Explaining the persistence of poverty and social exclusion in Australia

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Abstract

This paper investigates the extent of genuine state dependence in the processes of income poverty and social exclusion in Australia. Using a dynamic random-effects probit model with correlated random effects and accounting for endogeneity of initial conditions, it is found that there are genuine state dependence effects of 25% for income poverty and 34% for social exclusion. This suggests that policies aimed at preventing individuals experiencing either of these states will be particularly effective. Furthermore, the paper identifies significant dynamic spillover effects between the two processes. This implies that policy that prevents the experience of either outcome will reduce the probability of experiencing the other. These findings hold when accounting for the endogeneity of employment status because of possible feedback effects.

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1. Introduction

In recent years, there has been an expanded interest in the measurement and analysis of social exclusion that complements the vast existing literature on the topic of poverty dynamics. Australia has been no exception to this trend, with Scutella, Wilkins, and Horn (2009a) and Naidoo (2019) having recently developed unique measures of social exclusion. Furthermore, Australia's preeminent economic policy research centre - the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute) - publishes a social exclusion monitor annually with the intention of influencing public policy. The most recent estimates from the Melbourne Institute (2020) find that over 1.2 million Australians suffer from deep social exclusion. Furthermore, recent estimates by the Australian Council of Social Service (2020) found that 13.6 per cent of Australia's population live below the poverty line. Despite these significant estimates of poverty and social exclusion, these issues have not been a strong focus within the Australian policy environment due to the perception and portrayal of Australia as a wealthy nation with a robust social welfare infrastructure.

However, the COVID-19 pandemic has brought these issues to the forefront of policy debate, as widespread loss of employment has meant that more individuals than ever have become reliant on social support to remain out of poverty. This has been allowed to happen as income support has increased drastically through this period - with the introduction of JobSeeker and JobKeeper programs - to levels doubling pre-pandemic levels. However, as these policies have begun to expire and income support returns to its pre-pandemic level, there is a greater understanding throughout the community of the difficulty in surviving while experiencing low income.

The COVID-19 pandemic has also created a greater understanding of the multidimensional nature of disadvantage and the limitations of calculating disadvantage exclusively through the lens of material conditions. The last year has been defined by increased economic and unemployment uncertainty as the country has been thrust in and out of lockdown. The value of social inclusion, positive mental health outcomes, living free of long-term health conditions, and connectedness to the community have been reaffirmed as outcomes that were previously taken for granted were no longer a foregone conclusion. This effect was only magnified to those who already faced significant disadvantages before the pandemic.

It stands to reason that persistent disadvantage is more problematic for several reasons. Firstly, long periods of low-income lead to larger welfare losses than short or one-off spells do, as savings from earlier periods cannot be used to support oneself through this period. Furthermore, long periods have detrimental outcomes on self-perception, confidence, and mental health. Persistent disadvantage also means that the burden is unequally distributed amongst the population, bringing about equality concerns. While the primary goal of policy should be to minimise disadvantage, a secondary goal should be to ensure that poverty is not experienced disproportionately by a certain subset of individuals amongst the population. This justifies the study of persistent disadvantage.

When studying the persistence of poverty, there are two types of mechanisms that can explain why some people recurrently experience poverty. The first mechanism is that the individuals who experience persistent poverty have durable characteristics that make them susceptible to poverty in previous, current, and future periods. This includes both observed individual characteristics, such as age, sex, level of educational attainment, and the existence of health conditions, as well as unobserved characteristics, including low motivation levels, low ability levels, or other 'unfavourable' characteristics. The alternate mechanism through which poverty persistence may occur is through genuine state dependence. State dependence refers to the extent to which a previous experience of disadvantage increases the probability of an individual being subject to disadvantage in the future (Biewen, 2009). The existence of genuine state dependence income poverty or social exclusion implies a causal channel through which experience of these states increases future susceptibility to these outcomes. This could occur for many reasons, including due to stigmatisation, depreciation of human capital and/or demoralisation. Discerning between the two mechanisms

Despite increased interest in the topic, there is little research into the state dependence of income poverty and social exclusion in Australia. Although previous studies have investigated the drivers of income poverty and social exclusion, there has been no research into the state dependence of social exclusion of the working-age population in Australia, and limited research into state dependence of income poverty in Australia. This paper aims to address this gap in the existing research. The central hypothesis tested in this paper is whether past experiences of income poverty and social exclusion determine current income poverty and social exclusion status. As the experience of income poverty and social exclusion is likely to have significantly increased during the last year due to the pandemic, an understanding of the persistence of these phenomena has important policy implications. In the event there is a high degree of genuine state dependency in these processes, policy should be focussed on reducing the incidence of these phenomena in the current period, as doing so will reduce the long-term incidence, as well as having obvious immediate impacts. However, if the incidence of income poverty and social exclusion is explained largely by individual heterogeneity, then structural policy aimed at the subsets of the population most at risk will be more effective. Furthermore, this paper attempts to identify the degree to which the processes are interrelated by testing how past experience of income poverty increases the probability of experiencing social exclusion in the present and vice versa. The existence of interrelated dynamics between the two processes has important policy implications. It implies that policy aimed at reducing the incidence of one form of disadvantage will have positive spillover effects into reducing the incidence of the other.

The remainder of the paper is organised as follows. Section 2 provides an overview of the existing literature on the topics of social exclusion, state dependence, and dynamics of disadvantage while also outlining the contribution of this paper to this pre-existing literature. Section 3 outlines the dataset used and some of its limitations while also providing justification for the measures of social exclusion and income poverty used in the paper. It also provides some descriptive statistics and raw transition probabilities for the sample. Section 4 then outlines the econometric methodology used within the paper to estimate the degree of state dependence in income poverty and social exclusion while justifying each of the different specifications. Results of the main specifications outlined are provided in section 5, while section 6 provides further results that highlight the robustness of the results. A discussion of the results and their implications for policymakers is provided in section 7. Finally, section 8 concludes with an overview of the central findings.

2. Related literature

The concept of social exclusion was introduced in the late 1970s to recognise and capture marginalisation in French society, before later developing into a broad concept describing complex, systematic disadvantages (United Nations Economic Commission for Europe, 2018). It has since been adopted by the European Union, with most countries now producing indicators of social exclusion to measure progress in improving the circumstances of the disadvantaged (Scutella et al., 2009a). Levitas (2006) identifies social exclusion as a multidimensional process that involves the denial of, or lack of access to, sufficient resources, the inability to participate in normal relationships and activities available to the majority of people in a society, whether in economic, social, cultural, or political spheres. Levitas et al. (2007) notes that social exclusion can be a measure of not just the quality of life of individuals but also the equity and cohesion of society as a whole. This approach to quantifying multidimensional disadvantage aligns with Sen's (2000) capability approach, as it focuses on the multiplicity of deprivations faced by the most disadvantaged and the interrelated dynamics of these deprivations. The lack of a clear and accepted definition has meant that the terms social exclusion, individual well-being, and multidimensional poverty are often used interchangeably (United Nations Economic Commission for Europe, 2018). However, there are specific differences between the two concepts. While poverty highlights an outcome, being a state of disadvantage, “social exclusion draws attention to both the outcome and the process by which individuals become or remain systematically disadvantaged” (Madanipour, Cars & Allen, 1998).

The ambiguity over the definition of social exclusion has meant that there exists significant differences in the dimensions of disadvantage included in social exclusion measures. The Melbourne Institute has developed the Social Exclusion Monitor to measure social exclusion across seven life domains. The domains used are material resources, employment, education and skills, health and disability, social connection, community, and personal safety (Scutella, 2009a). Naidoo (2019) constructs a multidimensional individual well-being indicator framework using economic stability, physical health, mental health, personal relationships, community and social participation, and neighbourhood environment as the dimensions of well-being. This framework explicitly recognises the inter-relationship between the dimensions of well-being.

Genuine state dependence occurs when the experience of an outcome in one year raises the risk of experiencing that same outcome in the next year (Heckman, 1981a). However, as individuals with 'favourable' personal characteristics are likely to leave poverty earlier, the state dependence observed may not be genuine (Andriopoulou & Tsakloglou, 2011). Therefore, the literature controls for individual heterogeneity, both observed and unobserved, to determine the true extent of genuine state dependence.

The literature finds that poverty state dependence remains significant even after controlling for both observed and unobserved individual heterogeneity effects. This finding is robust to the econometric approach used. Hazard rate models have been a popular approach to modelling poverty transitions, allowing for the analysis of poverty spells. One of the first applications of this was implemented by Bane and Ellwood (1986), who define a poverty spell as "a continuous period during which income falls below the poverty line". Their analysis - which uses the data from the US Panel Study on Income Dynamics (PSID) from 1970-1982 - found evidence of state dependence in poverty status after controlling for personal characteristics. This methodology has been applied to samples from Spain (Cantó-Sánchez, 1996), Germany (Biewen, 2006), and international comparisons (Andriopoulou & Tsakloglou, 2011; Biewen, 2009), all of which find that state dependence in poverty status exists even after controlling for individual heterogeneity. Cappellari and Jenkins (2003) utilise a first-order Markov model to examine the determinants of low-income transitions, using a trivariate probit model to model initial conditions and sample attrition directly. They apply this model to data from the British Household Panel Survey for the 1990s, finding significant state dependence in poverty status after controlling for individual heterogeneity.

Dynamic discrete choice models are an increasingly popular methodology for studying state dependence. These models have been applied to study a range of topics, including labour market participation (Haan, 2006), criminology (Turanovic & Ogle, 2018), social assistance receipt (Cappellari & Jenkins, 2008), and employment status (Heckman, 1981a). The approach originated with the latter paper, where Heckman (1981a) studied whether the past experience of unemployment was a determinant of future unemployment by including lagged unemployment in a dynamic random-effects probit model that controls for individual heterogeneity and initial conditions. Wooldridge (2005) develops a similar approach to identifying state dependence that similarly accounts for initial conditions and unobserved heterogeneity, finding evidence of persistence in union membership. Biewen (2009) uses the Wooldridge (2005) approach to identify significant state dependency in poverty status, while also demonstrating the existence of feedback effects between previous poverty status and future employment status and household composition. This implies that the inclusion of these variables violates exogeneity in a dynamic discrete choice model. Giarda and Moroni (2015) apply Heckman's dynamic random-effects model to the EU-SILC data finding a significant degree of state dependence in income poverty. The relevant increases in probability were Italy (23 per cent), France (19 per cent), Greece (29 per cent), Portugal (24 per cent), Spain (16 per cent) and the UK (8 per cent).

Poggi (2007) tests the degree of state dependence of social exclusion in Spain from 1994 to 1999, finding significant dependence effects after controlling for individual heterogeneity. Devicienti and Poggi (2011) study the interrelated dynamics of social exclusion and income poverty in Italy. The paper extends the Wooldridge (2005) approach to initial conditions to a bivariate case, jointly estimating state dependence of both income poverty and social exclusion while also including the lagged status of the alternate disadvantage measure in the estimation of each equation. Their results confirm that poverty and social exclusion share common traits and should be characterised by interrelated dynamics, as they find that the coefficients of each of the cross-lagged dependent variables are highly significant. Furthermore, they find evidence of significant state dependence for each process, even when including cross-lagged effects, suggesting that while the two processes are interrelated, they are distinct processes.

Regarding Australia specifically, Martinez Jr. and Perales (2013) utilise data from 2001 to 2013 from the Household, Income and Labour Dynamics (HILDA) survey to study multidimensional poverty dynamics. They find that the deprivations in health, material resources, social support, and education increased over the 13-year period, while offsetting decreases in safety, employment, and community participation. Rodgers (2010) estimates the rates of chronic and temporary poverty in Australia using a components of variance model, which decomposes income changes into permanent income and transitory income components, finding a significant degree of persistence in poverty. Sila and Dugain (2019) use a multivariate probit model to analyse income poverty dynamics in Australia, concluding that people living alone, lone parents, part-time and casual workers, and Indigenous Australians are at the highest risk of poverty. However, Sila and Dugain's (2019) paper doesn't identify state dependence in income poverty, nor account for possible violations of the assumption of strict exogeneity by including employment and household composition variables. Buddelmeyer and Verick (2007) investigate the socio-economic drivers of poverty transitions in Australia by using a first-order Markov model as introduced by Cappellari and Jenkins (2003) - finding that tertiary education and employment status are key factors that reduce susceptibility to poverty. They also identify a significant degree of persistence in poverty experience.

Scutella, Wilkins, and Kostenko (2009b) use a tobit model to formally investigate the demographic characteristics associated with social exclusion experiencing, finding that females, the elderly, single persons, lone parents, Indigenous Australians, and people born in non-English speaking countries are most at risk. Scutella, Wilkins, and Kostenko (2013) investigate the degree of persistence in social exclusion by identifying raw spell-lengths of social exclusion, finding that short-term exclusion is more frequent than long-term exclusion. However, their analysis does not differentiate between genuine and spurious persistence. Miranti and Yu (2015) utilise the first eight waves of the HILDA to investigate the degree of state dependency in social exclusion among older Australians, finding significant genuine state dependence. However, there has been no research that investigates the state dependence of social exclusion amongst the working-age population in Australia.

This paper contributes to the existing literature by addressing this gap in the research whilst also making additional contributions. In the understanding of the paper, it is the first paper to provide estimates of income poverty and social exclusion that follows Biewen (2009) methodology in allowing for feedback effects between previous poverty and social exclusion experience and employment status. Furthermore, it investigates the degree to which the processes of income poverty and social exclusion are interrelated whilst endogenously modelling unemployment. This is done by expanding the methodology used by Devicienti and Poggi (2009) to a dynamic random effects trivariate probit model that jointly estimates income poverty, social exclusion, and employment status. It is likely that this is the first paper to investigate the degree to which the processes of income poverty and social exclusion are interrelated that accounts for feedback effects to employment status, and the first paper to estimate the degree to which state dependence explains social exclusion in Australia.

3 Data

3.1. The HILDA

3.1.1. Overview of the data

The paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. The HILDA is a large-scale longitudinal survey that is representative of the Australian population funded by the Department of Social Services. The survey is Australia's first and only large-scale, nationally representative household panel survey, now spanning 19 waves (Watson and Wooden, 2010). The first wave of the survey was completed in 2001 and included a sample of 13,969 individuals, referred to as Original Sample Members (OSMs). Subsequent waves cover OSMs and all members of the OSMs' household regardless of age. OSM household members are referred to as Permanent Sample Members (PSMs). Subsequent waves also include any children or individuals co-residing with an OSM or PSM in later waves. Furthermore, in response to both changes in national demographics and sample attrition, top-up samples are used to ensure that the survey remains nationally representative. This is achieved by including Additional Sample Members (ASMs) in the 11th and 18th waves. The individuals included in ASM are those who belong to demographics that have become underrepresented within the survey.

3.1.2. Limitations of the data.

There are several limitations of the HILDA data which must be acknowledged. Firstly, the most disadvantaged subsets of the population, including the homeless, the incarcerated and those residing in mental institutions, are outside the scope of the survey. This is because there is no practical way to survey these subsets of the population practically available. As it can be safely assumed that members of these groups will experience social exclusion and income poverty at a higher rate than the rest of the population, this limitation is likely to cause the panel to underestimate the true prevalence of these outcomes.

Furthermore, there is the issue of non-random sample attrition, as is common amongst longitudinal surveys. Sample attrition will cause bias in the estimates if sample non-response occurs in a non-random way that is linked to the processes of social exclusion or poverty. Similarly, non-random sample attrition will likely lead to an underrepresentation of the socially excluded and income poor in the sample.

A further limitation of HILDA data is that some subsets of the population are underrepresented. Immigrants and Indigenous Australians, two groups who may be expected to experience social exclusion and poverty at a higher prevalence, are underrepresented. Despite the inclusion of ASMs in wave 11, the underrepresentation of Indigenous Australians is still prevalent. A further problem with relying on solely HILDA data is that the sample sizes of those groups at risk of multidimensional poverty are often relatively small, making identifying patterns within this group potentially inaccurate. This problem can be particularly evident when looking for patterns within the already underrepresented groups, such as Indigenous Australians.

3.1.3. *Sample Criteria*

This paper focuses on the working-age population of Australia, defined as those between the age of 25 and 65. The justification for covering just the working-age population is that central to the concept of social exclusion is relativity, meaning the sample chosen should be roughly comparable in the chosen indicators for each of the chosen dimensions of social exclusion. What it means to be in good health in old age or childhood can vary significantly from what it means to be in good health as an adult, and it may be argued that poor health, social and economic outcomes are more damaging during different stages of the life cycle. While differing life-cycle effects still exist within the working-age population group as defined in this paper, the indicators of social exclusion remain more stable and universally relevant to this sample. Furthermore, life-cycle effects are controlled for in the analysis of the population.

Secondly, the paper focuses on wave 11 to wave 18 of the HILDA. This period is chosen because the chosen indicators are available across all waves. Furthermore, limiting the focus to the most recent periods provides an overview of how social exclusion is currently occurring. Additionally, as the ASMs were added to the sample in wave 11, this sample should be more nationally representative than a sample made up of earlier periods.

