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Understanding the Drivers of Poverty Dynamics in Australian Households

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ABSTRACT

Understanding the Drivers of Poverty Dynamics in Australian Households*

Using longitudinal household data and an econometric model of conditional poverty transitions, this paper contributes to the growing literature on poverty dynamics in Australian households. The results reveal that a range of household head, partner and demographic characteristics in addition to life-changing events have an impact on both the likelihood of remaining poor and slipping into poverty. These findings have important implications for Australian policymakers: tertiary education and employment are key factors in keeping households out of poverty; having a disability increases the probability of becoming poor and remaining in such a situation; households in outer-regional or remote areas are more likely to become poor and continue to live under such hardship; and finally, life-changing events, especially becoming separated, can lead households into persistent poverty. These results are robust to a range of poverty definitions. By drawing on research that utilizes such longitudinal data, policymakers will be much better informed about the drivers of material deprivation in Australia and subsequently how best to design policies that target and support the most vulnerable households.

JEL Classification: D31, I32, C23, C35

Keywords: poverty dynamics, state dependence, attrition, household panel data

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1 Introduction

Until the emergence of longitudinal household data, the prevailing wisdom was that poverty was a persistent problem for specific households. However, this perception was based on cross-sectional poverty figures, which mask the degree of income mobility and short-term changes in household characteristics. More specifically, these figures do not indicate whether it is the same households that experience poverty as commonly believed, or whether households only temporarily suffer periods of low income as a result of changes in employment, health status, family structure and other factors. Once the same households can be observed over time, a very different picture emerges: the majority of households in high income countries only temporarily enter poverty, though the longer they remain poor, the lower the probability of exiting.[1]

In the Australian context, the opportunity to research poverty dynamics has been enhanced with the establishment of the Household, Income and Labour Dynamics (HILDA) Survey. In line with other studies using the same definition of income poverty and data set, such as Headey, Marks, and Wooden (2005) and Saunders and Bradbury (2006), analyzing all waves of HILDA (2001-2004) reveals that in fact only around 4% of the population is persistently income poor in all four years.[2] Though this figure does not take into account left and right-censoring of the data, this suggests that a significantly smaller number of households are at risk of long-term income poverty. At the same time, short spells of poverty can nonetheless have long lasting effects for those experiencing such hardship, and therefore, also need to be taken seriously by policymakers.

Other studies have investigated poverty dynamics in Australian households using alternative data sources. Saunders and Bradbury (2006) investigate income poverty and

[1] For a good summary of both the international and Australian findings on household poverty dynamics, see Headey, Marks, and Wooden (2005)

[2] The income poverty definition is based on the 50% of the median (modified) OECD equivalised household income.

mobility using Australian Bureau Statistics (ABS) data sets, and stress that these data sources pose serious measurement challenges, which in turn distort estimates of income poverty. In another recent study, Abello and Harding (2006) analyzes the dynamics of child poverty in Australia using ABS' Survey of Employment and Unemployment Patterns (SEUP) over a three year period (1995-1997). This study on child poverty finds that though there is considerable income mobility, the transitions are not substantial, and in fact there is less mobility than in other OECD countries.

Using the HILDA Survey, this paper contributes to this growing literature by investigating the socio-economic drivers of these transitions, which is vital information for policymakers and has not yet been adequately analyzed in previous work. The econometric model used in the paper enables us to separately identify the impact of various household and demographic characteristics on the probability of persisting in poverty and on the likelihood of entering poverty, while controlling for non-random attrition and the endogeneity of poverty in initial period. The model also provides predictions regarding the duration of income poverty spells and the probability of becoming income poor in any given year. That is, even though we only use 4 years of data, we are nonetheless able to make predictions over a much longer time horizon.

The findings based on this model underscore the importance of using longitudinal data and have important implications for Australian policymakers: tertiary education and employment are key factors in keeping households out of poverty; having a disability increases the probability of becoming poor and remaining in such a situation; households in outer-regional or remote areas are more likely to become poor and continue to live under such hardship; and finally, life-changing events, especially becoming separated, can lead households into poverty.

The remainder of the paper is structured as follows. In sections 2 and 3 we discuss the

HILDA Survey and what the descriptive statistics reveal, while the econometric methodology is presented in section 4. In section 5 we present the results using a sample from the HILDA data set, and investigate the sensitivity of these estimates to different definitions of income poverty. In this section we also compare average versus genuine state dependence in poverty dynamics and derive predicted durations of income poverty spells. Finally, in section 6 we conclude.

2 Data and the Definition of Income poverty

2.1 Sample criteria

For the analysis in this paper we take advantage of the first four waves of the Household, Income and Labour Dynamics (HILDA) Survey.[3] The HILDA Survey is a household-based panel study which collects information on household and individual income, demographics, and labour market dynamics. Interviews are conducted annually with all adult members of each household. The first wave of the panel in 2001 consisted of 7,682 households and 19,914 individuals. The main advantage of this data set is that as a longitudinal survey it follows individuals and households over time. This provides one of the first large-scale opportunities to estimate the determinants of poverty dynamics in Australian households. Other studies, as discussed above, have relied on data provided by the Australian Bureau of Statistics, though there are serious data issues with these sources; see Saunders and Bradbury (2006) for a discussion on the advantages and disadvantages of different Australian poverty data.

