beta'X(i) + \gamma_0(j)]\}$$

$\theta^h(a_j|X)$ is the hazard function for high ability employers, whereas $\theta^l(a_j|X)$ is the hazard function for low ability employers. The Heckman-Singer approach involves estimating a different random intercept for each of the employer groups. Holding constant the observable characteristics of the sampled employers, $\theta(a_j|X)$ shifts upwards or

⁷² Negative duration dependence refers to duration having a negative impact on the hazard rate, i.e., the longer the employership spell, the lower the chance of exiting from employership. Positive duration dependence refers to spell length increasing the probability of the spell ending at a point of time.

⁷³ I have attempted to carry out the Heckman-Singer approach with three or more points of support but the model failed to converge.

downwards depending on the contribution of unobserved differences. In this model, the contribution to the sample likelihood for an employer with spell length T is the probability-weighted sum of the contributions arising were they a Type H or a Type L employer, i.e.

$$4-4) \quad L = m_h L(u_h) + (1 - m_h) L(u_l)$$

where

$$L(u_h) = \left(\frac{\theta^h(a_j|X)}{1 - \theta^h(a_j|X)} \right)^c \prod_{k=1}^T [1 - \theta^h(a_j|X)]$$

$$L(u_l) = \left(\frac{\theta^l(a_j|X)}{1 - \theta^l(a_j|X)} \right)^c \prod_{k=1}^T [1 - \theta^l(a_j|X)]$$

c is the censoring indicator which equals one if the spell is right-censored. m_h and $1 - m_h$ are the proportion of the population that comprises the type H and type L employers, respectively. These proportions are represented below:

$$m_h = \frac{\exp \eta_h}{\exp \eta_h + \exp \eta_l}$$

Parameters η_h and η_l are to be estimated in the likelihood function.

Using the above empirical strategy, I assess the following hypotheses:

H3: Years of paid work experience, before entry into employership, have a negative influence on employership spell length, ceteris paribus.

Although years of work experience can inform a prospective employer of their ability, the individual may find their experience to be better rewarded by working for another employer.

H4: Tertiary education or higher has a positive impact on employership spell length, ceteris paribus.

Within the sample, I find employers with a bachelor's degree or higher are less likely to exit employership than less educated employers. This hints that individuals use higher education as a proxy for entrepreneurial ability.

H5: General cognitive, mathematics, resource management and pattern recognition skills have a positive impact on employership spell length, *ceteris paribus*.

Successful employers should have the ability to spot, hire, combine and manage employees of different skillsets. As the general cognitive and resource management skills include the relevant skills/abilities (see Appendix 7.3.4) such as monitoring, negotiation, operations analysis, persuasion, management of personal resources and instructing, I hypothesise employers that are relatively highly proficient with general cognitive or resource management skills are more likely to survive in employership.

Also, employers need to make effective investment and saving decisions. Those who can are more likely to succeed as an employer than those who can't. As summarised by Ćumurović and Hyll (2016), individuals with higher financial literacy make investments with higher rates of return. Mathematics (or numeracy) skills are found to be positively correlated with the individual's financial literacy (Lusardi 2012; Ghazal, Cokely, and Garcia-Retamero 2014; Skagerlund et al. 2018). I hypothesis that employers who score more highly on the mathematics factor are more likely to survive in employership.

Successful employers should likewise be individuals who entered employership because they could identify profitable market opportunities through recognising 'patterns' in the latest market trends (Baron 2006). Thus, employers with high levels of pattern recognition are more likely to survive in employership because of their ability to find a worthwhile business venture.

H6: Technical specialisation has no significant relationship with employership spell length, *ceteris paribus*.

This hypothesis is based on Lazear's (2005) jack-of-all-trades theory – individuals with a specialised human capital background (such as technical specialisation) are less prone to enter self-employment.

4.6 Results

To illustrate the impacts of the explanatory variables on the employer's propensity to exit, I estimate hazard ratios from the underlying continuous-time model by exponentiating the estimated coefficients of Equation 4-3 and Table 4-6. A hazard ratio represents the proportionate difference in the hazard rate, i.e., the probability of an individual leaving employership in wave t , conditional on surviving up to wave $t - 1$, with a unit change in X_j , *ceteris paribus*. A unit increase in the variable, X_j , changes the

employership hazard by $[100 \times (\exp \hat{\beta}_j - 1)]\%$. Table 4-6 presents only the coefficient estimates of the human capital variables, which are the main interest of this chapter. The full set of estimates for the control variables are available in Table A4.6.1 within the appendix.

Specification (1) estimates a ‘naïve’ cloglog model in which I do not control for the employer’s specific human capital (i.e., the skills they acquired from their previous occupations). Specification (2) estimates the full cloglog model where I add controls for every human capital variable and the employer’s individual and firm characteristics. Specification (3) estimates the full cloglog model with the Heckman and Singer approach.

In specifications (1) to (3) of Table 4-6, I controlled for annual unemployment rates of the 13 major statistical regions as defined in section 2.2.3. As mentioned in section 3.7, these unemployment rates represent local economic conditions and assume the economic environment is homogeneous among individuals within each region. This is an unrealistic assumption. To disaggregate regional unemployment, I match the respondent’s SA4 location to SA4 unemployment rates reported in Table 16 of the ABS Detailed Labour Force Surveys ABS (2019b) by the date of the respondent's interview.⁷⁴ I then re-estimated Equation 4-3, controlling for SA4 unemployment, with the main results presented in specification (4) of Table 4-6.⁷⁵

Across all specifications of Table 4-6, there is evidence of negative duration dependence, i.e., employers are less likely to exit employership the longer they stay in the employment state. This result is consistent with earlier studies of self-employment survival and the Jovanovic (1982) theory of entrepreneurial learning. Further, the estimates of $\hat{\rho}$ across specifications (1) to (4) are significantly less than zero, confirming that the shape of the hazard is monotonically decreasing.

In addition, Table 4-6 shows that work experience and education have no significant influence on employership hazard rates. As a result, I reject **H3** and **H4**. I note that the coefficient estimates of some education variables are large in magnitude. For example, relative to employers who completed 11 years or fewer of formal schooling (for brevity, I refer to this group as the dropped-out employers), employers with secondary schooling (as their highest level of education achieved) have 15.0 to 23.3 per cent (e.g., $\exp(-0.265)$

⁷⁴ For example, if a wave 2001 respondent is interviewed in July, I assign them the ABS SA4 unemployment rate as measured in July 2001. If a wave 2005 respondent is interviewed in January of the following year (2006), I assign them the unemployment rate as measured in January 2006.

⁷⁵ Both aggregated and disaggregated unemployment variables are time invariant variables. These variables observe the relevant unemployment rates during the year of exit (from employership) or the year of right-censoring.

– 1 = -0.233) smaller hazard rates. But, these estimates are imprecise, and we cannot conclude that there is a relationship between education and employership survivability.

TABLE 4-6: DEPARTURE FROM EMPLOYERSHIP – SINGLE RISK CLOGLOG MODEL

	Specifications			
	(1)	(2)	(3)	(4)
Duration	-0.914*** (0.065)	-0.890*** (0.066)	-0.489*** (0.153)	-0.481*** (0.150)
Work experience prior entry (Years)	-0.005 (0.008)	-0.005 (0.008)	-0.004 (0.010)	-0.003 (0.010)
<u>Highest level of education achieved (0/1)</u>				
Year 12	-0.162 (0.134)	-0.136 (0.136)	-0.255 (0.189)	-0.265 (0.190)
Certificate	0.122 (0.107)	0.153 (0.107)	0.162 (0.143)	0.161 (0.146)
Diploma	0.135 (0.141)	0.205 (0.144)	0.240 (0.189)	0.202 (0.192)
Bachelor's degree or higher	-0.118 (0.110)	-0.008 (0.121)	-0.037 (0.161)	-0.031 (0.164)
<u>Skills</u>				
Cognitive		-0.300* (0.156)	-0.437** (0.213)	-0.484** (0.215)
Technical specialisation		0.018 (0.155)	0.009 (0.213)	-0.034 (0.211)
Mathematics		-0.122 (0.134)	-0.184 (0.182)	-0.172 (0.184)
Resource management		-0.181 (0.137)	-0.294 (0.194)	-0.275 (0.192)
Pattern recognition		-0.142 (0.138)	-0.288 (0.197)	-0.264 (0.197)
No. of observations	2,360			
Log-likelihood	-1,265.42	-1,260.14	-1,255.28	-1,255.04
Unobserved heterogeneity	NO	NO	YES	YES
Unemployment measurement	Major	Major	Major	SA4

Notes: Specifications (1) and (2) are estimated with Stata -cloglog- command. Specifications (3) and (4) use Stata -glamm- command to estimate the cloglog model with unobserved heterogeneity. Estimates are based on a pooled sample of 21-64 years old individuals who transitioned into employership, once, between waves 2002 and 2016. Standard errors are displayed in parentheses. Also included, but not reported, are controls for the number of employees at place of business, age (specified as a quadratic), marital status, number of dependent children, impairment, household income prior entry into employership (logged) and the regional unemployment rate. 'Major' refers to unemployment rates measured for each of the 13 major statistical regions as defined in section 2.2.3. 'SA4' refers to unemployment rates for each SA4 local labour market. Section 3.7 defines SA4. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

Interpretation of the skill variables' coefficients is not as straightforward as the education or work experience variables. A 10 percentage point increase in the j^{th} percentile score corresponds to a change in the employer's hazard rate by $\exp(0.1 \hat{\beta}_j) - 1$ per cent. To illustrate, a 10 percentage point increase in the percentile score of the general cognitive skill (under specification (1)) reduces the employer's hazard rate by 2.96 per cent (i.e., $\exp(0.1 \times -0.3) - 1 = -0.02955$). The effect becomes even stronger after controlling for the individual's control variables and their unobserved heterogeneity. As shown under specification (3), a 10 percentage point increase in the score reduces the employership hazard rate by 4.26 per cent. Table 4-6 reveals that employers with relatively high general cognitive scores are more likely to survive in employership, thus I partially accept **H5**. I further accept **H6**, as Table 4-6 showed that the technical specialisation skill has no statistically significant relationship with the employer's employership hazard rates.

The control variables in specification (4) are too of interest. From Table A4.6.1, we see that employers with "5 to 19" or "20 to 49" people employed at their place of business have significantly smaller hazard rates compared to employers with fewer than 5 'employees'. This is expected as the firm's size is positively correlated with dismissal and exit costs (Millán et al. 2012). Hence, risks of failure brought about by negative business cost shocks are diminished (Brüderl et al. 1992; Baptista et al. 2014). The employer's age is also negatively associated with the employership hazard rates – a year increase in the employer's age decreases the probability that he/she exits employership, a finding consistent within the self-employment survival literature. Age matters because older workers have more established professional networks than their younger counterparts (Millán et al. 2012). Through knowledge spillovers, older workers have a bigger information pool about business opportunities and conditions than their junior counterparts. A married employer has a 25.2 per cent lower hazard rate than a single/divorced employer. This is because married employers likely have the financial support of their spouse which can help cover any negative business income shocks. Last, specification (4) of Table A4.6.1 shows that a 10 percentage point increase in the unemployment rate decreases the employer's hazard rate by 0.5 per cent. According to the literature, unemployment affects self-employment in two opposite ways: via the 'recession-push' and 'prosperity-pull' effects (Thurik et al. 2008; Parker 2009; Millán et al. 2012). The 'recession-push' hypothesis says that unemployment reduces the opportunities of gaining wage/salary employment and individuals prefer to remain as an

employer as a result – this signifies a negative relation between employership hazard rates and unemployment. In contrast, the ‘prosperity-pull’ hypothesis suggests that employers experience a decline in market demand for their products and services during times of substantial unemployment. Because of reduced revenues, employers are ‘pulled’ out from employership – this implies a positive relationship between employership hazard rates and unemployment. However, it’s more likely that the coefficient estimate is representing the net effects of both the ‘push’ and ‘pull’ hypothesis given its small magnitude (Parker 2008).

4.7 Robustness

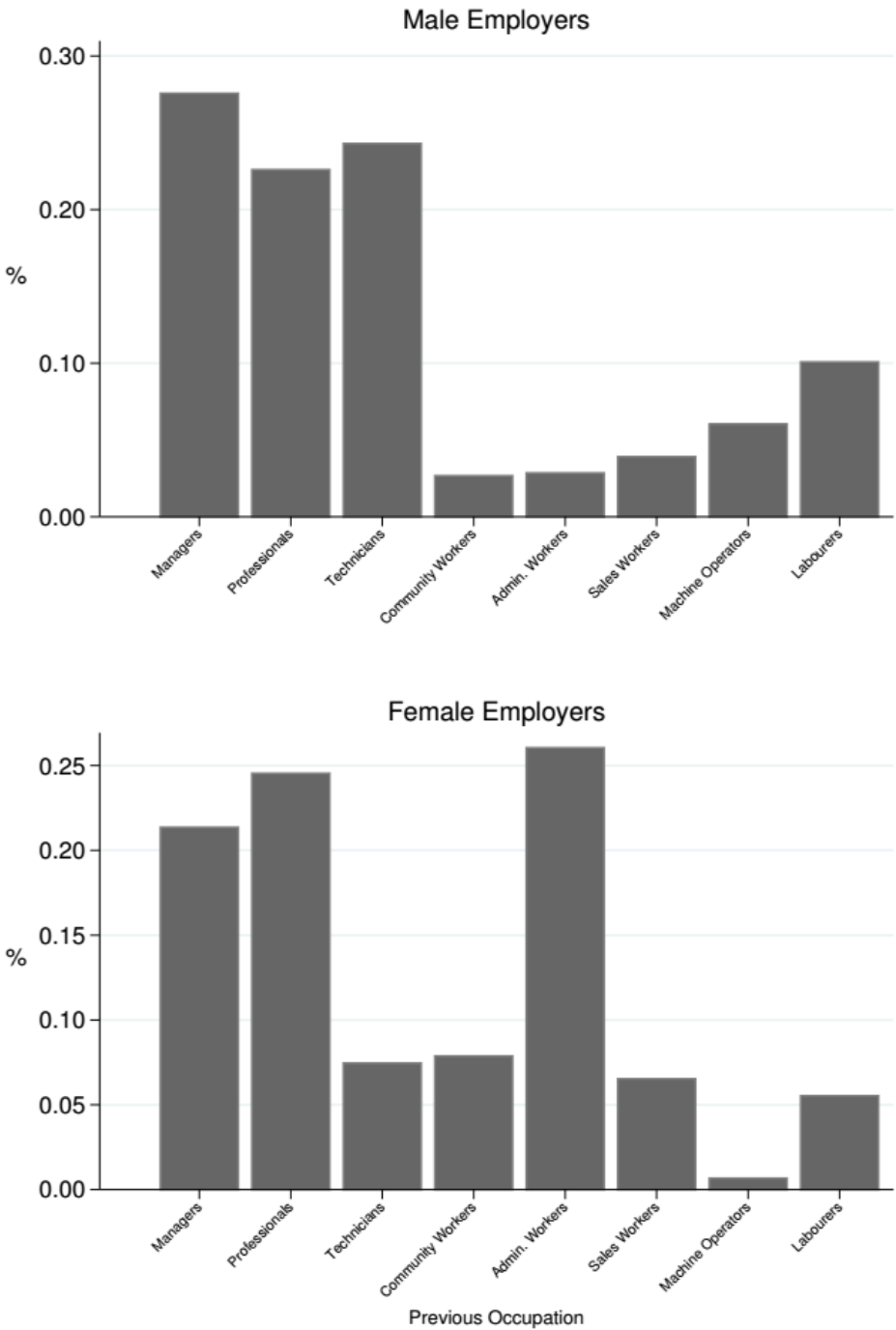
4.7.1 Employership Hazard Rates by Gender

Figure 4-2 and every specification in Table A4.6.1 suggest there is no substantial difference in survival rates between male and female employers. Yet, Figure 4-11 indicates that the distribution of earlier occupations is different between male and female employers. For example, a larger fraction of female employers than male employers were previously administrative (admin.) workers. In addition, a larger proportion of male employers than female employers were previously technicians. Given this gender-based difference in occupational distribution and the statistical similarity in male and female employership hazard rates, I examine if the human capital variables have differing impacts on male and female employership hazard rates.

I re-estimate Equation 4-3 separately for male and female employers and report the subsequent results in Table 4-7. Duration has a substantive and statistically significant negative effect on male employership hazard rates. In contrast, the duration effect on female employership hazard rates is insignificant. The education effects on hazard rates appear to differ between male and female employers. Male employers with a bachelor’s degree or higher have a significant negative effect on employership hazard rates, whereas it is statistically insignificant for female employers – male employers with a bachelor’s degree or higher have a 32.2 per cent smaller hazard rate than male employers who dropped out of school. In comparison, having a certificate increases the female employer hazard rate by 70.3 per cent, whereas it has no meaningful influence on male employership hazard rates. The cognitive skill still has a negative influence on both the male and female employership hazard rates, although the coefficient is only statistically significant (at 10 per cent) among male employers. Further, each added score in resource

management reduces employership hazards but the effect is much greater for female employers; a 10 percentage point increase in the resource management score significantly decreases female employership hazard rates by about 8.6 per cent. On the other hand, it reduces male employership hazard rates by 1 per cent and is statistically insignificant.

FIGURE 4-11: OCCUPATION DISTRIBUTION PRIOR TO ENTRY INTO EMPLOYERSHIP



Notes: Occupations are classified according to the 1-digit level of the ANZSCO classification system.
Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

TABLE 4-7: DEPARTURE FROM EMPLOYERSHIP – SINGLE RISK CLOGLOG MODEL – BY GENDER

	Male	Female
Duration	-0.611*** (0.217)	-0.096 (0.257)
Work experience prior entry (Years)	-0.020 (0.019)	-0.010 (0.017)
<u>Highest level of education achieved (0/1)</u>		
Year 12	-0.258 (0.236)	-0.245 (0.365)
Certificate	0.001 (0.169)	0.534* (0.308)
Diploma	0.393 (0.268)	-0.185 (0.379)
Bachelor's degree or higher	-0.389* (0.230)	0.483 (0.327)
<u>Skills</u>		
Cognitive	-0.511* (0.261)	-0.654 (0.528)
Technical specialisation	-0.167 (0.261)	0.151 (0.459)
Mathematics	0.022 (0.232)	-0.625 (0.404)
Resource management	-0.097 (0.262)	-0.903** (0.444)
Pattern recognition	-0.279 (0.247)	-0.190 (0.379)
No. of observations	1,545	815
Log-likelihood	-788.777	-452.322
Unobserved heterogeneity	YES	YES
Unemployment measurement	SA4	SA4

Notes: Specifications (Male) and (Female) are estimated with Stata's -glamm- command to estimate the cloglog model with unobserved heterogeneity. Estimates are based on a pooled sample of 21-64 years old individuals who transitioned into employership, once, between waves 2002 and 2016. Standard errors are displayed in parentheses. Also included, but not reported, are controls for the number of employees at place of business, age (specified as a quadratic), marital status, number of dependent children, impairment, household income prior entry into employership (logged) and the regional unemployment rate. 'SA4' refers to unemployment rates for each SA4 local labour market. Section 3.7 defines SA4. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

It is unclear why education, cognitive skill and resource management skill influence hazard rates differently for male and female employers. An explanation is that there are gender differences in the industry distribution of employers; within my sample, about 80 per cent of female employers are located within service industries, whereas 59 per cent of male employer's report to be in a service industry;⁷⁶ 13 and 33 per cent of female and male employers, respectively, report being in the goods-producing industry;⁷⁷ and around 7 and 8 per cent of female and male employers, respectively, are working within "Agriculture, forestry and fishing" industries. The human capital variables capacity to proxy for entrepreneurial ability could vary across industries; for example, it could be that the general cognitive skill is more relevant for male employers active within goods-producing industries than for female employers within service industries. Alternatively, some human capital variables, such as a bachelor's degree or higher, are better rewarded by working for another employer in some industries. Given this discussion, I examine how the effects of the human capital variables differ across goods-producing and service industries.⁷⁸

4.7.2 Employership Hazard Rates by Industry

I separate my working sample into employers active in service-producing or goods-producing industries (See section 2.2.3 for a definition of these industries). I re-estimate Equation 4-3 (with SA4 unemployment) separately for these subgroups and present the results in Table 4-8. The results show that working experience has no substantive and significant influence on employership exit rates. Education has no impact on employership hazard rates within goods-producing industries, but employers with a certificate III or IV as their highest educational achievement have a 47.1 per cent higher hazard rate than employers who dropped out of school.

⁷⁶ Service industries include the wholesale trade, retail trade, accommodation and food services, transport, postal and warehousing, information media and telecommunications, financial and insurance services, rental, hiring and real estate services, professional, scientific and technical services, administrative and support services, public administration and safety, education and training, health care and social assistance, arts and recreation services, and other services industries (ABS 2012).

⁷⁷ Goods-producing includes the following industries: Mining; Manufacturing; Electricity, Gas, Water and Waste Services; and Construction (ABS 2012).

⁷⁸ I initially attempted to examine how the human capital variables influence employership hazard rates within agriculture, forestry and fishing industries. Unfortunately, the sample of employers working within those industries is too small to allow for the cloglog model to converge.

TABLE 4-8: DEPARTURE FROM EMPLOYERSHIP – SINGLE RISK CLOGLOG MODEL –
BY INDUSTRIES

	Goods-Producing	Service
Duration	-0.122 (0.274)	-0.425* (0.247)
Work experience prior entry (Years)	-0.028 (0.030)	0.002 (0.013)
<u>Highest level of education achieved (0/1)</u>		
Year 12	-0.621 (0.448)	0.022 (0.233)
Certificate	0.301 (0.317)	0.386* (0.214)
Diploma	0.531 (0.527)	0.362 (0.256)
Bachelor's degree or higher	-0.160 (0.471)	0.146 (0.215)
<u>Skills</u>		
Cognitive	-0.175 (0.550)	-0.656** (0.291)
Technical specialisation	0.243 (0.888)	-0.258 (0.270)
Mathematics	-0.403 (0.478)	-0.010 (0.247)
Resource management	-1.349*** (0.518)	-0.095 (0.238)
Pattern recognition	-0.238 (0.525)	-0.465* (0.255)
No. of observations	606	1,552
Log-likelihood	-312.08	-810.92
Unobserved heterogeneity	YES	YES
Unemployment measurement	SA4	SA4

Notes: All specifications are estimated with Stata -glamm- command to estimate the cloglog model with unobserved heterogeneity. Estimates are based on a pooled sample of 21-64 years old individuals who transitioned into employership, once, between waves 2002 and 2016. Standard errors are displayed in parentheses. Also included, but not reported, are controls for the number of employees at place of business, age (specified as a quadratic), marital status, number of dependent children, impairment, household income prior entry into employership (logged) and the regional unemployment rate. 'SA4' refers to unemployment rates for each SA4 local labour market. Section 3.7 defines SA4. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

4.8 Conclusion

Self-employment is high on the Australian political agenda, but the group of self-employed workers responsible for creating jobs (i.e., the employers) experiences significantly high exit rates; in my sample, I establish that 50 per cent of employers do not make it past their first year of being an employer. Such a high rate of exit is costly for the employers (who spent time and resources on the venture), former employees who have been let go, and other third parties such as financial intuitions and lenders. Pro-entrepreneurial policies that do not understand why some employers survive while others exit risk being ineffective. Thus, employership survival is a key topic of economic and social importance but there has yet to be a concrete consensus on the positive determinants of employership survivability.

The literature suggests that individuals with an accurate belief of their unobservable entrepreneurial ability are most likely to survive in employership via selection effects – they enter employership if they believe that they can succeed as an employer. Individuals form their ability beliefs based on pre-entry experiences such as education and work experience (Cooper et al. 1994; Cressy 1999; van Praag and Cramer 2001). I hypothesised there exists skills and abilities that are better proxies of entrepreneurial ability than others, but traditional measures of human capital (i.e., education and work experience), as used by earlier self-employment studies, are poor descriptors of the individual's capabilities. Instead, I constructed better measures of the employer's skill/ability set by examining their previous occupation (just prior their entry into employership) and the occupation's skill requirements as described by O*NET. From O*NET, I extracted the importance ratings of 35 skills and 21 cognitive abilities for each occupation recorded in the database. I then allocate each of those elements into one of five distinct occupational skill groups. This is the first study in the self-employment literature that unpacks the skills/abilities acquired from the individual's working experience. Further, most of the self-employment literature treats the self-employed as a homogenous group. Since employers differ from solo self-employment workers in the way they manage their business and the constraints they face (Cowling et al. 2004), there is no reason to assume that the determinants of employership survival are the same as the determinants of solo self-employment survival.