3.2. Measurement of Income Poverty and Social Exclusion.

3.2.1. *Income Poverty*

In line with previous studies, an individual is defined as experiencing income poverty if their household equivalent income is less than 60% of the median household equivalent income level. Household equivalent size is calculated according to the guidelines set out by the OECD equivalence scale, which assigns a value of 1 to the first household member, a value of 0.7 to each additional adult, and a value of 0.5 to each child in the household (OECD, 2013). Total household income is then divided by this equivalised household size to give the household equivalised income. Equivalised household income has the benefit of accounting for differences in a household's composition and size, allowing for comparability in the financial position of different households. It also acknowledges that some individuals who may not earn a high income themselves benefit from the income of other household members, and therefore do not suffer from income poverty despite their low personal income.

3.2.2. *Social Exclusion*

To identify the socially excluded, the paper adopts the framework of the counting approach first introduced by Alkire and Foster (2009). Firstly, a deprivation score, y_{it}^{d}, is calculated for each dimension, d, whereby the arithmetic mean of all n_j component indicators is calculated, as shown in Equation 1. The dimensions, d, included are economic stability, physical health, mental health, personal relationships, and community and social participation.

$$y_{it}^{d} = \frac{\sum_{c=1}^{n_j} y_{it}^{c}}{n_j} \qquad (1)$$

In line with the Alkire and Foster (2009) measure, henceforth AF measure, an individual is said to be deprived in dimension d if their deprivation score, y_{it}^{d}, exceeds some cutoff level, k_d as shown in Equation 2. For this paper, k_d is taken to be 0.3, and Y_{it}^{d} is a binary indicator taking value one if an individual is deprived in the relevant dimension and zero otherwise.

$$Y_{it}^{d} = 1\left[y_{it}^{d} \geq \mathrm{k_d}\right] \qquad (2)$$

However, while the AF measure calculates overall deprivation by summing the number of dimensions in which an individual experiences deprivation, the measure used in this paper sums the deprivation score for each dimension, j, to calculate y_{it}^{SE}, as shown in Equation 3. This approach is often referred to as the 'sum-score approach' and follows closely the methodology used by papers similarly exploring the prevalence of social exclusion in Australia (Scutella et al., 2009).

$$y_{it}^{SE} = \sum_{d=1}^{n_d} y_{it}^{d} \qquad (3)$$

An individual is then said to be experiencing social exclusion if y_{it}^{SE} exceeds some cutoff, k_{SE}, as illustrated in equation 4. For this paper k_{SE} is taken as 1.5, meaning that an individual is said to be experiencing social exclusion if $y_{iit}^{SE} \geq 1.5$, although sensitivity testing occurs for different levels of k_{SE}.

$$Y_{it}^{SE} = 1[y_{it}^{SE} \geq \mathrm{k_{SE}}] \qquad (4)$$

There are several justifications for diverging from the AF methodology. Firstly, this approach to measurement encapsulates the interrelated dynamics of the different dimensions. An individual who is close to the cutoff in all dimensions intuitively may experience as great, if not more, significant social exclusion than an individual who is deprived in one dimension but experiences low levels of deprivations in all others. Similarly, it removes the individual subjective weighting that may occur. A sum-score approach also benefits from being robust to individual subjective weightings of the dimensions of disadvantage. For example, an introverted individual who places no importance and gains no satisfaction from deep personal relationships may not value this dimension and willingly experiences deprivation here but in no other aspects. Whereas the AF measure would identify this individual as socially excluded, this measurement would not.

Similarly, the measurement is robust to the idea that individuals make trade-offs between dimensions, often subconsciously. Due to scarcity, many individuals must sacrifice some aspects of their wellbeing and trade-off between dimensions. This measure is more robust to this, treating individuals who spread the sacrifice across dimensions equally to those who concentrate their sacrifice into one dimension.

A further advantage of this methodology is that it is sensitive to just one cutoff instead of two. A drawback of the AF measure is that the identification method is used dual-cutoff points and is therefore sensitive to specific changes while being insensitive to others. This means that small changes around the cutoff can cause the deprivation level to vary discontinuously in achievements. This drawback is common to any measure that attempts to place a binary status on disadvantage, including income poverty measures. However, this issue is exacerbated with the counting approach, due to the use of dual cutoff points. The measure used is still sensitive to changes in Y_{it}^{SE} around the cutoff, k.

2.3.3. *Social Exclusion Dimensions*

The dimensions and indicators of social exclusion used in this paper closely follow those used in Naidoo's measure of social exclusion (2019). The dimensions utilised in this framework are economic stability, physical health, mental health, personal relationships, community and social participation and neighbourhood environment. Each domain has between 9 and 18 indicators in Naidoo's framework, meaning that it is less sensitive to changes in a single indicator. Furthermore, it suffers less from loss of information and sensitivity around the cutoff for individual indicators by allowing non-binary scores for indicators where possible. As compared to the measure created by Scutella (2009), this definition of social exclusion takes a more outcome-based, wellbeing focussed approach to the concept of social exclusion. Naidoo (2019) justifies the exclusion of education and employment as dimensions of social exclusion because it is unclear if these dimensions are predictors influencing wellbeing or if they are aspects of wellbeing. Preceding in this way allows education and employment to be included in the model as individual-level characteristics. Therefore, it does not make the value judgement that one sub-group represents more of an achievement than another, such as full-time workers and retirees. This allows each domain's intrinsic value to be indisputable, as a higher score in each indicator represents what would close to be considered an improvement in quality of life universally. A further difference in this measure is its' separate treatment of physical and mental health. This keeps with the internationally recognised SF-36 health screening instrument, which identifies physical functional-health, and emotional and mental wellbeing, as separate phenomena.

This paper adjusts the Naidoo (2019) framework in several ways. Firstly, to reduce noise-based variations in the measures, indicators that are not available in all waves are removed. While year dummies largely capture this noise at an aggregate level, they do not remove the effect at the individual level. Inclusion of indicators not available across all waves raises the possibility that an individual can meet the criteria for experiencing social exclusion in one year but not the next despite no changes in their circumstance. Furthermore, the neighbourhood environment dimension is not included because eight of the nine indicators are not available in every wave.

Table 1 gives the complete list of indicators used. Each indicator is scored between 0 and 1, from left to right of the operational form column, with 1 indicating the most deprived in that indicator and zero being the least. For an indicator with three options, the indicator would have possible scores; 0, 0.5 and 1. As aforementioned, this reduces sensitivity to small changes in responses compared to using indicators that take only binary outcomes 0 and 1, reflecting that deprivation rarely occurs in a dichotomous fashion. The operational form column represents the options available to the survey respondents for that given question, with some questions having up to 10 responses, while others have just two responses. The scores for each indicator are scaled between 0 and 1, with a score of 0 being given to the first response in the operational form column and a score of 1 being given to the highest score response for each indicator. The rest of the scores are then given at even intervals, dependent on the number of responses. For example, for an indicator with five possible responses, the indicator values would be 0, 0.25, 0.5, 0.75 and 1.

Table 1 also provides the incidence of each indicator used in the measure of social exclusion. Furthermore, it provides the mean score for each domain and the proportion of the population identified as being deprived within each domain. The proportion deprived varies between 13.5% for physical health and 15.6% for economic stability. This low level of variation between the proportion of the population deprived in each dimension suggests that the measures achieve the relativity goal of social exclusion measurements. However, there is a greater level of variation between the mean scores in each dimension, ranging from 0.171 in economic stability to 0.259 in personal relationships. Furthermore, the Table highlights that the mean total score is 0.901 for the sample, with 15.9% of the population identified as suffering from social exclusion.

Table 1. Operational form and mean score for each dimension and composite indicator of social exclusion

Social exclusion dimensions with indicators	Operational form	Mean score
Economic stability *(4 indicators)*		**0.171**
Deprivation rate in dimension: 17.4%		
Difficulty raising $3000 in an emergency	1 Could raise easily … 4 Could easily raise	0.205
Prosperity given current needs and financial responsibilities	1 Prosperous … 6 Very poor	0.191
Household income below different median levels	1 None 2 70% 30 60% 4 50%	0.146
Physical health *(16 indicators)*		**0.190**
Deprivation rate in dimension: 13.5%		
Vigorous activities	1 Not limited at all … 3 Limited a lot	0.358
Moderate activities	1 Not limited at all … 3 Limited a lot	0.163
Lifting or carrying groceries	1 Not limited at all … 3 Limited a lot	0.140
Climbing several flights of stairs	1 Not limited at all … 3 Limited a lot	0.192
Climbing one flight of stairs	1 Not limited at all … 3 Limited a lot	0.102
Bending, kneeling or stooping	1 Not limited at all … 3 Limited a lot	0.204
Walking more than one kilometre	1 Not limited at all … 3 Limited a lot	0.181
Bathing or dressing yourself	1 Not limited at all … 3 Limited a lot	0.118
Reduced the time spent on work or other activities due to physical health	1 No … 2 Yes	0.175
Accomplished less than would like	1 No … 2 Yes	0.235
Were limited in the kind of work	1 No … 2 Yes	0.198
Had difficulty performing work or other activities	1 No … 2 Yes	0.211
Bodily pain in the last 4 weeks	1 No bodily pain … 6 Very severe	0.198
How much did pain interfere with normal work	1 Not at all … 5 Extremely	0.237
Self-assessed health	1 Excellent … 5 Poor	0.160
Expect my health to get worse	1 Definitely false … 5 Definitely true	0.169
Mental health *(17 indicators)*		**0.191**
Deprivation rate in dimension: 13.7%		
Get sick a little easier than other people	1 Definitely false … 5 Definitely true	0.343
As healthy as anybody I know	1 Definitely true … 5 Definitely false	0.156
My health is excellent	1 Definitely true … 5 Definitely false	0.216
Feel full of life	1 All of the time … 6 None of the time	0.138
Have a lot of energy	1 All of the time … 6 None of the time	0.178
Felt worn out	1 None of the time … 6 All of the time	0.274
Felt tired	1 None of the time … 6 All of the time	0.161
Extent emotional health interfered with normal social activities	1 Not at all … 5 Extremely	0.135
Time emotional problems interfered with social activities	1 None of the time … 6 All of the time	0.162
Cut down the amount of time spent on work/other activities	1 No … 2 Yes	0.119
Accomplished less than would like	1 No … 2 Yes	0.207
Didn't do work/other activities as carefully as usual	1 No … 2 Yes	0.178
Been a nervous person	1 None of the time … 6 All of the time	0.149
Felt so down in the dumps nothing could cheer you up	1 None of the time … 6 All of the time	0.121
Felt calm and peaceful	1 All of the time … 6 None of the time	0.266
Felt down	1 None of the time … 6 All of the time	0.157
Been a happy person	1 All of the time … 6 None of the time	0.280
Personal relationships *(10 indicators)*		**0.259**
Deprivation rate in deprivation: 14.5%		
People don't visit me as often as I would like	1 Strongly disagree … 7 Strongly agree	0.278
Often need help from other people but can't get it	1 Strongly disagree … 7 Strongly agree	0.259
Lots of friends	1 Strongly agree … 7 Strongly disagree	0.187
No one to confide in	1 Strongly disagree … 7 Strongly agree	0.284
No one to lean on in times of trouble	1 Strongly disagree … 7 Strongly agree	0.219
Someone who can always cheer me up when I'm down	1 Strongly agree … 7 Strongly disagree	0.243
Often feel very lonely	1 Strongly disagree … 7 Strongly agree	0.264
Enjoy the time I spend with people who are important to me	1 Strongly agree … 7 Strongly disagree	0.273
When something's on my mind, talking with people can make me feel better	1 Strongly agree … 7 Strongly disagree	0.209
Usually find someone to help me out when I need	1 Strongly agree … 7 Strongly disagree	0.213
Community and social participation *(5 indicators)*		**0.177**
Deprivation rate in dimensions: 14.5%		
Satisfaction with neighbourhood you live in	1 Extremely satisfied … 10 Extremely dissatisfied	0.154
Feeling part of your local community	1 Strong feeling of … 10 Not at all	0.268
Member of sporting, hobby, community or political based club or association	1 Yes … 2 No	0.227
Volunteer your spare time	1 Yes …. 2 No	0.131
How safe you feel	1 Extremely safe … 10 Extremely unsafe	0.105

Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

The majority of the previous research exploring social exclusion in Australia follows the measure introduced by Scutella et al. (2009a). This measure of social exclusion uses the domains of material resources, employment, education and skills, health, social support, community participation, and personal safety to comprise social exclusion. Although there is intuitiveness to this definition, there are some practical drawbacks to this methodology. Firstly, the measurement of these dimensions uses a small number of indicators, being as low as three in specific dimensions. Furthermore, many of these indicators are not available for each year of the survey. This means that the number of indicators within a single indicator can fall to as low as one for some domains in some years, making the measure highly sensitive to marginal changes in response. For example, an individual whose response to the question "Rate your satisfaction with the safety of your neighbourhood on a 1-10 scale" is 5 will have a score of 1 in the safety domain, while an individual who gives a score of 6 will receive a score of 0. This is a problem with using binary outcomes for each individual indicator, as it suffers from information loss. The chosen measure remedies this issue by allowing for scores between 0 and 1 for each indicator. Utilising binary outcomes for responses with a scale of responses significantly increases the sensitivity of the measure, as illustrated above. Furthermore, in the Scutella et al. (2009) measure, deprivations in employment and education domains are significantly lower than others, having prevalence rates below 5% in the sample chosen. As Alkire, Apablaza, Chakravarty, and Yalonetzky (2015) state, “dimensions should have no objective hierarchy”, but by including dimensions with a much lower prevalence of deprivation under these indicators, an implicit hierarchy exists.

3.2.4. *Intensity of Disadvantage*

Although the paper considers poverty and social exclusion as binary states, the intensity of disadvantage experienced by individuals varies in a non-dichotomous manner. Therefore, identifying those most severely deprived is of great importance. Intuitively, someone whose income is significantly below the poverty line is much more disadvantaged than an individual whose income is marginally below the cutoff. Equity concerns mean that policy aimed towards aiding the most deeply deprived is a priority. For this reason, marginal, deep, and severe income measures of both poverty and social exclusion are developed to complement the already existing definitions. In addition to having important policy implications, these alternate measures also are a method fr testing the sensitivity of the results of the main specification to the cutoff points used.

Table 2 displays the cutoff points for each of these intensity levels of income poverty and social exclusion and the incidence of the level of deprivation. Marginal disadvantage refers to those individuals who only slightly avoid falling into each category, with scores just above (below) the cutoff point. Marginal income poverty has an 18.6% incidence rate, while marginal social exclusion has an incidence rate of 22.3%. Similarly, deep disadvantage refers to the individuals who fall below the chosen cutoff but not significantly so, with deep income poverty having an incidence of 6.83% and deep social exclusion having an incidence of 8.21%. Lastly, severe disadvantage refers to those individuals who fall significantly below the cutoff point. This refers to the individuals who are intensely deprived, the most at risk in society. Severe income poverty has an incidence rate of 3.18%, and deep social exclusion has an incidence rate of 3.84%, demonstrating that the proportion of the sample experiencing these outcomes is relatively low.

Table 2. Definitions and incidence of income poverty and social exclusion classifications

	(1)		(2)	
Classification	Income poverty		Social exclusion	
	Cutoff	Incidence	Cutoff	Incidence
Marginal disadvantage	Household equivalised income ≤ 70% of median	18.60%	$Y_{it}^{se} \geq 1.25$	28.31%
Disadvantage (reference)	Household equivalised income ≤ 60% of median	11.80%	$Y_{it}^{se} \geq 1.5$	18.64%
Deep disadvantage	Household equivalised income ≤ 50% of median	6.83%	$Y_{it}^{se} \geq 2$	8.34%
Severe disadvantage	Household equivalised income ≤ 40% of median	3.18%	$Y_{it}^{se} \geq 2.5$	3.84%

Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

3.3. Descriptive Statistics

Table 3 provides descriptive statistics for the sample. The first column provides the proportion of the sample that belongs to the demographic characteristic identified, while columns 2 and 3 identify the proportion of the relevant demographic subset suffering from income poverty and social exclusion.

In terms of the proportion of the population, it is important to note the demographic characteristics with a low prevalence rate through the sample. These included retired (noting the sample excludes individuals aged 65 or above), households with four or more children, and Indigenous Australians. Column 2 and Column 3 demonstrate that social exclusion and income poverty impact different population subsets disproportionately. Individuals who are not employed, have four or more children in their household and have low levels of educational attainment experience income poverty and social exclusion to a greater extent than the sample mean.