The estimation sample used in the subsequent analysis in this paper, and hence our population of interest, consists of working age individuals who are not full-time students

[3]HILDA release 4.1

and who live in households where the head is also of working age. We define working age to be 25 years or more, but less than 55 years. Though elderly-led households are more likely to be income poor than those with a prime-aged head, such households are dropped to avoid the impact of retirement decisions on poverty dynamics, especially to abstract from the implications of the old age pension for income levels. We believe, nonetheless, that this an important issue in its own right and requires separate analysis to that effect.[4]

Households that report non-positive disposable income are excluded on the basis that the income levels of these households are affected by self-employment and taxation minimization issues. Finally, we do not use observations from households which consist of multiple families and groups in order to be clear about the unit of analysis.[5]

2.2 Definition of income poverty

As commonly done in the analysis of poverty in OECD countries, this paper focuses primarily on income poverty based on the equivalised disposable income of the household, which is defined as the total household disposable income divided by the equivalised household size. The equivalised household size is calculated according to the OECD definition, which allocates a weighting of 1.0 to the first adult, 0.5 to other household members aged 14 or over, and 0.3 to those aged less than 14.[6] This measure implies that we expect two routes for households to enter or exit poverty: 1. changes in household

[4]See, for example, how poverty estimates vary by age in Headey, Marks, and Wooden (2005)

[5]As a result of our working age selection criteria, individuals in multiple families and group households have a lower poverty rate (4.2%) than the average (7.8%) and thus have the opposite effect of dropping older Australians from the sample. Out of the original 73,109 person-year observations, 433 observations are dropped because of non-positive disposable household income. The working age restriction reduces the number of observations to 26,358. A further 222 full-time students and 801 individuals in multiple-family or group households are dropped resulting in the final estimation sample of 25,335 person-year observations. Due to a lack of observations, it is unfortunately not possible to separately identify indigenous households in the analysis.

[6]For example, a couple with two young children who are less than 14 years old would have an equivalised size of 2.1.

disposable income as result of employment status or other non-labour sources of income; 2. changes in household structure due to such events as marriage, divorce, death, and the birth of children.

Consequently, a household is defined in this paper as being in poverty if the equivalised household income is below 50% of the median, a threshold which has been widely employed in Australia and other industrialized countries. Based on this definition, the income poverty rate for our working age (25-54) sample decreased from 8.8% in 2001 to 7.8% in 2002 and stabilized at 7.6% in 2003 and 2004. The corresponding headcount poverty rates for the Australian population based on the same definition are 14.2%, 13.1%, 12.6%, and 12.8%. These income poverty rates are similar to the highest levels found in the European Union. For example, in 2001 Ireland had the highest income poverty rate of 15%, followed by Greece at 14%, which is where Australia would have placed in the overall ranking (Dennis and Guis 2004).

Given the arbitrariness of these definitions, there has been considerable discussion about their relevance for policymakers. This debate, especially in the case of Australia, has raised two main points: 1) the primary focus on income poverty as opposed to a more multi-dimensional approach; and 2) data quality problems and associated measurement issues (see Saunders and Bradbury (2006) for an in-depth discussion of these issues). As part of future research, the methodology used in the analysis could be expanded to investigate the dynamics of a broader, multi-dimensional definition of poverty; for example, along the lines of Amartya Sen's capability approach (see (Sen 1999)) and the sociological conceptualization as discussed in Saunders and Bradbury (2006). To address the second point, we check the sensitivity of our results in section 5.6 with the findings based on other definitions of income poverty.

3 Preliminary Statistics on Poverty Persistence and Dynamics

As stressed in the introduction to this paper, the cross-sectional estimates for the poverty rate in Australia include a large number of households who are only temporarily income poor. According to the raw transition rates from one year to the next, as displayed in Table 1, only around 4.5% of working age individuals living in non-poor households become income poor in the following period. In contrast, of those who are in poverty, over half (53.4%) exit in the next period, with the rest remaining income poor.

These rates are for the non-attriting sub-sample, and if attrition is correlated with the probability of becoming income poor, estimates will be biased. A preliminary indication of this bias is captured by the difference in attrition rates for individuals below and above the income poverty threshold[7]. While 11.4% of non-poor individuals exited the sample by the next period, 15.5% of those in income poverty attrited, suggesting that the process of attrition is non-random and possibly correlated with poverty status. The potential for attrition to bias our estimates is addressed in the econometric methodology employed in this paper, as explained in the next section.

In line with the findings for three waves of HILDA data as presented in Headey, Marks, and Wooden (2005), the vast majority of our sample (88.1%) do not experience any form of income poverty during all four years (2001-2004) (see Table 2). 8.0% and 2.6% of our sample are income poor for one and two of the four years, respectively, while less than 1% of individuals in our sample remain in poverty from 2001 to 2004. This again illustrates the considerable dynamics in household incomes.