With a sample of employers who I observed to transition into employership between the years 2001 and 2016, I find that cognitive skill is a significant determinant of employership survival. I infer that employers experienced in occupations that consider general cognitive skills to be important entered employership with the correct belief that

they will succeed. Resource management and pattern recognition skills also have positive but statistically insignificant effects on surviving in employership. I further present evidence that the employers' education and general stock of work experience have no significant effects on increasing employership survivability. Cognitive skill has a significant positive impact on male employership survivability, but resource management has a more significant and stronger effect on decreasing female employers' hazard rates. Skills may affect male and female employers differently because of gender-based differences in industry distribution, with female employers being more likely than men to be working in service industries. Following this argument, I split my sample between employers in goods-producing and service industries. I find resource management to be a strong determinant of employership survival in goods-producing industries. Employers in service industries are more likely to survive with higher cognitive and pattern recognition scores.

My results suggest that if policymakers seek to stimulate job creation via self-employment, especially within service industries, then they should focus on encouraging individuals with significant experience in occupations where cognitive skill matter most. Doing so would lower exit rates from employership, which will increase the net job creation rates by the new employers. Also, it can lessen the risk of wasting resources on individuals that cease being employers after a short period. Alternatively, if policymakers want to increase employership activity in goods-producing industries, then they should focus on incentivising individuals experienced in occupations where resource management skills are considered important. Further, if policymakers wish to address the clear gender gap in employership rates, as shown in Figure 3-6, then they should prioritise on promoting women experienced in occupations where resource management skills are considered important to be self-employed.

There are several limitations with using the HILDA Survey and O*NET to analyse the employership determinants of survival. First, I only observe a portion of the employers' lifetime labour decisions and cannot control for the individual's previous employership experience (if any) before their first interview. A dataset with a detailed diary of the individual's employment history would allow future studies to perform a more robust analysis of general (i.e., education and general work experience) and specific human capital (the five occupational skill groups) effects on employership survival. Second, I did not consider the different exit destinations for employers. Employers exiting into wage/salary employment may have different determinants of failure than their

counterparts exiting into solo self-employment or non-employment. However, the current sample is too small to generate any reliable estimates from discrete competing hazard models. Also, a competing risk model with interval-censored data imposes the strict assumption that transitions out of employership can only occur at the boundaries of the intervals, i.e., individuals leave employership at the time of their interview (Jenkins 2005). This is unrealistic as a continuous-time process generates the employership survival time.

The biggest issue in this chapter is that my measures of occupations skills are prone to be ‘imprecise’. Table 4-6 shows that the coefficient estimates of the mathematics, resource management and pattern recognition are large but imprecise. This is because measures of skills and abilities from the O*NET database for each occupation are likely noisy as they are based on at least 15 observations. While DOL ETA (2005, p. B-6) claims that the O*NET measures are often based on many more observations, it is unclear how many more for any occupation. Also, the O*NET database provides occupation-specific mean values of skill/ability importance. Job-level information is not easily accessible, and occupation-level measurements may mask important skills/abilities variation within each occupation category. Without public access to the original micro-data, the precision of the O*NET measures cannot be properly evaluated (Handel 2016). Third, my estimates of skill scores are reliant on matching 4-digit level ANZSCO occupation codes to the O*NET-SOC taxonomy. Despite employing the “Job Outlook” website to aid with the exercise, I recognise that matching ANZSCO occupations to their most relevant O*NET occupation requires some form of subjectivity. Last, the 4-digit level ANZSCO classifications are more aggregated than the O*NET-SOC taxonomy; the former identifies 358 occupations, whereas the latter identifies 974 occupations. This further adds more noise to the measures of relative skill/ability importance. Nevertheless, HILDA and O*Net remain as the best sources of data for the individual’s occupational background and understanding what are the skills or abilities they likely acquired from earlier occupations. As a result, to ensure more precise predictions about employership survivability, future research should attempt to identify the employer’s occupational background at the 5-digit level (see Appendix 2.3 for a summary of the ANZSCO classification structure). In addition, an exercise to match the 5-digit ANZSCO codes to their counterparts in the O*NET-SOC taxonomy would be beneficial.

Chapter 5

Job Satisfaction and the Self-Employed

5.1 Introduction

As stated earlier, a common belief held by policymakers across industrialised economies is that the self-employed are a vital engine of economic growth and job creation. It is no surprise, therefore, that policymakers dedicate significant resources to stimulate self-employment. Despite their attempts, the ABS LFS (ABS 2019c) show that since January 1991 employership and solo self-employment rates have declined.⁷⁹ In January 1991, 7.46 and 11.11 per cent of all employed persons were employers and solo self-employed workers, respectively.⁸⁰ By December 2016, the percentage of employed persons who were employers or solo self-employed had fallen to 6.17 or 10.06 per cent, respectively.⁸¹ This is puzzling as, according to Figure 5-1, the decline is occurring during periods (between the years 2001 and 2008) where unemployment is falling and as the employment to population (EP) ratio among 20-64 years old individuals is reaching record highs.⁸² This goes against the ‘pull’ hypothesis (assuming employers are ‘genuine’ entrepreneurs): self-employment rates should rise when unemployment rates are falling. This is because as low unemployment reduces the risk of business failure, encouraging individuals to become self-employed (Thurik et al. 2008; Parker 2009; Millán et al. 2012).

Economic incentives are a key component in determining the individual’s decision to be employers suggesting that individuals are finding employership to be less attractive than wage or salary employment. Without understanding the underlying reasons for this decline in employership, any pro-entrepreneurial policy risks being ineffectual. This is a topic of economic importance because a shortage of employers can contribute to long-term negative consequences for economic growth and job opportunities (Blanchflower, Oswald, and Stutzer 2001; Koellinger and Thurik 2012).

The empirical evidence from the self-employment literature overwhelmingly shows that individuals are more satisfied being self-employed (Hundley 2001; Benz and Frey

⁷⁹ 1991 is the earliest available ABS’ LFS (that I know of).

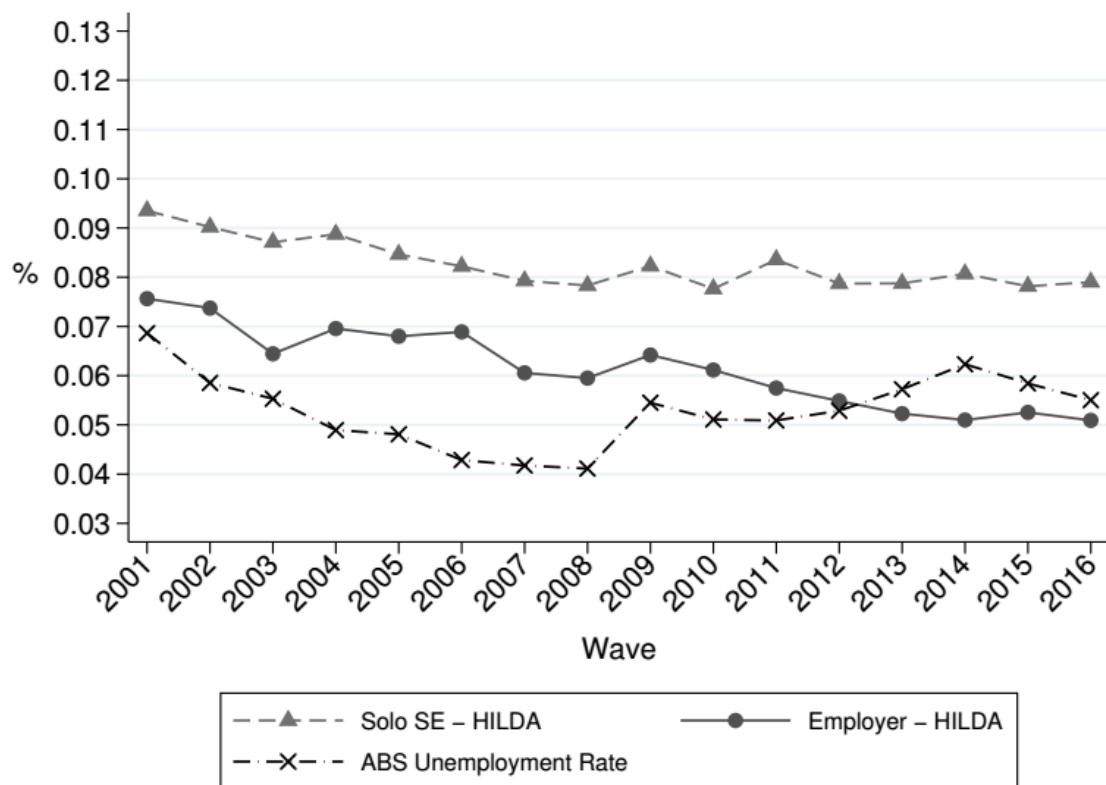
⁸⁰ Atalay, Kim, and Whelan (2014) suggest the increasing rates of labour force participation by women workers over 55 years of age, are responsible for this trend as these women are less likely than other demographic groups to be self-employed. According to Figure 1-2, there is truth to Atalay, Kim, and Whelan claims. The solo self-employment rate stabilised in and after the year 2007, but the employership rate continues to decline.

⁸¹ I chose December 2016 as I only have HILDA data from waves 2001 to 2016.

⁸² Among 20-64 years old, the EP ratio increased from 69.9% in January 2001 to 75.9% in December 2016. As of March 2019, the ratio further increased to 77.0%. The EP ratios are based on the original figures reported in ABS (2019a).

2004, 2008a) instead of being in wage/salary employment. However, the existing self-employment and job satisfaction literature primarily relied on data from European countries and the US, and only a couple of studies separated the solo self-employed from employers (Taylor 2004; Hessels et al. 2015). Thus, a potential explanation for the falling employership rate is that employers are becoming less satisfied with their jobs than wage/salary employees within the Australian labour market. An alternative explanation is that major hurdles may be dissuading individuals from entering employership. Aside from the first-employee hiring threshold (Fairlie and Miranda 2017), hurdles include the financial and material costs of starting up a business, ongoing regulatory compliance, being at an informational disadvantage against incumbent and larger businesses and a ‘fear of failure’ to starting up their own business (Disney and Gathergood 2009; Productivity Commission 2015; Steffans and Omarova 2018).

FIGURE 5-1: HILDA SELF-EMPLOYMENT AND ABS UNEMPLOYMENT TRENDS



Notes: Self-employment rates are defined as the proportion of employed persons (aged 15-64 years) who are self-employed (either as an employer or solo self-employed). HILDA self-employment rates are population-weighted. I used responding person population weights, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24).

Source: waves 1 to 16 of the HILDA Survey (Release 16). ABS unemployment rates come from Table 2 of the ABS Detailed Labour Force Surveys, December 2018 (Cat. No. 6291.0.55.001).

To establish that there are barriers to employership entry, I adopt a similar empirical approach to that used by Blanchflower and Oswald (1992) and Kawaguchi (2008).⁸³ Both studies argue that under free entry into self-employment, the average returns to self-employment and wage/salary employment should be similar. These studies use job satisfaction as a proxy for self-employment returns because income provides an incomplete measure, in that it does not capture any non-pecuniary benefits associated with either self-employment or wage/salary employment. There is some evidence that this omission is significant for the self-employed, where many individuals have been found to be willing to forego wages or salary for the opportunity to be their own boss (Hamilton 2000; Hundley 2001; Benz and Frey 2004; 2008a; 2008b). Blanchflower and Oswald (1992) and Kawaguchi (2008) hypothesized that, with barriers to self-employment entry, average job satisfaction (which is an amalgamation of monetary and non-pecuniary benefits) would be greater than the average job satisfaction among wage/salary employment. The intuition is that individuals require a premium to pay the costs of overcoming the hurdles of self-employment entry. Using British and US survey data, Blanchflower and Oswald (1992) and Kawaguchi (2008) report that the self-employed are significantly more satisfied with their jobs than their wage/salary employee counterparts, suggesting that there are barriers to entry into self-employment.

First impressions from Figure 5-1 suggests a correlation between solo self-employment rates and unemployment rates. As unemployment rates fell between the years 2001 and 2008, so did solo self-employment. When unemployment rates increased after the year 2008, solo self-employment rates stabilised and even rose slightly after 2012. Based on this observation there is a concern that unemployed individuals are disguising themselves as solo self-employed workers, i.e., individuals are solo self-employed to avoid being unemployed (Earle and Sakova 2000). I attempt to identify if the solo self-employed are primarily disguised unemployed individuals by comparing their reported job satisfaction scores against their counterparts in employership and wage/salary employment. If the solo self-employed are less satisfied than wage/salary employees, then there are obstacles hindering solo self-employed workers from becoming an employee *ceteris paribus*.

Understanding the motives of the solo self-employed can better guide the implementation of pro-entrepreneurial policies. To maximise the efficiency and returns

⁸³ These are the only two studies (that I know of) that use job satisfaction differences as evidence for self-employment entry barriers.

of any pro-entrepreneurial policy, the policies should prioritise firms with the highest growth potential. This includes employers but not individuals who are likely to dissolve their business the moment any suitable employment opportunities arise (Poschke 2013a). On the other hand, if solo self-employed workers are more satisfied with their jobs than their wage/salary counterparts, then policymakers can increase social welfare by encouraging more entries into solo self-employment.

Taylor (2004) and Hessels et al. (2015) are the only studies that distinguish employers from solo self-employment when examining the relationship between self-employment and job satisfaction. Both studies find evidence that employers and solo self-employed workers are significantly more satisfied with their jobs than their wage/salary counterparts. Both their studies used longitudinal household data from the UK or the EU, respectively, and earlier studies of self-employment and job satisfaction also focused on populations within Western Europe and the US, there is a limited understanding of the relationship between job satisfaction and employers/solo self-employed workers within the context of Australian labour markets. This chapter seeks to remedy this shortage by using longitudinal data on Australian households. I use self-reported measures of job satisfaction from the HILDA Survey, covering the years 2001 to 2016, to proxy for both the monetary and non-pecuniary returns of employership and solo self-employment. If there are significant self-employment entry barriers, and if the solo self-employed are self-employed out of necessity, then we should expect employers and the solo self-employed to report significantly higher and lower job satisfaction scores, respectively, than wage/salary employees.

In the HILDA Survey, the job satisfaction variable is not a continuous outcome variable. Instead, it is a categorical variable that is scored on an 11-point Likert scale ranging from 0 (Individuals totally dissatisfied with their main job) to 10 (Individuals totally satisfied with their main job). Individuals must choose one of the discrete scores that best reflects the range that their job satisfaction falls into. The standard multivariate ordinary least squares (OLS) regression technique is insufficient as it assumes that the “dependent (predicted) variable of interest is measured on a continuous, interval scale” (Peel, Goode, and Moutinho 1998, p. 77). When the dependent variable is categorical, “then a number of serious problems may arise with the OLS model: (i) meaningless predictions outside the range, or between the values, of the scale of the nominal or categorical dependent variable may occur; (ii) invalid hypothesis testing may occur in respect of the coefficients of the explanatory variables” (Peel, Goode, and Moutinho

1998, p. 77). Ordinal modelling techniques, such as ordered logit models, better allow us to estimate the effects of the individual's self-employment status on their underlying job satisfaction (Williams 2016). However, we cannot ignore the possibility that there are unobservable personality differences that correlate with job satisfaction and the decision to be self-employed. To account for individual-specific unobserved heterogeneity, I use the "Blow-up and Cluster" (BUC) estimator (Baetschmann et al., 2015). This estimator allows me to estimate an ordered logit model with individual fixed effects. No other study in the self-employment literature has used the BUC estimator (or an ordered logit model with individual fixed effects) to study the relationship between self-employment and job satisfaction.

This chapter is structured as follows: Section 5.2 reviews the empirical studies investigating the relationship between self-reported measures of job satisfaction and the decision to be self-employed. Section 5.3 augments the employment sectoral choice model from Chapter 3 with the theory of procedural utility (Benz and Frey 2008a). This section motivates my empirical strategy to use job satisfaction differences to show the existence of entry barriers to self-employment. Section 5.4 describes the HILDA sample used in this chapter's analyses and presents a set of descriptive statistics that describe the observable job satisfaction differences between employers, the solo self-employed and wage/salary employees. Section 5.5 describes the empirical strategy and summarises the BUC estimator. Section 5.6 presents the estimates generated by both the BUC estimator and the OLS regression with fixed effects. The results from both estimators are qualitatively the same; employership and solo self-employment satisfaction scores are significantly higher than the scores for wage/salary employment. I also find no significant differences in job satisfaction between solo self-employed workers and employers. Section 5.7 performs a series of robustness checks where I find no significant qualitative differences in my estimates. Section 5.8 concludes the chapter where I suggest that there are barriers to entry into both employership and solo self-employment. Further, I argue that the average Australian solo self-employed workers are not self-employed out of necessity as they have significantly higher job satisfaction rates than wage/salary employees.

5.2 Literature Review

Tracing back to Knight (1921), the empirical evidence from the self-employment literature supports the notion that an attractive feature of self-employment is independence in the workplace, something that is commonly referred to as a desire for ‘being one’s own boss’. This ‘desire’ might explain why individuals enter self-employment despite there being a possibility they will earn less and be exposed to higher risk. For example, Taylor (1996) find that, with 1991 BHPS data and a probit model, individuals who value ‘initiative’ or ‘enjoyment of work itself’ as the most important job aspects are significantly more prone to become self-employed. Hamilton (2000) finds US self-employed males have lower median incomes and income growth than wage/salary employees. Moskowitz and Vissing-Jørgensen (2002) find US self-employed workers are more likely to invest in undiversified and relatively risky businesses with a rate of return no greater than what is obtainable from diversified and less risky investment portfolio. van Praag and Versloot (2007b) reviewed 14 studies published in journals with the highest impact (i.e., English language studies published in AA or A ranked economic journals, as defined by the Dutch Tinbergen Institute Research School) and find the mean and median incomes of the self-employed to be no greater than those earned in wage/salary employment.⁸⁴ These studies suggest non-pecuniary elements, such as greater autonomy, are significant determinants of self-employment entry.

Blanchflower and Oswald (1992) provide evidence that the self-employed have higher job satisfaction than their wage/salary counterparts. Their analysis draws upon UK longitudinal and US cross-section data from the National Child Development Study (NCDS) and General Social Surveys (GSS), respectively.⁸⁵ Regressing the ordinal job satisfaction variable (this variable is a multiple-point Likert scale where higher scores represent greater job satisfaction) against the individual’s self-employment status (i.e., was the individual self-employed) with an ordered probit model. They show that the self-employed report significantly higher job satisfaction scores than wage/salary employees. This is also the first study (that I know of) that uses differences in reported job satisfaction scores as evidence of entry barriers into self-employment. Blanchflower and Oswald (1992) used job satisfaction scores as a proxy of non-pecuniary and monetary returns to

⁸⁴ van Praag and Versloot (2007b) reviewed 87 analyses from 57 studies. However, only fourteen of these analyses focus on the income differential between self-employed workers and wage/salary employees.

⁸⁵ Blanchflower and Oswald (1992) restricted their empirical analysis to individuals from the NCDS who were employed or self-employed at the time of their interview in 1981. Since the GSS samples an independent group of individuals each year, Blanchflower and Oswald focus on individuals from surveys covering the years 1972 to 1990.

employment and assume the expected returns of being self-employed should be equal to that of wage/salary employment in the long run. Their findings suggest the self-employed are earning ‘supernormal rents’; this is only possible if entry barriers are preventing individuals from entering self-employment. Hundley (2001) confirms Blanchflower and Oswald (1992) findings that the self-employed are more satisfied than their wage/salary counterparts. Hundley (2001) adapted a between-group earnings decomposition technique (Oaxaca 1973) to analyse how variations in job characteristics contribute to the differences in job satisfaction. With US survey data from the 1977 Quality of Employment Survey, 1997 National Study of the Changing Work Force and the GSS covering the years 1989 to 1996, Hundley (2001) finds that greater levels of independence and autonomy within self-employment explain a significant portion of the difference in job satisfaction between self-employed workers and wage/salary employees. Although both employees and self-employed workers value autonomy and independence, Hundley (2001) suggests self-employed workers value those traits more.

A plausible concern is that self-employment does not actually make individuals more satisfied. Instead, intrinsically happier or more satisfied individuals may have a higher propensity to become self-employed, or there are unobservable personality differences correlated with both job satisfaction and the decision to be self-employed. Benz and Frey (2004, 2008a) took advantage of the fall of the Berlin wall in 1989 to create a ‘natural experiment’ to explore if self-employment increases the individual’s job satisfaction. In this context, there were severe restrictions on entry into self-employment in East Germany until the wall came down. Thus, after the wall fell, there was an exogenous increase in self-employment within East Germany. Benz and Frey (2004, 2008a) estimated an ordered logit model where they regressed an ordinal job satisfaction variable against the individual’s self-employment status before and after the fall of the wall (they also controlled for working hours per week and total income) with data drawn from wave 1990 of the GSOEP (East Germans were first sampled in 1990 and every year thereafter). They find East Germans who moved into self-employment in 1990 are significantly more satisfied than both wage/salary employees and those who were self-employed before the wall collapsed. They also controlled for the individual’s life satisfaction in 1985. Their intuition was that if only satisfied individuals become self-employed, then the inclusion of the life satisfaction in 1985 variable should minimise the effect of moving into self-employment in 1990 on reported job satisfaction. Instead, there was no qualitative and quantitative change to the estimated coefficient on the ‘newly self-employed’ variable.

Overall, they showed that becoming self-employed causally increases the individual's job satisfaction, irrespective of income gained or hours worked. Benz and Frey (2008a) take this as evidence of 'procedural utility': "people value not only outcomes but also the conditions and processes leading to outcomes" (Benz and Frey 2008a, p.362).

Later studies have confirmed the findings reported by Benz and Frey (2004, 2008a). These studies do so by controlling for panel-data fixed effects or correlated random effects to find that unobserved individual-specific heterogeneity and self-selection into self-employment do not explain the greater levels of job satisfaction (Taylor 2004; Andersson 2008; Kawaguchi 2008; Hessels, Millán, and Román 2015). Similar to Benz and Frey (2004, 2008a), these studies regress an ordinal job satisfaction variable against the individual's self-employment status. A notable exception in the literature is Binder and Coad (2013, 2016) who used matching estimators to derive the causal effect of being self-employed on reported life satisfaction scores (Binder and Coad 2013) and job satisfaction scores (Binder and Coad 2016).

Taylor (2004) draws upon data from waves 1992 to 2001 of the BHPS to analyse the differences in job satisfaction between self-employed workers and wage/salary employees. Further, Taylor (2004) is one of the first (to my knowledge) studies to separate employers from the solo self-employed. Using an ordered probit model with correlated random effects, Taylor (2004) finds both employers and solo self-employed workers have significantly higher job satisfaction scores than their wage/salary counterparts, even after controlling for employment income and hours worked. Taylor (2004) also provides evidence of 'procedural utility' by showing that employership or solo self-employment leads to higher satisfaction with work itself. In addition, they show that employers are significantly more satisfied with their jobs than the solo self-employed.

Using data from the Swedish Level-of-Living Survey covering the years 1991 and 2001, Andersson (2008) collapsed the ordinal job satisfaction variable into a dummy variable that equals 1 if the respondent is "very satisfied with work". Andersson then estimates a conditional fixed-effects logit model to find that self-employment leads to an increase in job satisfaction, even after controlling for the individual's observable characteristics (i.e., age, gender, marital status, housing status and the number of children).

Similar to Blanchflower and Oswald (1992) approach, Kawaguchi (2008) provides evidence of entry barriers into self-employment by showing that the self-employed have significantly higher returns (proxied by job satisfaction scores) than wage/salary

employees. Unlike Blanchflower and Oswald (1992), Kawaguchi (2008) controlled for individual unobserved heterogeneity with an ordered probit model with correlated random effects. Kawaguchi (2008) finds evidence of entry barriers into self-employment; the self-employed are significantly more satisfied with their jobs than wage/salary employees.

Binder and Coad (2013) used the nearest-neighbour and propensity score matching estimators with UK data drawn from waves 1996 to 2006 of the BHPS to investigate the relationship between self-employment and job satisfaction. They matched individuals from self-employment (i.e., the treatment group) with individuals not in self-employment (i.e., the control group). The control group represents the counterfactual – how satisfied an individual would be if he/she had not chosen to be self-employed. Thus, the difference in job satisfaction between the treatment and control groups is the causal effect of being self-employed on job satisfaction. The nearest-neighbour technique matches the self-employed individual to the nearest neighbour (for each of the dimensions of the individual's observable characteristics) from the control group. The propensity score estimator matches the self-employed to observations from the control group with similar propensities to be self-employed. For both matching estimators, Binder and Coad (2013) find individuals who switch from wage/salary employment to self-employment have significantly higher life satisfaction scores. Binder and Coad (2016) used the same matching strategy with German data from waves 1997 to 2010 of the SOEP. Similar to their earlier results, they find individuals who moved into self-employment from wage/salary employment to have significantly larger life and job satisfaction scores than their counterparts who remained in wage/salary employment.