Table 3. Descriptive statistics

	(1) Proportion of population	(2) Proportion in income poverty	(3) Proportion in social exclusion
Mean	-	11.8%	18.6%
Age brackets:			
<35	28.15%	10.81%	16.14%
35 - 54	49.71%	11.36%	18.15%
>= 55	22.15%	14.01%	22.72%
Employment status:			
Full time	52.19%	3.86%	8.58%
Part time	19.70%	10.06%	14.57%
Retired	3.66%	23.86%	37.18%
Other	24.48%	28.30%	40.46%
Household structure:			
0 kids	50.86%	10.82%	19.09%
1 kid	18.06%	10.54%	19.84%
2 kids	20.50%	9.67%	14.92%
3 kids	8.06%	17.63%	18.44%
4+ kids	2.52%	39.04%	30.19%
Lone parent	26.65%	10.93%	38.09%
Sole person	14.05%	11.38%	28.32%
Sex:			
Female	51.76%	12.76%	20.43%
Male	48.24%	10.75%	16.63%
Educational attainment			
Low	18.57%	23.18%	34.29%
Mid	46.38%	11.85%	19.45%
High	35.06%	5.69%	9.17%
Background:			
Indigenous Australian	7.88%	18.98%	21.67%
Non-English speaking country	12.43%	16.81%	21.21%
Other:			
Father unemployed at 14	15.75%	16.09%	22.79%
Lives remotely	36.34%	15.42%	22.13%

Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

3.5. Raw transition probabilities

Table 4 presents the raw transition probabilities of income poverty and social exclusion for the sample. It provides an overview of the persistency and state dependence of the two processes. The raw probability of entry into a state is the proportion of the population that experiences the disadvantage in the current year conditional on not experiencing that form of disadvantage the previous year. Conversely, the exit probability is the proportion of the sample which does not experience the given form of disadvantage in the reference year but experienced it the year before. The persistence rate and remain rate calculate the probability of remaining in the state in both years.

Table 4. Raw transition probabilities

	(1) Income poverty	(2) Social exclusion
Entry rate: pr(1|0)	5.48%	7.45%
Persistence rate: pr(1|1)	58.28%	68.39%
Exit rate: pr(0|1)	41.72%	31.61%
Remain: pr(0|0)	94.52%	92.55%

Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

From Table 4, the proportion of the sample who enter into poverty is 5.48%, while the proportion who exit poverty in any given year is 41.72%. This implies a significant persistency in income poverty, as the proportion who remain in this state is 58.28%. This demonstrates that there is poverty is highly persistent. The proportion of the population who enter social exclusion is 7.45%, while the proportion of the sample who leave social exclusion is 31.61%. Therefore, there is a higher degree of persistence in social exclusion than income poverty within the sample, with the proportion who remain deprived being 68.39%. The highly persistent nature of these processes justifies the study of differentiating between the mechanisms of genuine state dependence and individual heterogeneity in creating this state dependence.

4. Econometric Specification

4.1. Overview

In following the majority of literature concerned with the persistence of binary outcomes, a dynamic random-effects probit model is used to estimate state dependence in income poverty and social exclusion. The aim of these dynamic specifications is to determine the degree of state dependence that exists within a process by modelling state dependence through the lagged dependent variable, Y_{it-1}. The coefficient associate with the lagged dependent variable captures the degree to which experiencing a state in the previous period impacts the probability of the future experience of that state.

However, simply adding the lagged dependent variables as an additional covariate (Song, Kuo, Derby, Liption, & Hall, 2011) leads to maximum likelihood estimators that are highly inconsistent due to the initial conditions problem. In the case of poverty dynamics, the initial conditions problem exists because the first period observed is not the beginning of the stochastic process that leads to experiencing the outcome. Formally, while the values of the response variables for the periods $s = 0, \dots, T$ are observed, the stochastic process starts at period $s < 0$. In the literature, there are two main approaches to addressing the initial conditions problem. Heckman (1981b) proposes jointly estimating the initial response with subsequent responses, modelling what amounts to a linearised approximation of the reduced form for the latent variable in the initial period. Alternatively, Wooldridge (2005) approaches the problem by conditioning on the response at the initial period y_{i0}. This approach uses a Conditional Maximum Likelihood (CML) estimator that considers the distribution conditional on the observed individual heterogeneity and initial conditions.

In addition to the initial conditions problem, another issue that can lead to inconsistent estimators if not addressed is the endogenous covariates problem. This occurs when the random intercept is not independent of the covariates. To identify the degree of state dependence, we must assume that there is no correlation between unobserved heterogeneity and the outcome variable (Heckman 1981a,b). It follows that by including only the lagged dependent variable, one cannot assess the presence or evaluate the magnitude of genuine state dependence because there will be a correlation between the unobserved heterogeneity and the outcome variable. This occurs due to the omission of individual-level time-constant explanatory variables correlated with the observed covariates.

Skrondal and Rabe-Hesketh (2014) show that both the initial conditions problem and the endogenous covariates problem i addressed by modelling the individual unobserved heterogeneity component, shown in Equations 5 and 6. Their approach is itself an extension of the Wooldridge (2005) estimator. Other variations of the Wooldridge estimator condition on Y_{i0} but model unobserved effects by including within-unit averages computed on the time-varying independent variables (Stewart 2007; Biewen 2009). The use of the within-unit averages has the advantage of being parsimonious while also being applicable to unbalanced panels. However, such a model tends to provide biased estimates because the conditional distribution of the unobserved effects depends more on the value of the initial period than on the values of the other periods of the explanatory variables (Rabe-Hesketh & Skrondal, 2013). Rabe-Hesketh and Skrondal (2013) show that the following specification can solve the issue of overweighing the initial period while still being parsimonious and applicable to unbalanced panels. This is achieved through augmenting the model with the initial period and time-averaged values of the time-varying explanatory variables, $\boldsymbol{Z_{i0}}$ and $\overline{\boldsymbol{Z_i}}$, as shown in Euation 6.

$$y_{it}^* = \gamma y_{it-1} + \boldsymbol{\beta Z_{it}} + c_i + u_{it} \tag{5}$$

$$c_i = \alpha_0 + \alpha_1 Y_{i0} + \boldsymbol{\alpha_2} \overline{\boldsymbol{Z_i}} + \boldsymbol{\alpha_3 Z_{i0}} + a_i \tag{6}$$

The latent outcome variable, y_{it}^*, represents the chance of an individual, *i*, experiencing a given state (income poverty or social exclusion) in year *t*. The outcome variable is a function of time-varying explanatory variables, Z_{it}, that are assumed to be strictly exogenous conditional on the individual-specific unobserved effect,

c_i. The coefficient of the lagged dependent variable, γ, captures the degree of genuine state dependence, and u_{it} is an idiosyncratic error term, with mean zero and variance σ^2.

In the specification, α_0 captures the constant unobserved heterogeneity effect while α_1 captures the impact of the initial condition of the dependent variable, Y_{i0}, in explaining unobserved heterogeneity. The vectors of coefficients, α_2 and α_3, capture correlation between the initial conditions and time-averaged values of the strictly exogenous time-varying variables and unobserved heterogeneity. Statistically significant coefficients within these vectors imply that the characteristics are correlated with unobserved factors positively associated with the outcome variable (Grotti and Cutuli, 2018). Holding the assumption that c_i captures unobserved heterogeneity and that the vector of explanatory variables included in Z_{it} are strictly exogenous, then the lagged variable of the response variable can be interpreted as genuine state dependence (Grotti and Cutuli, 2018).

$$Y_{it} = 1[y_{it}^* = \gamma y_{it-1} + \boldsymbol{\beta Z_{it}} + \alpha_0 + \alpha_1 y_{i0} + \boldsymbol{\alpha_2 \overline{Z_i}} + \boldsymbol{\alpha_3 Z_{i0}} + a_i + u_{it} > 0] \qquad (7)$$

Equation 7, where Y_{it} is a binary response variable which takes value one if the latent propensity to poverty, y_{it}^*, is greater than zero is, obtained by substituting Equation 6 into Equation 5, is estimated by a Conditional Maximum Likelihood (CML) estimator.

An advantage of this model specification is that it remains parsimonious and applicable to unbalanced panels. Applicability to unbalanced panels is important for several reasons. Firstly, it reduces information loss, as it does not exclude specific observations. Secondly, and most significantly, it reduces the impact of sample attrition and selection bias on the results. Attrition bias occurs if the reasons for an individual exiting the survey are non-random and linked to the processes of income poverty and social exclusion. Sample bias occurs if specific subsets of the population with differing susceptibility to poverty and exclusion are more likely to be included within the sample. This is a significant problem for panel data studies that is exacerbated by using balanced panels.

Furthermore, Devicienti and Poggi (2007) note that this methodology has some advantages in dealing with selection and attrition problems, being that it allows selection and attrition to depend on initial conditions. It, therefore, can differ across different levels of initial conditions, allowing individuals with different initial conditions to have separate missing data probabilities. This implicitly considers attrition and selection bias without directly modelling these processes. These benefits to dealing with sample and attrition bias are common to the RHS method, which comes with the added advantage of allowing for unbalanced panels, meaning that the issues are minimised under such a specification.

4.1.1. Choice of explanatory variables

While the explanatory variables included in the vector $\boldsymbol{Z_{it}}$ change between specifications, the complete specification includes both time-varying variables and time-constant variables. The time-varying variables considered are; the number of dependents, employment status, being a lone parent, living alone, and living in a non-urban area. The time constant variables included are: educational attainment; gender; father being unemployed at 14; Indigenous Australian heritage; and being born in a non-English-speaking country. The unobserved heterogeneity component is, ci, is modelled from the initial conditions and within-unit averages of the time-varying explanatory variables. A set of year dummies are included in all specifications to account for macroeconomic differences between years.

For the estimators to be efficient, all time-constant and time-varying predictors must be strictly exogenous (Andriopolou & Tsaklogous, 2011). The model implies strict exogeneity conditional on individual unobserved effects, ci. Therefore, identifying state dependence requires current deprivation status be unrelated to the value of the regressors in future periods. As the unobserved heterogeneity term includes previous values of the regressors, violation of the exogeneity assumption occurs if there are feedback effects from poverty or social exclusion to future values of the covariates included within the model. Explanatory variables such as age, gender, heritage (Indigenous Australian and born in a non-English-speaking country), and father's employment status at 14 cannot depend on past poverty status. Educational attainment is also assumed to be exogenous in similar research (Biewen, 2009; Andriopolou & Tsakolgous, 2011). However, past social exclusion and poverty experiences may affect employment status, fertility decisions and household structure (being a lone parent, living alone and living in a non-urban area). There is no commonly accepted test for checking the exogeneity assumption. Therefore, a common practice throughout the literature is to rerun the model, excluding the variables that could theoretically violate the exogeneity assumption, and then compare the coefficients (Biewen, 2009).

For this reason, specifications are also included, which exclude variables that may violate exogeneity. The first such specification excludes just employment status. This is the variable for which the assumption of exogeneity would seem most problematic. Another specification excludes the number of dependents in the household and the dummies for being a lone parent and living alone.

4.3. Bivariate model with endogenous employment

Equation 8 and Equation 9 introduce bivariate model that allows for feedback effects between previous dependent variable status (income poverty and social exclusion) and employment status.

$$Y_{it} = 1[y_{it}^{*} = \gamma_1 Y_{it-1} + \boldsymbol{\beta_1 Z_{it}} + \zeta E_{it} + c_{1i} + u_{1it} > 0] \tag{8}$$

$$E_{it} = 1[e_{it}^{*} = \gamma_2 Y_{\mathrm{it}-1} + \boldsymbol{\beta_2 \mathrm{Z}_{it}} + \mathrm{c}_{2\mathrm{i}} + \mathrm{u}_{2\mathrm{it}} > 0] \tag{9}$$

In this specification, Z_{it}, is a vector of strictly exogenous variables, Y_{it} and e_{it} are binary indicator functions equal to one if their respective latent propensities for disadvantage are positive and zero otherwise. The definition of unemployment used in this specification covers all individuals who are not employed at the time of the survey, excluding retirees. This implies that it includes both individuals who are actively seeking employment and those who are not. The justification for this definition is that definitions of unemployment that focus just on those actively seeking employment exclude individuals who have become disenchanted with the labour market.

$$c_{1i} = \alpha_{10} + \boldsymbol{\alpha_{11}}\, \overline{\boldsymbol{Z_i}} + \alpha_{12}\overline{E_i} + \alpha_{13}Y_{i0} + \alpha_{14}E_{i0} + \boldsymbol{\alpha_{15} Z_{i0}} + a_{1i} \tag{10}$$

$$c_{2i} = \alpha_{20} + \boldsymbol{\alpha_{21}}\overline{\boldsymbol{Z_i}} + \alpha_{23}Y_{i0} + \alpha_{24}E_{i0} + \boldsymbol{\alpha_{25} Z_{i0}} + a_{2i} \tag{11}$$

To test for the existence of exogeneity in employment status, we are interested in γ_2, as a statistically significant coefficient suggests the existence of feedback effects between disadvantage and current employment status. The lagged dependent variable impacting the future value of the employment variable would constitute a violation of the strict exogeneity condition. In the existence of feedback effects, the above specification allows for the estimation of state dependence of both income poverty and social exclusion while including the impact of employment status. This is preferred because it is expected that employment status will have a significant explanatory role in the processes of income poverty and social exclusion. Therefore, its' absence could lead to significant attenuation bias.

The idiosyncratic error terms, u_{1it} and u_{2i} , are assumed to follow a bivariate normal distribution with zero means. The random-effects correlation covariance matrix is given as below, where the residuals are allowed to be freely correlated. Inference of significant correlation in the residuals is provided in section 4.4.2.

$$\Sigma_a = \begin{pmatrix} \sigma_{a1}^2 & \sigma_{a1}^2\sigma_{a2}^2\rho_{12} \\ \cdot & \sigma_{a2}^2 \end{pmatrix} \tag{12}$$

4.4. Methodology for capturing spillover effects

4.4.1. Bivariate model

To identify the degree to which the dynamics of poverty and social exclusion are interrelated, a dynamic random-effects bivariate probit model is used to estimate the joint probability of experiencing the two forms of disadvantage. This allows for correlated unobserved heterogeneity between income poverty and social exclusion. The equations must be jointly estimated if the cross-lag effects are statistically significant, or if there is a statistically significant correlation in the random-effects error terms, ρ_a. Joint estimation allows the assumption of independence in the random-effects errors of the two equations to be relaxed. If we expect that there are common elements to the idiosyncratic shocks that make an individual at risk of poverty and social exclusion, then joint estimation of the two processes is necessary (Devicienti & Poggi, 2007).

$$Y_{it}^{IP} = 1[y_{it}^{IP} = \gamma_{11}Y_{it-1}^{IP} + \gamma_{12}Y_{it}^{SE} + \boldsymbol{\beta_1 Z_{it}} + c_{1i} + u_{1it} > 0] \tag{13}$$

$$Y_{it}^{SE} = 1[y_{it}^{SE} = \gamma_{21}Y_{it-1}^{IP} + \gamma_{22}Y_{it}^{SE} + \boldsymbol{\beta_2 Z_{it}} + c_{2i} + u_{2it} > 0] \tag{14}$$

Equation 15 models The unobserved heterogeneity term for both equations. It consists of an individual constant, the time-averaged vector of strictly exogenous variables, the initial conditions for both income poverty and social exclusion, and the initial conditions for the strictly exogenous variables.

$$c_{ji} = \alpha_{j0} + \boldsymbol{\alpha_{j1}}\,\overline{\boldsymbol{Z_i}} + \alpha_{j2}Y_{i0}^{IP} + a_{14}Y_{i0}^{SE} + \boldsymbol{\alpha_{15} Z_{i0}} + a_{ji} \tag{15}$$

The random-effects correlation covariate matrix is the same as shown in Equation 12. Statistically significant and positive correlation, ρ_a, can be seen as indicating that those individuals whose unobserved factors mean they are more likely to experience income poverty are also more likely to experience social exclusion due.

4.4.2. *Trivariate model with endogenous employment*

Lastly, a trivariate model is specified to estimate the degree of spillover effects between social exclusion and income poverty state dependence while accounting for feedback effects in employment status. The calculations of these dynamic spillover effects involve jointly estimating Equations 16-18 by CML methods.

$$Y_{it}^{IP} = 1[y_{it}^{IP} = \gamma_{11}y_{it}^{IP} + \gamma_{12}y_{it-1}^{SE} + \gamma_{13}E_{it-1} + \boldsymbol{\beta_1 Z_{it}} + \zeta_1 E_{it} + c_{1i} + u_{1it} > 0] \tag{16}$$

$$Y_{it}^{SE} = 1[y_{it}^{IP} = \gamma_{21}y_{it}^{IP} + \gamma_{22}y_{it-1}^{SE} + \gamma_{23}E_{it-1} + \boldsymbol{\beta_2 Z_{it}} + \zeta_2 E_{it} + c_{2i} + u_{2it} > 0] \tag{17}$$

$$E_{it} = 1[e_{it}^{*} = \gamma_{31}y_{it}^{IP} + \gamma_{32}y_{it-1}^{SE} + \gamma_{33}E_{it-1} + \boldsymbol{\beta_3 Z_{it}} + c_{3i} + u_{3it} > 0] \tag{18}$$

Y_{it}^{IP}, Y_{it}^{SE}, and E_{it} are binary indicators for income poverty, social exclusion, and unemployment, respectively. Z_{it} is a vector of strictly exogenous variables, α captures the genuine state dependence and dynamic spillover effects of income poverty and social exclusion, and ξ captures the feedback effects from income poverty and social exclusion to employment status. The unobserved heterogeneity term, c_{ji}, is modelled as shown in Equation 19.

$$c_{ji} = \alpha_{j0} + \boldsymbol{\alpha_{j1}}\,\overline{\boldsymbol{Z_i}} + \alpha_{j2}\overline{E_i} + \alpha_{j3}y_{1i0} + \alpha_{j4}y_{2i0} + a_{j5}E_{i0} + \boldsymbol{\alpha_{j6} Z_{i0}} + a_{ji} \tag{19}$$

The unobserved heterogeneity term again controls for the initial conditions of each of the three endogenously modelled outcomes as well as the strictly exogenous variables. Time-averaged values for each of the strictly exogenous variables, as well for the employment variable for $j = 1,2$. It is not, however, included in the unobserved heterogeneity term for the employment equation, c_{3i}.