As also discussed in Headey, Marks, and Wooden (2005), following the poverty transitions over all available years reveals that the risk of remaining poor increases with

[7]Attrition in our context simply means that next period's poverty status is not observed/defined.

poverty duration, while the likelihood of becoming poor decreases with length of time out of poverty. Moreover, the poor tend to experience multiple spells of poverty, an important issue discussed in Stevens (1999).

These summary statistics underscore the importance of understanding the nature of poverty dynamics and persistence. The main contribution of this paper is to subsequently take the analysis to the next step by investigating what factors drive this process. To this end, we consider a range of household head characteristics and household variables.[8] The mean values of these variables are listed in Table 3, in column (1) for those who are not income poor and in column (2) for those in poverty.

These summary statistics show that income poor individuals are more likely to live in a household where the head is female, an early school leaver, come from a non-English speaking background, or disabled. Not surprisingly, the head in poor households is less likely to be in full-time employment and have fewer years of work experience than those in non-poor units. The situation is reversed for heads who only have part-time work; they are in fact more likely to be in poverty. In terms of the partner's characteristics, the impact of education, employment, background and disability status is similar to that of the head. Interestingly, individuals living in households where the partner is part-time employed are actually more likely to be non-poor, reflecting the voluntary choice of spouses to take up such employment. The individual characteristics reveal that those with a poor understanding of the interview and needing help during the exercise both are more likely to be in a poor household.

Finally, looking at the household variables implies that poor households are also more likely to consist of single parents or lone persons, and less likely to be made up of couples with or without children. These households are also more represented in South Australia

[8]The household head is defined as the oldest male member in couple households or the oldest member in lone person or single parent households.

and less so in Victoria, with little difference in the other States. The number of workers is significantly higher in non-poor households.

These preliminary statistics provide evidence that there are systematic differences between the characteristics of income poor and non-poor households. In the next section, the impact of these covariates on poverty transitions is investigated using a methodology, which also controls for unobserved heterogeneity, endogeneity of poverty in the initial period, and non-random attrition.

4 Econometric Model

To identify the impact of the different socio-economic variables on poverty transitions, we adopt the methodology applied in Cappellari and Jenkins (2004) as this model is able to address two potentially important sources of bias in the analysis: bias from ignoring the initial conditions and bias resulting from non-random attrition.[9] Firstly, since it is difficult to assume that being poor in the first period is exogenous and uncorrelated with unobserved characteristics the model includes an equation for the poverty status in the initial period. Secondly, the panel of households is incomplete as a result of attrition. If the process of attrition is non-random and somehow correlated with poverty status, as argued above, estimates will be biased as a result of endogenous selection. To address this the model includes an equation to model attrition (or its flipside, retention). The model thus consists of three equations: the main equation of interest for conditional current poverty status; an equation for the poverty status in the initial period (initial conditions); and finally, an equation for retention in the sample from one wave to the next[10].

[9] See Cappellari and Jenkins (2004) for a much more detailed and technical discussion of the model.

[10] A more intuitive way of thinking about this modelling framework is to view it as a single uniform framework for estimating two transitions separately. The first transition to be estimated would be income poverty entry; that is, being income poor in period t conditional on not being income poor in period t-1. A straightforward probit on income poverty status in period t on the subsample of persons not

Let the latent propensities for these three equations be represented by P_t^*, P_{t-1}^*, and R_t^* and modelled using the following linear specifications:

$$P_{it}^* = [(P_{it-1})\gamma_1\prime + (1 - P_{it-1})\gamma_2\prime]Z_{it-1} + \tau_i + \zeta_{it} \quad (1)$$

$$P_{it-1}^* = \beta\prime X_{it-1} + \mu_i + \delta_{it-1} \quad (2)$$

$$R_{it}^* = \psi\prime W_{it-1} + \eta_i + \xi_{it}, \quad (3)$$

where Z_{it-1} is a vector of covariates which have an impact on the conditional poverty status in the current period. The vector of covariates for the initial poverty equation X_{it} is the same as Z_{it-1} with additional exclusion restrictions, and similarly, W_{it} is vector of variables which determine retention, including those in Z_{it-1}, plus a number of exclusion restrictions.[11]

The error term in each equation is assumed to consist of a normally distributed individual-specific component (τ_i, μ_i, η_i) and a white noise component $(\zeta_{it}, \delta_{it-1}, \xi_{it})$. It is further assumed that the joint distribution of these error terms is trivariate standard normal. The unobserved heterogeneity, i.e. the individual-specific component of the error term, is thus parameterized through the normalized covariance matrix of the joint error distribution as follows:

$$\rho_1 = corr(\eta_i + \xi_{it}, \tau_i + \zeta_{it}) = cov(\eta_i, \tau i) \quad (4)$$

$$\rho_2 = corr(\mu_i + \delta_{it-1}, \tau_i + \zeta_{it}) = cov(\mu_i, \tau_i) \quad (5)$$

$$\rho_3 = corr(\mu_i + \delta_{it-1}, \eta_i + \xi_{it}) = cov(\mu_i, \eta_i) \quad (6)$$

income poor in period t-1 would, however, lead to biased estimates, though this could be addressed by using a Heckman-type correction approach. The second transition, exit out of income poverty, would be estimated separately in a similar fashion. The approach used in this paper unifies these two separate estimations into a single estimation framework and incorporates a third dimension - attrition. Attrition is a binary outcome so the model can also be defined in terms of retention, which is what is used here.