Hessels et al. (2015), with data from waves 1994 to 2001 of the ECHP, regress the individual's reported job satisfaction against their self-employment status with an ordinary least squares (OLS) regression with fixed-effects to control for the individual's unobserved heterogeneity.⁸⁶ Similar to Taylor (2004), Hessels et al. (2015) separated employers from the solo self-employed. Hessels et al. (2015) also show that employers and solo self-employed workers have significantly higher job satisfaction scores than wage/salary employees. Unlike Taylor (2004), they find no significant differences in job satisfaction between employers and solo self-employed workers.

⁸⁶ Hessels et al. (2015) also estimated generalised ordered logit models, but these models do not control for any unobserved individual-specific differences between self-employed workers and wage/salary employees.

A potential explanation for the discrepancy between Taylor (2004) and Hessels et al. (2015) is that the job satisfaction dependent variable is structurally different in each study. The job satisfaction dependent variable in Taylor (2004) is a 6-point Likert-scale where higher scores represent greater job satisfaction.⁸⁷ In contrast, Hessels et al. (2015) collapsed the 6-point scale job satisfaction dependent variable into a 3-point scale ranging from 1 to 3: (1) dissatisfied, (2) neither dissatisfied nor satisfied and (3) satisfied. This inevitably means a loss of information as Hessels et al. (2015) reduced the variation in the ordinal dependent variable. Further, Hessels et al. (2015) use of linear regression with fixed effects and an ordinal dependent variable risks creating biased estimates (Baetschmann et al. 2015; Schröder and Yitzhaki 2017). This is because the linear regression imposes the assumption that the implied distance between any two points on the job satisfaction scale is equal for every individual (i.e., the cardinality assumption). Schröder and Yitzhaki (2017) suggest this assumption problematic as individuals hold heterogeneous distance concepts. For example, individuals may consider the latent distance between any two points to be equal while others consider the latent distance to be of a convex (or even concave) shape. Further, the linear regression assumes the ordered dependent variable is continuous. This cannot be the case as job satisfaction scores are discrete and responses beyond the minimum and maximum score are impossible (Christensen 2015). Thus, we should prefer the results in Taylor (2004) results because of his use of an ordered probit model with correlated random effects. However, his empirical strategy is not without weaknesses. The issue with ordered probit models with correlated random effects is that it assumes the individual's unobserved heterogeneity is equally correlated with the observable characteristics across all observable periods (Wooldridge 2002, p. 582). I discuss the empirical strategy in Taylor (2004) in more detail in section 5.6.

Overall, the body of evidence reviewed above suggests a consensus that the self-employed are more satisfied with their job than wage/salary workers. This field, however, needs more exploration for three main reasons. First, there is a lack of analyses on job satisfaction differences between employers and the solo self-employed. This distinction is important because the former represents cases of genuine entrepreneurship (Earle and Sakova 2000) while necessity conditions may drive the latter - individuals with limited

⁸⁷ Likert (1932) scales are a fixed choice response format designed to measure attitudes or opinions. It is assumed the intensity of experiences is linear. The scale offers respondent multiple pre-coded responses to express how much they agree or disagree with a statement. The scale also includes a neutral point being neither agree nor disagree.

employment opportunities may choose to be solo self-employed (Congregado, Golpe, and Carmona 2010; Congregado, Golpe, and Parker 2012).

There is evidence suggesting that genuine self-employed workers have significantly higher satisfaction scores than their necessity counterparts. For example, Block and Koellinger (2009) distinguish self-employed workers who started their venture because of lack of work choices (i.e., necessity entrepreneurs) from those pursuing an entrepreneurial opportunity (i.e., opportunity entrepreneurs). Using an ordered logit model and data drawn from an online German Survey (completed by early-stage self-employed workers or individuals planning to become self-employed) in 2008, they find evidence that necessity entrepreneurs are less satisfied with their start-ups than their opportunity equivalents. Cueto and Pruneda (2017) split the self-employed into those with a preference for self-employment (the opportunity self-employed) and those who prefer to be in wage employment (the necessity self-employed). Using ordered logit models with data from waves 2006 to 2010 of the Spanish Quality of Life at Work Survey, they show that the opportunity self-employed are more satisfied than employees whereas the reluctant self-employed workers are less satisfied. Although they do not distinguish between opportunity and necessity self-employed workers, VandenHeuvel and Wooden (1997) split the self-employed into contractors dependent on one client (i.e., dependent contractors) and contractors with multiple clients (i.e., independent contractors). It is fair to assume independent contractors are more likely to be genuinely self-employed than dependent contractors. After estimating an ordered logit model with Australian data drawn from the ABS' 1994 Population Survey Monitor, VandenHeuvel and Wooden (1997) discovered that independent and dependent contractors are more satisfied and no more satisfied than wage/salary employees, respectively.⁸⁸

Second, studies (Taylor 2004; Hessels et al. 2015) that examined the differences in job satisfaction between the solo self-employed and employers have yet to adopt techniques to using a nonlinear estimator while controlling for individual unobserved heterogeneity with fixed-effects. This study will be the first to use the BUC estimator to estimate an ordered logit model with individual fixed effects to reveal job satisfaction differences (if any) between employers, solo self-employed and wage/salary workers. The BUC estimator has the benefit of avoiding the bias inherent in the cardinality assumption of linear regression (Hessels, Millán, and Román 2015), and relaxes a strong assumption

⁸⁸ A table summarising the empirical strategies, the studies associated with each strategy and the main outcomes is available in Appendix 5.1.

imposed by an ordered probit model with correlated random effects (Taylor 2004). The ordered probit model with correlated random effects assumes that the individual-specific unobserved heterogeneity is equally correlated with all time-period characteristics of the individual, whereas the BUC estimator makes no such assumption.

Third, despite the fact that Australia outperforms most other developed economies in terms of business aspirations and prevalence of innovative start-ups (Steffans and Omarova 2018), a significant majority of earlier studies focused on analysing populations within Europe and the United States of America. I remedy this by using Australian household panel data from the HILDA Survey.

5.3 Theory and Propositions

I assume, in each period t , an individual enters the employment state (employership, solo self-employment or wage/salary employment) that endows them with the highest possible expected utility. Expected utility in employership and solo self-employed depends on two elements: the expected profit and the non-pecuniary benefit of being self-employed. For simplicity, I follow the Lucas (1978) model where ability is a time-invariant single-dimensional observable quantity heterogeneous across the population.⁸⁹ Also, I assume everyone in this economy is risk-neutral.

In each period t , the solo self-employed expected profit function is $\pi_t(\theta)$ and their only unit of production is their own ability. An employer's expected profit function is $\pi_t(\theta, L_t)$ where they hire in at least one employee (i.e., $L_t \geq 1$). The expected utility function of being solo self-employed at time t is: -

$$U_{solo,t} = \pi_t(\theta, 1) + \lambda$$

and the employer's expected utility function is: -

$$U_{emp,t} = \pi_t(\theta, L_t) + \lambda$$

where λ is a time-invariant parameter representing the 'procedural' utility of being self-employed. Alternatively, the individual can be a wage/salary employee and receive a

⁸⁹ Entrepreneurial ability is an innate trait that does not 'improve' or 'degrade'. This thesis and Lechmann & Wunder (2017) find limited evidence of any entrepreneurial 'learning by doing'. If 'learning by doing' played a major role, the extent of true (cross) state dependence in employership should be much higher (see Table 3-11 for the estimates).

wage/salary rate, $w_t(x_t)$, dependent on their observable characteristics, x_t . For wage/salary (wage) employees, their expected utility function at t is the wage they earn,

$$U_{wage,t} = w_t(x_t)$$

Under plausible assumptions with no obstacles to self-employment entry, individuals become employers if $U_{emp,t} > U_{wage,t}$. It follows directly that, in equilibrium, individuals are indifferent between being an employer, solo self-employed or a wage employee; i.e.,

$$U_{emp,t} = U_{wage,t} = U_{solo,t}$$

This framework allows for $\pi_t(\theta, L_t) < w_t(x_t)$ when the benefits of being your own boss (λ) are large enough. However, if there are multiple barriers of entry into employership (such a significant fixed cost of entry) the equilibrium is not reachable. These barriers include the initial costs of hiring your first employees, limited access to finance, a higher skill requirement to be an employer because of technological change, increased competition from foreign firms or increased costs of regulatory compliance. These costs are represented by a time-varying parameter γ_t . Also, considering the solo self-employed is the only unit of production in their own business, I assume they do not experience significant entry costs. The equilibrium condition between employership and wage/salary employment (or solo self-employment) is now,

$$U_{emp,t} - \gamma_t = U_{wage,t}$$

and

$$U_{emp,t} - \gamma_t = U_{solo,t}$$

The above equations imply employers will have to earn supernormal returns to justify entry into employership, i.e., $U_{emp,t} > U_{wage,t}$ and $U_{emp,t} > U_{solo,t}$. Employment utility is a combination of income and non-pecuniary benefits (e.g., the utility of ‘being your own boss’) associated with the employment state. I use job satisfaction as a proxy for employment utility as Clark (1997, p. 344) has observed that “job satisfaction may be as

close as we are likely to come to a proxy measure of utility at work”. The employment state’s job satisfaction should include the utility derived from income gained and the ‘procedural’ utility of work within that employment statue (e.g., the ability to work autonomously).

H6: Employers are more satisfied, overall, with their job than wage/salary employees, *certeris paribus*.

H7: Employers are more satisfied, overall, with their job than solo self-employment workers, *certeris paribus*.

Suppose we initially assume Australian solo self-employed workers mainly consist of people who are self-employed out of necessity. They prefer to be wage/salary employees but there are no available employment opportunities. Thus, they enter solo self-employment until labour market opportunities improve. This implies that for the solo self-employed, $U_{wage,t} > U_{solo,t}$. This leads to another hypothesis:-

H8: The wage/salary employees are more satisfied, overall, with their job than solo self-employment workers, *certeris paribus*.

Hypothesis **H8** suggests a solo self-employed worker is usually self-employed out of necessity (they become self-employed to escape unemployment). However, if I were to reject this hypothesis, then there is insufficient evidence to classify the average solo self-employed worker as necessity self-employed.

5.4 Data and Descriptive Statistics

This study uses data from waves 2001 to 2016 of the HILDA Survey. The sample includes only employed individuals, aged 21 to 64 years. I drop any respondent who reports being unemployed or ‘not in the labour force’ at the date of the interview and any unpaid family worker. This leaves me with an initial working sample of 129,920 observations involving 20,086 individuals. The primary outcome variable used in this analysis is a single-item measure of overall job satisfaction, scored on an 11-point scale ranging from 0 (individuals totally dissatisfied with their main job) to 10 (Individuals totally satisfied with their main job). In each wave, respondents choose a score in response to the question “All things considered, how satisfied are you with your job?”. For respondents working multiple jobs at the time of the interview, the query refers to their main job (i.e., the job where they earn most of their income from). I dropped an additional 59 observations (comprising 3 individuals) with missing satisfaction information, leaving

me a sample size of 129,861 observations for 20,083 individuals. I note that the sample is an unbalanced panel of persons in paid employment.

Table 5-1 provides a pooled sample distribution by employment choice. My sample primarily comprises individuals working in a wage/salary job. Around 17 to 23 per cent and 10 to 13 per cent of sampled males and females, respectively, are self-employed with solo self-employment being more common than employership.

TABLE 5-1: EMPLOYMENT TYPE DISTRIBUTION BY SEX

Year	Male			Female		
	Wage Emp.	Solo SE.	Employer	Wage Emp.	Solo SE.	Employer
2001	0.769	0.128	0.102	0.871	0.068	0.060
2002	0.777	0.123	0.100	0.868	0.072	0.060
2003	0.797	0.113	0.090	0.876	0.074	0.050
2004	0.784	0.118	0.097	0.873	0.074	0.053
2005	0.791	0.114	0.095	0.878	0.069	0.053
2006	0.794	0.111	0.095	0.881	0.065	0.054
2007	0.804	0.110	0.086	0.894	0.061	0.046
2008	0.809	0.108	0.083	0.894	0.061	0.046
2009	0.801	0.109	0.090	0.884	0.067	0.049
2010	0.805	0.107	0.088	0.898	0.059	0.044
2011	0.809	0.110	0.081	0.889	0.069	0.042
2012	0.818	0.105	0.077	0.897	0.063	0.040
2013	0.820	0.103	0.077	0.899	0.065	0.035
2014	0.819	0.108	0.073	0.902	0.063	0.035
2015	0.817	0.107	0.075	0.903	0.059	0.037
2016	0.827	0.100	0.073	0.898	0.068	0.034

Note: The estimates reported are weighted annual person observations of the entire HILDA Survey employed sample, i.e., individuals who report being in at least one job at the time of the interview. This includes individuals whose main job is part-time. Estimates are weighted by the responding population weight. This is calculated from the household weight, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24).

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 5-2: OVERALL JOB SATISFACTION

Overall job satisfaction mean (0-10)	Male				Female			
	Wage Emp.	Solo SE.	Employ.	LR	Wage Emp.	Solo SE.	Employ.	LR
2001	7.403	7.734	7.687	18.60***	7.740	7.896	7.989	4.31
2002	7.499	7.665	7.783	9.30***	7.635	7.867	7.993	8.99**
2003	7.483	7.562	7.665	3.42	7.696	8.190	7.879	17.63***
2004	7.448	7.652	7.564	6.94**	7.649	7.948	7.892	9.89***
2005	7.522	7.392	7.617	3.57	7.666	7.835	8.171	18.72***
2006	7.434	7.371	7.522	1.35	7.645	7.687	8.085	12.66***
2007	7.523	7.567	7.758	7.18**	7.688	7.957	8.133	16.03***
2008	7.568	7.509	7.728	3.50	7.711	8.039	8.183	22.38***
2009	7.519	7.594	7.806	11.03***	7.609	7.809	7.732	3.74
2010	7.512	7.416	7.532	1.44	7.592	7.943	7.951	16.18***
2011	7.512	7.426	7.766	10.72***	7.634	7.871	7.907	10.45***
2012	7.542	7.376	7.812	17.37***	7.646	7.932	8.169	28.93***
2013	7.503	7.432	7.957	33.83***	7.607	7.964	8.204	46.93***
2014	7.532	7.454	7.863	16.10***	7.625	7.748	8.320	28.04***
2015	7.505	7.385	7.695	8.71**	7.636	7.976	7.871	16.95***
2016	7.548	7.610	7.901	19.82***	7.637	7.823	7.840	6.23**

Note: All magnitudes are weighted population average estimates of the entire HILDA Survey employed sample, i.e., individuals who report being in at least one job at the time of the interview. This includes individuals whose main job is part-time. Estimates are weighted by the responding population weight. This is calculated from the household weight, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24). The null hypothesis is that the reported job satisfaction scores in wage/salary employment, solo self-employment or employership are equal. Likelihood ratio (LR) tests for the equality of job satisfaction scores among the employed groups (for each gender) were conducted. Significance of the LR test statistics are represented by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 5-3: JOB SATISFACTION DIFFERENCES BETWEEN WAGE/SALARY
EMPLOYMENT AND EMPLOYERSHIP

Year	Male		Female	
	Employer – Wage Satisfaction	LR	Employer – Wage Satisfaction	LR
2001	0.284***	7.46	0.249*	3.16
2002	0.284***	7.11	0.358**	6.94
2003	0.182*	2.92	0.183	1.54
2004	0.116	1.31	0.243*	3.39
2005	0.095	0.99	0.505***	17.33
2006	0.088	0.80	0.440***	12.55
2007	0.235***	7.07	0.445***	10.23
2008	0.160	2.68	0.472***	15.85
2009	0.287***	10.62	0.123	0.87
2010	0.020	0.05	0.359***	7.19
2011	0.254***	8.82	0.273**	5.31
2012	0.270***	12.47	0.523***	20.50
2013	0.454***	32.00	0.597***	34.66
2014	0.331***	14.38	0.695***	27.05
2015	0.190**	5.50	0.235*	3.53
2016	0.353***	19.45	0.203	1.96

Note: All magnitudes are weighted population average estimates of the entire HILDA Survey employed sample, i.e., individuals who report being in at least one job at the time of the interview. This includes individuals whose main job is part-time. Estimates are weighted by the responding population weight. This is calculated from the household weight, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24). The null hypothesis is that the reported job satisfaction differences between wage/salary employment and employership are zero. Likelihood ratio (LR) tests for the equality of job satisfaction scores among the employed groups (for each gender) were conducted. Significance of the LR test statistics are represented by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

Table 5-2 presents population-weighted annual cross-sectional estimates of mean overall job satisfaction by employment type and sex. While estimates fluctuate from year to year, employers appear to be more satisfied with their jobs than solo self-employed workers and wage/salary employees. However, the mean difference between employers and solo self-employed workers is smaller than that between employers and wage/salary workers. The table also suggests male and female solo self-employed workers are more satisfied than wage/salary employees. This contradicts **H8** and suggests that the average solo self-employed worker prefer being self-employed than being in wage/salary employment

Table 5-3 presents population-weighted annual differences in reported job satisfaction between employers and the wage/salary employees. Using the likelihood ratio

(LR) test, I find the job satisfaction differences to be statistically significant in select periods. In addition, I note that there isn't a clear increasing or decreasing trend in job satisfaction differences for employed males or females. Nevertheless, during the years of 2013, 2014, and 2016, the differences between male employership and wage/salary job satisfaction are larger than the difference observed in 2001. For women, the job satisfaction differences observed during the years 2005 – 2008 and 2012 – 2015 are larger than the differences observed during the years 2001 and 2002. Given the context of declining employership rates, the fact that employers are reporting higher job satisfaction scores than their wage/salary counterparts in years after 2001 suggests there are potential barriers hindering entry into employership and that it is increasing.

Table 5-4 provides the pooled job satisfaction distribution, by employment type, and shows job satisfaction responses concentrating around the upper end of the 0-10 scale. Male and female self-employed workers are more likely to respond with a score of 8 or higher than wage/salary employees – employees are more prone to report a score of 0 to 7 than either solo self-employed workers or employers. It is rare for any individual to be 'Totally dissatisfied' with their job.

TABLE 5-4: DISTRIBUTION OF OVERALL JOB SATISFACTION RESPONSES

Overall job satisfaction (0-10)	Male			Female		
	Wage Emp.	Solo SE.	Employer	Wage Emp.	Solo SE.	Employer
0	0.003	0.003	0.002	0.003	0.002	0.004
1	0.005	0.004	0.004	0.005	0.003	0.001
2	0.009	0.012	0.007	0.008	0.007	0.003
3	0.016	0.015	0.014	0.013	0.013	0.009
4	0.023	0.022	0.020	0.019	0.015	0.015
5	0.059	0.067	0.055	0.057	0.059	0.055
6	0.083	0.086	0.067	0.081	0.058	0.053
7	0.220	0.208	0.178	0.196	0.159	0.145
8	0.315	0.311	0.324	0.304	0.300	0.307
9	0.184	0.173	0.224	0.208	0.220	0.221
10	0.083	0.100	0.105	0.107	0.166	0.187

Note: All magnitudes are weighted population average estimates of the entire HILDA Survey employed sample, i.e., individuals who report being in at least one job at the time of the interview. This includes individuals whose main job is part-time. Estimates are weighted by the responding population weight. This is calculated from the household weight, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24).

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 5-5: SATISFACTION WITH DIFFERENT ASPECTS OF MAIN JOB

	Male				Female			
	Wage Emp.	Solo SE.	Employer	LR	Wage Emp.	Solo SE.	Employer	LR
The work itself	7.531	7.740	7.938	472.31***	7.587	8.011	7.972	311.16***
Job security	7.823	6.877	7.925	973.48***	7.924	7.291	8.217	344.63***
The hours worked	7.169	6.819	6.609	462.13***	7.313	7.239	7.084	18.90***
Flexibility to balance non-work commitments	7.290	7.755	7.327	374.81***	7.446	8.154	7.930	568.26***
Total pay	7.018	6.246	6.799	816.84***	6.966	6.457	6.884	259.71***

Note: All magnitudes are weighted population average estimates of the entire HILDA Survey employed sample, i.e., individuals who report being in at least one job at the time of the interview. This includes individuals whose main job is part-time. Estimates are weighted by the responding population weight. This is calculated from the household weight, adjusted for person non-response and person-level benchmarks (Summerfield et al. 2017, Section 4.24). Likelihood ratio (LR) tests for the equality of job satisfaction scores among the employed groups (for each gender) were conducted. Significance of the LR test statistics are represented by: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 5-6: MALE SUMMARY STATISTICS

	Wage Emp. Mean/(Std.)	Solo SE. Mean/(Std.)	Employer Mean/(Std.)
Overall job satisfaction (mean on 0-10 scale)	7.525 (1.679)	7.582 (1.693)	7.757 (1.587)
Marital status (0/1)	0.717 (0.450)	0.776 (0.417)	0.878 (0.328)
Impaired (0/1)	0.152 (0.359)	0.217 (0.412)	0.163 (0.369)
Equivalised disposable household income (\$)	60,588.849 (37017.543)	53,973.623 (54786.250)	74,288.088 (68558.796)
<u>Number of dependents (0/1)</u>			
<u>(0-14 years old)</u>			
0	0.643 (0.479)	0.639 (0.480)	0.523 (0.500)
1	0.141 (0.349)	0.138 (0.345)	0.159 (0.366)
2	0.152 (0.359)	0.143 (0.350)	0.205 (0.404)
≥ 3	0.064 (0.245)	0.080 (0.271)	0.113 (0.317)
Weekly working hours	42.013 (11.902)	42.011 (17.244)	51.044 (14.580)
Part-time employed (0/1)	0.124 (0.329)	0.262 (0.440)	0.084 (0.277)
Tenure with current employer or business	6.967 (8.107)	10.363 (10.468)	12.060 (9.723)
<u>Industry sector (0/1)</u>			
Agriculture, forestry and fishing	0.025 (0.156)	0.118 (0.323)	0.103 (0.304)
Goods-producing	0.304 (0.460)	0.383 (0.486)	0.321 (0.467)
Service	0.671 (0.470)	0.499 (0.500)	0.576 (0.494)
<u>Occupation (0/1)</u>			
Managers	0.146 (0.353)	0.198 (0.399)	0.427 (0.495)
Professionals	0.219 (0.414)	0.195 (0.396)	0.208 (0.406)
Tech. & trades workers	0.206 (0.405)	0.328 (0.469)	0.223 (0.416)
Community & personal service workers	0.069 (0.253)	0.036 (0.186)	0.012 (0.108)
Clerical & administrative workers	0.085 (0.280)	0.020 (0.141)	0.017 (0.129)

Sales workers	0.051 (0.220)	0.031 (0.173)	0.026 (0.160)
Machinery operators & drivers	0.121 (0.326)	0.080 (0.271)	0.036 (0.186)
Labourers	0.103 (0.304)	0.113 (0.317)	0.052 (0.221)
Urban area (0/1)	0.899 (0.301)	0.757 (0.429)	0.787 (0.410)
Regional unemployment (%)	5.276 (1.087)	5.310 (1.096)	5.308 (1.120)
<u>Highest level of education achieved (0/1)</u>			
Year 11 or lower	0.185 (0.388)	0.226 (0.418)	0.175 (0.380)
Year 12	0.151 (0.359)	0.107 (0.309)	0.119 (0.324)
Certificate	0.295 (0.456)	0.375 (0.484)	0.322 (0.467)
Diploma	0.093 (0.291)	0.098 (0.298)	0.102 (0.302)
Bachelor's degree or higher	0.275 (0.446)	0.194 (0.396)	0.282 (0.450)
Only one job	0.070 (0.255)	0.076 (0.264)	0.068 (0.251)
<u>Age (0/1)</u>			
21-25 years old	0.147 (0.354)	0.050 (0.218)	0.023 (0.150)
26-30 years old	0.141 (0.348)	0.080 (0.271)	0.063 (0.243)
31-35 years old	0.132 (0.339)	0.093 (0.291)	0.094 (0.292)
36-40 years old	0.129 (0.335)	0.124 (0.329)	0.125 (0.331)
41-45 years old	0.128 (0.334)	0.139 (0.346)	0.178 (0.383)
46-50 years old	0.117 (0.322)	0.149 (0.356)	0.184 (0.388)
51-55 years old	0.101 (0.302)	0.141 (0.348)	0.156 (0.363)
≥ 56 years old	0.104 (0.306)	0.224 (0.417)	0.177 (0.382)
No. of individuals	8,412	1,099	694
No. of observations	53,556	7,885	5,830