A trivariate normal distribution with zero mean and $\sigma_{a_{ji}}^2$ variance is assumed for the residuals a_{1i}, a_{2i} and a_{3i}. The residuals are allowed to be freely correlated.

$$\rho_{21} = corr(a_{2i}, a_{1i}) \tag{20}$$

$$\rho_{31} = corr(a_{3i}, a_{3i}) \tag{21}$$

$$\rho_{32} = corr(a_{3i}, a_{2i}) \tag{22}$$

The above correlations can be interpreted as representing the association between the unobserved individual heterogeneity factors that determine each of the indicators. Significant and positive correlation between outcomes, ρ_{jk}, can be interpreted as meaning that individuals with unobserved heterogeneity that leads to increased probability in outcome *j* also have unobserved factors that lead them to be more at risk of outcome *k*. For example, if ρ_{12} is statistically significant and positive, it implies that individuals who are more likely to experience social exclusion (or income poverty) are also more like to be unemployed.

4.5. Average Partial Effects

Average partial effects are calculated in order to determine the relative magnitudes of state dependence and the other explanatory variables on the probability of experiencing an outcome. Average partial effects show the impact of a change in the lagged dependent variable on the current dependent variable. The partial effect refers to the difference in the probability of experiencing poverty (or social exclusion) between these two fixed states where the lagged dependent variable is equal to 0 and 1. The average partial effect is then calculated by taking the average of these partial effects over the entire sample. In addition to the lagged dependent variables, the APE is calculated for other explanatory variables found to be statistically significant in the relevant probit regression. For ease of comparison between the explanatory variables, continuous variables such as age are transformed into brackets. This means that all APEs refer to the difference in binary states instead of marginal changes.

4.6. Methodology to test the robustness

4.6.1. Further exogeneity tests.

Following the methodology of Biewen (2009), dynamic random-effects trivariate probit specifications are used that explicitly model feedback effects between disadvantage measures, Y_{it}, employment status, E_{it}, and household level variables, H_{it}. If there is evidence of feedback effects between lagged disadvantage status and the household level variables, then these variables will be in violation of the strict exogeneity assumption if not endogenously modelled. The existence of feedback effects is captured in the coefficient, γ_{33}. Furthermore, as the earlier specifications model employment endogenously, the existence of feedback effects between employment status and household structure variables would also constitute a violation of strict exogeneity. Therefore, γ_{32} being statistically significant would indicate that the given household variable must either be excluded from the specification or modelled explicitly to maintain the assumption of strict exogeneity.

$$Y_{it} = 1[y_{it}^* = \boldsymbol{\beta_1 Z_{it}} + \gamma_{11} y_{it-1} + c_{1i} + u_{1it} > 0] \tag{23}$$

$$E_{it} = 1[e_{it}^* = \boldsymbol{\beta_2 Z_{it}} + \gamma_{21} y_{it-1} + \gamma_{22} e_{\text{it}-1} + c_{2\text{i}} + u_{2it} > 0] \tag{24}$$

$$H_{it} = 1[h_{it}^* = \boldsymbol{\beta_3 Z_{it}} + \gamma_{31} y_{it-1} + \gamma_{32} e_{it-1} + \gamma_{33} h_{it-1} + c_{3i} + u_{3it} > 0] \tag{25}$$

In this specification, Z_{it}, is a vector of strictly exogenous variables, Y_{it}, E_{it}, and H_{it} are binary indicator functions equal to 1 if the respective latent propensities are positive and 0 otherwise. To test for the existence of exogeneity in employment status and household formation, we are interested in ρ_2 and ρ_3, as statistically significant coefficients suggest the existence of feedback effects, as the lagged dependent variable (income poverty or social exclusion) impacts future values of these explanatory variables. This would be a violation of the strict exogeneity condition. The same strategy as seen in Equations 27 and 28 is adopted to deal with endogeneity in the above specification.

$$c_{1i} = \alpha_{10} + \alpha_{11} Y_{i0} + \boldsymbol{\alpha_{12} \overline{Z_i}} + \boldsymbol{\alpha_{13} Z_{i0}} + a_{14} E_{i0} + a_{15} H_{i0} + \alpha_{16} \overline{H_i} + \alpha_{17} \overline{E_i} + a_{1i} \tag{26}$$

$$c_{2i} = \alpha_{20} + \alpha_{21} Y_{i0} + \boldsymbol{\alpha_{22} \overline{Z_i}} + \alpha_{23} \boldsymbol{Z_{i0}} + a_{24} E_{i0} + a_{25} H_{i0} + \alpha_{26} \overline{H_i} + a_{2i} \tag{27}$$

$$c_{3i} = \alpha_{30} + \alpha_{31} Y_{i0} + \boldsymbol{\alpha_{32} \overline{Z_i}} + \boldsymbol{\alpha_{33} Z_{i0}} + a_{34} E_{i0} + a_{35} H_{i0} + a_{3i} \tag{28}$$

A trivariate normal distribution with zero mean and $\sigma_{a_{ji}}^2$ variance is assumed for the residuals a_{1i}, a_{2i} and a_{3i}. The residuals are allowed to be freely correlated similarly to as shown in Equations 20-22.

4.6.2. *Sensitivity to cutoff points*

The earlier defined definitions for deep and severe income poverty and social exclusion are used to test the sensitivity of the results to the chosen cutoff points and identify the degree of state dependence amongst the most highly disadvantaged. To do this, Equations 16 to 18 are re-estimated with these alternate measures used as the dependent variables.

4.6.3. *Sensitivity to the definition of unemployed*

The primary specification uses a definition of unemployment that includes all individuals who are neither working full-time, working part-time, nor self-employed. This implicitly includes those who choose not to participate in the labour market as being unemployed. This definition is appealing as it recognises that lack of employment, no matter the reason, is a mechanism through which social exclusion can occur while also including individuals who have become detached from the labour market in the definition. To ensure that the results are robust to the definition of unemployment used, an alternative definition, which requires that an individual be both actively seeking work and unable to find work, is also considered. The trivariate model specified in Equations 16, 17 and 18 are again jointly estimated using this definition of unemployment.

4.6.4. *State dependence of individual dimensions of social exclusion.*

Identifying whether state dependence exists within each dimension of social exclusion and whether dynamic spillover effects exist between dimensions of social exclusion determines the most effective policy response to social exclusion. A multivariate dynamic random-errors multivariate probit model is estimated to test for the existence of genuine state dependence in each dimension of social exclusion individually. Each domain of social exclusion is included as an outcome variable in this specification, with cross-lagged effects included for each domain.

$$Y_{it}^{d} = 1[y_{it}^{d} = \beta_d Z_{it} + \gamma_{d1} Y_{it}^{1} + \gamma_{d2} Y_{it}^{2} + \gamma_{d3} Y_{it}^{3} + \gamma_{d4} Y_{it}^{4} + \gamma_{d5} Y_{it}^{5} + c_{di} + u_{dit} > 0] \tag{29}$$

$$c_{di} = \alpha_{d0} + \alpha_{d1} Y_{i0}^{1} + \alpha_{d2} Y_{i0}^{2} + \alpha_{d3} Y_{i0}^{3} + \alpha_{d4} Y_{i0}^{4} + \alpha_{d5} Y_{i0}^{5} + \boldsymbol{\alpha_{d6}} \overline{\boldsymbol{Z_i}} + \boldsymbol{\alpha_{d7}} \boldsymbol{Z_{i0}} + a_{di} \tag{30}$$

The joint estimation of Equation 29 for $d \in (1,2,\ldots,5)$, allows for the identification of both the state dependence of deprivation in each dimension, as well as the interrelated dynamics between the different dimensions. The genuine state dependence effects are captured through the coefficients γ_{dd}, while dynamic spillover effects are captured through the coefficient γ_{dj}, where $j \in (1,2,\ldots,5;-d\}$.The specification allows for free correlation between the random-effect error terms, a_{di}, of each equation, as shown in Equation 31.

$$\rho_{dj} = corr(a_{di}, a_{ji}) \tag{31}$$

5. Results

5.1. Univariate dynamic random-effects probit model

The results of the estimation of the univariate dynamic random-effects probit models (Eq. 7) for income poverty and social are presented in Table 5 and Table 6. This estimation identifies genuine state dependence whilst controlling for initial conditions and endogenous covariates. Specifications 1-3 each estimate Equation 7 for both income poverty and social exclusion while using a different set of explanatory variables to account for individual heterogeneity. Table 5 presents the results for the state dependence effect and the coefficients associated with the vector $\boldsymbol{Z_{it}}$, which models individual observed heterogeneity. Table 6 includes the estimation of the unobserved heterogeneity term, c_i.

Specification 1 shows the results when the assumption of strict exogeneity is relaxed, with all individual-level characteristics included within the vector $\boldsymbol{Z_{it}}$. Under this specification, the coefficients of the lagged dependent variables are highly significant for both income poverty and social exclusion, with coefficients of 0.664

and 0.403, respectively. This suggests that genuine state dependence exists in both processes. Furthermore, Specification 1 shows that low educational attainment, being from a non-English speaking country, not being employed full-time, being a lone parent and having four or more dependents all significantly increase the probability of experiencing both income poverty and social exclusion. Conversely, females and individuals with a high level of educational attainment are less at lower risk of both income poverty and social exclusion.

Table 5. Results from the estimation of Equation 7 – Lagged dependent variable and vector of explanatory variables Z_{it} only

	(Specification 1) Complete		(Specification 2) Weak exogeneity		(Specification 3) Strict exogeneity	
	Income poverty	Social exclusion	Income poverty	Social exclusion	Income poverty	Social exclusion
Lagged dependent variable	0.640***	0.403***	0.646***	0.447***	0.651***	0.448***
	(0.026)	(0.024)	(0.026)	(0.024)	(0.026)	(0.024)
Age: <35	-0.003	0.034	0.017	0.059	-0.018	0.051
	(0.056)	(0.053)	(0.056)	(0.052)	(0.055)	(0.051)
Age: >55	0.017	0.043	0.045	0.074	0.026	0.071
	(0.051)	(0.049)	(0.051)	(0.048)	(0.051)	(0.048)
Low educational attainment	0.218***	0.223***	0.352***	0.337***	0.361***	0.346***
	(0.028)	(0.034)	(0.029)	(0.034)	(0.031)	(0.035)
High educational attainment	-0.415***	-0.453***	-0.476***	-0.495***	-0.539***	-0.536***
	(0.030)	(0.033)	(0.031)	(0.034)	(0.032)	(0.034)
Father unemployed at 14	-0.003	-0.015	0.180***	0.151***	0.180***	0.169***
	(0.034)	(0.041)	(0.036)	(0.041)	(0.037)	(0.042)
Indigenous Australian	0.002	-0.354***	0.474***	0.195***	0.454***	0.169***
	(0.047)	(0.057)	(0.049)	(0.056)	(0.050)	(0.056)
Non-English-speaking country	0.397***	0.232***	0.429***	0.283***	0.424***	0.272***
	(0.034)	(0.041)	(0.036)	(0.041)	(0.038)	(0.042)
Female	-0.281***	-0.126***	0.015	0.078***	0.086***	0.120***
	(0.026)	(0.030)	(0.026)	(0.028)	(0.025)	(0.028)
Lives in a non-urban area	0.066	-0.022	0.083	-0.007	0.081	-0.006
	(0.060)	(0.056)	(0.059)	(0.055)	(0.059)	(0.055)
Number of dependents: 1	-0.024	-0.019	-0.003	0.003		
	(0.044)	(0.040)	(0.044)	(0.040)		
Number of dependents: 2	0.041	-0.023	0.063	-0.002		
	(0.054	(0.050)	(0.054)	(0.049)		
Number of dependents: 3	0.351***	0.057	0.384***	0.074		
	(0.070)	(0.070)	(0.070)	(0.069)		
Number of dependents: 4+	0.563***	0.193*	0.615***	0.215**		
	(0.101)	(0.107)	(0.101)	(0.105)		
Lone parent	0.287***	0.139**	0.274***	0.099*		
	(0.058)	(0.057)	(0.057)	(0.056)		
Lives alone	0.081	0.112**	0.089	0.099**		
	(0.052)	(0.048)	(0.051)	(0.047)		
Employed part-time	0.290***	0.272***				
	(0.038)	(0.034)				
Retired	0.695***	0.432***				
	(0.096)	(0.097)				
Unemployed	0.645***	0.932***				
	(0.038)	(0.045)				

Notes: standard errors in parentheses. *** p<0.001, ** p<0.005, *p<0.1. Year dummies included to control for macroeconomic factors.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Unemployed refers to anyone who is neither working full-time, part-time nor retired. All coefficients relative to being full-time employed.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

Columns 2 and 3 show the estimation of Equation 7 while excluding variables that may violate the strict exogeneity assumption. Column 2 includes all of the variables in the complete specification outside of employment status, as this is the variable that least plausibly meets the exogeneity assumption. Column 3 includes only the variables that can be considered strictly exogenous: educational attainment, age, gender, Indigenous heritage, and non-English-speaking country heritage. When comparing the results of Specifications 2 and 3 with that of Specification 1, considerable differences in the coefficients for the vector Z_{it} are noticed. The coefficients associated with the dummy variable for being female are of particular interest. In the complete specification, there is a significantly negative coefficient associated with the variable, while in the strict exogeneity, there is a significantly positive coefficient estimated. A similar effect is observed for the coefficient associated with the dummy variable for Indigenous Australians. The strict exogeneity specification has highly significant and positive coefficients associated with the dummy for Indigenous Australian for both outcomes. In contrast, the complete specification has a significant and negative coefficient associated with the variable for the social exclusion equation and no significant effect in the income poverty equation.

These large differences could be due to bias owing to feedback effects associated with employment status or because omitting employment status from the specification leads to attenuation bias. This could occur if unemployment is high amongst the Indigenous Australian and female populations, leading the impacts of employment on social exclusion and poverty to be captured by these other variables. The results from the strictly exogenous specification are preferred, as this is a critical assumption to the methodology. However, to further investigate the large discrepancy, specifications that account for feedback effects to employment status are later estimated.