[11] The exclusion restrictions on the determinants of the three outcomes are necessary for the model to be identified. See Cappellari and Jenkins (2004) for a discussion of sufficient conditions for identification and a set of alternative restrictions.

The first coefficient ρ_1 identifies the correlation between unobserved individual-specific factors that determine retention over two periods and conditional current poverty status, while ρ_2 captures the correlation between the unobserved individual-specific factors determining the poverty status in the initial period and current poverty status. Finally, ρ_3 is the correlation parameter for the association between the unobserved individual-specific factors affecting initial poverty status and retention over two periods. It is important to keep in mind that the interpretation of these correlation coefficients relates to the unobserved heterogeneity terms. By estimating these three correlation coefficients, one can test for the ignorability of controlling for the initial conditions and attrition. Ignorability here simply means that the different equations in the model could be estimated seperately without leading to biased estimates, which would be the case if all ρ's would be zero. The trivariate standard normal distribution is evaluated using the GHK simulator with 250 random draws.

In section 5, we report mean marginal effects rather than coefficient estimates for ease of interpretation of the results.[12]

5 Results - Dynamics of Income Poverty

5.1 Model specification

Before turning to the estimates for the conditional poverty equation, we compare sample means with predicted values generated from the estimates in order to test how good our model is at fitting the data. Firstly, the sample proportion of households who were poor

[12]The mean marginal effect of a particular variable, e.g. 'female', is computed by first setting the female dummy to 1 for all individuals in the sample, while keeping all other variables at their observed value, and predict the outcome of the dependent variables for each individual ($\hat{Y}_1$). This is repeated under a scenario where the female dummy is set to 0 for all individuals ($\hat{Y}_0$). For each individual we then compute the marginal effect: $\hat{Y}_1$ - $\hat{Y}_0$. The mean marginal effect is obtained by averaging over all individuals.

in the base year is 0.0788, which compares closely to the predicted proportion of 0.0790. Secondly, the sample and predicted proportions for being retained from one period to the next are also very similar - 0.8933 and 0.8934, respectively. The predictions for conditional poverty also reveals that the model does a good job at replicating the sample means. In the case of remaining in poverty from one year to the next (and thus also being retained) the sample and predicted means are 0.4516 and 0.4528. For the proportions of households entering poverty, the values are both 0.0441. These figures all indicate that the specified model comes very close to replicating sample means.

The next test for model specification is provided by the estimates of ρ_1, ρ_2, ρ_3, which capture the correlation between the unobserved error terms in equations (1)-(3). As illustrated in Table 4, none of these correlations are statistically significant, which implies that all three equations could in fact be estimated separately without affecting the estimates of the mean marginal effects, though joint estimation importantly improves efficiency. The correlations do have the expected signs with unobserved heterogeneity for poverty and retention negatively correlated and unobserved heterogeneity for initial and conditional poverty positively correlated.

Finally, standard errors are robust to heterogeneity and clustered at the household-level, where the household is defined in the year it is first observed and remains constant over the subsequent periods.

5.2 The drivers of poverty persistence and entry

Unlike the estimates discussed in Cappellari and Jenkins (2004) for the United Kingdom, we find using four waves of HILDA that a number of variables are important determinants of both poverty persistence and entry as reported in columns (1) and (2) of Table 4, respectively.

In terms of household head characteristics, younger heads and those with a university education and more work experience are less likely to remain in poverty from one year to the next. Any form of tertiary education and being employed either part-time or full-time, with the latter having the largest marginal effect (15.9 percentage points), all decrease the probability of entering poverty. If the household head has a long-term health problem or disability, the conditional probability of both poverty persistence and entry are higher. The only partner characteristics that appear to have an impact on poverty status is employment, both part- and full-time, but only in the case of poverty entry.

With respect to household variables, having children aged 10-14 years and living in a city reduces the likelihood of remaining in poverty. Living in either a city or inner-regional area decreases the probability of entering into poverty, highlighting the vulnerability of remote households.

An important insight provided by these results is the role of life-changing events in affecting the vulnerability of households of becoming and remaining poor. The estimates presented in Table 4 show that becoming separated has a significant impact on increasing both the probability of remaining poor over two periods (by 15.1 percentage points) and entering from one year to the next (by 7.6 percentage points). Clearly, the departure of an income-earner puts families at risk of experiencing material hardship. In contrast, a birth in the household decreases the likelihood of persisting in poverty, and by a considerable margin of 17.2 percentage points. This most likely reflects either the impact of a baby in a household on the urgency of maintaining a decent income or the contribution of government assistance on household incomes.

5.3 Initial poverty status

The methodology employed in this paper controls for the endogeneity of poverty status in the initial period as represented by equation (2). Looking at Table 5, it is evident that a similar set of variables are significantly associated with poverty in the initial period as found in the case of conditional poverty status.