Note: The above statistics are derived from a pooled and unbalanced panel sample comprising 21-64 years old females from years 2002 to 2016 of the HILDA Survey. I report standard deviations of the means in parentheses.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 5-7: FEMALE SUMMARY STATISTICS

	Wage Emp. Mean/(Std.)	Solo SE. Mean/(Std.)	Employer Mean/(Std.)
Overall job satisfaction (mean on 0-10 scale)	7.679 (1.688)	7.929 (1.671)	8.009 (1.647)
Marital status (0/1)	0.682 (0.466)	0.797 (0.403)	0.907 (0.291)
Impaired (0/1)	0.160 (0.367)	0.207 (0.405)	0.146 (0.353)
Equivalised disposable household income (\$)	61,273.075 (39442.255)	58,090.609 (53243.412)	71,235.892 (63619.369)
<u>Number of dependents (0/1)</u>			
<u>(0-14 years old)</u>			
0	0.653 (0.476)	0.587 (0.492)	0.527 (0.499)
1	0.157 (0.363)	0.147 (0.354)	0.157 (0.364)
2	0.141 (0.348)	0.179 (0.383)	0.191 (0.393)
≥ 3	0.049 (0.217)	0.087 (0.282)	0.125 (0.331)
Weekly working hours	32.080 (13.009)	27.621 (17.685)	34.588 (19.089)
Part-time employed (0/1)	0.461 (0.498)	0.636 (0.481)	0.463 (0.499)
Tenure with current employer or business	6.277 (7.150)	7.727 (8.493)	10.174 (8.863)
<u>Industry sector (0/1)</u>			
Agriculture, forestry and fishing	0.008 (0.089)	0.090 (0.286)	0.105 (0.307)
Goods-producing	0.072 (0.258)	0.089 (0.285)	0.173 (0.378)
Service	0.920 (0.271)	0.821 (0.384)	0.722 (0.448)
<u>Occupation (0/1)</u>			
Managers	0.085 (0.279)	0.176 (0.381)	0.386 (0.487)
Professionals	0.306 (0.461)	0.306 (0.461)	0.167 (0.373)
Tech. & trades workers	0.039 (0.195)	0.074 (0.261)	0.049 (0.216)
Community & personal service workers	0.155 (0.362)	0.142 (0.349)	0.032 (0.177)
Clerical & administrative workers	0.242 (0.428)	0.157 (0.364)	0.298 (0.457)

Sales workers	0.094 (0.292)	0.050 (0.219)	0.028 (0.165)
Machinery operators & drivers	0.011 (0.106)	0.016 (0.125)	0.012 (0.109)
Labourers	0.068 (0.251)	0.079 (0.270)	0.027 (0.162)
Urban area (0/1)	0.896 (0.305)	0.768 (0.422)	0.748 (0.434)
Regional unemployment (%)	5.284 (1.083)	5.291 (1.065)	5.359 (1.137)
<u>Highest level of education achieved (0/1)</u>			
Year 11 or lower	0.204 (0.403)	0.238 (0.426)	0.287 (0.453)
Year 12	0.155 (0.361)	0.103 (0.304)	0.160 (0.366)
Certificate	0.175 (0.380)	0.194 (0.395)	0.143 (0.350)
Diploma	0.110 (0.313)	0.139 (0.346)	0.122 (0.328)
Bachelor's degree or higher	0.356 (0.479)	0.326 (0.469)	0.288 (0.453)
Only one job	0.094 (0.291)	0.119 (0.324)	0.075 (0.263)
<u>Age (0/1)</u>			
21-25 years old	0.144 (0.351)	0.043 (0.203)	0.017 (0.130)
26-30 years old	0.129 (0.336)	0.074 (0.261)	0.057 (0.231)
31-35 years old	0.116 (0.320)	0.108 (0.310)	0.109 (0.311)
36-40 years old	0.123 (0.329)	0.152 (0.359)	0.157 (0.363)
41-45 years old	0.137 (0.343)	0.157 (0.364)	0.174 (0.379)
46-50 years old	0.132 (0.338)	0.144 (0.351)	0.175 (0.380)
51-55 years old	0.113 (0.317)	0.133 (0.340)	0.147 (0.354)
≥ 56 years old	0.106 (0.308)	0.190 (0.392)	0.166 (0.372)
No. of individuals	8,790	658	357
No. of observations	54,082	4,381	2,741

Note: The above statistics are derived from a pooled and unbalanced panel sample comprising 21-64 years old females from years 2002 to 2016 of the HILDA Survey. Standard deviations of the means are reported in parentheses.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

The HILDA Survey also measures the respondent's satisfaction with multiple aspects of their jobs. This includes their satisfaction with the work itself, job security, the hours worked in their job, their flexibility to balance work and non-work commitments and the total pay from their job. These measurements are taken before interviewers questioned respondents on their overall job satisfaction. Table 5-5 presents populated weighted averages of satisfaction scores associated with different aspects of the job, by sex and employment type. Self-employed workers (both employers and solo self-employed workers) are, on average, less satisfied with their total pay than wage/salary employees. Also, I observe both employers and solo self-employed workers being less satisfied, on average, with the hours required to work in their business than wage/salary employees. The average self-employed worker is more satisfied with the work itself and the 'flexibility to balance work and non-work commitments' than the average wage/salary employee. These two elements of satisfaction suggest to us that the self-employed are more satisfied with their job than wage/salary employees because of the greater levels of job independent/autonomy in self-employment. This descriptive fact is consistent with earlier studies proposing self-employment is a source of 'procedural utility'.

The main explanatory variables are a set of dummy variables showing the respondent's employment status in each wave. It includes two dummy variables that equal one if the respondent is an employer and if the respondent is a solo self-employed worker. I treat wage/salary employment as a reference category for this analysis. I also include several individual-specific independent control variables, such as family structure, educational attainment, industry sector, employment characteristics and aggregate market conditions. Aside from job satisfaction, Table 5-6 and Table 5-7 summarise the control variables included in this study's empirical analyses with detailed definitions provided earlier in section 2.2.3. However, age is no longer a continuous variable but is now treated as a categorical variable representing the age group the respondent belongs to (Age groups are displayed in Table 5-6 and Table 5-7).⁹⁰ I drop any observations with missing data on any of their control variables. This leaves a final sample of 128,475 observations (20,010 individuals) to investigate the relationship between overall job satisfaction and employment status.

Table 5-6 presents sample means and standard deviations, by employment type, of male respondents' observable characteristics. The table shows that the average male solo

⁹⁰ Initially, this variable was continuous, but this prevented the ordered logit with fixed effects model from converging.

self-employed worker is voluntarily self-employed as they have longer tenure within their ongoing business than the average wage/salary employee with their current employer. In addition, a substantial proportion of solo self-employed workers treat their business as a part-time job, with the percentage even higher among female solo self-employed workers (although a significant portion of female wage/salary employees and employers are also working part-time). The summary statistics also show that the self-employed are engaged in each of the three main industries groups. There is a considerable presence of self-employed workers in service industries, but the self-employed are more active in “agriculture, forestry and fishing” and “goods-producing industries” than wage/salary employees. Further, Table 5-7 suggests women are more likely to work in service industries than male workers. Unsurprisingly, a higher share of self-employed workers (both solo self-employed workers and employees) are likely to classify themselves as managers than their wage/salary counterparts. In addition, the male and female solo self-employed are more likely to identify themselves as technical and trades workers.

Finally, male employers work 9 hours longer, on average, than wage/salary or solo self-employed workers. In comparison, the average female employer works only 2 hours extra than the average female wage/salary employee. However, female employers work, on average, 7 hours longer than the typical female solo self-employed worker. I observe female solo self-employed workers work the least hours in a week on average, but this is because 63 per cent of them work part-time.

5.5 Empirical Strategy

A key advantage of using the HILDA Survey is its nature as a longitudinal dataset. With corresponding estimators, such data potentially solve the endogeneity problem arising from correlated time-invariant unobserved individual-specific effects. Especially when such effects both influence the individual’s decision to be self-employed and their job satisfaction.

I primarily use ordered logit models with fixed effects to investigate whether employers are more satisfied with their job than solo self-employed workers and wage/salary employees and if solo self-employed workers are less satisfied with their job than wage/salary employees. I begin by specifying a latent variable model of the form:

$$5-1) \quad y_{i,t}^* = \alpha_i + \beta'_E E_{i,t} + \gamma' X_{i,t} + \delta_t + \epsilon_{i,t}, \quad i = 1, \dots, N, \quad t = 1, \dots, T$$

where $y_{i,t}^*$ is a latent variable describing job satisfaction of individual i at time t ; $E_{i,t}$ is a set of two dummy variables identifying if individual i was a solo self-employed worker or an employer at time t ; $X_{i,t}$ is a set of other observable and time-varying individual-specific variables; α_i is an individual-specific parameter capturing their time-invariant and unobserved characteristics; δ_t represents the time/survey fixed effects; and $\epsilon_{i,t}$ is a random error term.

$y_{i,t}^*$ is unobservable but we can observe the individual's reported job satisfaction scores. I relate the discrete and ordinal satisfaction scores to the latent satisfaction variable as follows:

$$y_{i,t} = k \text{ if } \tau_k < y_{i,t}^* < \tau_{k+1}, \quad k = 1, \dots, K$$

where thresholds τ are assumed to be strictly increasing ($\tau_k < \tau_{k+1} \forall k$) with $\tau_1 = -\infty$ and $\tau_{K+1} = \infty$. I also assume that ϵ_{it} is independent and identically distributed with a logistic cumulative distribution function as follows:

$$F(\epsilon_{i,t} | x_{i,t}, \alpha_i) = F(\epsilon_{i,t}) = \frac{1}{1 + \exp(-\epsilon_{i,t})} \equiv \Lambda(\epsilon_{i,t})$$

The probability of observing outcome k for individual i at time t is

$$\begin{aligned} 5-2) \quad Pr(y_{i,t} = k | X_{i,t}, E_{i,t}, \alpha_i, \delta_t) &= \Lambda(\tau_{k+1} - \alpha_i - \beta'_E E_{i,t} - \gamma' X_{i,t} - \delta_t) \\ &\quad - \Lambda(\tau_k - \alpha_i - \beta'_E E_{i,t} - \gamma' X_{i,t} - \delta_t) \end{aligned}$$

where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function.

Baetschmann, Staub, and Winkelmann (2015) highlight two problems with the direct maximum log-likelihood estimation of Equation 5-2. First, the thresholds, τ_k , and the fixed effect parameter, α_i , cannot be identified. Only the difference between the two parameters, $\alpha_{i,k} = \tau_k - \alpha_i$, can be identified. The second issue is when T is relatively small and treated as a constant. With fixed T asymptotics, $\alpha_{i,k}$ cannot be estimated consistently, even as the number of cross-section units increases. This is known as the incidental parameters problem (Neyman and Scott 1948). This problem will lead to biased estimates of $\alpha_{i,k}$, β_E , γ and δ_t , especially in short panels.

One response to these problems is to dichotomise the ordered outcome variable into a binary variable and then applying the Chamberlain estimator for the conditional fixed effects binary logit (Chamberlain 1980). A simple example is Andersson (2008) who classifies employees as having high satisfaction with their jobs if they report being “very satisfied with work”, and all other workers as having low job satisfaction. More formally, let us define a variable $d_{i,t}^k = I(y_{i,t} \geq k)$ where $I(\cdot)$ is the indicator function and k is a cut-off integer between 2 and K . $d_{i,t}^k$ is equal to one if $y_{i,t}$ is greater than or equal to the chosen cut-off value and zero otherwise. The probability of observing a particular sequence of outcomes $d_i^k = (d_{i,1}^k, \dots, d_{i,T}^k)$ conditional on the number of ones in the sequence $g_i = \sum_{t=1}^T j_{i,t}$ is given by:

$$Pr\left(d_i^k = j_i \mid \sum_{t=1}^T d_{i,t}^k = g_i\right) = \frac{\exp(j_i' X_i \beta)}{\sum_{l_i \in B_i} \exp(j_i' X_i \beta)}$$

where $j_i = (j_{i,1}, \dots, j_{i,T})$, $j_{it} \in \{0,1\}$, X_i is a $T \times L$ matrix with t^{th} row equal to $X_{i,t}$, L is the number of regressors (including the solo self-employment and employership status variables), β is a vector containing the coefficients β_E, γ and δ_t and B_i is the set of all possible l_i vectors with the same number of ones as d_i^k , i.e.,

$$B_i = \{j \in \{0,1\}^T \mid \sum_{t=1}^T j_t = g_i\}$$

Chamberlain shows that maximising the conditional log-likelihood $LL^k = \sum_{i=1}^N \log [\Pr(d_i^k = j_i \mid \sum_{t=1}^T d_{i,t}^k = g_i)]$ gives consistent estimates of β_E, γ and δ_t . But a weakness with the Chamberlain estimator is that individuals with constant $d_{i,t}^k$ do not contribute to the likelihood (they are constantly above or below any cut-off we choose). Any choice of a cut-off (k) leads to some observations being discarded.

Alternate estimators attempted to improve on Chamberlain’s method by either using all of the $K - 1$ cut-offs (Das and van Soest 1999) or identifying an ‘optimal’ cut-off for each individual (Ferrer-i-Carbonell and Frijters 2004). They are called the Das and van Soest (DvS), and the Ferrer-i-Carbonell and Frijters (FF) estimators, respectively.⁹¹ The DvS estimator involves using the Chamberlain estimator to estimate Equation 5-2 using

⁹¹ Dickerson, Hole, and Munford (2014) offer a concise summary of the DvS and FF estimators.

all of the $K - 1$ cut-offs and combine the estimates in a second step. The DvS weights the estimates by their variance so that

$$\beta^{DvS} = \arg \min_b (\beta^{2'} - b', \dots, \beta^{K'} - b')^{-1} \Omega^{-1} (\beta^{2'} - b', \dots, \beta^{K'} - b')$$

where Ω^{-1} is an estimate of the variance-covariance matrix of the coefficients and β^{DvS} is a vector of coefficients comprising β_E , γ and δ_t . However, depending on the sample, some cut-off values create tiny estimation samples leading to convergence problems and/or imprecise estimates. In contrast, the FF estimator uses only one cut-off, but each individual will have their own ‘optimal’ cut-off. The optimal cut-off is defined as the value which minimises the individual’s Hessian matrix at an initial estimate of β_E , γ and δ_t . As noted by Baetschmann, Staub, and Winkelmann (2015), the choice of the cut-off is endogenous and the FF estimator risks being inconsistent.

In this chapter, I use the BUC (“blow-up and cluster”) estimator proposed by Baetschmann, Staub, and Winkelmann (2015). The ordered logit fixed effects model is estimated by using all the $K - 1$ cut-offs simultaneously, imposing the restriction that $\beta^2 = \beta^3 = \dots = \beta^K$. As a result, the estimator uses every variation in the ordered dependent variable and is unbiased, even in small samples. In practice, the BUC estimator ‘blows up’ the dataset where each person-year observation is repeated $K - 1$ times, each time applying a different cut-off when collapsing the ordinal dependent variable into a binary one. This increases the effective sample size tenfold. The model is then estimated on this expanded sample using the Chamberlain approach as explained above. The standard errors are adjusted to control for within-person clustering among the observation copies.

A potential flaw with the ordered logit model is the assumption of parallel regression, where the relationship between each pair of outcome groups is the same. For example, the coefficients that describe the relationship between the lowest and higher categories of the ordinal variable are the same as those that describe the relationship between the next lowest category and all higher categories. Because the relation between every pair of category responses is the same, there is only a single set of coefficients (Boes and Winkelmann 2006). Millán et al. (2013) and Hessels et al. (2015) offer evidence that the parallel regression assumption, in the context of job satisfaction and its relationship with self-employment, is violated. They encourage using the generalised ordered logit model

as it relaxes the proportional odds assumption, but the model too has its own weaknesses. The most prominent one being that the model can produce negative predicted probabilities (McCullagh and Nelder 1989, p. 155). Also, any violations of the proportional odds assumption may be caused by heterogeneous error variances and unobserved heterogeneity (Fullerton 2009). Williams (2016) suggests that a choice model that explicitly accounts for this heterogeneity in residual variability can fit the data about as well as the generalised ordered logit model. Given that the BUC estimator controls for individual unobserved heterogeneity with fixed-effects and that its standard errors are adjusted for heteroscedasticity across individuals, I argue that it is appropriate for this chapter's analysis.

Another feature of the ordered logit model is that marginal probabilities change sign exactly once moving stepwise from the first to the last outcome. This is known as the 'single crossing property'. If β is positive, then the marginal probability effects start negative and then become positive. If β is negative, marginal effects start positive and then become negative. This imposes a restriction on marginal effects on the distribution of job satisfaction outcomes by design (Boes and Winkelmann 2006). Nevertheless, the ordered logit model with individual fixed effects is the best model to handle the discrete ordinal nature of the dependent job satisfaction variable while controlling for the individual's unobserved heterogeneity.

Last, as employment characteristics differ considerably between men and women, with a greater proportion of women working part-time and fewer hours than men, I perform separate analyses by gender.

5.6 Results

Table 5-8 presents results from estimating pooled ordered logit, OLS with fixed effects and ordered logit with fixed effects models separately for men and women (Table A5.2.1 offers the estimates of the full model). In a first step, I run pooled ordered logit models, by gender, with control variables accounting for differences between self-employed and wage/salary workers unrelated to pecuniary and non-pecuniary work outcomes. The subsequent results are reported in specifications (1) and (2). The specifications show that male employers are statistically more satisfied with their jobs than wage/salary workers. In contrast, male solo self-employed workers are no more satisfied than their wage/salary counterparts. Among women, however, both employers

and solo self-employed workers are more satisfied with their jobs than wage/salary workers.

A concern with the estimates of specifications (1) and (2) is that they risk reflecting personality differences among the three groups as discussed in Chapter 3 (individuals are employers because of individual-specific preferences). In addition, the pooled ordered logit model requires the parallel regression assumption, but I find evidence that my sample violates this assumption. In a separate exercise, I re-estimated Equation 5-1 without imposing the parallel regression assumption (i.e., I estimated a generalised ordered logit model). I then performed a Wald test, testing whether the coefficients of the variables in the 10 equations are all equal (i.e., the parallel regression holds). I find, for either males or females, the Wald tests reject the null hypothesis of the parallel regression assumption.⁹²

I address these concerns with specifications (3) to (6). Specifications (3) and (4) comprise estimates of an OLS regression with fixed effects for males and females, respectively. Specifications (5) and (6) are the main specifications of interest in this chapter. They comprise estimates of the BUC estimator for males and females, respectively. Despite the difference in treatment of the dependent variable, both approaches find, for either gender, employers or solo self-employed workers are more satisfied than their wage/salary counterparts. The evidence supports **H6**. However, the evidence is insufficient to support **H8**. Both employers and solo self-employed workers are earning supernormal returns (in the form of utility) implying an impediment to entry into the self-employment sector. This further counters any perception of solo self-employed workers being self-employed out of necessity. At least in Australia, solo self-employed workers are choosing to be self-employed.

⁹² The null hypothesis is that the coefficient estimates are jointly equal across 10 equations. The Wald test involves a chi-square test statistic with 711 degrees of freedom. At a significance level of 5 per cent, I reject the null hypothesis of the parallel regression assumption with a test statistic of 4,809.37 for males. For females, the test statistic is 17,323.83.

TABLE 5-8: OVERALL JOB SATISFACTION MODEL AND REGRESSION ESTIMATES

	Without FE Ordered Logit		With FE			
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)
<u>Employment Status (t-1)</u>						
Solo SE	-0.028 (0.044)	0.214*** (0.052)	0.121** (0.038)	0.209*** (0.048)	0.182** (0.057)	0.305*** (0.069)
Employership	0.189*** (0.052)	0.299*** (0.073)	0.155*** (0.043)	0.230*** (0.060)	0.249*** (0.068)	0.360*** (0.092)
Log-Likelihood	-120,976.41	-109,573.18	-107,646.45	-99,746.37	-80,798.18	-75,201.88
Wald chi ²	699.483	1,025.499	-	-	525.714	579.946
Degrees of freedom	79	79	78	78	79	79
Pseudo R ²	0.009	0.014	-	-	0.013	0.015
No. of observations	67,271	61,204	67,271	61,204	222,429	205,613
No. of individuals	10,205	9,805	10,205	9,805	7,717	7,327

Note: The estimation sample comprises all employed persons observed during the waves 2001-2016 of the HILDA survey. Robust standard errors are reported in parentheses. The reference category under 'self-employment status' is persons in paid/salaried employment. All equations include, but not reported, are controls for age (specified as a categorical variable), marital status, impairment, equivalised household income (logged), number of dependent children, hours usually worked in a week (specified as a quadratic), part-time employment status, job tenure, location (urban vs rural), the regional unemployment rate, educational attainment, working in a single or multiple jobs, occupation, industry year and missing income indicators. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 5-9: TESTS OF THE EQUALITY OF COEFFICIENTS

<u>Testing the equality of coefficients</u>			
$H_0: \beta_{\text{solo}} = \beta_{\text{employer}}$			
$H_A: \beta_{\text{solo}} \neq \beta_{\text{employer}}$			
<u>OLS with FE</u>	<i>F</i>	Degrees of freedom	Prob. >F
Specification (3) - Males	0.77	1, 10204	0.3800
Specification (4) - Females	0.13	1, 9804	0.7223
<u>BUC estimator</u>	<i>Chi</i> ²	Degrees of freedom	Prob. >F
Specification (3) - Males	1.07	1	0.3012
Specification (4) - Females	0.35	1	0.5546

Note: Estimates above are sample averages of the predicted probabilities being in solo self-employment or employership in wave t given their employment choice in Wave t-1. These estimates come from Table 5-8.

Source: Author calculations from waves 2001 to 2016 of the HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

However, it is not obvious if the evidence from Table 5-8 supports hypothesis **H7** (employers having a significant job satisfaction lead over solo self-employed workers). Although the employer coefficient estimates in specifications (3) to (6) are larger than the ones for solo self-employment, the differences appear to be small. In response, I test for the equality between the employer and the solo self-employment coefficients, by estimation method and gender. My null hypothesis states there is equality between the two coefficient estimates. Overall, the empirical estimates from Table 5-8 are consistent with self-employed workers earning supernormal returns.

The estimates from Table 5-9 suggest we do not reject the null hypothesis. There is insufficient evidence to support **H7**. Instead, employers and solo self-employed workers are similarly satisfied with their job. This holds for both men and women. By rejecting **H7**, I propose individuals, given they overcame entry barriers, are self-selecting themselves into solo self-employment or employership. It is more evidence against the idea that a significant portion of solo self-employed workers are necessity entrepreneurs. My findings are similar to Hessels, Millán, and Román (2015) who reported that self-employed workers were more satisfied than wage/salary employees but, after controlling for fixed-effects, the solo self-employed will not be more satisfied if they transition into employership.

However, my results contradict Taylor's (2004) findings as Taylor finds that employers have significantly higher job satisfaction than the solo self-employed. A likely explanation is Taylor's use of an ordered probit model with Mundlak's (1978) restriction. Taylor's specification is such that:

$$y_{it}^* = X'_{it}\gamma + \bar{X}'_{i,t}a_2 + \eta_i + w_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T$$

where y_{it}^* is the latent job satisfaction variable, X'_{it} is a vector of individual's characteristics, η_i represents the individual-specific and time-invariant unobserved individual-specific effect and w_{it} represents the random error. The issue with the Mundlak restriction is that it strongly assumes that the individual-specific effect is equally correlated with all time-period X'_{it} . In contrast, the ordered logit model with individual fixed effects avoids making such an assumption by allowing the possibility of correlations between X'_{it} and the individual's unobserved heterogeneity.

A concern with the estimates of specifications (5) and (6) is that we cannot interpret them as marginal effects. They represent changes in the log odds of reporting a higher level of job satisfaction. For example, in specification (5), male employers can expect a 0.249 increase in their log odds of being in a higher level of job satisfaction, *ceteris paribus*. An advantage of using an OLS regression with fixed-effects is that marginal effects are more easily assessed. Specification (3) from Table 5-8 suggests being an employer increases the male job satisfaction score by 0.155 relative to wage/salary employment. Specification (4) shows that being an employer increases female job satisfaction by 0.230. In addition, being solo self-employed increases the individual's job satisfaction score from 0.121 (for males) to 0.209 (for females).