Table 6. Results from the estimation of Equation 7 – unobserved heterogeneity term, c_i, only

	(1) Complete specification		(2) Weak exogeneity		(3) Strict exogeneity	
	Income poverty	Social exclusion	Income poverty	Social exclusion	Income poverty	Social exclusion
Time average variables:						
Age: <35	0.119	-0.058	0.032	-0.131	-0.067	-0.127***
	(0.097)	(0.103)	(0.100)	(0.104)	(0.100)	(0.104)
Age: >55	-0.130	-0.180*	0.012	-0.069	-0.093	-0.091
	(0.086)	(0.093)	(0.087)	(0.093)	(0.089)	(0.093)
Lives remotely	0.205**	-0.019	0.208**	0.026	0.230**	0.014
	(0.100)	(0.108)	(0.103)	(0.109)	(0.105)	(0.110)
Number of dependents: 1	0.008	0.215**	-0.145*	0.112		
	(0.080)	(0.085)	(0.082)	(0.086)		
Number of dependents: 2	-0.025	0.142	-0.105	0.110		
	(0.092)	(0.098)	(0.095)	(0.099)		
Number of dependents: 3	0.059	0.082	0.136	0.243*		
	(0.121)	(0.137)	(0.126)	(0.139)		
Number of dependents: 4	0.586***	0.153	0.990***	0.593***		
	(0.101)	(0.216)	(0.185)	(0.220)		
Lives alone	0.167*	0.613***	0.220**	0.598***		
	(0.091)	(0.097)	(0.092)	(0.097)		
Lone parent	0.259**	0.706***	0.541***	0.899***		
	(0.110)	(0.125)	(0.113)	(0.127)		
Employment status: Part-time	0.356***	0.172**				
	(0.075)	(0.081)				
Employment status: Retired	0.453***	0.501***				
	(0.169)	(0.191)				
Employment status: Not working	0.967***	0.762***				
	(0.072)	(0.078)				
Initial conditions:						
Dependent variable at t = 0	0.989***	1.783***	1.371***	2.076***	1.483***	2.166***
	(0.036)	(0.043)	(0.039)	(0.045)	(0.042)	(0.046)
Age: <35	-0.073	-0.089	-0.051	-0.069	0.094	-0.026
	(0.063)	(0.074)	(0.066)	(0.076)	(0.068)	(0.076)
Age: >55	0.089	-0.083	0.258***	0.110	0.281***	0.126*
	(0.061)	(0.073)	(0.064)	(0.074)	(0.067)	(0.074)
Lives remotely	-0.11	0.107	-0.107	0.075	-0.121	0.085
	(0.069)	(0.082)	(0.072)	(0.084)	(0.076)	(0.085)
Number of dependents: 1	0.107**	-0.044	0.149***	-0.018		
	(0.049)	(0.057)	(0.052)	(0.059)		
Number of dependents: 2	0.065	-0.176**	0.020	-0.222***		
	(0.059)	(0.068)	(0.062)	(0.071)		
Number of dependents: 3	0.044	-0.079	-0.147*	-0.268***		
	(0.080)	(0.098)	(0.085)	(0.101)		
Number of dependents: 4	-0.232*	-0.228	-0.632***	-0.562***		
	(0.124)	(0.160)	(0.133)	(0.166)		
Lives alone	-0.021	-0.293***	-0.036	-0.275***		
	(0.063)	(0.072)	(0.065)	(0.073)		
Lone parent	-0.013	-0.176**	-0.111	-0.271***		
	(0.071)	(0.087)	(0.075)	(0.090)		
Employment status: Part-time	-0.029	-0.124**				
	(0.045)	(0.052)				
Employment status: Retired	0.153	0.303**				
	(0.116)	(0.149)				
Employment status: Not working	-0.182***	-0.351***				
	(0.046)	(0.055)				
Constant	-2.643***	-2.458***	-2.547***	-2.320***	-2.344***	-2.241***
	(0.050)	(0.052)	(0.050)	(0.051)	(0.043)	(0.044)
Log-likelihood	-17556	-21444	-18525	-22397	-18796	-22530

Notes: standard errors in parentheses. *** p<0.001, ** p<0.005, *p<0.1. Year dummies included to control for macroeconomic factors.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Unemployed refers to anyone who is neither working full-time, part-time nor retired. All coefficients relative to being full-time employed.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

Table 6 shows that unobserved heterogeneity is important in explaining persistence in both processes. In all specifications, the initial conditions for the dependent variable are statistically significant, positive in size, and large in magnitude. This reflects the importance of controlling for initial conditions and shows that individuals experience of poverty and social exclusion in the first period is associated with unobserved heterogeneity that increases the probability of the future experience of these outcomes. Furthermore, robust across Specifications 1 and 2, the time-averaged dummy for having four or more children is associated with unobserved heterogeneity that increases the risk of income poverty. Initial period status for the lone parent and living alone dummy variables are statistically significant and negative in sign in the social exclusion equation, indicating that it is associated with unobserved heterogeneity that lowers the risk of this form of disadvantage. However, as the coefficients associated with the current experience of these conditions, as shown in Table 5, are of greater magnitude than the corresponding initial conditions coefficients, we can conclude that the risk associated with these conditions are most significant to those who transition from not experiencing these outcomes to experiencing them.

Table 7. Average Partial Effects for the dynamic random-effects univariate probit model

	(1) Complete specification		(2) Weak exogeneity		(3) Strict exogeneity	
	Income poverty	Social exclusion	Income poverty	Social exclusion	Income poverty	Social exclusion
Lagged dependent variable	0.085***	0.054***	0.087***	0.063***	0.088***	0.063***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age: <35						
Age: >55						
Low educational attainment	0.027***	0.031***	0.047***	0.049***	0.049***	0.051***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
High educational attainment	-0.044***	-0.053***	-0.046***	-0.062***	-0.051***	-0.063***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Father unemployed at 14			0.020***	0.019***	0.020***	0.022***
			(0.004)	(0.004)	(0.005)	(0.005)
Indigenous Australian		-0.039***	0.058***	0.025***	0.055***	0.022***
		(0.007)	(0.005)	(0.005)	(0.006)	(0.007)
Non-English-speaking country	0.047***	0.030***	0.051***	0.037***	0.051***	0.036***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Female	-0.030***	-0.020***		0.010***	0.009***	0.015***
	(0.003)	(0.004)		(0.003)	(0.003)	(0.003)
Lives in a non-urban area						
Number of dependents: 1						
Number of dependents: 2						
Number of dependents: 3	0.041***		0.042***			
	(0.007)		(0.008)			
Number of dependents: 4	0.072***	0.024*	0.074***	0.028**		
	(0.011)	(0.013)	(0.011)	(0.013)		
Lone parent	0.034***	0.017**	0.032***	0.013*		
	(0.006)	(0.007)	(0.006)	(0.007)		
Lives alone		0.014**		0.013**		
		(0.006)		(0.006)		
Employment status: Part-time	0.031***	0.032***				
	(0.004)	(0.004)				
Employment status: Retired	0.080***	0.053***				
	(0.010)	(0.012)				
Employment status: Not working	0.073***	0.130***				
	(0.004)	(0.004)				

Notes: standard errors in parentheses. Average partial effects calculated only for coefficients found to be significant at least the 10% level in corresponding probit regression.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Unemployed refers to anyone who is neither working full-time, part-time, nor retired. All coefficients relative to being full-time employed.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

Table 7 presents the average partial effects of the lagged dependent variable and for all statistically significant explanatory variables in the vector $\boldsymbol{Z_{it}}$. From Table 7, it is evident that experiencing social exclusion in the previous period is associated with a 4.3 percentage point (pp) increase in the probability of social exclusion in the current period. Income poverty presents a higher degree of genuine state dependence, with the previous period increasing the risk of poverty by 6.2 pp. The similarity between these estimates of genuine state dependence and those found when using the weakly and strictly exogenous specification suggests that the inclusion of these plausibly endogenous variables does not bias the estimates of genuine state dependence.

Table 7 also demonstrates how poverty and social exclusion risk vary by observed characteristics. Low educational attainment is associated with a 2.7 to 4.9 pp increased risk of income poverty and a 3.1 to 5.1 pp increased risk of social exclusion. Similarly, high educational attainment is associated with a reduced probability of experiencing both social exclusion (-5.3 to -6.3 pp) and poverty (-4.4 to -5.1 pp). These results show that education has a significant impact on disadvantage, robust across all specifications, indicating that improving educational outcomes is an important policy lever in addressing disadvantage.

Furthermore, as compared to working full-time, working part-time is associated with a 3.1 pp increase in the risk of experiencing income poverty and a 3.2 pp increase in the risk of social exclusion. Not working is associated with a 7.3 pp increased risk of income poverty and a 13.0 pp increased risk of social exclusion. Retirees are also at a significantly higher risk of income poverty (8.0 pp) and social exclusion (5.3 pp). These results show that employment status significantly impacts the risk of experiencing income poverty and social exclusion. However, the inclusion of the variable likely violates the assumption of strict exogeneity. For this reason, specifications that explicitly model employment status are now investigated.

5.*2.* Bivariate dynamic random-effects probit model

5.2.1. Income poverty and social exclusion with unemployment endogenously modelled

To control for feedback effects from social exclusion and income poverty to future employment status, models that explicitly model unemployment are used. Unemployment in this model is a binary response variable, taking value zero if self-employed, employed part-time, employed full-time, or retired, and one if not currently working, irrespective of labour market participation status.

Table 8. Estimation of state dependence for income poverty and social inclusion with endogenous unemployment

	(1) Income poverty		(2) Social exclusion	
VARIABLES	Income poverty	Unemployed	Social exclusion	Unemployed
Lagged dependent variable	1.203***	0.235***	1.320***	0.253***
	(0.019)	(0.022)	(0.017)	(0.020)
Unemployment status	0.668***		0.273***	
	(0.030)		(0.044)	
Lagged unemployment status		1.832***		2.047***
		(0.017)		(0.014)
Age: <35	-0.049	0.023	-0.018	0.012
	(0.048)	(0.043)	(0.043)	(0.042)
Age: >55	0.014	0.094**	0.047	0.092**
	(0.045)	(0.042)	(0.040)	(0.041)
Low educational attainment	0.156***	0.112***	0.148***	0.123***
	(0.018)	(0.018)	(0.017)	(0.018)
High educational attainment	-0.356***	-0.004	-0.298***	0.011
	(0.019)	(0.016)	(0.016)	(0.016)
Father unemployed at 14	-0.017	0.327***	0.023	0.326***
	(0.022)	(0.019)	(0.020)	(0.019)
Indigenous Australian	-0.081***	1.055***	-0.160***	1.109***
	(0.031)	(0.029)	(0.030)	(0.028)
Non-English-speaking country	0.265***	-0.031	0.122***	0.032
	(0.021)	(0.020)	(0.020)	(0.020)
Female	-0.048***	0.189***	0.006	0.219***
	(0.015)	(0.014)	(0.013)	(0.014)
Time average variables:				
Unemployment status	0.343***		0.401***	
	(0.047)		(0.044)	
Age: <35	0.011	-0.113*	0.012	-0.069
	(0.071)	(0.063)	(0.064)	(0.063)
Age: >55	-0.105*	0.094	-0.066	0.034
	(0.064)	(0.059)	(0.057)	(0.059)
Initial conditions:				
Dependent variable	0.567***	0.152***	0.783***	0.265***
	(0.020)	(0.023)	(0.017)	(0.020)
Unemployment status	-0.120***	0.508***	-0.094***	
	(0.025)	(0.018)	(0.024)	
Age: <35	0.018	0.070**	-0.056	0.069**
	(0.039)	(0.035)	(0.035)	(0.035)
Age: >55	0.153***	0.114***	0.039	0.155***
	(0.037)	(0.034)	(0.034)	(0.034)
Constant	-1.888***	-1.862***	-1.664***	-1.871***
	(0.026)	(0.024)	(0.024)	(0.024)
ρ_a	-0.219***		0.150***	
	(0.019)		(0.017)	
Log-Likelihood:	-40389		-45134	

Notes: standard errors in parentheses. *** p<0.001, ** p<0.005, *p<0.1. Year dummies included to control for macroeconomic factors.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Unemployed refers to anyone who is neither working full-time, part-time nor retired.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

Table 8 presents the results of the joint estimation of Equation 8 and Equation 9, where the endogenous variable employment is explicitly modelled. Specification 1 shows the results for the specification for income poverty, while Specification 2 shows the results for social exclusion. The results show that the null hypothesis of independence in the idiosyncratic errors and random effects errors of the two equations can be rejected as $\rho_a \neq 0$, indicating that joint estimation of both the dependent variable and employment status is required.

Furthermore, the coefficient associated with the lagged dependent variable in the unemployment equation is statistically significant and positive in both specifications. This indicates that previous period experiences of disadvantage impact future period values of employment status, implying that including these variables in the univariate probit model would violate the assumption of strict exogeneity.

The results associated with the income poverty equation in Specification 1 were mostly in line with prior expectations. The results show a sizeable and significant genuine state dependence effect, the magnitude of which substantially surpasses the impact of being unemployed, which is also statistically significant. Low educational attainment significantly increased the probability of experiencing poverty, while high educational attainment significantly decreased the risk of income poverty.

The results of the unemployment equation corresponding to income poverty show that there is also significant genuine state dependence in the experience of unemployment. Even after controlling for other variables, the experience of unemployment in one period led to a higher probability of being unemployed in future periods. The results also suggest a strong relationship between father being unemployed at 14 and future period unemployment, suggesting intergenerational transmission of unemployment. This highlights that current period unemployment not only increases the risk of future unemployment for an individual but also increases the probability of unemployment for that individual's children. While females are at a lower risk of income poverty after controlling for other factors (including unemployment), they are at a significantly greater risk of being unemployed. Together, these effects mean that females are less likely to experience income poverty if employed, but they are less likely to be employed. Taken in conjunction with the increased risk of income poverty for females found in the strictly exogenous univariate specification (Table 5), these results suggest that females are at greater risk of income poverty due to their higher susceptibility to unemployment. Expectedly, low education reduces employment prospects, while high educational attainment has the opposite effect. Indigenous Australians are far more likely to experience unemployment, while those born in non-English-speaking countries are less likely to be unemployed. There are several reasons why this could be the case, including that only Australian citizens are afforded unemployment benefits, that there is no disincentive effect of welfare payments. Furthermore, it could also be a reflection of the large number of immigrants who enter Australia on skilled-work visas.

Specification 2 of Table 8 shows the estimation of the social exclusion equation with endogenous unemployment. Similarly, the results show a large and significant genuine state dependence effect of social exclusion, showing that the process is largely reinforcing. Education impacts are in line with expectations, as low attainment increases the probability of exclusion, while high attainment has the opposite effect. Those born in a non-English country are at a significantly higher risk of social exclusion. Unemployment, similar to income poverty, has a large and significant impact on experiencing social exclusion. The highly significant impact of the initial condition of social exclusion and unemployment suggests that people with these characteristics have unobserved characteristics that are correlated with a higher risk of social exclusion.

Table 9 shows the APEs for the state dependence and the explanatory variables that were found to be statistically significant in Table 8. The results show that previous experience of income poverty increases the probability of future income poverty by 15.7 pp, while the previous experience of social exclusion increases it by 21.2 pp. Unemployment increases the probability of experiencing poverty and social exclusion by 4.3pp and 3.4 pp, respectively. Of note is that the genuine state dependence of poverty is of higher magnitude than the impact of being employed. This has significant policy implications, as it suggests that policy aimed at increasing employment is not as effective as measures that bring people out of poverty through measures such as increased welfare payments. This is similarly the case for social exclusion, but perhaps less surprisingly so.

While there is a high level of genuine state dependence in income poverty and social exclusion, Table 9 highlights a more dominant state dependence impact in the probability of experiencing unemployment (27.8 to 29.4 pp). The feedback effects for both estimations are significant, as previous poverty increases unemployment probability by 3.6 pp, while previous period social exclusion increases the probability by 3.9pp. Of note are barriers to employment for Indigenous Australians, who face a 16 to 17 pp higher probability of unemployment. Females also face a higher probability of unemployment at around 2.9-3.4 pp, suggesting structural barriers to employment. Finally, the employment status of one's father at 14 impacts the probability of being employed by 5 pp, suggesting a significant degree of intergenerational transmission of unemployment. This could indicate several mechanisms, including reduced investment in human capital during childhood and job matching by parents and children.

Table 9. Average Partial Effects for Income Poverty and Social Exclusion with Endogenous Employment

	(1) Income poverty		(2) Social exclusion	
VARIABLES	Income poverty	Unemployed	Social Exclusion	Unemployed
Lagged dependent variable	0.157***	0.036***	0.212***	0.039***
	(0.002)	(0.003)	(0.002)	(0.003)
Unemployment status	0.086***		0.044***	
	(0.004)		(0.004)	
Lagged unemployment status		0.278***		0.294***
		(0.002)		(0.002)
Age: <35				
Age: >55				0.014**
				(0.006)
Low educational attainment	0.020***	0.017***	0.024***	0.019***
	(0.002)	(0.003)	(0.003)	(0.003)
High educational attainment	-0.047***		-0.048***	0.002
	(0.002)		(0.003)	(0.002)
Father unemployed at 14	-0.002	0.050***	0.004	0.050***
	(0.003)	(0.003)	(0.003)	(0.003)
Indigenous Australian	-0.011***	0.160***	-0.026***	0.170***
	(0.004)	(0.004)	(0.005)	(0.004)
Non-English-speaking country	0.035***	-0.005	0.020***	0.005
	(0.003)	(0.003)	(0.003)	(0.003)
Female	-0.006***	0.029***	0.001	0.034***
	(0.002)	(0.002)	(0.002)	(0.002)

Notes: standard errors in parentheses. Average partial effects calculated only for coefficients found to be significant at least the 10% level in corresponding probit regression.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Unemployed refers to anyone who is neither working full-time, part-time nor retired. Year dummies included.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

5.2.2. Joint estimation of income poverty and social exclusion

Table 10 presents the estimation results of the bivariate model specified in Equation 13 and Equation 14. Firstly, the results show that the null hypothesis of independence in the errors and the random effects of the two equations can be rejected as ρ_a is statistically significant. This demonstrates that the joint estimation of the two equations is required. Table 10 shows that genuine state dependence remains large and significant for both processes even when cross-lags are added. The coefficients of the cross-lagged dependent variables are significant in both equations, indicating that there are dynamic spillover effects between the two processes, implying that they are interrelated. Together, these results suggest that while the processes of poverty and social exclusion have some common mechanisms, as evidenced by the significant cross-lag effects, there are also separate and unique mechanisms through which the persistence of these states occurs. This implies that effective responses to these outcomes require individualised policy, although secondary effects on the other form of disadvantage will occur from these policies.

Table 10 also highlights the importance of unobserved heterogeneity in explaining income poverty and social exclusion. There is a statistically significant positive association between the initial conditions of poverty and social exclusion and unobserved heterogeneity for both processes. This again confirms the importance of controlling for initial conditions. The remainder of the results largely mimic the results found in Specification 3 of Table 6, similarly finding an increased risk of poverty and social exclusion for females and Indigenous Australians, noting that employment status is not included within this model.