A number of exclusion restrictions are included in the specification for equation (2), which are important for the identification of the model. Heckman (1981) suggests to use exogenous variables from the pre-sample period in the specification for the initial condition (here P^*_{t-1}). We use parental background information available for the household head which are measured at the time the household head was 14 years of age. They are also interesting from an economic point view. The results show that having a father employed at the age of 14 decreases the probability of poverty in the initial period and that this effect is statistically significant. Therefore, in addition to contributing to identification, these estimates suggest that employment experiences of parents have intergenerational effects on their offspring in terms of labour market outcomes and ultimately income poverty.

5.4 Attrition

As discussed above, non-random attrition can potentially bias estimates. However, the estimates of the correlation coefficients as reported in section 5.1 reveal no evidence of such a bias. Nonetheless, the estimates for the retention equation (equation (3)), displayed in Table 5, provide an insight into the determinants of attrition in our sample.[13]

Households where the head is younger or from a non-English speaking background are less likely to be retained in our sample from one period to the next. In contrast, having a university education and being employed either full- or part-time increases the probability

[13]These results should not be generalised to attrition in the population.

of remaining in the sample. Similarly, education and employment status of the partner have a positive impact on retention.

The variable that indicates whether or not the respondent is living in a incomplete-responding household tells us if a responding member is more likely to also non-respond next time round or if the non-participating member is more likely to rejoin the survey. Our estimates indicate that the former is what happens.

The estimates of the impact of the exclusion restrictions on retention, as listed at the bottom of Table 5, highlights how the execution of the survey affects attrition, in addition to contributing to the identification of the econometric model. For the exclusion restrictions in the retention equation we can not rely on the suggestion by Heckman (1981) to use pre-sample exogenous variables. Instead we rely on the assessment of the interviewer who reports if the respondent behaved suspiciously or was cooperative during the interview, as well as the the length of the interview. It is easy to see why these variables would be expected to directly affect retention but do not affect poverty status (after controlling for all the other right hand side variables in the conditional and initial poverty equations). Behaving suspiciously during the interview and the length of the interview both increase the probability of attriting from the sample by about 10 and 6 percentage points, respectively. In comparison, being cooperative during the interview increases by about 12 percentage points the likelihood that the household remains in our sample. All three exclusion variables are statistically significant.

5.5 Average and genuine state dependence

The model used in this paper also allows a comparison of the average state dependence (ASD), a descriptive statistic, with a measure of genuine state dependence (GSD) derived from the model estimates (see Cappellari and Jenkins (2004)). The former is simply the

difference in the proportion of individuals that are income poor in period t-1 that remain income poor in period t and the proportion of individuals not income poor in period t-1 that become income poor in period t. This can be more formally specified as:

$$ASD = \left(\frac{\sum\limits_{\text{i}\in\{P_{it-1}=1\}} \Pr\left(P_{it}=1|P_{it-1}=1\right)}{\sum\limits_{i} P_{it-1}} \right) - \left(\frac{\sum\limits_{\text{i}\in\{P_{it-1}=0\}} \Pr\left(P_{it}=1|P_{it-1}=0\right)}{\sum\limits_{i} \left(1-P_{it-1}\right)} \right) \quad (7)$$

This measure of ASD does not control for individual heterogeneity and is therefore likely to overstate the extend of genuine state dependence. Genuine state dependence is defined as the difference in the conditional probability of being income poor in period t conditional on being income poor in t-1 and the conditional probability of being income poor in period t conditional on not being income poor in t-1. This probability is predicted for each individual and then averaged. More formally, GSD can be defined as:

$$GSD = \left(\frac{1}{N}\right) \sum_{i=1}^{N} \left[\Pr(P_{it}=1|P_{it-1}=1) - \Pr(P_{it}=1|P_{it-1}=0)\right] \quad (8)$$

Based on our parameter estimates in Table 4 we find a measure of GSD of 26.0% compared to our ASD measure of 50.2%, that is, about half (51.8%) of the observed unconditional state dependence is genuine state dependence. These rates are close to the findings by Cappellari and Jenkins (2004) who, using a different definition of poverty, find an ASD rate of 52.6% and a GSD rate of 31.0%.

A further intuitive measure that is easily derived from the estimated model is the predicted mean and median durations of a poverty spell, assuming a stationary environment. This allows us to make inference over a longer horizon even though we only have four years of data. The two components of equation (8) are the poverty persistence rate and the poverty entry rate. In a stationary environment, the reciprocal of one minus the poverty persistence rate is the mean duration of an income poverty spell. Based on the

estimates of Table 4, the mean poverty duration is 1.5 years. The median duration is calculated as the ratio of log(0.5) over the log of the poverty persistence rate, which is found to be shorter than the mean (0.6 years). In comparison, the mean and median duration of spell out of poverty are 12.4 and 8.2 years, respectively.

