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ABSTRACT

Persisting Disadvantages: A Study of the Dynamics of Cumulative Deprivation

Identifying populations at risk of deprivation is crucial for effective policy design. Yet, much existing research focuses on single aspects, such as income or material deprivation, and often abstracts from deprivation dynamics. This study addresses this gap by analyzing the dynamics and socio-economic gradient of cumulative deprivation using data from the 2005–2021 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Employing copulabased techniques and two econometric approaches—a Conditional Maximum Likelihood Estimator (CMLE) estimator and a two-stage Generalized Method of Moments (GMM) procedure—the analysis reveals significant state dependence, where past cumulative deprivation strongly predicts future deprivation. Schooling, employment, and parenthood emerge as key determinants. These findings underscore the importance of adopting multidimensional and temporal perspectives on deprivation, offering critical insights for more targeted and effective policy interventions.

JEL Classification: I31, I32, C33

Keywords: state dependence, cumulative deprivation, energy poverty, Generalized Method of Moments, Wooldridge Conditional Maximum Likelihood

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1. INTRODUCTION

The identification of populations at risk of deprivation is essential for formulating effective policy interventions. While there has been significant research on the topic, most studies have focussed on single aspects of deprivation such as income or material deprivation (see, for instance, Dewilde, 2008, Figari, 2012, and Verbunt and Guio, 2019). However, deprivation can be accumulative across domains and concentrate on specific population groups. Cumulative deprivation occurs when individuals occupy a low position in all well-being dimensions simultaneously (Decancq, 2020). For these individuals, disadvantages in one dimension are further reinforced by disadvantages in other dimensions. As Sen (1999) remarks, the coupling of disadvantages between different sources of deprivation is crucial to understand poverty and to design policies to tackle it. Aligned with this view, the target group in anti-poverty polices is typically the group consisting of individuals who accumulate disadvantages in several dimensions (Wolff and De-Shalit, 2007). More recently, Bárcena-Martín et al. (2020) highlight the need to consider the concurrence of multiple deprivations when analysing multidimensional poverty.

This paper examines the incidence, dynamics and socio-economic gradient of cumulative deprivation. Using the 2005-2021 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a micro panel survey representative of the Australian population, the paper focuses on three key domains of well-being, namely income, health and energy deprivation. To model transitions in cumulative deprivation, we employ two alternative approaches: a Conditional Maximum Likelihood Estimator (CMLE) for panel data and a Generalized Method of Moments (GMM) procedure. Both estimators account for state dependence in cumulative deprivation, acknowledging that a previous deprived condition significantly influences cumulative deprivation at a subsequent point in time. Furthermore, the two estimators offer a robust toolkit for addressing endogeneity issues arising from both reverse causality and unobserved heterogeneity (Leszczensky and Wolbring, 2022). The two approaches differ in controlling for unobserved heterogeneity. While the CMLE estimator necessitates an auxiliary distributional assumption on individual-specific effects, the GMM estimator eliminates individual-specific effects by taking first differences and then instruments the variation in the lagged dependent variable to mitigate potential serial correlation with the error term. The CMLE estimator offers greater efficiency, assuming the auxiliary distributional assumption is valid, but is inconsistent otherwise. On the other hand, the GMM estimator does not require a distributional assumption but may be less efficient (Stewart, 2007). Therefore, comparing the results from both sets of estimators allows an examination of the validity of distributional assumptions (Budría et al., 2023).

The paper contributes to the literature in two key dimensions. Firstly, the study uses a copula approach, which consists of transforming the original variables into positions (ranks) and focusing the analysis on the joint distribution of these positions. This methodology has the main advantage of capturing the interrelation between the different dimensions in multivariate, possibly non-linear and possibly non-Gaussian contexts. The use of copulas in the literature on multidimensional welfare and poverty dates to Decancq (2014), who applied several copula-based measures of multivariate association to analyze the dependence between income, health, and education in Russia. In a follow-up paper, Pérez and Prieto-Alaiz (2016) examined the dependence between the dimensions of the Human Development Index. Similarly, García-Gómez et al. (2021, 2024a) employed several copula-based generalizations of Spearman’s rank correlation coefficient to study the evolution of multivariate dependence between the three dimensions of the AROPE rate (income, work intensity, and material needs) in the European Union and in the Spanish regions, respectively. D’Agostino et al. (2023) and García-Gómez et al. (2024b) also focused on the AROPE dimensions, analyzing the evolution of lower tail dependence between them in the EU and Spain, respectively. Recently, copula-based techniques have been employed to examine cumulative deprivation in the European context (Decancq, 2023; Scarchilli, 2024).

Secondly, to the best of our knowledge, this is the first paper that addresses the study of cumulative deprivation from a dynamic perspective looking for evidence of genuine state dependence. While Decancq (2023) and Scarchilli (2024) examine the incidence and socio-economic determinants of cumulative deprivation, they do so through contemporaneous effects. However, there is the possibility that deprivation is a self-perpetuating state and subject to transitions in and out of it. This paper attempts to fill this gap by assessing the extent of cumulative deprivation persistence and testing to what extent individuals within risk groups face limited opportunities to escape from cumulative deprivation. The interest in this question is rooted in the literature on material hardship and poverty, which underscores the importance of accounting for inertia effects (Cappellari and Jenkins, 2004; Ayllón, 2013; Fabrizi and Mussida, 2020; Mussida and Sciulli, 2022).