Table 10. Bivariate probit model with dynamic spillover effects

VARIABLES	(1) Income Poverty	(2) Social Exclusion
Lagged poverty status	1.213***	0.208***
	(0.019)	(0.021)
Lagged social exclusion status	0.356***	1.333***
	(0.020)	(0.017)
Age: <35	-0.027	-0.005
	(0.047)	(0.042)
Age: >55	0.038	0.064*
	(0.043)	(0.039)
Low educational attainment	0.189***	0.174***
	(0.017)	(0.016)
High educational attainment	-0.315***	-0.294***
	(0.018)	(0.016)
Father unemployed at 14	0.078***	0.082***
	(0.020)	(0.019)
Indigenous Australian	0.218***	0.059*
	(0.029)	(0.028)
Non-English-speaking country	0.262***	0.119***
	(0.020)	(0.019)
Female	0.052***	0.067***
	(0.014)	(0.013)
Time average variables:		
Age: <35	-0.015	-0.016
	(0.070)	(0.063)
Age: >55	-0.113*	-0.066
	(0.062)	(0.055)
Initial conditions:		
Income poverty status	0.583***	0.040*
	(0.021)	(0.022)
Social exclusion status	0.107***	0.805***
	(0.021)	(0.018)
Age: <35	0.044	-0.034
	(0.038)	(0.034)
Age: >55	0.198***	0.063*
	(0.037)	(0.033)
Constant	-1.881***	-1.620***
	(0.026)	(0.023)
ρ_a	0.712***	
	(0.012)	
Log-Likelihood:	-41038	-41038

Notes: standard errors in parentheses. *** p<0.001, ** p<0.005, *p<0.1. Year dummies included to control for macroeconomic factors.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

Table 11 presents the average partial effects calculated for the dynamic random-effects bivariate probit model specified above. Experience of income poverty in the previous period is associated with a 16.1 pp increased probability of experiencing income poverty in the current period, as well as a 3.5 pp increased risk of experiencing social exclusion. Similarly, previous experience of social exclusion is associated with a 22.2 pp increased risk of experiencing social exclusion and a 4.7 pp increased risk of having income poverty. This highlights the fact that while there are interrelated dynamics, the processes are largely separate.

Table 11. Average partial effects of bivariate model with dynamic spillover effects

VARIABLES	(1) Income poverty	(2) Social Exclusion
Lagged Poverty	0.161***	0.035***
	(0.002)	(0.003)
Lagged Social Exclusion	0.047***	0.222***
	(0.003)	(0.003)
Age: <35		
Age: >55		0.011*
		(0.006)
Low educational attainment	0.025***	0.029***
	(0.002)	(0.003)
High educational attainment	-0.042***	-0.049***
	(0.002)	(0.003)
Father unemployed at 14	-0.010***	0.014***
	(0.003)	(0.003)
Background: Indigenous Australian	0.029***	0.008*
	(0.004)	(0.003)
Background: Non-English-speaking country	0.035***	0.020***
	(0.003)	(0.003)
Female	0.007***	0.011***
	(0.002)	(0.002)

Notes: standard errors in parentheses. Average partial effects calculated only for coefficients found to be significant at least the 10% level in corresponding probit regression.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

5.3. Trivariate dynamic random-effects model

Table 12 presents the estimation of the dynamic random effects trivariate probit model where income poverty, social exclusion and unemployment status are jointly estimated, as shown in Equations 16 to 18. This allows for the identification of genuine state dependence and dynamic spillover effects. Specification 2 in Table 12 also includes cross-lags of employment status in the estimation of income poverty and social exclusion, as well as cross-lags of poverty and social exclusion in the estimation of employment status. This specification identifies the dynamic spillover effects between the processes of unemployment, social exclusion, and income poverty.

Table 12. Trivariate probit model testing for dynamic spillover effects with employment status modelled endogenously

	(2) Doesn't include lagged employment status			(2) Includes lagged employment status		
VARIABLES	Income Poverty	Social Exclusion	Unemployed	Income Poverty	Social Exclusion	Unemployed
Lagged poverty status	1.154***	0.111***	0.143***	1.153***	0.112***	0.144***
	(0.020)	(0.021)	(0.023)	(0.020)	(0.021)	(0.023)
Lagged social exclusion status	0.218***	1.279***	0.239***	0.210***	1.283***	0.239***
	(0.021)	(0.017)	(0.021)	(0.021)	(0.017)	(0.021)
Lagged employment status			1.787***	0.305***	-0.112***	1.782***
			(0.017)	(0.032)	(0.031)	(0.017)
Employment status	0.448***	0.410***		0.273***	0.470***	
	(0.037)	(0.035)		(0.041)	(0.041)	
Age: <35	-0.045	-0.016	0.022	-0.042	-0.013	0.020
	(0.047)	(0.043)	(0.043)	(0.048)	(0.043)	(0.043)
Age: >55	-0.012	0.049	0.102**	0.021	0.056	0.103**
	(0.043)	(0.039)	(0.042)	(0.045)	(0.039)	(0.042)
Low educational attainment	0.149***	0.140***	0.092***	0.154***	0.139***	0.092***
	(0.018)	(0.016)	(0.018)	(0.018)	(0.016)	(0.018)
High educational attainment	-0.321***	-0.290***	0.030*	-0.326***	-0.290***	0.029*
	(0.019)	(0.016)	(0.016)	(0.019)	(0.016)	(0.016)
Father unemployed at 14	-0.010	0.016	0.316***	-0.001	0.011	0.316***
	(0.022)	(0.020)	(0.020)	(0.022)	(0.020)	(0.020)
Indigenous Australian	-0.049	-0.203***	1.065***	-0.013	-0.215***	1.066***
	(0.031)	(0.029)	(0.029)	(0.031)	(0.030)	(0.029)
Non-English-speaking country	0.258***	0.108***	-0.029	0.260***	0.108***	-0.029
	(0.021)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)
Female	-0.030**	0.009	0.196***	-0.026*	0.007	0.196***
	(0.015)	(0.013)	(0.014)	(0.015)	(0.013)	(0.014)
Time average variables:						
Employment status	0.376***	0.304***		0.200***	0.371***	
	(0.045)	(0.042)		(0.049)	(0.045)	
Age: <35	0.041	0.004	-0.097	0.003	-0.005	-0.097
	(0.052)	(0.063)	(0.063)	(0.072)	(0.064)	(0.063)
Age: >55	0.054	-0.049	0.067	-0.116*	-0.080	0.068
	(0.049)	(0.056)	(0.060)	(0.064)	(0.056)	(0.060)
Initial conditions:						
Income poverty status	0.554***	-0.002	0.077***	0.561***	-0.004	0.080***
	(0.021)	(0.022)	(0.024)	(0.021)	(0.022)	(0.024)
Social exclusion status	0.019	0.775***	0.140***	0.037*	0.772***	0.139***
	(0.022)	(0.018)	(0.022)	(0.022)	(0.018)	(0.022)
Unemployed status	-0.073***	-0.123***	0.485***	-0.076***	-0.123***	0.486***
	(0.025)	(0.023)	(0.018)	(0.025)	(0.023)	(0.018)
Age: <35	0.022	-0.054	0.070**	0.021	-0.050	0.070**
	(0.039)	(0.034)	(0.035)	(0.039)	(0.035)	(0.035)
Age: >55	0.176***	0.001	0.138***	0.178***	0.028	0.135***
	(0.038)	(0.033)	(0.035)	(0.038)	(0.033)	(0.035)
Constant	-1.945***	-1.674***	-1.913***	-1.933***	-1.676***	-1.914***
	(0.026)	(0.023)	(0.025)	(0.026)	(0.023)	(0.025)
ρ_{21}	0.489***			0.495***		
	(0.010)			(0.010)		
ρ_{31}	0.046***			0.034**		
	(0.014)			(0.016)		
ρ_{32}	0.072***			0.049***		
	(0.014)			(0.017)		
Log-Likelihood:	-61797			-61718		

Notes: standard errors in parentheses. *** p<0.001, ** p<0.005, *p<0.1. Year dummies included to control for macroeconomic factors.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Unemployed refers to anyone who is neither working full-time, part-time nor retired.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

The results of Table 12 confirm the importance of considering the correlations between random effects. The observation that ρ_{12}, ρ_{13} and ρ_{23} are all positive and statistically significantly implies that the unobserved heterogeneity that increases the probability of an individual experiencing income poverty, social exclusion or unemployment also increases the probability of experiencing each of the other two states. This is to be expected, as unobserved factors such as motivation, ability, and membership to discriminated against groups, would be expected to increase the probability of experiencing each outcome. Furthermore, the statistically significant impact of initial conditions demonstrates the importance of unobserved heterogeneity in explaining each of these processes.

Table 12 also demonstrates the existence of significant genuine state dependence effects for each of income poverty, social exclusion, and unemployment. These effects remain significant even after controlling for dynamic spillover effects and individual heterogeneity, both observed and unobserved. This highlights that there are mechanisms that are unique to each of these processes. This justifies considering income poverty and social exclusion as separate processes, as well as considering unemployment as separate from poverty. For policymakers, this implies that any program which directly lifts individuals out of poverty, social exclusion, or unemployment in the present will have long-term beneficial outcomes on future probabilities of entering these conditions.

In addition to genuine state dependence in all three measures of disadvantage, Table 12 show the existence of positive cross-effects in lagged deprivation. Poverty is positively influenced by previous period social exclusion and unemployment, while social exclusion is positively influenced by previous period social exclusion. The probability of being unemployed in the current period is increased by the experience of social exclusion and income poverty in the previous period, suggesting feedback effects. This again supports the need to model these processes jointly. These can be interpreted as evidence of the disincentive effects of low income and social exclusion, as well as evidence of structural barriers to employment among the disadvantaged. This could include effects such as limited professional networks, stigmatisation, or barriers to applying for jobs (regular access to the internet, ability to afford travel-related costs or reduced geographical mobility).

Table 12 also confirms the significant role of unobserved heterogeneity in the processes of income poverty, social exclusion and unemployment. The initial conditions of each outcome are statistically significant, indicating that initial period deprivation is associated with unobserved heterogeneity that increases the future risk of experiencing disadvantage. Furthermore, observed heterogeneity is again significant in explaining disadvantage status, with educational attainment, employment status and background dummies each having significant effects.

Table 13. Average Partial Effects for the trivariate specification with dynamic spillover effects

	(1)			(2)		
	Excludes lagged employment status			Includes lagged employment status		
VARIABLES	Income Poverty	Social Exclusion	Unemployed	Income Poverty	Social Exclusion	Unemployed
Lagged poverty status	0.251***	0.019***	0.023***	0.251***	0.019***	0.023***
	(0.094)	(0.019)	(0.023)	(0.093)	(0.011)	(0.013)
Lagged social exclusion status	0.031***	0.343***	0.039***	0.029***	0.343***	0.039***
	(0.022)	(0.077)	(0.022)	(0.021)	(0.078)	(0.022)
Lagged employment status			0.516***	0.043***	-0.017***	0.515***
			(0.074)	(0.030)	(0.011)	(0.075)
Unemployed	0.065***	0.075***		0.038***	0.087***	
	(0.042)	(0.036)		(0.027)	(0.041)	
Age: <35						
Age: >55			0.015**			0.016**
			(0.010)			(0.010)
Low educational attainment	0.022***	0.026***	0.014***	0.023***	0.025***	0.014***
	(0.014)	(0.012)	(0.009)	(0.015)	(0.012)	(0.009)
High educational attainment	-0.038***	-0.045***	0.005***	-0.039***	-0.045***	0.004*
	(0.033)	(0.030)	(0.003)	(0.033)	(0.030)	(0.003)
Father unemployed at 14			0.052***			0.052***
			(0.027)			(0.027)
Indigenous Australian		-0.030***	0.229***		-0.032***	0.229***
		(0.021)	(0.067)		(0.023)	(0.067)
Non-English-speaking country	0.037***			0.036***		
	(0.026)			(0.026)		
Female	-0.004***		0.030***	-0.003*		0.030***
	(0.003)		(0.019)	(0.003)		(0.019)

Notes: standard errors in parentheses. Average partial effects calculated only for coefficients found to be significant at least the 10% level in corresponding probit regression.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Unemployed refers to anyone who is neither working full-time, part-time nor retired.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

The APEs associated with the trivariate probit estimation shown are shown in Table 13. Column 2 presents the APEs of the preferred specification and, therefore, is the focus of this section. There is a high degree of genuine state dependence in income poverty, social exclusion and unemployment, as the experience of these states in the previous period increase the probability of future experience by 25.1 pp, 34.3 pp and 51.5 pp, respectively. Again, it is important to note that the definition of unemployment used in the paper includes individuals who are not actively seeking work, meaning that stay at home parents and other individuals who have stable preferences not to work are included in this measure. This somewhat explains the high degree of genuine state dependence in this outcome. For this reason, the above specification is completed again with an alternative definition of unemployment in the robustness section. The high degree of state dependence in both income poverty and social exclusion implies that policy aimed at reducing these phenomena in the current period is a highly effective measure in reducing future incidence. These specifications show that genuine state dependence is far more significant in explaining the persistency of these processes than individual heterogeneity.

While this specification identifies higher levels of genuine state dependence than previous specifications, it also identifies lower levels of dynamic spillover effects between income poverty and social exclusion. Lagged income poverty is associated with a 1.9 pp increased risk of social exclusion, and lagged social exclusion is associated with a 2.9 pp increased risk of income poverty. This highlights the importance of including employment status, as the higher APEs for the dynamic spillover effects found in Table 13 are partly due to attenuation bias. The existence of positive dynamic spillover effects provides further justification for policy measures that aim to reduce current income poverty and social exclusion, as each reduces the probability of experiencing the other.

Table 13 also identifies that being unemployed in the previous period led to a 4.3 pp increase in the probability of experiencing income poverty, but a 1.7 pp decrease in the probability of experiencing social exclusion. Previous experience of income poverty leads to a 2.3 pp increase in the probability of being unemployed, while the previous experience of social exclusion leads to a 3.9 pp increase. As poverty and social exclusion experiences have detrimental effects on future employment outcomes, the impetus exists to reduce these outcomes in the current period.

In terms of individual observed heterogeneity, being unemployed has the most considerable effect, leading to a 6.5 pp increase in the risk of poverty and a 7.5 pp increase in the risk of social exclusion. Low educational attainment increases the probability of experiencing income poverty, social exclusion, and unemployment, with associated APEs of 2.2 pp, 2.6 pp and 1.6 pp, respectively. High educational attainment has the opposite effect, reducing the risk of income poverty and social exclusion by 3.8 pp and 4.5 pp, respectively, while marginally increasing the risk of unemployment by 0.5 pp. Being born in a non-English-speaking country increases the risk of income poverty by 3.7pp. At the same time, Indigenous Australians are 3.0 pp less likely to experience social exclusion yet are 22.9 pp more likely to be unemployed. This lies in stark contrast to the results found in Table 11, where Indigenous Australians were at a marginally increased risk of social exclusion of 0.8 pp and a 2.9 pp increase in the risk of poverty. Together, this suggests that Indigenous Australians face higher levels of disadvantage and that this disadvantage is often transmitted through barriers to employment. Females had a 0.4 pp lower risk of experiencing income poverty but a 3.0pp higher risk of being unemployed. This could suggest that females face larger barriers to employment as well as reduced labour market participation. These results suggest that although the state dependence effect dominates, policy aimed at improving educational outcomes and labour market policy, particularly labour market policy focused on improving outcomes for females and Indigenous Australians, will reduce future incidence of disadvantage.

6. Robustness

6.1. Further exogeneity checks

Following closely the methodology of Biewen (2009) and Ayllón (2015), who identify the existence of feedback effects between household structure and employment status, trivariate models are estimated to test for the existence of feedback effects in a number of observed characteristics. This is done by endogenously modelling each of being a lone parent, living alone, and living remotely. Each of these variables is jointly estimated with unemployment and each of social exclusion and poverty. The Tables present selected results of these estimations, namely the impact of each of these possibly exogenous variables on the outcome variables, the existence of feedback effects, and the correlation between the error terms of the unobserved heterogeneity equations for each of the three outcomes. Feedback effects exist if the lagged dependent variable significantly impacts the household structure equation, implying that the strict exogeneity assumption is violated. This means that this variable must be explicitly modelled or excluded to maintain the assumption of strict exogeneity. Furthermore, a highly significant correlation in the error terms between the equations suggests that the unobserved factors that impact the unobserved heterogeneity of each term are correlated, again implying a violation of the strict exogeneity assumption.