5.6 Sensitivity of results to the definition of poverty

As alluded to in section 2 the choice of 50% of OECD (modified) equivalised household income is only one measure on a continuum of alternatives. A subset of all possible equivalising scales (ES) is captured by the following specification:

$$ES = [1 + \theta_1(Adults - 1) + \theta_2(Dependents - 1)]^{\alpha} \tag{9}$$

For instance, in the OECD Oxford scale θ_1, θ_2 and α are 0.7, 0.5 and 1, while in the modified OECD scale, the respective weights are 0.5, 0.3 and 1. Another commonly used scale, the square root of the household size, is captured by the parameterisation 1, 1, and 0.5, respectively. Table 6 compares our base case, 50% of median (modified) OECD equivalised household income, with the European standard of 60% of the median and a series of other equivalency scales at 50% of the median. Using the European cut-off of 60% of the median, we find that the headcount poverty rate in the 2001 population increases from 14.2% to 21.1%, but has almost no effect on the estimates of average and genuine state dependence.

6 Conclusion

Even during times of prosperity there remain pockets of disadvantaged households in OECD countries like Australia. It was generally believed that this was a persistent prob-

lem for specific households. However, with the increasing availability of longitudinal household data, a different picture has emerged: the majority of households in countries such as Australia only temporarily enter poverty, though the longer they remain poor, the lower their probability of exiting. In the Australian context, the HILDA data set has enabled researchers to fill in some of these gaps in our knowledge of the drivers of household income poverty dynamics.

Using HILDA data, the findings of this paper have important implications for Australian policymakers: tertiary education and employment are key factors in keeping households out of poverty; having a disability increases the probability of becoming poor and remaining in such a situation; households in outer-regional or remote areas are more likely to become poor and continue to live under such hardship; and finally, life-changing events, especially becoming separated, can lead households into persistent poverty.

By drawing on such research, policymakers will be much better informed about the determinants of income poverty in Australia and subsequently how best to design policies that target and support the most vulnerable households.

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A Tables

Table 1: **Poverty Transition Rates for the Population and Estimation Sample**

		Population		Estimation sample	
		Period t		*Period t*	
		Non-poor	Poor	Non-poor	Poor
Period t-1	Non-poor	93.4	6.6	95.5	4.5
	Poor	44.7	55.3	53.4	46.6

Based on unweighted data using all individuals. Definition of income poverty line is 50% of median OECD (modified) equivalised (imputed) disposable household income Source: HILDA 2001-2004; release 4.1.

Table 2: **Degree of Poverty Persistence for the Population and Estimation Sample**

Degree of persistence	Population (%)	Estimation Sample (%)
0 of 4 years	79.7	88.1
1 of 4 years	12.1	8.0
2 of 4 years	5.1	2.6
3 of 4 years	2.2	0.9
4 of 4 years	1.0	0.4

Based on balanced unweighted data using all individuals. Definition of income poverty line is 50% of median OECD (modified) equivalised (imputed) disposable household income Source: HILDA 2001-2004; release 4.1

Table 3: **Descriptive Statistics**

Variable	**All**	**Poor**	**Non-Poor**
Household head characteristics			
Age	40.35	41.44	40.26
Female	0.13	0.27	0.12
High educ: Year 11 or less	0.25	0.43	0.23
High educ: Year 12	0.10	0.11	0.10
High educ: diploma or certificate	0.40	0.36	0.40
High educ: university	0.25	0.10	0.27
Years work experience	20.80	17.80	21.06
Employed full-time	0.79	0.30	0.83
Employed part-time	0.09	0.13	0.09
Non-English speaking background	0.13	0.21	0.12
Long-term disability	0.17	0.40	0.15
HH head's partner characteristics			
Age	38.34	38.52	38.33
Education: Year 11 or less	0.34	0.43	0.34
Education: Year 12	0.17	0.22	0.16
Education: diploma or certificate	0.23	0.21	0.23
Education: university	0.26	0.14	0.27
Years work experience	15.17	11.39	15.39
Employed full-time	0.34	0.14	0.35
Employed part-time	0.37	0.21	0.38
Non-English speaking background	0.14	0.25	0.13
Long-term disability	0.13	0.24	0.13
Individual characteristics			
Poor understanding	0.04	0.12	0.03
Needed help with language	0.02	0.07	0.01
Father employed at 14	0.92	0.87	0.93
Mother employed at 14	0.53	0.48	0.53
Parents divorced/separated	0.22	0.25	0.22
Household characteristics			
Household type: couple with no children	0.19	0.10	0.19
Household type: couple with children	0.60	0.45	0.62
Household type: lone person	0.11	0.24	0.10
Household type: single parent	0.09	0.20	0.08
Children aged 0-4 present	0.25	0.26	0.25
Children aged 5-9 present	0.28	0.31	0.28

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Table 3 – continued from previous page

Variable	All	Poor	Non-Poor
Children aged 10-14 present	0.28	0.27	0.28
Number of workers	1.56	0.70	1.64
Household income imputed	0.29	0.28	0.29
Non-complete responding household	0.12	0.13	0.12
State: Victoria	0.25	0.20	0.25
State: NSW	0.30	0.29	0.30
State: Queensland	0.20	0.21	0.20
State: South Australia	0.09	0.15	0.09
State: Western Australia	0.10	0.10	0.10
State: Tasmania	0.03	0.04	0.03
State: Northern Territory	0.01	0.01	0.01
State: A.C.T.	0.02	0.01	0.02
City	0.62	0.54	0.62
Inner-regional	0.25	0.26	0.25
Outer-regional and remote	0.11	0.17	0.11

Source: HILDA 2001-2004; release 4.1. Maximum number of observations: 25335 individual-year observations. All results are rates (%) unless stated otherwise. The median of the (modified) OECD equivalised household disposable income is based on the distribution of income in the total population.