The paper extends the current state of knowledge by showing that there exists significant cumulative deprivation inertia among individuals in Australia. A reference individual is significantly more likely to be deprived if they were previously in that state, even when other factors remain constant. Moreover, the findings highlight the impact of socio-economic characteristics such as formal education, marriage, age, parenthood, and disability on cumulative deprivation. Additionally, there are notable labour market effects, with employed individuals being less likely to experience deprivation. The research also underscores the self-perpetuating nature of deprivation across all dimensions, particularly in the case of income.

The paper is structured as follows: Section 2 introduces the concept of cumulative deprivation and explores its measurement methodologies. Section 3 details the dataset and provides a comprehensive definition of the variables used in the analysis. Section 4 outlines the econometric framework employed in the study. Section 5 presents the main findings, assessing the degree of state dependence across different models and thresholds of cumulative deprivation. Finally, Section 6 concludes by summarizing the key insights and discussing their broader implications.

2. CUMULATIVE DEPRIVATION: CONCEPT AND MEASUREMENT

Cumulative deprivation occurs when individuals simultaneously occupy a low position across all considered well-being dimensions; see Decancq (2020, 2023). The aim of this paper is to analyze the incidence, dynamics and socio-economic gradient of cumulative deprivation. To capture this phenomenon, we use the copula methodology, which focuses on the positions of the individuals across the variables, rather than on the values that these variables attain for such individuals (for an introduction to copulas, see Nelsen, 2006; Durante and Sempi, 2015).

2.1. BASIC PROPERTIES OF COPULAS

Let the random vector $\boldsymbol{X} = (X_1, \dots, X_d)$ represent the relevant d dimensions of welfare and let F_i denote the marginal distribution of dimension i, with $i = 1, \dots, d$. Then, each original variable X_i is transformed by applying the so-called *probability integral transformation*, obtaining a transformed variable $U_i = F_i(X_i)$, which is a standard uniform random variable and attaches to each individual their relative position in dimension i. Then, the random vector $\boldsymbol{U} = (U_1, \dots, U_d)$ represents the relative position of individuals in the d dimensions of welfare and captures the distribution and alignment of the positions in the society. For instance, an individual with position vector (1, . . . , 1) will be top-ranked in all dimensions, whereas an individual with position vector (0, . . . , 0) will be bottom-ranked in all dimensions.

The copula function, C, is the joint distribution of the random vector $\boldsymbol{U} = (U_1, \dots, U_d)$. Hence, the copula is a d-dimensional cumulative distribution function, $C: \mathbb{I}^d \to \mathbb{I}$, with $\mathbb{I} = [0, 1]$, whose univariate marginals are U(0, 1). Therefore, for a given real vector $\boldsymbol{u} = (u_1, \dots, u_d) \in \mathbb{I}^d$,

$$C(\boldsymbol{u}) = p(\boldsymbol{U} \le \boldsymbol{u}) = p(U_1 \le u_1, \dots, U_d \le u_d) \qquad (1)$$

Hence, the value $C(\boldsymbol{u})$ represents the proportion of households in the population with positions outranked by $\boldsymbol{u}$.

The popularity of copulas in statistics relies on Sklar's Theorem (Sklar, 1959). This theorem establishes that, given a d–dimensional random vector $\boldsymbol{X} = (X_1, \dots, X_d)$ with joint distribution function $F(\boldsymbol{x}) = F(x_1, \dots, x_d) = p(X_1 \leq x_1, \dots, X_d \leq x_d)$ and univariate marginal distribution functions $F_i(x_i) = p(X_i \leq x_i)$, for $i = 1, \dots, d$, there exists a copula $C\colon \mathbb{I}^d \to \mathbb{I}$ such that, for all $(x_1, \dots, x_d) \in \mathbb{R}^d$,

$$F(x_1, \dots, x_d) = C\big(F_1(x_1), \dots, F_d(x_d)\big) \qquad (2)$$

Thus, copulas link joint distribution functions to their univariate marginals. Moreover, if $F_1, \dots, F_d$ are all continuous, the copula C in the previous equation is unique. Otherwise, C is uniquely determined on $Range\ F_1 \times \dots \times Range\ F_d$.

Some particularly important copulas are worth mentioning. First, the independent copula, $\pi(\boldsymbol{u}) = u_1 \times \dots \times u_d$, which accounts for the case where the variables $X_1, \dots, X_d$ are independent. Second, the commonotonic copula, $M(\boldsymbol{u}) = \min(u_1, \dots, u_d)$, which represents maximal positive dependence, that is, when each of the random variables $X_1, \dots, X_d$ is almost surely a strictly increasing function of any of the others. Moreover, any copula C satisfies the Fréchet-Hoeffding inequality, namely

$$W(\boldsymbol{u}) \leq C(\boldsymbol{u}) \leq M(\boldsymbol{u}) \qquad (3)$$

where $W(\boldsymbol{u}) = \max(u_1 + \dots + u_d - d + 1, 0)$ is only a copula in the bidimensional case (d = 2), in which case represents perfect negative dependence. However, W is not a copula for d > 2.