Table 14. Trivariate specification lone parent status explicitly modelled

		(1) Social Exclusion			(2) Income Poverty	
VARIABLES	Social exclusion	Unemployed	Lone Parent	Income poverty	Unemployed	Lone parent
Lagged dependent variable	1.305***	0.292***	0.229***	1.210***	0.250***	0.156***
	(0.017)	(0.020)	(0.033)	(0.019)	(0.022)	(0.036)
Unemployment status	0.386***		-1.062***	0.492***		-1.026***
	(0.035)		(0.065)	(0.037)		(0.067)
Lone parent	-0.123**	-1.103***		0.216***	-1.075***	
	(0.058)	(0.066)		(0.061)	(0.068)	
ρ_{21}	0.090***			-0.062***		
	(0.014)			(0.014)		
ρ_{31}	0.096***			-0.002		
	(0.019)			(0.019)		
ρ_{32}	0.658***			0.633***		
	(0.038)			(0.039)		

Notes: standard errors in parentheses. *** p<0.001, ** p<0.005, *p<0.1. Year dummies included to control for macroeconomic factors.
Unemployed refers to anyone who is neither working full-time, part-time nor retired.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

Table 14 shows the joint estimation of Equations 23, 24, and 25, the dummy variable for being a lone parent taken as the household structure outcome variable. The results shows that there are large and significant feedback effects between being a lone parent and previous period poverty and social exclusion. This violation of the exogeneity assumption implies that being a lone parent must be endogenously modelled. As the variable was of less interest than employment status and including this endogenously in the model would add greater complexity to the preferred specification, the lone parent dummy was not included in the preferred specification. However, it is interesting to note that when modelled endogenously, being a lone parent was associated with a significantly lower risk of income poverty but a significantly higher risk of social exclusion. Furthermore, it is associated with a substantially reduced probability of being unemployed. Taken together, this implies that lone parents are significantly less likely to be unemployed, likely due to the necessity of having to provide for their children. Furthermore, while the lower propensity to experience income poverty may lead to the assumption that policy is adequately supporting this group, the relatively small negative impact of being a lone parent compared to being unemployed suggests that many lone parents experience income poverty despite being employed. This could imply that further support is needed for this group.

Table 15. Trivariate specification with lives alone status explicitly modelled

		(1) Social Exclusion			(2) Income Poverty	
VARIABLES	Social exclusion	Unemployed	Lives alone	Income poverty	Unemployed	Lives alone
Lagged dependent variable	1.299***	0.291***	0.229***	1.215***	0.235***	0.055*
	(0.017)	(0.020)	(0.027)	(0.019)	(0.022)	(0.031)
Unemployment status	0.399***		-0.998***	0.500***		-0.949***
	(0.035)		(0.057)	(0.037)		(0.059)
Lives alone	-0.055	-0.890***		0.039	-0.844***	
	(0.046)	(0.055)		(0.051)	(0.057)	
ρ_{21}	0.083***			-0.067***		
	(0.014)			(0.014)		
ρ_{31}	0.058***			-0.019		
	(0.015)			(0.015)		
ρ_{32}	0.534***			0.506***		
	(0.031)			(0.033)		

Notes: standard errors in parentheses. *** p<0.001, ** p<0.005, *p<0.1. Year dummies included to control for macroeconomic factors.
Unemployed refers to anyone who is neither working full-time, part-time nor retired.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

Table 15 shows the trivariate estimation with the binary indicator for living alone is used as the household structure outcome variable. The Table shows that there are significant and large feedback effects between the lagged dependent variable and the lives alone dummy, implying that not modelling this variable endogenously would violate the strict exogeneity assumption. Furthermore, when living alone is explicitly modelled, it no longer remains statistically significant in explaining poverty or social exclusion. Furthermore, in the case of social exclusion, there is evidence of feedback effects between living alone and social exclusion, as the lagged dependent variable is highly significant in explaining current living arrangements. This demonstrates that the assumption of strict exogeneity is violated in this setting. Because living alone is not statistically significant when modelled endogenously, and because it violates exogeneity, it is not included in the preferred specification.

Table 16. Trivariate specification with lives in a non-urban area explicitly modelled

	(1)			(2)		
	Social Exclusion			Income Poverty		
VARIABLES	Social exclusion	Unemployed	Non-urban area	Income poverty	Unemployed	Non-urban area
Lagged dependent variable	1.309***	0.280***	0.018	1.220***	0.233***	0.005
	(0.016)	(0.020)	(0.034)	(0.019)	(0.022)	(0.039)
Unemployment status	0.398***		0.568***	0.498***		0.534***
	(0.035)		(0.075)	(0.037)		(0.078)
Lagged unemployment status		1.792***	-0.286***		1.824***	-0.265***
		(0.017)	(0.053)		(0.017)	(0.055)
Lives in non-urban area	0.028	0.454***		0.061	0.426***	
	(0.055)	(0.069)		(0.060)	(0.071)	
ρ_{21}	0.082***			-0.066***		
	(0.014)			(0.014)		
ρ_{31}	-0.032*			-0.014		
	(0.018)			(0.018)		
ρ_{32}	-0.251***			- 0.231***		
	(0.033)			(0.035)		

Notes: standard errors in parentheses. *** p<0.001, ** p<0.005, *p<0.1. Year dummies included to control for macroeconomic factors.
Unemployed refers to anyone who is neither working full-time, part-time nor retired.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

Table 16 presents the results of the joint estimation of Equations 23, 24, and 25, with the binary indicator for living in a non-urban area being used as the household structure outcome variable. The results show that the lagged dependent variable has no significant impact on the probability of living in a non-urban area, suggesting that it does not violate the assumption of strict exogeneity, as it relates to each of the income poverty and social exclusion equations. However, the significant and negative effect of the lagged unemployment status on the probability of living in a non-urban area suggests that it must be endogenously modelled if it is to be included. For this reason, as well as the fact that it does not significantly impact each of social exclusion and income poverty equations, the living in a non-urban area variable is not included in the preferred specification.

6.2. Deep and Severe Disadvantage

The dynamic random effect trivariate probit model specified in Equations 16 to 18 again estimated using the alternate cutoff scores for income poverty and social exclusion. The alternate cutoff points are those previously defined for deep and severe income poverty and social exclusion. This is done for two reasons: to test the sensitivity of the results to changes in the definitions of the outcome variables; and because from an equity perspective, we should be more concerned with reducing the incidence of deep and severe forms of disadvantage, as these individuals are facing far more burdensome disadvantage.

From Table 17, we can see that genuine state dependence remains highly significant for both the deep and severe definitions of income poverty and social exclusion. The coefficients of genuine state dependence for both deep income poverty, 1.109, and severe income poverty, 1.137, are marginally smaller than the coefficient of the reference measure of income poverty, 1.154. This suggests that the results are robust to the cutoff point chosen. The coefficients of genuine state dependence for deep social exclusion, 1.444, and severe social exclusion, 1.529, are significantly larger than the coefficient of genuine state dependence found for the reference measure of social exclusion, 1.279. This highlights that genuine state dependence in social exclusion is robust to the cutoff point chosen and highlights that deep and severe social exclusion are more reinforcing. This has important policy implications, as it implies that effective policy to help the most severely disadvantaged exit social exclusion is any policy that can alleviate these experiences of exclusion in any given year.

Table 17. Trivariate probit model with deep and severe disadvantage cutoff points

	(1) Deep disadvantage			(2) Severe disadvantage		
VARIABLES	Income poverty	Social exclusion	Unemployed	Income poverty	Social exclusion	Unemployed
Lagged poverty status	1.109***	0.123***	0.176***	1.137***	0.203***	0.234***
	(0.023)	(0.029)	(0.027)	(0.032)	(0.044)	(0.036)
Lagged social exclusion status	0.200***	1.444***	0.314***	0.191***	1.529***	0.350***
	(0.028)	(0.023)	(0.026)	(0.044)	(0.032)	(0.037)
Lagged employment status			1.797***			1.819***
			(0.017)			(0.017)
Employment status	0.429***	0.515***		0.369***	0.597***	
	(0.040)	(0.040)		(0.046)	(0.048)	
Age: <35	-0.055	-0.017	0.021	-0.060	-0.071	0.025
	(0.056)	(0.058)	(0.043)	(0.070)	(0.078)	(0.042)
Age: >55	-0.006	0.029	0.103**	0.062	0.001	0.097**
	(0.051)	(0.050)	(0.042)	(0.062)	(0.065)	(0.042)
Low educational attainment	0.109***	0.120***	0.108***	0.090***	0.106***	0.121***
	(0.020)	(0.020)	(0.018)	(0.025)	(0.026)	(0.018)
High educational attainment	-0.326***	-0.348***	0.010	-0.285***	-0.396***	-0.009
	(0.022)	(0.023)	(0.016)	(0.027)	(0.033)	(0.016)
Father unemployed at 14	0.028	-0.015	0.320***	-0.005	0.011	0.328***
	(0.024)	(0.025)	(0.019)	(0.030)	(0.032)	(0.019)
Indigenous Australian	0.003	-0.298***	1.076***	0.020	-0.263***	1.076***
	(0.034)	(0.038)	(0.029)	(0.041)	(0.047)	(0.029)
Non-English-speaking country	0.294***	0.031	-0.010	0.227***	-0.006	0.001
	(0.024)	(0.026)	(0.020)	(0.029)	(0.035)	(0.020)
Female	-0.048***	0.007	0.193***	-0.060***	0.017	0.190***
	(0.017)	(0.017)	(0.014)	(0.021)	(0.023)	(0.014)
Time average variables:						
Employment status	0.430***	0.315***		0.397***	0.395***	
	(0.051)	(0.052)		(0.063)	(0.066)	
Age: <35	0.014	-0.139	-0.093	0.061	-0.091	-0.103
	(0.083)	(0.086)	(0.063)	(0.105)	(0.118)	(0.063)
Age: >55	-0.062	-0.082	0.062	-0.059	-0.000	0.069
	(0.073)	(0.072)	(0.059)	(0.089)	(0.093)	(0.059)
Initial conditions:						
Income poverty	0.489***	0.116***	0.126***	0.377***	0.158***	0.118***
	(0.025)	(0.029)	(0.027)	(0.036)	(0.044)	(0.036)
Social exclusion	0.017	0.851***	0.153***	-0.071	0.880***	0.244***
	(0.030)	(0.025)	(0.029)	(0.049)	(0.036)	(0.040)
Unemployed	-0.081***	-0.135***	0.506***	-0.049	-0.187***	0.523***
	(0.028)	(0.029)	(0.018)	(0.034)	(0.037)	(0.018)
Age: <35	0.022	-0.015	0.072**	-0.034	-0.029	0.071**
	(0.045)	(0.046)	(0.035)	(0.057)	(0.062)	(0.035)
Age: >55	0.197***	0.036	0.134***	0.161***	0.004	0.129***
	(0.043)	(0.042)	(0.035)	(0.051)	(0.053)	(0.035)
Constant	-2.125***	-2.073***	-1.880***	-2.320***	-2.471***	-1.863***
	(0.030)	(0.031)	(0.025)	(0.037)	(0.042)	(0.025)
ρ_{21}	0.188***			0.120***		
	(0.012)			(0.017)		
ρ_{31}	-0.051***			-0.045***		
	(0.014)			(0.014)		
ρ_{32}	0.073***			0.039***		
	(0.014)			(0.014)		
Log-Likelihood:	-48344			-37698		

Notes: standard errors in parentheses. Average partial effects calculated only for coefficients found to be significant at least the 10% level in corresponding probit regression.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Unemployed refers to anyone who is neither working full-time, part-time, nor retired.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

6.3. Sensitivity to the definition of unemployment

The sensitivity of the results to the definition of unemployment is of particular interest. The main specification defines an individual as unemployed if they are neither working full-time, part-time, nor self-employed. This effectively includes those who are marginally attached to the workforce, those actively seeking employment but cannot, and those not employed and retirees. While this definition of unemployment was justified on the grounds that of interest in this analysis are all individuals who are not employed, irrespective of the reason, it is helpful to test the robustness of the results against the definition of unemployment traditionally used in economic statistics. This definition requires that an individual both be unemployed and actively seeking employment.

Comparing the results of Table 18 to column 1 of Table 13 illuminates several interesting points. Firstly, the degree of genuine state dependence in income poverty and social exclusion is robust to the chosen definition of unemployment. Secondly, this specification provides significantly larger estimates of dynamic spillover effects.

Thirdly, the coefficient of unemployment is smaller for both income poverty and social exclusion under this definition. This is particularly noticeable for income poverty, where the coefficient under this definition is just 0.214 compared to 0.448 under the previous definition. There are several possible reasons for this, including that a requirement of receipt of income support payments is actively looking for employment. This means that all the individuals who meet this definition of unemployment are eligible for government support, which is not the case when the previously given definition is used.

Table 18. Trivariate probit model with an alternative definition of unemployment

VARIABLES	(1) Income poverty	(2) Social exclusion	(3) Unemployed
Lagged poverty status	1.192***	0.171***	0.239***
	(0.020)	(0.021)	(0.031)
Lagged social exclusion status	0.323***	1.323***	0.179***
	(0.020)	(0.017)	(0.029)
Lagged employment status			1.112***
			(0.032)
Unemployed	0.214***	0.346***	
	(0.063)	(0.065)	
Age: <35	-0.031	-0.008	0.013
	(0.048)	(0.042)	(0.062)
Age: >55	0.043	0.066*	-0.024
	(0.044)	(0.039)	(0.064)
Low educational attainment	0.190***	0.168***	0.079***
	(0.017)	(0.016)	(0.025)
High educational attainment	-0.295***	-0.277***	-0.193***
	(0.019)	(0.016)	(0.025)
Father unemployed at 14	0.060***	0.070***	0.110***
	(0.021)	(0.019)	(0.027)
Indigenous Australian	0.230***	0.033	-0.175***
	(0.030)	(0.028)	(0.044)
Non-English-speaking country	0.259***	0.110***	0.087***
	(0.021)	(0.019)	(0.029)
Female	0.065***	0.078***	-0.066***
	(0.014)	(0.013)	(0.020)
Time average variables:			
Employment status	0.975***	0.662***	
	(0.083)	(0.080)	
Age: <35	-0.048	-0.045	0.092
	(0.071)	(0.063)	(0.091)
Age: >55	-0.084	-0.038	-0.186**
	(0.063)	(0.055)	(0.090)
Initial conditions:			
Income poverty	0.572***	0.023	0.089***
	(0.021)	(0.022)	(0.032)
Social exclusion	0.090***	0.798***	0.105***
	(0.021)	(0.018)	(0.030)
Unemployed	-0.076*	-0.076**	0.434***
	(0.040)	(0.038)	(0.037)
Age: <35	0.060	-0.020	-0.022
	(0.038)	(0.034)	(0.051)
Age: >55	0.198***	0.057*	-0.014
	(0.037)	(0.033)	(0.057)
Constant	-1.924***	-1.656***	-2.093***
	(0.026)	(0.023)	(0.035)
ρ_{21}	0.520***		
	(0.010)		
ρ_{31}	0.014		
	(0.022)		
ρ_{32}	0.043*		
	(0.024)		
Log-Likelihood:	-50320		

Notes: standard errors in parentheses. Average partial effects calculated only for coefficients found to be significant at least the 10% level in corresponding probit regression.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Unemployed refers to anyone who is neither working full-time, part-time, nor retired.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

Table 18 also illustrates that the coefficients associated with the Indigenous Australian and female dummies are starkly different when this measure of unemployment is used. Under the previous definition, there was no significant effect associated with the Indigenous Australian dummy on income poverty after controlling for employment status. However, under this definition, there is a significant and largely positive coefficient. The opposite effect is observed for social exclusion, where the coefficient is no longer statistically significant. Furthermore, while Indigenous Australians were at a far greater risk of being unemployed under the other definition, they are less likely to be unemployed when this definition is used. This suggests a low level of labour market participation amongst Indigenous Australians and that this low level of labour market participation largely explains the higher prevalence of income poverty. This implies that policy aimed at reducing barriers to labour market participation for indigenous Australians is essential.

The coefficient associated with being female in the unemployed equation similarly changes from significant and positive to significant and negative under this definition of unemployment, suggesting relatively low labour market participation. While this may partly reflect a higher propensity to take on household or child-rearing behaviour in lieu of employment, females are at statistically significant higher risk of experiencing income poverty and social exclusion when this definition of unemployment is used suggests that this cannot exclusively explain the shift. Instead, this combination of results hints that females are less likely to participate in the labour market even when facing income poverty or social exclusion, suggesting barriers to labour market participation.