To better quantify the relative causal effect of solo self-employment and employership on job satisfaction from specifications (5) and (6), I examined how a change in self-employment status affects the distribution of the outcome variable (all the outcome possibilities). For each job satisfaction score, I calculate the difference in probabilities before and after a shift in the individual's employership or solo self-employment status:

$$\Delta \Pr[y = j | X'_{it}, E'_{it}] = \Pr[y = j | X'_{it}, \Delta E'_{it}] - \Pr[y = j | X'_{it}, E'_{it}]$$

where j indexes the category of the job satisfaction variable y , X'_{it} represents the individual i vector of observable characteristics, E'_{it} represents the individual's employment status (if they were solo self-employed, an employer or in wage/salary employment) at year t , and $\Delta E'_{it}$ illustrates the change in the employer or solo self-employed dummy variable. The magnitudes of these marginal probabilities depend on

specific values of the individual's covariates. I estimate marginal effects of reporting a job satisfaction score, j , at the sample average of the dependent variable with the form:⁹³

$$\{P(y = j)[1 - P(y = j)] - P(y = j - 1)[1 - P(y = j - 1)]\} * \hat{\beta}$$

where j describes the level of “overall job satisfaction” and $P(y = j)$ is replaced by the relative sample frequencies of individuals reporting j instead of all other scores. Table 5-10 presents the marginal effects of being an employer or solo self-employed, instead of being a wage/salary employee, on job satisfaction by gender.

TABLE 5-10: MARGINAL EFFECTS OF BEING SELF-EMPLOYED ON OVERALL JOB SATISFACTION

	Men		Female	
	Solo SE.	Employer	Solo SE.	Employer
P(JS=0)	-0.00050*** (0.00016)	-0.00069*** (0.00019)	-0.00088*** (0.00020)	-0.00103*** (0.00027)
P(JS=1)	-0.00076*** (0.00024)	-0.00105*** (0.00029)	-0.00122*** (0.00028)	-0.00144*** (0.00037)
P(JS=2)	-0.00155*** (0.00048)	-0.00212*** (0.00058)	-0.00228*** (0.00052)	-0.00270*** (0.00069)
P(JS=3)	-0.00261*** (0.00081)	-0.00357*** (0.00098)	-0.00365*** (0.00083)	-0.00431*** (0.00111)
P(JS=4)	-0.00369*** (0.00115)	-0.00507*** (0.00139)	-0.00506*** (0.00114)	-0.00597*** (0.00153)
P(JS=5)	-0.00870*** (0.00271)	-0.01192*** (0.00326)	-0.01447*** (0.00328)	-0.01709*** (0.00438)
P(JS=6)	-0.01040*** (0.00324)	-0.01426*** (0.00390)	-0.01689*** (0.00382)	-0.01994*** (0.00511)
P(JS=7)	-0.01573*** (0.00490)	-0.02157*** (0.00591)	-0.02644*** (0.00599)	-0.03122*** (0.00800)
P(JS=8)	0.00806*** (0.00251)	0.01106*** (0.00303)	0.00422*** (0.00096)	0.00498*** (0.00128)
P(JS=9)	0.02304*** (0.00717)	0.03160*** (0.00865)	0.03769*** (0.00853)	0.04450*** (0.01141)
P(JS=10)	0.01283*** (0.00399)	0.01759*** (0.00482)	0.02899*** (0.00656)	0.03422*** (0.00877)

Note: The magnitudes above represent the marginal effects of being a solo self-employed worker or an employer on the probabilities of reporting a job score. Marginal effects are derived from estimates in specifications (5) and (6) Table 5-10.

Source: Author calculations from waves 2001 to 2016 of the HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

⁹³ I offer my thanks to Professor Kevin E. Staub for responding and assisting with my inquiries on deriving marginal effects from the BUC estimator. I derived marginal effects from an ado file provided by Professor Staub.

As explained earlier, the results exhibit the ‘single crossing’ property. Being self-employed, either as an employer or as a solo self-employed worker, has a negative influence on reporting scores lower than 8. However, self-employment has a significant and positive effect on reporting scores 8 and above relative to wage/salary employment. For men, solo self-employment and employership significantly strengthen the probability of ‘being satisfied’ – reporting a job satisfaction score of 8 or higher – by 4.44 percentage points ($P(JS \geq 8) = 0.0815 + 0.02329 + 0.01297$) and 6.48 percentage points, respectively. For females, either solo self-employment and employership are expected to increase their probability of ‘being satisfied’ by 7.32 and 8.82 percentage points, respectively.

Although we observe solo self-employed workers are better satisfied than wage/salary employees, it doesn’t imply that everyone entered self-employment voluntarily. In fact, an individual may have entered solo self-employment out of necessity, only to have higher job satisfaction because of the greater levels of work autonomy associated with self-employment. I further investigate if the average solo self-employed entered self-employment voluntarily or out of necessity. If the solo self-employed are self-employed out of necessity, then it stands to reason to expect them to have fewer employment opportunities than their wage/salary counterparts. Thus, the solo self-employed will be less satisfied with employment opportunities than wage/salary employees. Similar to job satisfaction, the HILDA Survey records self-reported measures of the respondent’s satisfaction with their employment opportunities with an 11-point scale ordinal variable. This variable records responses to the question “How satisfied or dissatisfied you are with your employment opportunities” and responses range from 0 (Individuals totally dissatisfied with their employment opportunities) to 10 (Individuals totally satisfied with their employment opportunities). I re-estimate Equation 5-1 by replacing the dependent variable with the individual’s self-reported satisfaction with their employment opportunities. The subsequent results are presented in specifications (1) and (2) of Table 5-11. Solo self-employed workers are no more or less satisfied with their employment opportunities than wage/salary workers. There is insufficient evidence to suggest that individuals are solo self-employed out of necessity. In fact, the evidence suggests that the number of solo self-employed individuals is not large enough.

TABLE 5-11: SATISFACTION WITH EMPLOYMENT OPPORTUNITIES AND LIFE

	Satisfaction with employment opp.		Satisfaction with free time		Satisfaction with health	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)
<u>Employment Status (t-1)</u>						
Solo SE	0.005 (0.055)	0.029 (0.066)	0.293*** (0.051)	0.239*** (0.062)	-0.043 (0.049)	0.187*** (0.060)
Employership	0.300*** (0.068)	0.240*** (0.090)	0.148** (0.063)	0.030 (0.081)	-0.019 (0.062)	-0.011 (0.086)
Log-Likelihood	-86,501.77	-80,163.20	-107,648.88	-104,879.11	-66,539.65	-63,072.30
Wald chi ²	944.063	858.991	2,320.684	1,765.401	1,365.406	1,493.271
Degrees of freedom	79	79	79	79	79	79
Pseudo R ²	0.024	0.022	0.069	0.053	0.039	0.041
No. of observations	234,790	217,388	300401	284665	184745	175269
No. of individuals	7,616	7,339	7,879	7,546	7,546	7,295

Note: The estimation sample comprises all employed persons observed during the waves 2001-2016. Robust standard errors are reported in parentheses. The reference category under 'self-employment status' is persons in paid/salaried employment. All equations include, but not reported, are controls for age (specified as a categorical variable), marital status, impairment, equivalised household income (logged), number of dependent children, hours usually worked in a week (specified as a quadratic), part-time employment status, job tenure, location (urban vs rural), the regional unemployment rate, educational attainment, working in a single or multiple jobs, occupation, industry year and missing income indicators. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

The results so far suggest self-employed workers enjoy higher job satisfaction than wage/salary employees but perhaps the differences in job satisfaction do not represent barriers preventing entry into self-employment. Instead, the self-employment job satisfaction premium is compensation for a loss in quality of life by being self-employed. Earlier studies associate self-employment with a variety of stressors including high workload and work intensity (Stephan 2018). Compared to other occupations, working conditions in self-employment are more intense, uncertain and complicated. Further, according to Table 5-6 and Table 5-7, employers work greater hours in a week, on average, than wage/salary employees, potentially resulting in work-family conflict (Parker 2009) and less free time. It has also been hypothesised that self-employment is more mentally straining than wage/salary jobs and could lead to lower health outcomes for the self-employed (Andersson 2008). This leads to another hypothesis to test,

H8A: Self-employed workers (in employership or solo self-employment) are less satisfied, overall, with the amount of free time they have and their health.

H8A suggests employers and solo self-employed workers have a job satisfaction premium over wage/salary employees because it is compensation for the loss in life quality brought about by being self-employed. If being self-employed has an adverse impact on the individual's health or the amount of free time they have, then there needs to be an incentive to be self-employed such as the ability to work independently. I investigate this line of thought by re-estimating Equation 5-1 with two different life satisfaction dependent variables. The first variable is an 11-point scale ordinal variable asking respondents "How satisfied or dissatisfied you are with the amount of free time you have?" and the second asks, "How satisfied or dissatisfied you are with your health?"

Specifications (3) and (4) of Table 5-11 present the effects of being an employer or a solo self-employed worker on the respondent's satisfaction with the amount of free time they have for males and females, respectively. Specifications (5) and (6) present the effects of employership or solo self-employment on the respondent's satisfaction with their health for males and females, respectively. We see that employership or solo self-employment have no adverse impacts on either of the life satisfaction variables. Instead, I have evidence suggesting that solo self-employed workers have significantly greater satisfaction than wage/salary employees with the amount of free time they have. In addition, solo self-employed women report having significantly higher health satisfaction than their wage/salary counterparts. With insufficient evidence supporting **H8A**, I

conclude by stating that the job satisfaction advantage, observed among self-employed workers, likely represents entry barriers to self-employment.

Overall, this chapter's analyses of reported satisfaction show the self-employed enjoy higher levels of job satisfaction and prompts the question of "why aren't more people entering self-employment?". There are additional benefits to promote individual entry into self-employment aside from job creation. As more individuals become self-employed, considerable welfare improvements can come about by encouraging individuals to be self-employed and thus increasing their job satisfaction level. The welfare effect is even stronger if increased satisfaction translates into productivity increases (Halkos and Bousinakis 2010). There is scope for policymakers to improve economic efficiency by minimising entry barriers into self-employment.

While I find evidence of entry barriers existing, it is not clear what these obstacles are or how large they can be. These questions are out of scope for this thesis, but earlier studies have uncovered several hurdles to self-employment entry. The most straightforward barrier is that starting up a business requires considerable investment. Empirical evidence suggests a positive relationship between access to wealth, capital or finance and the self-employment participation decision. Individuals are prevented from entering self-employment because of liquidity constraints (Evans and Leighton 1989; Lindh and Ohlsson 1996; Blanchflower and Oswald 1998; Taylor 2001; Disney and Gathergood 2009; Fairlie and Krashinsky 2012).

Entry barriers can likewise be institutional. Chowdhury, Terjesen, and Audretsch (2015) find the tax and regulatory burden to be a significant negative influence on firm start-up rates, a finding consistent with the Productivity Commission (2015) report about restrictions to new business entries. According to a survey by the Australian Chamber of Commerce and Industry (ACCI 2015), 53.3 per cent of surveyed businesses (65.5 per cent of sampled businesses hired less than 20 employees) spent over AU\$ 10,000 in regulatory compliance costs. This was a 6.4 per cent increase from the ACCI 2013 survey. The ACCI 2015 survey also showed that 73 per cent of surveyed businesses perceived an increase in regulatory burden over the previous 12 months. This suggests that regulatory entry barriers are increasing for employers. An approach to streamlining the regulatory process of entering self-employment can have substantial effects on reducing the observed self-employment shortage.

Entry obstacles are also skill-based. As Lazear (2004, p. 208) highlighted, the self-employed "although they need not be an expert in any single skill, they must be

sufficiently good at a wide variety to makes sure that the business does not fail.” Thus, rapid changes in technology introduce additional skill sets that the self-employed must be proficient in order to succeed. Policymakers offering training programmes to equip prospective self-employed workers with the skills (such as general cognitive skills) needed to survive in self-employment can remedy the self-employment shortage. The GEM revealed Australian school-aged entrepreneurial education lags behind the global average and suggests it to be a contributing factor to lower youth self-employment rates in Australia (GEM 2015).⁹⁴

I undertook my analysis on the assumption that all individuals were risk neutral. However, it is possible there is a significant portion of working individuals who are risk-averse. Even without entry barriers, expected utility between employership, solo self-employment and wage/salary employment will never be, on average, equal. Risk-averse individuals prefer the certain outcome of wage/salary employment than the uncertainty that is self-employment. Empirical evidence supports this view as given other things held constant, risk-aversion has a negative relationship with the decision to be self-employed (Caliendo, Fossen, and Kritikos 2009; Macko and Tyszka 2009; Brown et al. 2011). According to a GEM report that, when compared to the rest of the world, a higher proportion of Australians (with entrepreneurial opportunities) have a “fear of business failure”. The latest 2016/2017 report shows 42.9 per cent of surveyed Australians with entrepreneurial opportunities do not enter self-employment because of their fear of failure. In contrast, the average of other developed economies is 39.8 per cent (Steffans and Omarova 2018).⁹⁵ Using data from the GEM and the Global Leadership and Organizational Behavior Effectiveness study for 42 countries, Wennberg, Pathak, and Autio (2013) show that fear of failure has a negative effect on self-employment entry.

Another explanation is increasing globalisation and the Australian self-employment isolation from international markets. Steffans and Omarova (2018) find less than 15 per cent of Australian self-employed workers aim for a substantial share of revenue (over 25 per cent of revenue that comes from international clients), compared to the global average of 25 per cent. The average proportion of the Australian self-employed ignoring revenue from potential customers outside the domestic market is larger than the international average.

⁹⁴ The GEM defines youth entrepreneurship as the entrepreneurial rate among the 18-24 years old age group.

⁹⁵ The GEM classifies the following economies as ‘developed’: Japan, Italy, Germany, France, Belgium Denmark, Spain, Finland, Norway, Slovenia, Ireland, Sweden, Switzerland, Luxembourg, Greece, Taiwan, Austria, Estonia, Netherlands, Portugal, Puerto Rico, United Kingdom, Slovakia, Singapore, Canada, Australia, United States, Trinidad and Tobago, Qatar.

It is unclear if these barriers are economically meaningful. Evidence from the OLS with fixed effects model (see specifications (3) and (4) of Table 5-8) suggests being an employer or solo self-employed will increase an individual's job satisfaction score by less than 1 score. This is hard to quantify in terms of a shortage, i.e., how many people are being prevented from being self-employed. Marginal effects from the ordered logit with fixed effects model show being a solo self-employed worker or an employer increases the probability of 'being satisfied' by 4.44 to 8.82 percentage points. While significant, the marginal effects tell us nothing about the magnitude of the self-employment shortage in the Australian economy. We require further research to understand the scale of these obstacles.

5.7 Robustness

As described earlier in this thesis, a common deficiency of longitudinal household data is the gradual erosion of response, i.e., attrition. Further, my sample suffers from sample selection in the form of individuals becoming unemployed or leaving the labour force altogether. Following previous analyses of subjective well-being and job satisfaction measures using HILDA survey data (Wooden and Li 2014; Buddelmeyer, McVicar, and Wooden 2015), I change Equation 5-1 as follows,

$$5-3) y_{i,t}^* = \alpha_i + \beta'_E E_{i,t} + \gamma' X_{i,t} + \delta_t + s_{i,t+1} + a_{i,t+1} + \epsilon_{i,t}, \quad i = 1, \dots, N, \quad t = 1, \dots, T$$

$s_{i,t+1}$ is a dummy variable that equals one if the individual becomes non-employed next year $t + 1$. $a_{i,t+1}$ equals to one if the individual left the HILDA survey during the next wave. This approach is similar to the one taken in Chapter 3 to address the endogenous sample attrition problem. Respondents leave the sample when they stop co-operating with the HILDA Survey, become unemployed or leave the labour force. Since constructing $s_{i,t+1}$ and $a_{i,t+1}$ requires observations in Wave $t + 1$, I will lose one wave of data, comprising 9,544 observations. I estimate Equation 5-3 using an OLS with fixed effects model, and an ordered logit with fixed effects model with the BUC estimator. The results are presented within specifications (1) and (2) of Table 5-12. Although the magnitudes of the solo self-employed and employer coefficients differ slightly from the estimates within Table 5-8, including the selection variable makes little qualitative difference to our results. Employers and solo self-employed workers are still more

satisfied with their job than wage/salary employees. In addition, Table 5-13 shows employers are as satisfied as solo self-employed workers.

Another issue with the sample is that some self-employed workers are part of a family business and their role in it may be minor. It is possible their family members handle most of the day-to-day activities and the respondent is enjoying the outcomes while exerting minimal effort. This can cause an upward bias in the estimates of either the solo self-employed and/or employership coefficients (because of the minimal disutility of work). I cannot identify (and control for) how active they are in managing the business relative to their partners. As a workaround, I drop married self-employed workers who have not worked in their own businesses/farm during the financial year and/or reportedly work 0 hours a week.⁹⁶ This leads to an additional loss of 910 observations. I re-estimated Equation 5-3 with the restricted sample and present the subsequent results in specifications (3) and (4) of Table 5-12. As before, dropping these individuals did little to change my conclusions. Employers and solo self-employed workers still enjoy a significant job satisfaction advantage over their wage/salary counterparts. Table 5-13 further shows there is no qualitative difference in reported job satisfaction scores between employers or solo self-employed workers.

Last, I also drop 3,724 observations (comprising 996 individuals) working in ‘Agriculture, Forestry & Fishing’ (agriculture) industries. Again, dropping workers from industries that are structurally different from the rest of the economy made limited qualitative differences according to specifications (5) and (6) of Table 5-12 and Table 5-13.

⁹⁶ I also drop observations that refuse to state or don't know if they are not working on their own.

TABLE 5-12: OVERALL JOB SATISFACTION & ORDERED LOGIT ESTIMATES WITH SELECTION

	Full sample		Restricted sample		Restricted sample (No agriculture)	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)
<u>Employment Status (t-1)</u>						
Solo SE	0.170*** (0.059)	0.295*** (0.072)	0.182*** (0.061)	0.299*** (0.075)	0.201*** (0.063)	0.306*** (0.077)
Employership	0.224*** (0.070)	0.369*** (0.094)	0.226*** (0.072)	0.356*** (0.097)	0.228*** (0.077)	0.329*** (0.102)
Non-employed in wave t+1	-0.350*** (0.053)	-0.343*** (0.041)	-0.363*** (0.053)	-0.350*** (0.041)	-0.377*** (0.054)	-0.352*** (0.041)
Attrition in wave t+1	-0.121*** (0.066)	-0.104** (0.061)	-0.127*** (0.044)	-0.101** (0.047)	-0.124*** (0.045)	-0.096** (0.048)
Log-Likelihood	-73,890.49	-68,227.12	-72,864.99	-67,647.85	-69,123.69	-66,251.29
Wald chi ²	512.662	609.179	513.621	609.221	481.543	605.870
Degrees of freedom	80	80	80	80	79	79
Pseudo R ²	0.014	0.017	0.014	0.017	0.014	0.017
No. of observations	202,996	186,366	200,150	184,810	189,743	181,049
No. of individuals	7,425	7,018	7,396	7,000	7,136	6,896

Note: The estimation sample comprises all employed persons observed during the waves 2001-2015. Robust standard errors are reported in parentheses. The reference category under 'self-employment status' is wage/salary employment. All equations include, but not reported, are controls for age (specified as a categorical variable), marital status, impairment, equivalised household income (logged), number of dependent children, hours usually worked in a week (specified as a quadratic), part-time employment status, job tenure, location (urban vs rural), the regional unemployment rate, educational attainment, working in a single or multiple jobs, occupation, industry year and missing income indicators. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: Waves 2001 to 2015 of the HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE 5-13: TESTS OF THE EQUALITY OF COEFFICIENTS - ROBUSTNESS

<u>Testing the equality of coefficients</u>			
$H_0: \beta_{\text{solo}} = \beta_{\text{employer}}$			
$H_A: \beta_{\text{solo}} \neq \beta_{\text{employer}}$			
<u>BUC estimator with selection</u>	Chi^2	Degrees of freedom	Prob. >F
Specification (3) - Males	0.63	1	0.4260
Specification (4) - Females	0.59	1	0.4421
<u>BUC estimator with selection and restricted sample</u>	Chi^2	Degrees of freedom	Prob. >F
Specification (3) - Males	0.40	1	0.5255
Specification (4) - Females	0.34	1	0.5605
<u>BUC estimator with selection and restricted sample (No agriculture)</u>	Chi^2	Degrees of freedom	Prob. >F
Specification (5) - Males	0.14	1	0.7132
Specification (6) - Females	0.04	1	0.8323

Note: The above statistics are derived by using estimates from Table 5-12

Source: Waves 2001 to 2015 of the HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

5.8 Conclusion

This chapter makes several important contributions to the literature regarding the effects of self-employment on job satisfaction. First, I separate employers from solo self-employed workers which only a few studies have done.

Second, I show that one of the key findings from earlier studies – the association of self-employment with higher levels of job satisfaction – holds in the Australian labour market. I discover both employers and the solo self-employed are significantly more satisfied with their jobs than wage/salary employees. The estimates are ‘are consistent with self-employed workers earning supernormal returns. This finding, combined with the observed decline in self-employment rates, suggests there are barriers obstructing individuals from entering the self-employment sector. I discussed that these barriers are a combination of financial, regulatory and psychological barriers. Third, I provide evidence suggesting necessity conditions are not the main motivations of solo self-employed workers. Solo self-employed workers have significantly higher job satisfaction scores than their wage/salary employee counterparts and are as satisfied as employers. Further, I show that the solo self-employed have similar levels of employment opportunities (measured by self-reported satisfaction scores with their employment

opportunities) as their wage/salary counterparts. Fourth, a shortcoming of this strand of literature is the lack of nonlinear methods controlling for unobserved individual heterogeneity when examining the impact of employership or solo self-employment on job satisfaction. This is the first study to use an ordered logit with fixed effects model in the form of the BUC estimator to investigate the relationship between employership/solo self-employment and individual job satisfaction.

I also draw attention to the need for research to reveal the scale and significance of these hurdles. Subsequent research should also explore and measure the benefits of reducing self-employment entry barriers. For employers, a direct benefit is the increase of job creation in the Australian economy and the subsequent increase in economic growth and activity. Further, reduction of entry barriers for the solo self-employed can lead to a larger pool of self-employed workers which is positively correlated with high-growth start-up rates (Steffans and Omarova 2018). In addition, a larger pool of solo self-employed workers will allow established businesses to become more innovative and flexible by outsourcing work to “highly skilled freelancers who provide professional services to existing businesses” (Stel and Vries 2015, p. 78). Also, workers who prioritise work autonomy and freedom are made better off by encouraging their entry into solo self-employment, leading to a potential increase in social welfare. Last, an effort is needed to investigate what are the most effective policies to minimise the barriers of entry into self-employment. At the least, Steffans and Omarova (2018) identified the “fear of failure” and school-aged entrepreneurial education as significant obstacles for self-employment entry.

Conclusion

A common belief among policymakers and academics alike is that self-employment is an engine of economic and job growth. At the time of writing this thesis, self-employment was (and currently is) high on the Australian political agenda as the government is committed to “setting the right environment for small business to grow”. This viewpoint is further supported by GEM reports indicating that Australia is an entrepreneurial country. Yet, the number of studies covering Australian self-employment is limited when compared to those investigating the determinants of self-employment behaviour across the United States, United Kingdom and Europe. Further, there is a limited understanding of the transitional dynamics between solo self-employment and employership, and the skill-based determinants of employership survival. In addition, initial Australian statistics reveal a declining trend in employership and solo self-employment rates. Despite the potential of long-term negative consequences to economic growth and job opportunities, there has yet to be any study that thoroughly explains for this persistent decline. This thesis addresses these gaps in the self-employment literature with three distinct essays and individual-level longitudinal data from the Household, Income, and Labour Dynamics in Australia (HILDA) Survey. The first essay examines if solo self-employment is a stepping-stone into Australian employership, the second studies the skill-based determinants of employership survivability and the third uncovers evidence of Australian self-employment entry barriers by examining the difference in job satisfaction between self-employed workers and wage/salary employees.