Table 4: **Determinants of Conditional Poverty Status**

	Dependent variable: Poverty status (t)			
Variable	**Poverty**$_t$|**Poverty**$_{t-1}$		**Poverty**$_t$|**Non-Poverty**$_{t-1}$	
	Marginal Effect	z-value	Marginal Effect	z-value
Household head characteristics				
(Age 46-54)				
Age 25-35	-0.178	-3.76	-0.022	-1.06
Age 36-45	-0.095	-2.45	0.000	0.13
Female	-0.030	-0.95	-0.010	-0.81
(Education: Year 11 or less)				
Education: Year 12	0.005	0.10	-0.012	-1.07
Education: diploma or certificate	-0.015	-0.62	-0.016	-2.17
Education: university	-0.095	-2.57	-0.039	-4.11
Years work experience	-0.113	-2.94	0.000	0.43
Employed full-time	-0.109	-1.40	-0.159	-5.90
Employed part-time	-0.103	-1.66	-0.052	-3.86
Non-English speaking background	0.066	1.44	0.021	1.38
Long-term disability	0.057	2.91	0.017	2.29
HH head's partner characteristics				
(Age 46-54)				
Age 25-35	-0.013	-0.29	-0.012	-0.64
Age 36-45	0.050	0.69	-0.008	-0.55
(Education: Year 11 or less)				
Education: Year 12	0.089	1.28	0.021	1.24
Education: diploma or certificate	0.042	0.62	0.006	0.48
Education: university	-0.028	-0.37	-0.007	-0.51
Years work experience	-0.086	-1.54	0.017	-0.98
Employed full-time	0.059	0.44	-0.050	-3.23
Employed part-time	0.150	1.61	-0.028	-2.05
Non-English speaking background	0.056	0.94	0.015	0.66
Long-term disability	0.051	-0.77	0.013	0.95
Individual characteristics				
Life event: marriage	0.047	0.54	-0.029	-1.04
Life event: separation	0.151	2.35	0.076	5.14
Life event: reconciliation	-0.132	-1.48	-0.044	-1.53
Life event: birth	-0.172	-2.38	-0.013	-0.55
Life event: death	-0.143	-1.44	-0.009	-0.16

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Table 4 – continued from previous page

	Dependent variable: Poverty status (t)			
Variable	**Poverty**$_t$|**Poverty**$_{t-1}$		**Poverty**$_t$|**Non-Poverty**$_{t-1}$	
	Marginal Effect	z-value	Marginal Effect	z-value
Life events info not available	0.043	0.88	0.017	1.35
Poor understanding	0.060	1.19	0.026	1.67
Needed help with the language	0.056	0.91	0.044	1.44
Household characteristics				
(HH type: couple no children)				
HH type: couple with children	-0.020	-0.18	0.011	0.60
HH type: lone person	0.143	1.83	-0.002	-0.21
HH type: single parent	-0.025	-0.32	-0.017	-0.68
Children aged 0-4 present	0.003	1.20	0.015	0.93
Children aged 5-9 present	0.016	1.34	-0.005	-0.63
Children aged 10-14 present	-0.007	-1.97	-0.009	-0.73
Number of workers	-0.087	-1.22	0.016	-1.30
Household income imputed	-0.015	-0.09	0.042	3.30
Non-complete responding household	-0.266	-2.63	-0.003	-0.02
(State: VIC)				
State: NSW	-0.019	-0.40	-0.002	-0.21
State: Queensland	-0.032	-0.68	0.017	1.33
State: South Australia	0.100	1.91	0.021	1.02
State: Western Australia	0.015	0.31	0.025	1.35
State: Tasmania	0.062	0.73	-0.005	-0.18
State: Northern Territory/A.C.T	0.019	0.12	0.004	0.16
(Region: outer-regional and remote)				
City	-0.088	-2.05	-0.056	-3.46
Inner-regional	-0.031	-0.68	-0.024	-1.96
(Data from wave 3 and 4 block)				
Data from wave 1 and 2 block	-0.057	-1.36	0.004	0.30
Data from wave 2 and 3 block	-0.054	-1.33	0.007	0.75
ρ_1	-0.139	-1.54		
ρ_2	0.224	0.62		
ρ_3	-0.040	-1.08		
Log-likelihood	-12084.0			
Model chi-square	271.89			
Number of observations (household-year)	16769			

Source: HILDA 2001-2004; release 4.1. Standard errors adjusted for clustering on household identifier. Comparison groups are listed in parentheses. Z-values reported are for the coefficient estimates.