6.4. Analysis of individual dimensions of social exclusion

Table 19. State dependence and dynamic spillover effects in the dimensions of social exclusion

VARIABLES	(1) Economic	(2) Mental health	(3) General health	(4) Relationships	(5) Community
Lagged deprivation in economic stability	1.246***	0.190***	0.165***	0.210***	0.177***
	(0.018)	(0.022)	(0.022)	(0.021)	(0.024)
Lagged deprivation in mental health	0.149***	0.932***	0.379***	0.280***	0.158***
	(0.024)	(0.020)	(0.022)	(0.022)	(0.026)
Lagged deprivation in general health	0.159***	0.416***	1.036***	0.066***	0.185***
	(0.025)	(0.022)	(0.021)	(0.024)	(0.026)
Lagged deprivation in personal relationships	0.135***	0.273***	0.098***	0.976***	0.129***
	(0.022)	(0.021)	(0.022)	(0.018)	(0.023)
Lagged deprivation in community and social participation	0.131***	0.109***	0.138***	0.092***	1.143***
	(0.024)	(0.024)	(0.025)	(0.024)	(0.021)
Age: <35	-0.008	-0.031	0.008	-0.055	0.052
	(0.048)	(0.048)	(0.053)	(0.046)	(0.053)
Age: >55	-0.020	-0.061	0.030	-0.069	0.103**
	(0.048)	(0.047)	(0.044)	(0.043)	(0.051)
Low educational attainment	0.201***	0.014	0.093***	0.063***	0.092***
	(0.018)	(0.019)	(0.019)	(0.018)	(0.021)
High educational attainment	-0.452***	-0.026	-0.154***	-0.168***	0.073***
	(0.019)	(0.017)	(0.018)	(0.017)	(0.020)
Father unemployed at 14	0.054**	-0.061***	-0.090***	0.007	0.391***
	(0.022)	(0.023)	(0.024)	(0.021)	(0.022)
Indigenous Australian	-0.031	-0.359***	-0.201***	-0.359***	1.157***
	(0.034)	(0.038)	(0.037)	(0.036)	(0.029)
Non-English-speaking country	0.197***	-0.092***	0.058***	0.118***	0.084***
	(0.022)	(0.023)	(0.022)	(0.021)	(0.024)
Female	0.075***	0.109***	0.061***	-0.136***	0.009
	(0.015)	(0.015)	(0.015)	(0.014)	(0.016)
Time average variables:					
Age: <35	0.099	-0.035	-0.156*	0.052	-0.118
	(0.075)	(0.075)	(0.083)	(0.072)	(0.082)
Age: >55	-0.210***	-0.090	0.216***	0.073	-0.069
	(0.072)	(0.070)	(0.066)	(0.064)	(0.076)
Initial Conditions:					
Age: <35	0.005	0.058	-0.046	-0.003	0.051
	(0.039)	(0.039)	(0.042)	(0.038)	(0.043)
Age: >55	0.054	0.082**	0.044	-0.123***	0.150***
	(0.042)	(0.040)	(0.036)	(0.037)	(0.042)
Economic stability deprivation	0.669***	0.105***	0.155***	0.071***	0.117***
	(0.019)	(0.022)	(0.022)	(0.021)	(0.024)
General health deprivation	0.068***	0.237***	0.642***	0.005	0.073***
	(0.026)	(0.024)	(0.022)	(0.025)	(0.028)
Mental health deprivation	0.063**	0.523***	0.162***	0.141***	0.074***
	(0.025)	(0.022)	(0.023)	(0.023)	(0.027)
Personal relationships deprivation	0.098***	0.110***	0.007	0.639***	0.126***
	(0.023)	(0.022)	(0.023)	(0.019)	(0.024)
Community and social participation deprivation	0.104***	0.057**	-0.009	0.035	0.597***
	(0.024)	(0.024)	(0.025)	(0.024)	(0.022)
Constant	-1.643***	-1.688***	-1.671***	-1.392***	-2.029***
	(0.025)	(0.025)	(0.025)	(0.023)	(0.028)
Log-Likelihood:	-87089				

Unobserved heterogeneity error term correlations :

ρ_{21}	0.179***						
	(0.010)						
ρ_{31}	0.141***	ρ_{32}	0.598***				
	(0.010)		(0.010)				
ρ_{41}	0.175***	ρ_{42}	0.310***	ρ_{43}	0.206***		
	(0.010)		(0.010)		(0.010)		
ρ_{51}	0.149***	ρ_{52}	0.194***	ρ_{53}	0.164***	ρ_{54}	0.119***
	(0.011)		(0.011)		(0.011)		(0.011)

Notes: standard errors in parentheses. Average partial effects calculated only for coefficients found to be significant at least the 10% level in corresponding probit regression.
Educational attainment: low = didn't complete high school. High = completed tertiary education. Coefficients relative to mid = completed high school but no tertiary education.
Source: own calculations on HILDA 2011-2018, unbalanced sample of working age population (25-65).

From Table 19, we can see that joint estimation of the dynamic spillover effects between dimensions is necessary as there are highly statistically significant correlations between the individual-specific error terms between all dimensions. This justifies the decision to estimate the system of equations given in Equation 29 jointly. From the results, the first observation that we can make is that there is a highly statistically significant degree of genuine state dependence for each dimension of social exclusion. The most significant degree of genuine state dependence exists for community and social participation, followed by economic stability and personal relationships. The explanatory factors, Z_{it}, that impact deprivation status varies significantly by dimension. Similarly, the characteristics associated with unobserved heterogeneity that increase the probability of deprivation in the dimensions vary highly. The results also highlight that low educational attainment is associated with a statistically significant higher probability of deprivation in all dimensions except for mental health. In contrast, high educational attainment significantly decreases the probability of deprivation in all dimensions outside of community and social participation.

The other observation to be taken from Table 19 is the highly statistically significant cross-effects between the social exclusion dimensions. This supports the choice of measure, as social exclusion is meant to encapsulate an interrelated process whereby individuals are structurally excluded from all aspects of society. Particularly significant dynamic spillover effects can be observed between mental health and physical health in both directions, suggesting that the channels through which transmission of state dependence operate in both dimensions are similar. The existence of dynamic spillover effects between each dimension of social exclusion implies that any policy aimed at reducing the incidence of deprivation in any domain will also improve the outcomes in other dimensions in future periods.

Furthermore, unobserved heterogeneity plays a large role in explaining the risk of deprivation in all dimensions. Notably, each coefficient of correlation in the errors of the unobserved heterogeneity, ρ_{jk}, where j and k are dimensions of social exclusion, are positive and statistically significant. This implies that the unobserved time-invariant factors that mean that an individual is more at risk in any dimension is positively correlated with the time-invariant factors that increase the risk of deprivation in all other dimensions. The results also show that initial conditions are important, as they are highly correlated with unobserved characteristics that increase the probability of deprivation.

7. Policy Implications

This paper finds that genuine state dependence is significant in explaining persistent poverty and social exclusion. This finding is robust to the model used, as genuine state dependence exists when endogenously modelling unemployment and when only including strictly exogenous variables, as well as to the cutoff point used for defining income poverty and social exclusion. The results also suggest that individual heterogeneity, in both observed and unobserved characteristics, has a significant explanatory role in susceptibility to income poverty and social exclusion. There are distinct policy implications involved with each of these effects.

The results of the paper also uncover the existence of dynamic spillover effects between income poverty and social exclusion. However, as the estimates found for genuine state dependence far exceed those found for dynamic spillover effects, the two processes are considered to be largely separate with some interrelated dynamics.

7.1. Genuine State Dependence

The preferred specification, the trivariate specification that jointly estimates income poverty, social exclusion and unemployment, finds that previous period experience of poverty increases the probability of current poverty experience by 25.1 pp. While the degree of genuine state dependence is lower in other specifications, the effect remains large and significant throughout. This implies that an effective way to prevent future poverty is to reduce current incidence. Furthermore, there are significant feedback effects from past poverty experience to future experience of unemployment, as well as dynamic spillover effects from poverty to social exclusion. Therefore, economic policy aimed at reducing current poverty has positive second-order effects of reducing both social exclusion and unemployment. This provides further justification for implementing policies aimed at lifting individuals out of poverty in the current period, even if it comes at a high initial cost.

This conclusion is of particular relevance to the current policy environment within Australia. In response to the initial wave of lockdowns, and the associated economic downturn, from COVID-19, the Australian federal government introduced the JobSeeker and JobKeeper programs. The JobSeeker program provided fortnightly unemployment benefits of $1,300, while the JobKeeper program provided fortnightly payments of $1,500 to businesses significantly impacted by the pandemic induced economic downturn, conditional on keeping on all employees throughout the pandemic.

The results of this paper suggest that the JobSeeker program was highly justified as it not only helped to stave off an economic recession but also to reduce both current and future incidence of income poverty. However, while the fortnightly JobSeeker payments at the outset of the COVID-19 pandemic were up to $1,300, these fortnightly payments have fallen to $620 for a single person with no children. An individual receiving just this fortnightly payment would be experiencing deep income poverty. The high degree of state dependence in the experience of income poverty suggests that the size of these payments should be reconsidered, as not only does it reduce current disadvantage, but also reduces the future experience of poverty. The second-order effects of reducing the future incidence of social exclusion and unemployment provide further justification for increasing the size of these unemployment benefits.

Just as JobSeeker payments have been reduced to their pre-pandemic levels, the JobKeeper program has been discontinued. While the program was always intended to be a temporary measure to respond to the mass loss of jobs caused by the economic downturn and stay-at-home orders, the current situation suggests that this should be reconsidered. As Australia continues to be thrust into and out of lockdown as the government commits to a zero-transmission strategy to tackling COVID-19, many businesses must lay off employees as they are forced to close. During these intermittent lockdowns, the support provided to these businesses has been minimal and lacked timeliness, causing mass loss of jobs for individuals in industries highly affected by lockdown measures. The high degree of genuine state dependence in poverty suggests that the loss of income caused by these closures will have high long-term costs. This is supported by the high degree of genuine state dependence detected in unemployment, estimated at 51.5%. Together, these results suggest that the government must be quicker to provide support to businesses and their employees when areas move into lockdown. The re-introduction of JobKeeper payments to areas impacted by lockdowns should be considered.

Lastly, the existence of significant genuine state dependence of income poverty also provides implicit support to the introduction of a Universal Basic Income (UBI) program. As support for the launch of UBI programs grows globally, the results of this paper suggest that such a program would provide significant immediate and future benefits to the disadvantaged. UBI programs provide regular payments to all members of society of equal magnitude irrespective of income and wealth levels. The introduction of such a program to complement the current welfare system would significantly reduce the incidence of income poverty in the present, implying that it would also reduce future incidence of poverty, social exclusion, and unemployment.

Although the results from this paper identify greater genuine state dependence effects for social exclusion (34.1 pp) than for income poverty (25.1 pp), the policy implications are less clear. While evidence of poverty state dependence provides support for a policy that increases the income of low-earning individuals, the multi-dimensional nature of social exclusion means that there is no single policy guaranteed to reduce the incidence of social exclusion across the board. This is the case as the dimensions contributing towards the experience of social exclusion for one individual are not necessarily the same as for another individual.

The results of Table 19 show a significant degree of genuine state dependence in all dimensions of social exclusion, as well as considerable dynamic spillover effects between dimensions. This suggests that policy aimed at either reducing or preventing deprivation in any dimension of social exclusion will be effective. Dynamic spillover from previous experiences of social exclusion to the current experience of income poverty (3.1 pp), and feedback effects to future employment status (3.9 pp), provide further justification for policy aimed at reducing current social exclusion. This conclusion has important implications for many policy interventions currently being debated.

In Australia, many states have introduced programs that provide vouchers to individuals to be spent on community experiences, such as dining, going to the movies, or visiting cultural sites. These programs were enacted to both increase economic activity and induce spending in the industries most impacted by the pandemic induced economic downturn. The results of this paper suggest that these policies also provide significant future benefits through increasing community participation and encouraging interpersonal engagement, reducing social exclusion incidence in both the present and future. These long-term benefits should be included in the cost-benefit analysis of any similar programs currently up for debate, providing further evidence of their effectiveness.

There has recently been a push for increased mental health support to be provided under Medicare, Australia's public health insurance program. The large reported state dependence effect of social exclusion provides further evidence for why this should be provided. The paper finds significant state dependence in mental health deprivation and finds dynamic spillover effects from mental health to all other dimensions of social exclusion. This implies that the prevention and reduction of adverse mental health outcomes reduce social exclusion in both the present and future and, therefore, should be a priority of government policy.

While this paper has considered only the effects on the two previous policy debates, the implications of genuine state dependence in social exclusion is wide-ranging. It suggests that there are significant benefits to programs aimed at improving physical health outcomes, including expanded medical support and early-life intervention to support childhood development. Furthermore, it suggests that there are high long-term costs to lockdown measures that reduce community interaction, create barriers to personal relationships, and cause the deterioration of mental and physical health outcomes. Although the benefits of these lockdowns likely offset these costs, policy aimed at improving outcomes in each of these dimensions should be a priority following the conclusion of any lockdown measures.

7.2. Individual Heterogeneity

Although the focus of the paper has been on genuine state dependence in the processes of poverty and social exclusion, it has also detected that individual observed heterogeneity significantly impacts the probability of experiencing both income poverty and social exclusion. Therefore, structural policy aimed at enhancing characteristics observed to reduce income poverty and social exclusion should also be considered.

The results of this paper suggest that structural policy aimed at improving labour market outcomes is a particularly effective measure. Robust to the definition used and choice to model endogenously or exogenously, unemployment has a significant and large effect on probability of experiencing poverty and social exclusion. The preferred model (Specification 1, Table 13) finds that unemployment increases the probability of income poverty by 6.5 pp and social exclusion by 7.5 pp. These results are more noticeable under the alternate definition of unemployment, rising to 21.4 pp and 34.6 pp for poverty and social exclusion, respectively. Adding to the impetus to address labour market outcomes is the high degree of state dependence in the process (51.6 pp). These results provide further evidence in favour of measures similar to JobKeeper, which are aimed at maintaining employment during periods of lockdown, be readopted.

Furthermore, the paper provides evidence for policy aimed at decreasing barriers to labour market participation for Indigenous Australians and females. Table 10 shows that both Indigenous Australians and females are at higher risk of income poverty and social exclusion when employment status is not controlled for. In contrast, Table 12 shows that after controlling for employment, which is endogenously modelled in this specification, both groups are significantly less likely to experience disadvantage. However, Table 12 also demonstrates that both Indigenous Australians and females are significantly more likely to experience unemployment (22.9 pp and 3.0 pp, respectively). The results of Table 18, which uses the definition of unemployment that requires that the individual be seeking employment, adds further evidence to this. In this estimation, both females and Indigenous Australians are statistically less likely to experience unemployment, but statistically more likely to experience disadvantage, even after controlling for employment status.

A hypothesis that is consistent with these results is that women, even when facing income poverty, choose not to participate in the labour market knowing that income earned will be largely offset by childcare costs. This suggests that childcare subsidies would be an effective way to reduce the incidence of income poverty amongst females. Since 2013, childcare costs have increased by 38% in Australia, and while the 2021-22 Federal Budget introduced a $1.7b Childcare Package, much of the benefit of this package is borne by high-income households (Alexander, 2021). Therefore, childcare subsidies targeted at low-income households are an effective measure to improve employment outcomes and reduce income poverty for females.

Distinct policy is also required to address low labour market participation amongst Indigenous Australians, as this low level of participation largely explains the higher propensity towards unemployment amongst this group. There are significant barriers to employment for Indigenous Australians, including systematic racism, recruitment bias and access to professional networks that explain this low participation rate. Furthermore, demoralisation from previous experiences of adverse employment outcomes due to the aforementioned factors mean this cycle can become self-perpetuating. Therefore, the results of this paper support the use of positive discrimination in employment to address these barriers to labour market participation. The Australian Public Service currently adopts positive discrimination strategies by recruiting only Indigenous Australians for some positions and having a minimum quota for Indigenous Australians invited to interview for other positions. The results support the use of these strategies and indicate that the broader use of positive discrimination techniques is justified.

The results of the paper also suggest that improving educational attainment levels is an effective way of decreasing susceptibility to disadvantage. One such policy measure to achieve this is reducing the barriers to tertiary education. Although Australia's HECS system provides government subsidised loans for higher education for all citizens, which makes attending university possible for everyone, barriers to tertiary education have recently increased. Compulsory repayments of these loans at a younger age and with higher interest rates have increased the burden of HECS loans. The reduction in government funding to universities has reinforced this effect, as universities have primarily passed on the effect of reduced funding to students by increasing course costs (Zhou, 2020). However, the results of this paper support reducing barriers to tertiary education, as completion of tertiary education is associated with a 3.8 pp lower risk of poverty and a 4.5 pp lower risk of social exclusion. Therefore, the reversal of the recent trends of reduced funding to universities and the increased burden of HECS repayments should be reconsidered from a welfare perspective.

The results of the paper also find significant and positive correlation in the error terms of the unobserved heterogeneity terms for income poverty and social exclusion. This suggests that the unobserved, time-invariant factors that mean that an individual is at greater risk also make this individual at greater risk of social exclusion. Unobserved factors having this effect could include stigmatisation, breakdown of professional networks, demoralisation, and/or depreciation of human capital.

8. Conclusion

To conclude, this paper has demonstrated that there are significant genuine state dependence effects in the processes of income poverty and social exclusion. It has shown that these effects are robust to the choice of cutoff point, choice of explanatory variables, and the inclusion of endogenously modelled unemployment. The high degree of state dependence found in the preferred model, 25.1 pp for income poverty and 34.3 pp for social exclusion, suggests that policy should focus on preventing individuals from falling into these states due to the high degree of persistence in these outcomes. Furthermore, it justifies the use of policy that lifts people out of disadvantage in the short term, even if this occurs at great cost. The existence of statistically significant dynamic spillover effects between income poverty and social exclusion, as well as significant feedback effects from income poverty and social exclusion to employment status, provides further support for such interventions. The paper also identifies individual heterogeneity, both observed and unobserved, as playing an important role in explaining income poverty and social exclusion processes. The existence of individual heterogeneity suggests that structural policy aimed at increasing employment outcomes, educational attainment and reducing systematic barriers for

Indigenous Australians and females effectively reduces the incidence of disadvantage. Lastly, the paper detects statistically significant dynamic spillover between the two processes, although the magnitude of these effects are far outweighed by those of genuine state dependence. Experience of income poverty in the previous period was associated with a 1.9 pp increased probability of social exclusion, while the experience of social exclusion in the previous period increased susceptibility to income poverty by 3.1 pp. This indicates that while the processes of income poverty and social exclusion have interrelated dynamics, they are primarily separate phenomena.

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