The first essay is motivated by initial statistics showing that a minority of the self-employed hire any workers. This is a concern for policymakers seeking to increase job creation rates by stimulating self-employment activity unless the solo self-employed transition into employership at a meaningful rate. Despite this, there is a lack of an understanding of how the solo self-employed evolve over time. Based on an analysis of individual-level data from the HILDA Survey, I find evidence of true cross state and state dependence in employership. Being solo self-employed in one year increases the male or female’s relative probability of employership during the next year by 6 and 2 percentage points, respectively. Also, being an employer, this year, increases the male or female’s relative probability of employership next year by 18 and 8 percentage points, respectively. However, I argue that the extent of true cross state and state dependence in employership

are small when compared to observable rates of transitions into and persistence within employership. In comparison, 11 and 7.6 per cent of male and female solo self-employed workers, respectively, are observed to transition into employership each year. Annually, 75.64 and 69.12 per cent of male and female employers, respectively, remain in employership. While solo self-employment is a stepping-stone into employership, more so than wage/salary employment or non-employment, the empirical evidence suggests that individuals primarily become employers because of their unobserved preferences to be self-employed. In fact, if I assigned employership to an individual's initially observed employment state, the extent of true (cross) state dependence in employership is much higher. True cross state dependence in employership amounts to 20 and 11.6 to 14 percentage points for males and females, respectively. True state dependence amounts to 46 and 34 to 36 percentage points for males and females respectively. As a result, policies promoting entry into self-employment will have short-term and limited effects unless they target someone with an entrepreneurial background or a clear interest to be an employer.

According to the literature, the fact that true state dependence in employership is much smaller than observed annual persistency rates should not be a surprise. In fact, self-employment itself is a volatile employment state and only 50 per cent of employers sampled by the HILDA Survey will survive past their first year in employership. High rates of employership exits represent resources that could have been more efficiently allocated to firms with high-growth potential. Yet, despite being a topic of economic importance, the number of studies investigating self-employment survival is small and the number investigating employership survival is even smaller. There is a significant gap in the literature as the determinants of employership survival should differ from those of solo self-employment survival (Cowling et al. 2004). Further, a study of the determinants of employership survival would have greater implications for net job creation than determinants of solo self-employment survival. In the second essay of this thesis, I propose that the low rate of employership survivability is because of a mismatch between individual expectations and the skills required to be an employer – individuals overestimated their entrepreneurial ability. Prior to this study, most of the self-employment survival literature didn't separate employers from the solo self-employed. Even if they did, they used general measures of work experience that do not explicitly describe the skills/abilities the employers may have gained. These general measures of work experience risk treating years of experience in any occupation as equivalent to one another. Instead, I use measurements from O*NET to reveal the skills/abilities employers

acquired from their employment background and investigate if any of those skills/abilities are accurate proxies of entrepreneurial ability. Using discrete hazard modelling techniques and factor analysis, I show that employers experienced in occupations that consider general cognitive skills as important are more likely to survive in employership. A 10 percentage point increase in the percentile score of the general cognitive skill (of the employer's previous occupation) reduces the employer's hazard rate by 4.26 per cent. Policymakers seeking to stimulate job creation via employership should focus on encouraging individuals with significant experience in occupations where general cognitive skills matter most. However, I notice the determinants of employership survival differ between genders. While general cognitive skill is the main determinant of employership survival for male employers, I find resource management to be a statistically significant and positive determinant of female employership survivability: a 10 percentage point increase in the resource management score significantly decreases female employership hazard rates by about 8.6 per cent. The skill-based determinants of employership survival differ again after I separated goods-producing industries from service-producing ones. A 10 percentage point increase in the resource management score (of the employer's previous occupation) is associated with a significant decline in employership hazard rates by 12.6 per cent within goods-producing industries. In contrast, pattern recognition skills are associated with a decline in both employership hazard rates, but the effect is only statistically significant within service industries – a 10 percentage point increase in the percentile score reduces employership hazard rates within service industries by 4.5 per cent.

This thesis also highlighted the fact that employership rates have been falling over the years 2001 to 2016. By using job satisfaction scores as a proxy for overall returns to employment (i.e., the sum of monetary and non-pecuniary benefits), and the assumption that average returns are equal across all employment states in equilibrium, I find evidence of entry barriers into employership and solo self-employment. Entry barriers are likely rising because of increased regulatory compliance, fear of failure from running a business, changes in technology that require additional skills from the self-employed to succeed. This thesis is the first study to use the BUC estimator to estimate an ordered logit model with fixed effects to explore the relationship between self-reported job satisfaction scores and the individual's employership/solo self-employment status. I find that both employers and the solo self-employed are significantly more satisfied with their jobs than their wage/salary counterparts.

However, I suggested that employers/solo self-employed workers are more satisfied than wage/salary employees because the self-employment job satisfaction premium is compensation for a loss in quality of life by being self-employed. Despite evidence of self-employment having more stressors than wage/salary employment (e.g., adverse impacts on health and free time), I find no evidence that the self-employed have significantly lower life quality than wage/salary employees. In fact, I find the opposite for male and female solo self-employed worker and male employers. Male solo self-employed workers and employers report having significantly higher satisfaction with the amount of free time they have than wage/salary employees. I find female solo self-employed workers have significantly higher satisfaction with their free time and health than their wage/salary counterparts. Thus, the job satisfaction premium should not be seen as compensation for a loss in quality of life, but as evidence for entry barriers into self-employment. Subsequent research should explore what exactly are the barriers preventing individuals from entering self-employment in the Australian labour market and evaluate the potential gains from removing these supposed barriers.

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Appendices

Appendix 1.1: Key definitions, assumptions and limitations of the study

Definition: Employers

An individual who works in their own business with employees.

Definition: Solo self-employment

An individual who works in their own business with no employees.

Empirical Assumption and Limitations

1. Solo self-employment does not necessarily imply that there is only a single person working in the place of business. A solo self-employed worker can include a partner of a firm, owner-managers who hire employees on a short-term temporary basis or owners who us family members without pay. Anyone who owns a business (or part of one) and does not hire long-term employees are solo self-employed.
2. In each period, I assume individuals are working in their reported employment status for the whole period. This assumption is limiting as it is possible for individuals to transition between multiple job types in a year. For example, I assume that a respondent who reports being an employer in wave 2010 is an employer for the whole year. Unfortunately, I do not have a method to track if the individual remains in employership until wave 2011 or changed their employment status multiple times until then.

Appendix 2.1: Adjustments for Inflation

The equation used to convert income to December 2016 prices is as follows:

$$\begin{aligned} Income_{Year} \times & \left[\frac{110}{73.6} \times 1(Year = 2001) \right] + \left[\frac{110}{75.7} \times 1(Year = 2002) \right] \\ & + \left[\frac{110}{78.0} \times 1(Year = 2003) \right] + \left[\frac{110}{79.9} \times 1(Year = 2004) \right] \\ & + \left[\frac{110}{81.8} \times 1(Year = 2005) \right] + \left[\frac{110}{84.4} \times 1(Year = 2006) \right] \\ & + \left[\frac{110}{86.9} \times 1(Year = 2007) \right] + \left[\frac{110}{89.8} \times 1(Year = 2008) \right] \\ & + \left[\frac{110}{92.6} \times 1(Year = 2009) \right] + \left[\frac{110}{94.8} \times 1(Year = 2010) \right] \\ & + \left[\frac{110}{97.7} \times 1(Year = 2011) \right] + \left[\frac{110}{100.0} \times 1(Year = 2012) \right] \\ & + \left[\frac{110}{102.3} \times 1(Year = 2013) \right] + \left[\frac{110}{105.0} \times 1(Year = 2014) \right] \\ & + \left[\frac{110}{106.8} \times 1(Year = 2015) \right] + \left[\frac{110}{108.3} \times 1(Year = 2016) \right] \end{aligned}$$

Appendix 2.2: ANZSCO Classification Structure Details

ANZSCO comprises five hierarchical levels: Major groups, Sub-major groups, Minor groups, Unit groups, and Occupations (ABS 2013):

1. Major groups

This is the broadest level of classification. There are 8 major groups in ANZSCO represented by 1-digit codes and is available in the general release version of the HILDA Survey.

2. Sub-major groups

These are sub-divisions of the major groups. There are 43 sub-major groups in ANZSCO represented by 2-digit codes and are available in the general release version of the HILDA Survey.

3. Minor groups

These are sub-divisions of the sub-major groups. There are 97 minor groups in ANZSCO represented by 3-digit codes.

4. Unit groups

These are sub-divisions of the minor groups. There are 358-unit groups in ANZSCO represented by 4-digit codes. This is not available in the general release version of the HILDA Survey. These are only available within the unconfidentialised unit record data file of the HILDA Survey.

5. Occupations

These are sub-divisions of the unit groups. There are 998 groups in ANZSCO represented by 6-digit codes. These are not available in the general or restricted version of the HILDA Survey.

Appendix 2.3: Details on the Structure of the Australian Statistical Geography Standard (ASGS)

The ASGS is a framework comprising a coherent set of standardised regions (Australian Bureau of Statistics 2016a). While ASGS classification structures are split into two broad groups (The ABS and Non-ABS structures), the ABS provides the main structure hierarchy to disseminate a broad range of statistics. This structure has 7 hierarchical levels comprising, in ascending order (in terms of region size):

1. **Mesh Blocks**

Mesh Blocks are the smallest geographical area defined by the ABS. They broadly identify land use such as residential and commercial areas. As Mesh Blocks are small and do not overlap with each other, they are combined to approximate a range of other statistical regions.

2. **Statistical Area Level 1 (SA1)**

These are geographical areas built from whole Mesh Blocks. SA1s are generally designed to be the smallest unit for the release of census data and are predominantly rural or urban areas. Whole SA1s aggregate to form SA2.

3. **Statistical Area Level 2 (SA2)**

These are general purpose areas built up from the whole SA1s. They represent communities interacting together socially and economically.

4. **Statistical Area Level 3 (SA3)**

These are areas built from whole SA2s. Each SA3 unit comprises multiple SA2 units that share similar regional characteristics.

5. **Statistical Areal Level 4 (SA4)**

These areas are built from whole SA3s. These are the largest sub-state regions in the hierarchy. These units are specifically designed for the output of the ABS Labour Force Surveys and represent labour markets (or groups of labour markets) within each state and territory. Labour markets are a key consideration for the design of SA4s as each unit contains geographic locations where people work (labour demand) and where people live (labour supply).

6. **Australia (AUS) State and Territories (S/T)**

Australia is the largest spatial unit in the hierarchy and can be broken up into states and territories that are separately recognised in the ASGS:

- New South Wales
- Victoria
- Queensland
- South Australia
- Western Australia
- Tasmania
- Northern Territory
- Australian Capital Territory
- Jervis Bay Territory
- Territory of Christmas Island
- Territory of the Cocos (Keeling) Islands
- Territory of Norfolk Island

Greater Capital City Statistical Area (GCCSA)

Not part of the main structure, the GCCSA represents geographical areas built from the SA4s units. These areas include individuals who work or engage in recreation within the city but live in the small towns and rural areas surrounding the city. The GCCSA includes eight state/territory capital cities and the rest of the states/territories. There are 16 GCCSA regions covering the whole of Australia:

1. Greater Sydney
2. Rest of New South Wales
3. Greater Melbourne
4. Rest of Victoria
5. Greater Brisbane
6. Rest of Queensland
7. Greater Adelaide
8. Rest of South Australia
9. Greater Perth
10. Rest of Western Australia
11. Greater Hobart
12. Rest of Tasmania
13. Greater Darwin
14. Rest of Northern Territory

15. Australian Capital Territory

16. Other Territories⁹⁷

The general release version of the HILDA Survey adopts the ASGC 2001 major statistical region to classify the respondent's location. According to the Survey, the respondent resides in one of the following regions:

1. Sydney
2. Rest of New South Wales
3. Melbourne
4. Rest of Victoria
5. Greater Brisbane
6. Rest of Queensland
7. Adelaide
8. Rest of South Australia
9. Perth
10. Rest of Western Australia
11. Tasmania
12. Northern Territory
13. Australian Capital Territory

This is similar to the GCCSA structure, but the survey separated Tasmania from Northern Territory and does not separate Hobart from Tasmania.

⁹⁷ Other Territories include 18 non-spatial GCCSA special purpose codes such as Migratory-Offshore-Shipping and No Usual Address codes.

Appendix 2.4: Presence of Non-Random Attrition

TABLE A2.4.1: LOGIT ESTIMATES FOR PROBABILITY OF NON-RESPONSE AT $t + 1$ GIVEN
INDIVIDUAL RESPONDED AT t

Non-Response at $t + 1$	(1)	(2)
Employment status ($t+1$)		
Wage/Salary employment	0.931* (0.027)	0.849*** (0.028)
Solo self-employment	0.869** (0.044)	0.978 (0.053)
Employer	0.840** (0.050)	1.018 (0.064)
Male (0/1)		1.053* (0.028)
Age		0.958*** (0.008)
Age ² /100		1.025* (0.010)
Marital status (0/1)		0.745*** (0.022)
<u>How well speaks English (0/1)</u>		
Well		1.174** (0.064)
Not well		1.535** (0.205)
Not at all		2.197* (0.828)
Number of dependents (0-14 years old)		0.812*** (0.035)
<u>Location of birth (0/1)</u>		
English speaking		1.168*** (0.051)
Non-English speaking		1.124* (0.060)
<u>Self-assessed health (0/1)</u>		
Very good		0.978 (0.037)
Good		0.960 (0.038)
Fair		1.033 (0.052)
Poor		1.223* (0.096)
Impairment (0/1)		0.996 (0.033)

<u>How likely to move in the next 12 months (0/1)</u>	
Likely	0.791*** (0.037)
Neither / not sure	0.767*** (0.032)
Unlikely	0.618*** (0.024)
Very unlikely	0.529*** (0.019)
Interview length	1.014*** (0.001)
Urban	1.076 (0.047)
SEIFA 2011 index of disadvantage (0/1)⁹⁸	
2 nd decile	0.895* (0.049)
3 rd decile	0.961 (0.053)
4 th decile	0.895* (0.050)
5 th decile	0.982 (0.056)
6 th decile	0.940 (0.053)
7 th decile	0.845** (0.051)
8 th decile	0.919 (0.053)
9 th decile	0.969 (0.057)
10 th decile	0.888 (0.055)
Number of adults in Household	1.298*** (0.018)
Number of children in HH	1.075 (0.042)
<u>Dwelling type (0/1)</u>	
Semi-detached house	1.126** (0.050)
Flat – less than 3 stories	1.077 (0.054)
Flat – 3 stories or more	1.176** (0.068)
Others	1.001

⁹⁸ Base category is 1st decile. Socio-Economic Indexes for Areas (SEIFA) is a set of four indexes which rank geographical areas across Australia with ABS Census data (ABS 2017a). These indexes are ranked by a score based on the characteristics of the people, families and dwellings in these areas.

Home status (0/1)

Own a home w/o mortgage(s)	0.978 (0.033)
Renting home	1.246*** (0.041)
Others	1.098 (0.088)

Highest level of education achieved (0/1)

Year 12	0.766*** 2.206***
Certificate	(0.176) 1.087
Diploma	(0.114) 1.318
Bachelor's degree or higher	(0.257) 0.522*
Log household disposable income	(0.159) 0.797
Respondent's cooperation was fair, poor or very poor;	(0.165) 0.829
Interview was assisted	(0.126) 1.952***
English was a problem during interview	(0.137) 1.097
Eyesight was a problem during interview	(0.076) 1.004
Hearing was a problem during interview	(0.043) 2.206***
Reading was a problem during interview	(0.176) 1.087
Was somewhat or very suspicious of interview	(0.114) 1.318
Respondent's understanding was fair, poor or very poor	(0.257) 0.522*
Other adults influenced the interview	(0.159) 0.797

No. of individuals	21,244	21,244
No. of observations	134,652	134,652
Pseudo R^2	0.0152	0.0729
Log-Likelihood	-32,287.98	-30,394.93

Notes: Estimates are based on a pooled sample of 21-64 years old respondents from the years 2001 to 2015. Odds ratios are reported (e^{β}) instead of their coefficients (β). Robust standard errors of the odds ratios reported in parentheses. Robust standard errors are reported allowing for intrapersonal correlation among sampled observations. This model includes, but not reported, year and regional fixed effects. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Pseudo R^2 ' values equal 1 minus the ratio of the log-likelihood of the fitted function to the log-likelihood of a function with only an intercept term (Fitzgerald, Gottschalk, and Moffitt 1998).

Source: Author calculations from waves 2001 to 2015 of the HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

Appendix 3.1: Full Estimates for the Multinomial Logit Models

TABLE A3.1.1: NAIVE MULTINOMIAL LOGIT ESTIMATIONS WITH CONTROLS

	Labour Market State at Year t					
	Male			Female		
	Wage (1)	Solo SE (2)	Employer (3)	Wage. (4)	Solo SE (5)	Employer (6)
<u>Lagged Employment ($t-1$)</u>						
Wage	3.051*** (0.054)	1.309*** (0.090)	2.037*** (0.171)	3.175*** (0.037)	1.397*** (0.081)	1.908*** (0.128)
Solo SE	1.386*** (0.086)	4.425*** (0.119)	4.423*** (0.180)	1.501*** (0.082)	4.807*** (0.108)	3.901*** (0.147)
Employer	1.618*** (0.133)	3.752*** (0.150)	6.749*** (0.219)	1.555*** (0.109)	3.568*** (0.135)	6.084*** (0.171)
<u>Initial Employment ($t=0$)</u>						
Wage	0.303*** (0.059)	0.138 (0.099)	0.227 (0.157)	0.310*** (0.039)	0.139 (0.087)	-0.019 (0.134)
Solo SE	0.078 (0.098)	1.248*** (0.124)	0.928*** (0.175)	0.111 (0.093)	1.061*** (0.116)	0.860*** (0.164)
Employer	0.061 (0.132)	0.809*** (0.156)	1.583*** (0.191)	-0.056 (0.124)	0.566*** (0.159)	1.279*** (0.179)
Age	0.048** (0.020)	0.041 (0.036)	0.073 (0.049)	0.135*** (0.012)	0.095*** (0.027)	0.118** (0.041)
Age ² /100	-0.230*** (0.023)	-0.203*** (0.038)	-0.277*** (0.055)	-0.238*** (0.014)	-0.174*** (0.031)	-0.214*** (0.045)

Number of dependents (0-14 years old)	-0.111*** (0.024)	-0.097*** (0.032)	-0.007 (0.037)	-0.357*** (0.015)	-0.240*** (0.031)	-0.187*** (0.039)
Impaired (0/1)	-0.998*** (0.043)	-0.857*** (0.062)	-0.931*** (0.081)	-0.724*** (0.034)	-0.507*** (0.068)	-0.619*** (0.093)
Marital status (0/1)	0.218*** (0.049)	0.163** (0.072)	0.300** (0.095)	-0.346*** (0.036)	-0.076 (0.077)	0.177 (0.114)
Log household income (<i>t</i> -1)	0.235*** (0.031)	0.142*** (0.041)	0.472*** (0.057)	0.253*** (0.025)	0.118*** (0.045)	0.528*** (0.067)
Urban area (0/1)	0.045 (0.065)	-0.478*** (0.083)	-0.263** (0.105)	0.004 (0.050)	-0.386*** (0.086)	-0.321*** (0.108)
Regional unemployment (%)	-0.017 (0.028)	-0.063 (0.039)	-0.025 (0.047)	0.002 (0.021)	0.043 (0.040)	0.011 (0.053)
<u>Home status</u>						
Own a home with a mortgage(s)	0.712*** (0.120)	0.551*** (0.175)	0.594*** (0.216)	0.491*** (0.099)	-0.097 (0.172)	0.582** (0.247)
Own a home w/o mortgage(s)	0.086 (0.120)	0.181 (0.175)	0.154 (0.218)	0.136 (0.100)	-0.335* (0.175)	0.342 (0.246)
Renting home	0.417*** (0.119)	0.263 (0.177)	0.073 (0.222)	0.314*** (0.100)	-0.363** (0.175)	0.343 (0.264)
<u>Highest level of education achieved (0/1)</u>						
Year 12	0.387*** (0.069)	0.284*** (0.103)	0.573*** (0.132)	0.143** (0.049)	0.112 (0.111)	0.316** (0.132)
Certificate	0.240*** (0.054)	0.320*** (0.078)	0.329*** (0.102)	0.214*** (0.047)	0.429*** (0.095)	0.155 (0.128)

Diploma	0.380*** (0.080)	0.488*** (0.115)	0.517*** (0.140)	0.201*** (0.057)	0.549*** (0.103)	0.380** (0.154)
Bachelor's degree or higher	0.765*** (0.068)	0.637*** (0.098)	0.972*** (0.123)	0.471*** (0.044)	0.651*** (0.089)	0.405*** (0.121)
Years of working experience	0.152*** (0.012)	0.169*** (0.021)	0.194*** (0.028)	0.093*** (0.006)	0.126*** (0.015)	0.133*** (0.023)
Years of experience Squared/100	-0.063*** (0.020)	-0.111*** (0.033)	-0.115** (0.048)	-0.073*** (0.013)	-0.155*** (0.030)	-0.148*** (0.042)
<u>Location of birth (0/1)</u>						
English speaking	-0.026 (0.066)	0.108 (0.092)	0.090 (0.109)	-0.129** (0.055)	0.021 (0.103)	-0.082 (0.149)
Non-English speaking	-0.036 (0.067)	0.100 (0.098)	0.384*** (0.117)	-0.114** (0.048)	-0.105 (0.098)	0.102 (0.123)
No. of observations	65,751			73,183		
No. of individuals	9,217			9,770		
Log-Likelihood	-27,592.56			-32,365.82		

Notes: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category of the dependent variable is non-employment. Also included, but not reported, are year and regional fixed effects. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE A3.1.2: MULTINOMIAL LOGIT ESTIMATIONS WITH CORRELATED RANDOM EFFECTS

	Labour Market State at Year t					
	Male			Female		
	Wage (1)	Solo SE (2)	Employer (3)	Wage (4)	Solo SE (5)	Employer (6)
<u>Lagged employment ($t-1$)</u>						
Wage	2.267*** (0.072)	0.813*** (0.114)	1.488*** (0.203)	2.600*** (0.050)	1.145*** (0.104)	1.730*** (0.160)
Solo SE	0.948*** (0.111)	2.907*** (0.156)	3.270*** (0.225)	1.342*** (0.102)	3.366*** (0.145)	2.908*** (0.193)
Employer	1.052*** (0.166)	2.545*** (0.193)	4.731*** (0.277)	1.315*** (0.140)	2.513*** (0.184)	4.082*** (0.229)
<u>Initial employment ($t=0$)</u>						
Wage	0.870*** (0.095)	0.413*** (0.147)	0.388* (0.205)	0.728*** (0.061)	0.230* (0.124)	0.035 (0.193)
Solo SE	0.332** (0.146)	3.447*** (0.234)	2.863*** (0.283)	0.172 (0.131)	3.093*** (0.212)	2.764*** (0.294)
Employer	0.178 (0.189)	2.574*** (0.266)	4.439*** (0.335)	-0.072 (0.178)	2.047*** (0.263)	4.411*** (0.360)
Age	0.140** (0.058)	-0.066 (0.104)	0.066 (0.147)	0.410*** (0.031)	0.414*** (0.071)	0.572*** (0.097)
Age ² /100	-0.275*** (0.057)	-0.116 (0.098)	-0.246* (0.137)	-0.429*** (0.032)	-0.477*** (0.069)	-0.625*** (0.097)
Number of dependents (0-14 years old)	-0.257*** (0.045)	-0.226*** (0.060)	-0.190*** (0.068)	-0.565*** (0.032)	-0.320*** (0.057)	-0.267*** (0.067)

Impaired (0/1)	-0.693*** (0.064)	-0.567*** (0.092)	-0.548*** (0.117)	-0.384*** (0.049)	-0.284*** (0.101)	-0.303** (0.145)
Marital status (0/1)	0.043 (0.093)	-0.111 (0.137)	0.118 (0.168)	-0.376*** (0.070)	-0.142 (0.144)	-0.075 (0.218)
Log household income (<i>t</i> -1)	-0.033 (0.046)	-0.050 (0.062)	0.069 (0.081)	0.000 (0.033)	-0.019 (0.060)	0.170* (0.089)
Urban area (0/1)	0.411*** (0.131)	-0.136 (0.181)	0.298 (0.231)	0.055 (0.109)	-0.216 (0.195)	-0.008 (0.247)
Regional unemployment (%)	-0.021 (0.033)	-0.069 (0.047)	-0.045 (0.057)	-0.010 (0.024)	0.023 (0.048)	0.032 (0.063)
<u>Home status</u>						
Own a home with a mortgage(s)	0.731*** (0.183)	0.702*** (0.258)	0.631** (0.311)	0.399*** (0.139)	-0.112 (0.257)	0.527 (0.370)
Own a home w/o mortgage(s)	0.164 (0.185)	0.236 (0.259)	0.008 (0.312)	0.081 (0.143)	-0.397 (0.260)	0.283 (0.365)
Renting home	0.699*** (0.183)	0.632** (0.260)	0.340 (0.322)	0.417*** (0.141)	-0.250 (0.248)	0.540 (0.383)
<u>Highest level of education achieved (0/1)</u>						
Year 12	0.146 (0.337)	0.586 (0.546)	0.360 (0.684)	-0.069 (0.223)	-0.184 (0.467)	-0.094 (0.571)
Certificate	0.126 (0.249)	0.768* (0.415)	0.943* (0.535)	0.428*** (0.152)	0.386 (0.312)	0.631* (0.379)
Diploma	0.713* (0.408)	1.278** (0.627)	0.771 (0.742)	0.206 (0.274)	0.589 (0.520)	0.424 (0.599)
Bachelor's degree or Higher	1.403*** (0.430)	1.828*** (0.653)	1.238 (0.758)	0.493* (0.268)	0.292 (0.577)	-0.182 (0.707)