Table 5: **Determinants of Initial Poverty Status and Retention**

	Poverty status (t-1)		**Retention**	
Variable	Marginal Effect	z-value	Marginal Effect	z-value
Household head characteristics				
(Age 46-54)				
Age 25-35	-0.044	-3.40	-0.044	-1.96
Age 36-45	-0.018	-2.04	-0.004	-0.31
Female	-0.007	-0.77	0.018	1.07
(Education: Year 11 or less)				
Education: Year 12	0.000	-0.04	0.016	1.33
Education: diploma or certificate	-0.007	-1.13	0.012	1.50
Education: university	-0.041	-5.72	0.019	2.00
Years work experience	-0.001	-2.30	-0.001	-0.92
Employed full-time	-0.139	-9.35	0.079	4.63
Employed part-time	-0.042	-3.96	0.050	3.25
Non-English speaking background	0.028	2.70	-0.047	-3.32
Long-term disability	0.023	3.35	-0.041	1.86
HH head's partner characteristics				
(Age 46-54)				
Age 25-35	-0.022	-1.58	0.031	1.94
Age 36-45	-0.008	-0.72	0.028	2.15
(Education: Year 11 or less)				
Education: Year 12	0.018	1.35	0.033	2.47
Education: diploma or certificate	-0.003	-0.25	0.039	3.12
Education: university	0.000	0.03	0.058	3.73
Years work experience	0.022	-2.29	-0.040	0.62
Employed full-time	-0.015	-0.95	0.010	0.53
Employed part-time	0.001	0.04	0.034	2.12
Non-English speaking background	0.031	2.07	-0.017	-0.82
Long-term disability	0.028	0.79	-0.015	1.10
Individual characteristics				
Poor understanding	0.028	1.90	-0.025	-1.22
Needed help with the language	0.018	0.95	-0.045	-1.25
Household characteristics				
(HH type: couple no children)				
HH type: couple with children	0.015	0.80	-0.022	-1.24
HH type: lone person	0.043	2.01	0.060	2.93

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Table 5 – continued from previous page

	Poverty status (t-1)		**Retention**	
Variable	Marginal Effect	z-value	Marginal Effect	z-value
HH type: single parent	-0.006	-0.27	0.019	0.61
Children aged 0-4 present	0.007	0.46	0.034	1.78
Children aged 5-9 present	0.017	1.58	0.026	1.83
Children aged 10-14 present	-0.013	-1.09	0.018	1.30
Number of workers	0.021	-2.73	-0.080	-2.03
Household income imputed	0.031	2.81	-0.031	-2.49
Non-complete responding household	-0.040	-2.00	-0.159	-4.58
(State: VIC)				
State: NSW	0.003	0.28	0.005	0.49
State: Queensland	0.000	0.02	0.020	1.61
State: South Australia	0.050	2.95	0.049	2.80
State: Western Australia	0.015	1.17	0.010	0.51
State: Tasmania	0.010	0.45	-0.004	-0.12
State: Northern Territory/A.C.T	-0.018	-0.72	0.051	1.62
(Region: outer-regional and remote)				
City	-0.047	-4.20	0.018	1.18
Inner-regional	-0.010	-0.86	0.031	2.04
(Data from wave 3 and 4 block)				
Data from wave 1 and 2 block	0.010	1.07	-0.026	-2.09
Data from wave 2 and 3 block	-0.003	-0.33	-0.003	-0.09
Exclusion restrictions				
Father employed at 14	-0.022	-2.37		
Mother employed at 14	-0.004	-0.59		
Parents divorced/separated ever	0.000	-0.04		
Cooperative during interview			0.118	3.86
Suspicious during interview			-0.097	-3.85
Length of interview			-0.057	-2.40

Source: HILDA 2001-2004; release 4.1. Standard errors adjusted for clustering on household identifier. Comparison groups are listed in parentheses. Z-values reported are for the coefficient estimates.

Table 6: **Statistics based on alternative poverty measures using the estimation sample**

Poverty measure	θ_1	θ_2	α	cut-off as %of median	2001 headcount poverty rate (%) (populat.)	ASD (%)	GSD (%)	GSD/ ASD (%)	poverty entry rate (%)	median duration poverty spell (years)	mean duration poverty spell (years)	median duration non-poor spell (years)	mean duration non-poor spell (years)
OECD Modified	0.7	0.5	1	50	14.2	50.2	26.0	51.8	8.1	0.6	1.5	8.2	12.4
OECD Mod.(EU)	0.7	0.5	1	60	21.1	55.1	27.5	49.9	11.4	0.7	1.6	5.7	8.8
Oxford scale	0.5	0.3	1	50	11.9	45.8	26.0	56.9	8.6	0.7	1.5	7.7	11.6
Square root	1	1	0.5	50	14.9	56.0	25.6	45.8	9.4	0.7	1.5	7.0	10.6
Alternative 5	1	0.2	0.25	50	16.8	51.5	17.3	33.6	7.2	0.5	1.3	9.3	13.9
Alternative 6	1	0.8	0.5	50	14.9	50.1	21.5	43.0	9.1	0.6	1.4	7.3	11.0
Alternative 7	0.6	0.8	1	50	12.4	44.1	17.6	39.8	9.2	0.5	1.4	7.2	10.9

Source: HILDA 2001-2004; release 4.1. Based on unweighted data using all individuals in our sample, except for the 2001 headcount poverty rate which is based on the population, not the sample. Household equivalence size (ES) is based on the formula $ES = [1 + \theta_1(Adults - 1) + \theta_2(Dependents - 1)]^{\alpha}$.