Years of working experience	0.112*** (0.040)	0.314*** (0.075)	0.382*** (0.104)	-0.083*** (0.022)	-0.021 (0.050)	-0.020 (0.069)
Years of working experience squared	-0.152** (0.061)	-0.414*** (0.103)	-0.459*** (0.137)	-0.030 (0.041)	0.063 (0.084)	-0.003 (0.110)
<u>Location of birth (0/1)</u>						
English speaking	-0.054 (0.087)	0.147 (0.129)	0.136 (0.159)	-0.159** (0.071)	0.074 (0.139)	0.050 (0.208)
Non-English speaking	-0.124 (0.086)	0.060 (0.134)	0.633*** (0.165)	-0.110* (0.061)	-0.068 (0.129)	0.338* (0.183)
No. of observations	65,751			73,183		
No. of individuals	9,217			9,770		
Log-Likelihood	-26,398.78			-30,982.90		
$Cov(a_{i,Wage}, a_{i,j})$	1.572*** (0.116)	0.890*** (0.130)	1.019*** (0.172)	1.190*** (0.070)	0.433*** (0.097)	0.405*** (0.141)
$Cov(a_{i,Solo}, a_{i,j})$		3.748*** (0.322)	3.146*** (0.328)		3.259*** (0.305)	2.564*** (0.311)
$Cov(a_{i,Emp}, a_{i,j})$			4.819*** (0.463)			4.886*** (0.496)

Note: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category of the dependent variable is non-employment. Also included, but not reported, are controls for year, regional fixed effects and individual-specific time averages of the exogenous characteristics. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a)

Appendix 3.2: True (Cross) State Dependence Robustness Checks

TABLE A3.2.1: MULTINOMIAL LOGIT ESTIMATIONS WITH CORRELATED RANDOM EFFECTS – CONTROLLING FOR ATTRITION AND SA4 UNEMPLOYMENT

	Labour Market State at Year t					
	Male			Female		
	Wage (1)	Solo SE (2)	Employer (3)	Wage (4)	Solo SE (5)	Employer (6)
<u>Lagged employment ($t-1$)</u>						
Wage	2.304*** (0.078)	0.876*** (0.119)	1.516*** (0.208)	2.650*** (0.053)	1.182*** (0.109)	1.803*** (0.167)
Solo-SE	1.070*** (0.118)	2.995*** (0.165)	3.384*** (0.232)	1.383*** (0.105)	3.342*** (0.154)	2.878*** (0.201)
Employer	1.112*** (0.174)	2.616*** (0.205)	4.806*** (0.290)	1.369*** (0.146)	2.492*** (0.195)	4.068*** (0.241)
<u>Initial employment ($t=0$)</u>						
Wage	0.854*** (0.099)	0.360** (0.152)	0.262 (0.209)	0.671*** (0.062)	0.206 (0.129)	-0.015 (0.199)
Solo SE	0.235 (0.151)	3.344*** (0.242)	2.633*** (0.289)	0.173 (0.132)	3.164*** (0.223)	2.880*** (0.300)
Employer	0.079 (0.192)	2.405*** (0.272)	4.167*** (0.345)	-0.121 (0.179)	2.109*** (0.274)	4.417*** (0.366)
Attrition in $t+1$	-0.243*** (0.085)	-0.184 (0.129)	-0.323** (0.158)	-0.117* (0.069)	-0.121 (0.143)	-0.396** (0.191)

SA4 Unemployment (%)	-0.018 (0.014)	-0.028 (0.020)	-0.053** (0.025)	-0.013 (0.010)	0.018 (0.020)	-0.010 (0.025)
No. of individuals	60,413			67,284		
No. of observations	8,916			9,472		
Log-Likelihood	-24,222.35			-28,470.50		
$Cov(\alpha_{i,Waae}, \alpha_{i,i})$	1.470*** (0.121)	0.726*** (0.133)	0.835*** (0.178)	1.053*** (0.071)	0.334*** (0.099)	0.271* (0.144)
$Cov(\alpha_{i,Solo}, \alpha_{i,j})$		3.423*** (0.329)	2.734*** (0.335)		3.268*** (0.328)	2.617*** (0.333)
$Cov(\alpha_{i,Emp}, \alpha_{i,j})$			4.274*** (0.474)			4.785*** (0.511)

Notes: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category of the dependent variable is non-employment. Also included, but not reported, are controls for age (specified as a quadratic), marital status, number of dependent children, impairment, country / region of birth, educational attainment, cumulative years of work experience (specified as a quadratic), home ownership, household income at $t-1$ (logged), location (urban vs rural), year, regional fixed effects and individual-specific time averages of the exogenous characteristics. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

TABLE A3.2.2: PREDICTED PROBABILITIES OF BEING SOLO/EMPLOYER
SELF-EMPLOYED GIVEN PREVIOUS EMPLOYMENT STATE – USING TABLE A3.2.1
ESTIMATES

Previous employment state	Predicted Prob. Of being self-employed at year t	
	Solo SE (1)	Employer (2)
Panel A. Males		
Non-employment	0.093*** (0.006)	0.032*** (0.004)
Wage employment	0.054*** (0.003)	0.030*** (0.002)
Solo self-employment	0.245*** (0.011)	0.095*** (0.006)
Employer	0.156*** (0.009)	0.221*** (0.015)
Panel B. Females		
Non-employment	0.038*** (0.003)	0.016*** (0.002)
Wage employment	0.026*** (0.002)	0.018*** (0.001)
Solo self-employment	0.175*** (0.011)	0.039*** (0.003)
Employer	0.094*** (0.009)	0.096*** (0.009)

Notes: Estimates above represent sample averages of the predicted probabilities being in solo self-employment/employership in wave t given their employment choice in wave $t-1$. Specifications (1) and (2) are based on estimates from Table A3.2.1. Standard errors are in parentheses and are calculated using the Delta method. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE A3.2.3: MULTINOMIAL LOGIT ESTIMATIONS WITH CORRELATED RANDOM EFFECTS – DROPPING WORKERS IN AGRICULTURE INDUSTRIES

	Labour Market State at Year t					
	Male			Female		
	Wage (1)	Solo SE (2)	Employer (3)	Wage (4)	Solo SE (5)	Employer (6)
<u>Lagged employment ($t-1$)</u>						
Wage	2.392*** (0.080)	0.932*** (0.123)	1.584*** (0.224)	2.694*** (0.054)	1.282*** (0.115)	1.902*** (0.183)
Solo-SE	1.159*** (0.125)	3.191*** (0.175)	3.599*** (0.251)	1.466*** (0.112)	3.642*** (0.166)	3.193*** (0.223)
Employer	1.177*** (0.184)	2.701*** (0.218)	5.012*** (0.313)	1.459*** (0.154)	2.851*** (0.212)	4.495*** (0.273)
<u>Initial employment ($t=0$)</u>						
Wage	0.829*** (0.100)	0.252* (0.151)	0.224 (0.211)	0.648*** (0.062)	0.091 (0.127)	-0.056 (0.206)
Solo SE	0.144 (0.156)	3.054*** (0.251)	2.446*** (0.301)	0.073 (0.138)	2.865*** (0.228)	2.583*** (0.309)
Employer	-0.073 (0.199)	2.087*** (0.282)	3.974*** (0.363)	-0.232 (0.198)	1.781*** (0.297)	4.157*** (0.395)
Attrition in $t+1$	-0.209** (0.088)	-0.068 (0.134)	-0.280* (0.166)	-0.120* (0.070)	-0.083 (0.146)	-0.440** (0.203)
SA4 Unemployment (%)	-0.018 (0.014)	-0.024 (0.022)	-0.061** (0.027)	-0.014 (0.010)	0.020 (0.021)	-0.014 (0.027)
No. of observations	57,027			65,532		
No. of individuals	8,650			9,369		

Log-Likelihood	-22,175.13			-26,897.56		
$Cov(\alpha_{i,Wage}, \alpha_{i,j})$	1.408*** (0.118)	0.636*** (0.132)	0.769*** (0.186)	1.043*** (0.071)	0.234** (0.099)	0.112 (0.143)
$Cov(\alpha_{i,Solo}, \alpha_{i,j})$		3.104*** (0.337)	2.508*** (0.347)		2.765*** (0.310)	1.980*** (0.304)
$Cov(\alpha_{i,Emp}, \alpha_{i,j})$			3.980*** (0.496)			3.963*** (0.517)

Notes: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category of the dependent variable is non-employment. Also included, but not reported, are controls for age (specified as a quadratic), marital status, number of dependent children, impairment, country / region of birth, educational attainment, cumulative years of work experience (specified as a quadratic), home ownership, household income at $t-1$ (logged), location (urban vs rural), year, regional fixed effects and individual-specific time averages of the exogenous characteristics. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE A3.2.4: PREDICTED PROBABILITIES OF BEING SOLO/EMPLOYER
SELF-EMPLOYED GIVEN PREVIOUS EMPLOYMENT STATE – USING TABLE
A3.2.3 ESTIMATES

Previous Employment State	Predicted Prob. of Being Self-Employed at Year t	
	Solo SE. (1)	Employer (2)
Panel A. Males		
Non-employment	0.083*** (0.006)	0.028*** (0.004)
Wage employment	0.047*** (0.003)	0.026*** (0.002)
Solo self-employment	0.248*** (0.013)	0.094*** (0.006)
Employer	0.149*** (0.010)	0.225*** (0.018)
Panel B. Females		
Non-employment	0.032*** (0.003)	0.013*** (0.002)
Wage employment	0.023*** (0.001)	0.015*** (0.001)
Solo self-employment	0.184*** (0.013)	0.040*** (0.004)
Employer	0.101*** (0.011)	0.104*** (0.012)

Notes: Estimates above represent sample averages of the predicted probabilities being in solo self-employment/employership in wave t given their employment choice in wave $t-1$. Specifications (1) and (2) are based on estimates from A3.2.3. Standard errors are in parentheses and are calculated using the Delta method. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE A3.2.5: MULTINOMIAL LOGIT ESTIMATIONS WITH CORRELATED RANDOM EFFECTS – CONTROLLING FOR NON-RANDOM ATTRITION, SA4 UNEMPLOYMENT AND IMPUTATION

	Labour Market State at Year t					
	Male			Female		
	Wage (1)	Solo SE (2)	Employer (3)	Wage (4)	Solo SE (5)	Employer (6)
<u>Lagged employment ($t-1$)</u>						
Wage	2.315*** (0.078)	0.912*** (0.121)	1.580*** (0.214)	2.661*** (0.054)	1.201*** (0.111)	1.821*** (0.169)
Solo-SE	1.068*** (0.123)	3.063*** (0.173)	3.452*** (0.241)	1.387*** (0.108)	3.352*** (0.158)	2.883*** (0.205)
Employer	1.061*** (0.179)	2.584*** (0.211)	4.777*** (0.301)	1.384*** (0.153)	2.537*** (0.203)	4.081*** (0.250)
<u>Initial employment ($t=0$)</u>						
Wage	0.843*** (0.099)	0.348** (0.153)	0.186 (0.211)	0.660*** (0.062)	0.193 (0.130)	-0.045 (0.203)
Solo SE	0.231 (0.153)	3.307*** (0.249)	2.606*** (0.296)	0.154 (0.133)	3.153*** (0.227)	2.850*** (0.308)
Employer	0.099 (0.195)	2.370*** (0.277)	4.159*** (0.354)	-0.160 (0.181)	2.072*** (0.276)	4.427*** (0.376)
Attrition in $t+1$	-0.244*** (0.086)	-0.167 (0.130)	-0.293* (0.160)	-0.125* (0.069)	-0.141 (0.144)	-0.402** (0.193)
SA4 Unemployment (%)	-0.018 (0.014)	-0.032 (0.021)	-0.058** (0.025)	-0.013 (0.010)	0.021 (0.020)	-0.010 (0.025)
Log household income ($t-1$) imputation flag	-0.031 (0.053)	0.089 (0.072)	0.024 (0.086)	0.069* (0.036)	0.180** (0.075)	0.310*** (0.092)

No. of observations	59,870			66,910		
No. of individuals	8,897			9,461		
Log-Likelihood	-23,705.66			-28,081.21		
$Cov(\alpha_{i,Wage}, \alpha_{i,j})$	1.455*** (0.120)	0.682*** (0.136)	0.797*** (0.185)	1.033*** (0.071)	0.330*** (0.100)	0.269* (0.148)
$Cov(\alpha_{i,Solo}, \alpha_{i,j})$		3.258*** (0.337)	2.689*** (0.347)		3.247*** (0.337)	2.633*** (0.349)
$Cov(\alpha_{i,Emp}, \alpha_{i,j})$			4.341*** (0.499)			4.856*** (0.540)

Notes: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category of the dependent variable is non-employment. Also included, but not reported, are controls for age (specified as a quadratic), marital status, number of dependent children, impairment, country / region of birth, educational attainment, cumulative years of work experience (specified as a quadratic), home ownership, household income at $t-1$ (logged), location (urban vs rural), year, regional fixed effects and individual-specific time averages of the exogenous characteristics. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).

TABLE A3.2.6: PREDICTED PROBABILITIES OF BEING SOLO/EMPLOYER
SELF-EMPLOYED GIVEN PREVIOUS EMPLOYMENT STATE – USING TABLE
A3.2.5 ESTIMATES

Previous Employment State	Predicted Prob. of Being Self-Employed at Year t	
	Solo SE. (1)	Employer (2)
Panel A. Males		
Non-employment	0.091*** (0.006)	0.031*** (0.004)
Wage employment	0.053*** (0.003)	0.030*** (0.002)
Solo self-employment	0.248*** (0.012)	0.094*** (0.006)
Employer	0.155*** (0.009)	0.214*** (0.015)
Panel B. Females		
Non-employment	0.037*** (0.003)	0.016*** (0.002)
Wage employment	0.026*** (0.002)	0.018*** (0.001)
Solo self-employment	0.174*** (0.011)	0.039*** (0.003)
Employer	0.095*** (0.010)	0.094*** (0.009)

Notes: Estimates above represent sample averages of the predicted probabilities being in solo self-employment/employership in wave t given their employment choice in wave $t-1$. Specifications (1) and (2) are based on estimates from Table A3.2.5. Standard errors are in parentheses and are calculated using the Delta method. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author calculations from waves 2002 to 2015 of the HILDA Survey.

Appendix 4.1: O*NET and Occupation Specific Skills and Abilities (DOT ETA 2019d)

In the sub-sections below, I summarise and define the elements that make up the cognitive abilities and skills used in Chapter 4.

Cognitive Abilities

1. Oral Comprehension - The ability to listen to and understand information and ideas presented through spoken words and sentences.
2. Written Comprehension - The ability to read and understand information and ideas presented in writing.
3. Oral Expression - The ability to communicate information and ideas in speaking so others will understand.
4. Written Expression - The ability to communicate information and ideas in writing so others will understand.
5. Fluency of Ideas - The ability to come up with many ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity).
6. Originality - The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
7. Problem Sensitivity - The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing there is a problem.
8. Deductive Reasoning - The ability to apply general rules to specific problems to produce answers that make sense.
9. Inductive Reasoning - The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).
10. Information Ordering - The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).
11. Category Flexibility - The ability to generate or use different sets of rules for combining or grouping things in different ways.

12. Mathematical Reasoning - The ability to choose the right mathematical methods or formulas to solve a problem.
13. Number Facility - The ability to add, subtract, multiply, or divide quickly and correctly.
14. Memory – The ability to remember information such as words, numbers, pictures, and procedures.
15. Speed of Closure - The ability to quickly make sense of, combine, and organize information into meaningful patterns.
16. Flexibility of Closure - The ability to identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material.
17. Perceptual Speed - The ability to quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns. The things to be compared may be presented at the same time or one after the other. This ability also includes comparing a presented object with a remembered object.
18. Spatial Orientation - The ability to know your location in relation to the environment or to know where other objects are in relation to you.
19. Visualization - The ability to imagine how something will look after it is moved around or when its parts are moved or rearranged.
20. Selective Attention - The ability to concentrate on a task over a period without being distracted.
21. Time-Sharing - The ability to shift back and forth between two or more activities or sources of information (such as speech, sounds, touch, or other sources).

Basic Skills

1. Reading Comprehension - Understanding written sentences and paragraphs in work-related documents.
2. Active Listening - Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.
3. Writing - Communicating effectively in writing as appropriate for the needs of the audience.
4. Speaking - Talking to others to convey information effectively.
5. Mathematics - Using mathematics to solve problems.

6. Science - Using scientific rules and methods to solve problems.
7. Critical Thinking - Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.
8. Active Learning - Understanding the implications of new information for both current and future problem-solving and decision-making.
9. Learning Strategies - Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things.
10. Monitoring - Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action.

Cross-Functional Skills

1. Social Perceptiveness - Being aware of others' reactions and understanding why they react as they do.
2. Coordination - Adjusting actions in relation to others' actions.
3. Persuasion - Persuading others to change their minds or behaviour.
4. Negotiation - Bringing others together and trying to reconcile differences.
5. Instructing - Teaching others how to do something.
6. Service Orientation - Actively looking for ways to help people.
7. Complex Problem Solving - Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.
8. Operations Analysis - Analysing needs and product requirements to create a design.
9. Technology Design - Generating or adapting equipment and technology to serve user needs.
10. Equipment Selection - Determining the kind of tools and equipment needed to do a job.
11. Installation - Installing equipment, machines, wiring, or programs to meet specifications.
12. Programming - Writing computer programs for various purposes.
13. Operation Monitoring - Watching gauges, dials, or other indicators to make sure a machine is working properly.
14. Operation and Control - Controlling operations of equipment or systems.
15. Equipment Maintenance - Performing routine maintenance on equipment and determining when and what kind of maintenance is needed.

16. Troubleshooting - Determining causes of operating errors and deciding what to do about it.
17. Repairing - Repairing machines or systems using the needed tools.
18. Quality Control Analysis - Conducting tests and inspections of products, services, or processes to evaluate quality or performance.
19. Judgment and Decision Making - Considering the relative costs and benefits of potential actions to choose the most appropriate one.
20. Systems Analysis - Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.
21. Systems Evaluation - Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system.
22. Time Management - Managing one's own time and the time of others.
23. Management of Financial Resources - Determining how the money will be spent to get the work done, and accounting for these expenditures.
24. Management of Material Resources - Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.
25. Management of Personnel Resources - Motivating, developing, and directing people as they work, identifying the best people for the job.

Appendix 4.2: Factors and Their Occupation Characteristics

Using estimates from Table 4-3, I group each skill/ability to their corresponding group as follows:

1. Cognitive Skills/Abilities
 - i. Active Learning
 - ii. Active Listening
 - iii. Complex Problem Solving
 - iv. Critical Thinking
 - v. Instructing
 - vi. Judgement and Decision Making
 - vii. Learning Strategies
 - viii. Management of Personnel Resources
 - ix. Monitoring

- x. Negotiation
- xi. Operations Analysis
- xii. Persuasion
- xiii. Reading Comprehension
- xiv. Science
- xv. Service Orientation
- xvi. Social Perceptiveness
- xvii. Speaking
- xviii. Systems Analysis
- xix. Systems Evaluation
- xx. Time Management
- xxi. Writing
- xxii. Category Flexibility
- xxiii. Deductive Reasoning
- xxiv. Flexibility of Closure
- xxv. Fluency of Ideas
- xxvi. Inductive Reasoning
- xxvii. Information Ordering
- xxviii. Memory
- xxix. Oral Comprehension
- xxx. Oral Expression
- xxxi. Originality
- xxxii. Problem Sensitivity
- xxxiii. Speed of Closure
- xxxiv. Written Comprehension
- xxxv. Written Expression

2. Technical Specialisation

- i. Equipment Maintenance
- ii. Equipment Selection
- iii. Installation
- iv. Operation Control
- v. Operation Monitoring
- vi. Quality Control Analysis
- vii. Repairing

- viii. Troubleshooting
- ix. Spatial Orientation
- x. Visualization
- 3. Mathematics
 - i. Mathematics
 - ii. Programming
 - iii. Technology Design
 - iv. Mathematical Reasoning
 - v. Number Facility
- 4. Resource Management
 - i. Coordination
 - ii. Management of Financial Resources
 - iii. Management of Material Resources
- 5. Pattern Recognition
 - i. Perceptual Speed
 - ii. Selective Attention
 - iii. Time-Sharing

Appendix 4.3: Matching Vague Occupations with Their O*NET Counterparts

As described in this thesis, among the groups at the unit level, there are ‘not further defined (n.f.d)’ categories. These ‘n.f.d’ unit categories are represented by codes ending with the digit(s) ‘0’ and represent incomplete occupation information within the HILDA Survey. Below, I summarise the ‘n.f.d’ occupations discovered in Chapter 4’s analytical sample. Instead of dropping their observations, I performed the following exercise:

Managers n.f.d (1000)

In the data, this group is known as “Managers-NFI”. This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the sub-major “Chief Executives, General Managers and Legislators” (11) group⁹⁹.

Specialist Managers n.f.d (1300)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the sub-major “Specialist Managers” (13) group.

Financial Brokers and Dealers, and Investment Advisers n.f.d (2220)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the minor “Financial Brokers and Dealers, and Investment Advisers” (222) group.

Natural and Physical Science Professionals n.f.d (2340)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the minor “Natural and Physical Science Professionals” (234) group.

School Teacher n.f.d (2410)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the minor “School Teachers” (241) group.

ICT Professionals n.f.d (2600)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the sub-major “ICT Professionals” (26) group.

Business and Systems Analysts, and Programmers n.f.d (2610)

⁹⁹ I exclude “Legislators” from this group. This is because there is insufficient O*NET information that can be linked to Australian “Legislators”. Since no other employers were previously legislators, I ignore the “Legislators” occupation in this exercise.

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the minor “Business and Systems Analysts, and Programmers” (261) group.

Panel beaters, and Vehicle Body Builders, Trimmers and Painters n.f.d (3240)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the minor “Panel beaters, and Vehicle Body Builders, Trimmers and Painters” (324) group.

Wood Trades Workers n.f.d (3940)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the minor “Wood Trades Workers” (394) group.

Machinery Operators and Drivers n.f.d (7000)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the sub-major “Machinery Operators and Drivers” (7000) group.

Automobile, Bus and Rail Drivers n.f.d (7310)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the minor “Automobile, Bus and Rail Drivers” (731) group.

Labourers n.f.d (8000)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the sub-major “Labourers” (8000) group.

Cleaners and Laundry Workers n.f.d (8110)

This occupation takes the average of skills/abilities importance ratings assigned to unit occupations within the minor “Cleaners and Laundry Workers” (811) group.

Other hospitality workers (8119)

This is the only occupation in this list that is fully defined at the unit level. However, I am unable to find “Other hospitality workers” closest O*NET counterparts. I fix this by taking the average of skills/abilities importance ratings assigned to unit occupations within the minor group “Hospitality Workers” (431).

Appendix 4.4: Derivation of the Proportional Hazard Model with a Complementary Log-Logistic Link

We know that employership survival times fall within the interval a_j and a_{j-1} where:

$$\begin{aligned} S(a_j|X(i)) &= \exp \left[- \int_0^{a_j} \theta(u|X(i)) du \right] \\ &= \exp \left[- \int_0^{a_j} \lambda \theta_0(u) du \right] \\ &= \exp \left[- \lambda \int_0^{a_j} \theta_0(u) du \right] \\ &= \exp[-\lambda \Theta_0(a_j)] \end{aligned}$$

where $S(a_j|X(i))$ is a survival function that gives the probability that the employer will survive beyond the interval point a_j , $\lambda = \exp\{\beta'X(i) + u_i\}$, $X(i)$ represents a vector of the employer's observable explanatory and control variables, and u_i represents the individual's time-invariant and person-specific unobserved heterogeneity. The integral baseline hazard $\Theta_0(a_j)$ can be expressed as $-\ln S_0(a_j)$. Consider the discrete density of duration $f(a_j)$:

$$\begin{aligned} f(a_j|X(i)) &= F(a_j|X(i)) - F(a_{j-1}|X(i)) \\ &= [1 - S(a_j|X(i))] - [1 - S(a_{j-1}|X(i))] \\ &= S(a_{j-1}|X(i)) - S(a_j|X(i)) \end{aligned}$$

And the discrete-time hazard function defined as:

$$\begin{aligned} \theta(a_j|X(i)) &= \frac{f(a_j|X(i))}{1 - F(a_{j-1}|X(i))} \\ &= \frac{S(a_{j-1}|X(i)) - S(a_j|X(i))}{S(a_{j-1}|X(i))} \end{aligned}$$

$$\begin{aligned}
&= 1 - \frac{S(a_j|X(i))}{S(a_{j-1}|X(i))} \\
&= 1 - \frac{\exp[-\lambda\theta_0(a_j)]}{\exp[-\lambda\theta_0(a_{j-1})]} \\
\theta(a_j|X(i)) &= 1 - \exp[\lambda\{\theta_0(a_{j-1}) - \theta_0(a_j)\}] \\
1 - \theta(a_j|X(i)) &= \exp[\lambda\{\theta_0(a_{j-1}) - \theta_0(a_j)\}]
\end{aligned}$$

Taking logs of both sides:

$$\ln[1 - \theta(a_j|X(i))] = \lambda\{\theta_0(a_{j-1}) - \theta_0(a_j)\}$$

Multiplying by -1:

$$-\ln[1 - \theta(a_j|X(i))] = \lambda\{\theta_0(a_j) - \theta_0(a_{j-1})\}$$

Taking logs of both sides again:

$$0-1) \quad \ln\{-\ln[1 - \theta(a_j|X(i))]\} = \ln \lambda + \ln\{\theta_0(a_j) - \theta_0(a_{j-1})\}$$

Note that:

$$\begin{aligned}
\theta_0(a_j) &= 1 - \frac{S_0(a_j)}{S_0(a_{j-1})} \\
\theta_0(a_j) &= 1 - \frac{\exp[-\theta_0(a_j)]}{\exp[-\theta_0(a_{j-1})]}
\end{aligned}$$

Therefore:

$$0-2) \quad -\ln[1 - \theta_0(a_j)] = \theta_0(a_j) - \theta_0(a_{j-1})$$

Substituting Equation 0-3 into 0-4 gives us

$$\begin{aligned}
\ln\{-\ln[1 - \theta(a_j|X(i))]\} &= \ln \lambda + \ln\{-\ln[1 - \theta_0(a_j)]\} \\
\ln\{-\ln[1 - \theta(a_j|X(i))]\} &= \ln\{\exp(\beta'X(i))\} + \ln\{-\ln[1 - \theta_0(a_j)]\} \\
\ln\{-\ln[1 - \theta(a_j|X(i))]\} &= \beta'X(i) + \ln\{-\ln[1 - \theta_0(a_j)]\}
\end{aligned}$$

If we define:

$$\gamma_0(j) = \ln\{-\ln[1 - \theta_0(a_j)]\} = \ln\{\Theta_0(a_j) - \Theta_0(a_{j-1})\}$$

Then

$$\ln\{-\ln[1 - \theta(a_j|X(i))]\} = \beta'X(i) + u_i + \gamma_0(j)$$

Taking the exponents of both sides:

$$-\ln[1 - \theta(a_j|X(i))] = \exp[\beta'X(i) + u_i + \gamma_0(j)]$$

Multiplying by -1:

$$\ln[1 - \theta(a_j|X(i))] = -\exp[\beta'X(i) + u_i + \gamma_0(j)]$$

Taking exponents of both sides

$$1 - \theta(a_j|X(i)) = \exp\{-\exp[\beta'X(i) + u_i + \gamma_0(j)]\}$$

$$\theta(a_j|X(i)) = 1 - \exp\{-\exp[\beta'X(i) + u_i + \gamma_0(j)]\}$$

Appendix 4.5: Factor Loadings

TABLE A4.5.1: ROTATED FACTOR LOADINGS (PATTERN MATRIX) AND UNIQUE VARIANCES (UNSUPPRESSED FACTOR LOADINGS)

Traits	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Unique
Active Learning	0.870	-0.140	0.234	0.129	0.008	0.153
Active Listening	0.816	-0.397	0.057	0.102	0.142	0.142
Complex Problem Solving	0.836	0.032	0.348	0.152	0.011	0.157
Coordination	0.587	-0.151	-0.045	0.587	0.218	0.238
Critical Thinking	0.865	-0.062	0.306	0.104	0.063	0.141
Equipment Maintenance	-0.217	0.886	-0.124	-0.085	-0.005	0.146
Equipment Selection	-0.163	0.903	-0.011	-0.045	-0.112	0.143
Installation	-0.036	0.652	-0.038	-0.055	-0.196	0.531
Instructing	0.781	-0.117	-0.038	0.257	0.027	0.309
Judgment and Decision	0.809	-0.071	0.287	0.234	0.077	0.197
Learning Strategies	0.812	-0.110	0.070	0.193	-0.005	0.286
Management of Financial Resources	0.250	0.005	0.456	0.705	-0.053	0.230
Management of Material Resources	0.249	0.188	0.359	0.728	-0.051	0.242
Management of Personnel Resources	0.618	-0.010	0.125	0.585	0.116	0.247
Mathematics	0.308	-0.029	0.851	0.119	0.071	0.162
Monitoring	0.682	0.042	0.014	0.293	0.299	0.358
Negotiation	0.602	-0.326	0.019	0.529	0.122	0.235
Operation and Control	-0.176	0.864	0.050	-0.002	0.291	0.136
Operation Monitoring	-0.318	0.801	-0.076	0.007	0.277	0.175
Operations Analysis	0.513	0.066	0.399	0.175	-0.310	0.447
Persuasion	0.659	-0.343	0.027	0.479	0.066	0.213
Programming	0.380	0.081	0.610	-0.080	-0.182	0.438
Quality Control Analysis	-0.087	0.839	0.176	0.050	0.094	0.245
Reading Comprehension	0.823	-0.295	0.320	-0.004	-0.006	0.133
Repairing	-0.195	0.888	-0.121	-0.076	-0.047	0.151
Science	0.594	0.159	0.380	-0.183	-0.019	0.443
Service Orientation	0.523	-0.397	-0.185	0.336	0.187	0.387
Social Perceptiveness	0.647	-0.390	-0.228	0.336	0.190	0.229
Speaking	0.791	-0.441	-0.006	0.173	0.066	0.146
Systems Analysis	0.760	0.032	0.456	0.242	-0.077	0.150
Systems Evaluation	0.777	0.036	0.415	0.266	-0.066	0.147
Technology Design	0.367	0.407	0.458	0.122	-0.252	0.412

Time Management	0.632	-0.080	0.084	0.488	0.121	0.334
Troubleshooting	-0.164	0.927	-0.007	-0.017	0.069	0.108
Writing	0.828	-0.328	0.246	0.025	-0.007	0.146
Category Flexibility	0.611	0.039	0.493	0.132	0.113	0.353
Deductive Reasoning	0.851	-0.056	0.345	0.079	0.098	0.137
Flexibility of Closure	0.480	0.395	0.376	0.000	0.457	0.264
Fluency of Ideas	0.777	-0.058	0.294	0.309	-0.131	0.194
Inductive Reasoning	0.859	-0.064	0.308	0.008	0.110	0.151
Information Ordering	0.636	0.114	0.484	0.080	0.207	0.299
Mathematical Reasoning	0.377	-0.061	0.844	0.099	0.050	0.130
Memory	0.706	-0.032	0.212	0.089	0.165	0.421
Number Facility	0.311	-0.055	0.829	0.173	0.114	0.171
Oral Comprehension	0.792	-0.387	0.052	0.092	0.174	0.182
Oral Expression	0.799	-0.440	-0.012	0.128	0.113	0.139
Originality	0.746	-0.082	0.241	0.324	-0.162	0.248
Perceptual Speed	0.130	0.531	0.347	-0.020	0.599	0.221
Problem Sensitivity	0.735	0.177	0.171	0.144	0.359	0.250
Selective Attention	0.343	0.271	0.107	-0.016	0.523	0.524
Spatial Orientation	-0.272	0.532	-0.162	0.124	0.310	0.505
Speed of Closure	0.581	0.228	0.292	0.097	0.424	0.336
Time Sharing	0.401	0.182	-0.134	0.260	0.577	0.387
Visualization	0.094	0.703	0.270	0.198	0.033	0.384
Written Comprehension	0.812	-0.314	0.300	0.013	0.032	0.151
Written Expression	0.828	-0.339	0.223	0.046	0.016	0.147

Notes: Rotated factor loadings of cognitive abilities, basic skills and cross-functional skills importance ratings.

Source: O*NET Release 22.1 (Department of Labor Employment and Training Administration / National Center for O*NET Development 2017).

TABLE A4.5.2: FACTOR SCORE REGRESSION COEFFICIENTS TABLE

Traits	Cognitive	Technical	Math.	Res. Manag.	Pattern Recog.
Active Learning	0.088	0.029	-0.030	-0.050	-0.074
Active Listening	0.075	-0.027	-0.066	-0.062	0.082
Complex Problem Solving	0.074	0.046	0.005	-0.033	-0.080
Coordination	-0.014	-0.007	-0.055	0.196	0.077
Critical Thinking	0.087	0.032	-0.004	-0.076	-0.030
Equipment Maintenance	0.072	0.156	-0.084	-0.038	-0.104
Equipment Selection	0.075	0.173	-0.058	-0.017	-0.211
Installation	0.025	0.041	-0.020	-0.010	-0.075
Instructing	0.045	0.020	-0.061	0.027	-0.035
Judgment and Decision	0.039	0.016	-0.003	0.021	-0.010
Learning Strategies	0.051	0.022	-0.047	0.003	-0.051
Management of Financial Resources	-0.084	-0.011	0.081	0.291	-0.048
Management of Material Resources	-0.063	0.014	0.045	0.286	-0.064
Management of Personnel Resources	-0.009	0.010	-0.027	0.184	0.010
Mathematics	-0.095	-0.051	0.267	0.018	0.077
Monitoring	0.017	0.009	-0.035	0.035	0.072
Negotiation	-0.014	-0.021	-0.037	0.175	0.039
Operation and Control	-0.002	0.108	0.000	0.003	0.197
Operation Monitoring	-0.012	0.073	-0.020	0.030	0.158
Operations Analysis	0.017	0.022	0.016	0.014	-0.114
Persuasion	0.001	-0.016	-0.046	0.163	0.005
Programming	0.007	0.009	0.055	-0.042	-0.063
Quality Control Analysis	0.006	0.071	0.014	0.018	-0.002
Reading Comprehension	0.088	-0.006	0.025	-0.152	-0.058
Repairing	0.078	0.159	-0.087	-0.033	-0.142
Science	0.033	0.019	0.016	-0.078	-0.028
Service Orientation	0.004	-0.017	-0.043	0.060	0.052
Social Perceptiveness	0.026	-0.018	-0.096	0.088	0.076
Speaking	0.073	-0.022	-0.088	-0.001	0.011
Systems Analysis	0.044	0.043	0.051	0.043	-0.150
Systems Evaluation	0.049	0.048	0.033	0.057	-0.149
Technology Design	0.017	0.037	0.026	0.008	-0.111
Time Management	0.001	0.004	-0.025	0.106	0.013
Troubleshooting	0.063	0.200	-0.061	-0.005	-0.055

Writing	0.085	-0.005	-0.005	-0.116	-0.056
Category Flexibility	0.002	0.002	0.043	-0.008	0.021
Deductive Reasoning	0.080	0.025	0.017	-0.097	0.010
Flexibility of Closure	0.003	0.013	0.043	-0.059	0.189
Fluency of Ideas	0.047	0.036	-0.009	0.071	-0.158
Inductive Reasoning	0.088	0.024	0.002	-0.138	0.019
Information Ordering	0.007	0.005	0.048	-0.031	0.062
Mathematical Reasoning	-0.099	-0.059	0.321	-0.005	0.069
Memory	0.021	0.006	-0.004	-0.021	0.027
Number Facility	-0.101	-0.056	0.249	0.049	0.108
Oral Comprehension	0.054	-0.024	-0.048	-0.052	0.090
Oral Expression	0.080	-0.028	-0.092	-0.038	0.059
Originality	0.037	0.029	-0.017	0.066	-0.138
Perceptual Speed	-0.039	0.000	0.079	-0.047	0.331
Problem Sensitivity	0.032	0.019	-0.021	-0.021	0.131
Selective Attention	0.001	0.000	0.002	-0.026	0.117
Spatial Orientation	-0.012	0.012	-0.013	0.034	0.070
Speed of Closure	0.005	0.005	0.016	-0.021	0.134
Time Sharing	-0.003	-0.001	-0.035	0.038	0.169
Visualization	0.001	0.041	0.014	0.042	-0.025
Written Comprehension	0.069	-0.013	0.020	-0.120	-0.014
Written Expression	0.080	-0.009	-0.012	-0.101	-0.034

Notes: Scoring coefficients are derived by using the Bartlett method based on varimax rotated factors.

Source: O*NET Release 22.1 (Department of Labor Employment and Training Administration / National Center for O*NET Development 2017).

Appendix 4.6: Full Estimates for the Cloglog Model

TABLE A4.6.1: DEPARTURE FROM EMPLOYERSHIP – SINGLE RISK CLOGLOG MODEL

	Specifications			
	(1)	(2)	(3)	(4)
Duration	-0.914*** (0.065)	-0.890*** (0.066)	-0.489*** (0.153)	-0.481*** (0.150)
Work experience prior entry (Years)	-0.005 (0.008)	-0.005 (0.008)	-0.004 (0.010)	-0.003 (0.010)
<u>Highest level of education achieved (0/1)</u>				
Year 12	-0.162 (0.134)	-0.136 (0.136)	-0.255 (0.189)	-0.265 (0.190)
Certificate	0.122 (0.107)	0.153 (0.107)	0.162 (0.143)	0.161 (0.146)
Diploma	0.135 (0.141)	0.205 (0.144)	0.240 (0.189)	0.202 (0.192)
Bachelor's degree or higher	-0.118 (0.110)	-0.008 (0.121)	-0.037 (0.161)	-0.031 (0.164)
<u>Skills</u>				
Cognitive		-0.300* (0.156)	-0.437** (0.213)	-0.484** (0.215)
Technical specialisation		0.018 (0.155)	0.009 (0.213)	-0.034 (0.211)
Mathematics		-0.122 (0.134)	-0.184 (0.182)	-0.172 (0.184)
Resource management		-0.181 (0.137)	-0.294 (0.194)	-0.275 (0.192)
Pattern recognition		-0.142 (0.138)	-0.288 (0.197)	-0.264 (0.197)
<u>Business Size (0/1)</u>				
5 to 19 employees	-0.637*** (0.093)	-0.628*** (0.094)	-0.860*** (0.150)	-0.896*** (0.153)
20 to 49 employees	-0.637*** (0.201)	-0.603*** (0.202)	-0.721*** (0.263)	-0.730*** (0.267)
>50 employees	-0.274 (0.241)	-0.248 (0.242)	-0.399 (0.326)	-0.391 (0.324)
Age	-0.100*** (0.030)	-0.099*** (0.031)	-0.120*** (0.042)	-0.123*** (0.042)
Age ²	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Number of dependents (0/1) (0-14 years old)	-0.006 (0.035)	-0.006 (0.035)	-0.008 (0.046)	-0.011 (0.046)

Marital status (0/1)	-0.222** (0.103)	-0.210** (0.104)	-0.284** (0.137)	-0.291** (0.138)
Ln net disposable income	-0.050 (0.060)	-0.044 (0.061)	-0.045 (0.083)	-0.058 (0.083)
Unemployment (%)	-0.078** (0.037)	-0.077** (0.038)	-0.106** (0.052)	-0.056** (0.027)
Male	-0.113 (0.083)	-0.108 (0.091)	-0.158 (0.130)	-0.169 (0.131)
No. of observations	2,360			
Log-likelihood	-1,265.42	-1,260.14	-1,255.28	-1,255.04
Unobserved heterogeneity	NO	NO	YES	YES
Unemployment measurement	Major	Major	Major	SA4

Notes: Specifications (1) and (2) are estimated with Stata -cloglog- command. Specifications (3) and (4) use Stata -glamm- command to estimate the cloglog model with unobserved heterogeneity. Estimates are based on a pooled sample of 21-64 years old individuals who transitioned into employership, once, between waves 2002 and 2016. Standard errors are displayed in parentheses. 'Major' refers to unemployment rates measured for each of the 13 major statistical regions as defined in section 2.2.3. 'SA4' refers to unemployment rates for each SA4 local labour market. Section 3.7 defines SA4. The reference individual did not complete Year 12, owns a business with less than 5 employees, has an 'other' home status and was born in Australia. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, unconfidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017b).

Appendix 5.1: Job Satisfaction Methodology Summary

TABLE A5.1.1: JOB SATISFACTION METHODOLOGY SUMMARY

<u>Methodology</u>	<u>Studies</u>	<u>Outcomes</u>
Ordered logit model	Blanchflower and Oswald (1992); VandenHeuvel and Wooden (1997); Benz and Frey (2004, 2008a); Block and Koellinger (2009); Cueto and Pruneda (2017)	The self-employed report significantly higher job satisfaction scores than wage/salary employees. Independent and dependent contractors are more satisfied and no more satisfied than wage/salary employees, respectively. Necessity entrepreneurs are less satisfied with their start-ups than their opportunity equivalents.
Between-group earnings decomposition technique	Hundley (2001)	Greater levels of independence and autonomy within self-employment explain a significant portion of the difference in job satisfaction between self-employed workers and wage/salary employees.
Ordered probit model with correlated random effects	Taylor (2004); Kawaguchi (2008)	Employers and solo self-employed workers have significantly higher job satisfaction scores than their wage/salary counterparts, even after controlling for employment income and hours worked. Employers are significantly more satisfied with their jobs than

		the solo self-employed (Taylor 2004).
Conditional fixed-effects logit model	Andersson (2008)	Self-employment leads to an increase in job satisfaction, even after controlling for the individual's observable characteristics (i.e., age, gender, marital status, housing status and the number of children).
Propensity score matching	Binder and Coad (2013, 2016)	Individuals who moved into self-employment from wage/salary employment to have significantly larger life and job satisfaction scores than their counterparts who remained in wage/salary employment.
Ordinary least squares regression with fixed effects.	Hessels et al. (2015),	Employers and solo self-employed workers have significantly higher job satisfaction scores than wage/salary employees. No significant differences in job satisfaction between employers and solo self-employed workers.

Appendix 5.2: Full Estimates for the BUC Model

TABLE A5.2.1: OVERALL JOB SATISFACTION REGRESSION ESTIMATES

	Without FE Ordered Logit		With FE			
	Male (1)	Female (2)	OLS		BUC	
			Male (3)	Female (4)	Male (5)	Female (6)
<u>Employment Status (t-1)</u>						
Solo SE	-0.028 (0.044)	0.214*** (0.052)	0.121*** (0.038)	0.209*** (0.048)	0.182*** (0.057)	0.305*** (0.069)
Employership	0.189*** (0.052)	0.299*** (0.073)	0.155*** (0.043)	0.230*** (0.060)	0.249*** (0.068)	0.360*** (0.092)
Marital status (0/1)	0.108** (0.034)	0.093** (0.031)	-0.059** (0.029)	-0.023 (0.030)	-0.092** (0.044)	-0.026 (0.044)
Impaired (0/1)	-0.263*** (0.032)	-0.270*** (0.032)	-0.104*** (0.021)	-0.147*** (0.025)	-0.157*** (0.031)	-0.213*** (0.036)
Log Eq. disposable household income (\$)	0.151*** (0.025)	0.086*** (0.025)	0.084*** (0.018)	0.027 (0.019)	0.130*** (0.027)	0.040 (0.029)
<u>Number of dependents (0/1) (0-14 years old)</u>						
1	-0.049 (0.033)	-0.067 (0.035)	0.010 (0.026)	-0.017 (0.029)	0.012 (0.042)	-0.019 (0.044)
2	0.027 (0.038)	0.057 (0.041)	0.024 (0.031)	-0.002 (0.037)	0.036 (0.049)	0.003 (0.057)
≥ 3	0.052 (0.055)	0.121* (0.059)	-0.012 (0.046)	0.031 (0.055)	-0.025 (0.073)	0.051 (0.086)

Weekly working hours	-0.017*** (0.004)	-0.016*** (0.003)	0.007** (0.003)	0.001 (0.003)	0.011** (0.005)	0.001 (0.004)
(Working hours ²)/100	0.009* (0.004)	0.004 (0.004)	-0.011*** (0.003)	-0.012*** (0.003)	-0.016*** (0.005)	-0.017*** (0.005)
Part-time employed (0/1)	-0.231*** (0.056)	-0.083* (0.039)	-0.079** (0.039)	-0.036 (0.029)	-0.111* (0.059)	-0.051 (0.044)
Tenure with current employer or business	0.001 (0.002)	0.000 (0.002)	-0.018*** (0.002)	-0.022*** (0.002)	-0.030*** (0.003)	-0.035*** (0.003)
Urban area (0/1)	-0.075 (0.049)	-0.085 (0.053)	0.003 (0.044)	-0.116** (0.051)	0.009 (0.067)	-0.180** (0.080)
Regional unemployment (%)	-0.040*** (0.012)	-0.022 (0.013)	-0.027*** (0.010)	-0.028** (0.011)	-0.046*** (0.016)	-0.044** (0.017)
<u>Highest level of education achieved (0/1)</u>						
Year 12	-0.204*** (0.056)	-0.260*** (0.053)	-0.028 (0.122)	0.014 (0.093)	-0.047 (0.169)	0.030 (0.136)
Certificate	-0.144** (0.049)	-0.246*** (0.050)	-0.198* (0.102)	-0.194*** (0.073)	-0.288** (0.130)	-0.260** (0.106)
Diploma	-0.301*** (0.063)	-0.449*** (0.056)	-0.142 (0.123)	-0.040 (0.108)	-0.221 (0.176)	-0.043 (0.156)
Bachelor's degree or higher	-0.441*** (0.055)	-0.565*** (0.050)	-0.282** (0.132)	-0.222** (0.099)	-0.446** (0.183)	-0.306** (0.150)
Only one job	-0.078 (0.042)	-0.170*** (0.037)	-0.116*** (0.032)	-0.149*** (0.029)	-0.179*** (0.048)	-0.221*** (0.043)
<u>Age (0/1)</u>						
26-30 years old	-0.051 (0.036)	0.007 (0.034)	-0.047 (0.037)	0.053 (0.038)	-0.067 (0.058)	0.077 (0.057)
31-35 years old	-0.097* (0.043)	0.008 (0.042)	-0.086* (0.052)	0.037 (0.057)	-0.126 (0.082)	0.048 (0.086)

36-40 years old	-0.078 (0.047)	0.009 (0.047)	-0.096 (0.068)	-0.020 (0.074)	-0.153 (0.108)	-0.044 (0.113)
41-45 years old	-0.052 (0.048)	0.081 (0.045)	-0.121 (0.082)	-0.036 (0.089)	-0.197 (0.133)	-0.070 (0.137)
46-50 years old	0.003 (0.049)	0.094* (0.045)	-0.111 (0.097)	-0.077 (0.104)	-0.178 (0.158)	-0.147 (0.162)
51-55 years old	0.061 (0.052)	0.177*** (0.049)	-0.133 (0.111)	-0.077 (0.121)	-0.220 (0.183)	-0.150 (0.190)
≥ 56 years old	0.371*** (0.057)	0.415*** (0.057)	-0.110 (0.127)	-0.013 (0.140)	-0.167 (0.210)	-0.047 (0.220)
Log-Likelihood	-120,976.41	-109,573.18	-107,646.45	-99,746.37	-80,798.18	-75,201.88
Wald chi ²	699.483	1,025.499	-	-	525.714	579.946
Degrees of freedom	79	79	78	78	79	79
Pseudo R ²	0.009	0.014	-	-	0.013	0.015
No. of observations	67,271	61,204	67,271	61,204	222,429	205,613
No. of individuals	10,205	9,805	10,205	9,805	7,717	7,327

Note: The estimation sample comprises all employed persons observed during the waves 2001-2016 of the HILDA survey. Robust standard errors are reported in parentheses. The reference category under 'self-employment status' is persons in paid/salaried employment. All equations include, but not reported, occupation, industry, region, year and missing income indicators. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: HILDA Survey Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute of Applied Economic and Social Research 2017a).