As argued above, in this paper we use copulas to measure and study cumulative deprivation. At this point, two issues may be of interest. On one hand, one can be interested in quantifying the incidence of cumulative deprivation in a society, that is, the proportion of individuals that suffer from cumulative deprivation. On the other hand, the interest may lie in identifying those individuals who suffer from cumulative deprivation to study its dynamics and socio-economic gradient.

2.2. THE INCIDENCE OF CUMULATIVE DEPRIVATION

To quantify the extent of cumulative deprivation in a society, Decancq (2020) proposes to use the diagonal section of the copula.[1] The diagonal section of a d-dimensional copula C is the function $\delta_C(u) : \mathbb{I} \to \mathbb{I}$ defined by

$$\delta_C(u) = C(u, \dots, u) \text{ for all } u \in \mathbb{I} \qquad (4)$$

[1] Decancq (2020) denotes this function *downward diagonal dependence curve*.

Hence, in the well-being setting, for each relative position u the diagonal section of the copula gives the proportion of individuals in the society who occupy a position lower than or equal to u in all dimensions of welfare simultaneously. That is, the diagonal section of the copula quantifies the incidence of cumulative deprivation in a society. For instance, if we consider income, energy conditions and health as the three dimensions of well-being, $\delta_C(0.25) = C(0.25, 0.25, 0.25)$ gives the proportion of individuals in the society that are simultaneously in the first quartile in the three dimensions considered.

The diagonal section of the copula has the following properties:[2]

1. $\delta_C(u) \leq u$ for all $u \in \mathbb{I}$.
2. $\delta_C(0) = 0$ and $\delta_C(1) = 1$.
3. $\delta_\pi(u) = u^d$ for all $u \in \mathbb{I}$.
4. $\delta_M(u) = u$ for all $u \in \mathbb{I}$.

To illustrate these properties and the usefulness of this function, Figure 1 shows, in black, the diagonal section of the copula C of a trivariate distribution. Moreover, the diagonal section of the independence copula π is represented in blue, whereas that of the comonotonic copula M is depicted in red. The closer the diagonal section of a copula C is to the red line, the higher the incidence of cumulative deprivation. Therefore, this function is a useful tool to compare the cumulative deprivation across societies or to analyze its evolution over time. In Section 5.1, we use the diagonal section of the copula to quantify the level of cumulative deprivation in Australia.

-Insert Figure 1 here-

In practice, the diagonal section is estimated non-parametrically using the empirical version of the copula. In particular, let $\{(X_{1j}, \ldots, X_{dj})\}_{j=1,\ldots,n}$ be a sample of n serially independent random vectors from the d-dimensional vector $\boldsymbol{X} = (X_1, \ldots, X_d)$ with associated copula C. Then, it is possible to estimate non-parametrically the copula by its corresponding empirical version, namely

$$\hat{C}_n(\boldsymbol{u}) = \frac{1}{n}\sum_{j=1}^{n}\prod_{i=1}^{d} 1_{\{\tilde{U}_{ij} \leq u_i\}}, for\ all\ \boldsymbol{u} = (u_1, \ldots, u_d) \in \mathbb{I}^d \tag{5}$$

where $\mathbf{1}_A$ denotes the indicator function on a set A and $\widetilde{U}_{ij}$ are the transformed data to $[0, 1]$ by scaling ranks, i.e.,

$$\widetilde{U}_{ij} = \frac{R_{ij}}{n},$$

[2] For a more detailed discussion on the properties of the diagonal section, we refer the interested reader to Nelsen (2006) and Fernández-Sánchez and Úbeda-Flores (2018).

where R_{ij} denotes the rank of X_{ij} among $\{X_{i1}, \dots, X_{in}\}$ with $i = 1, \dots, d$ and $j = 1, \dots, n$.

Then, the diagonal section of the copula is estimated non-parametrically as $\hat{\delta}_{C,n}(u) = \hat{C}_n(u, \dots, u)$. For instance, if we consider income, energy conditions and health as the three dimensions of well-being, $\hat{\delta}_{C,n}(0.25)$ calculates the sample proportion of individuals who are simultaneously in the first quartile in these three dimensions.

2.3. IDENTIFICATION OF CUMULATIVE DEPRIVATION

In this section we identify individuals in the society that suffer from cumulative deprivation. To that aim, Decancq (2023) proposes to focus on the maximal relative position of an individual across the different dimensions, that is, the highest position he/she obtains across all dimensions considered. Individuals with a low maximal position occupy a low position in all dimensions. For instance, if we consider again income, energy conditions and health as the three welfare dimensions, an individual with position vector (0.1, 0.25, 0.15) has a maximal position of 0.25, which means that he/she is in the first quartile in the three dimensions simultaneously.

Low maximal positions convey high chances of suffering from cumulative deprivation. We can identify those individuals suffering from cumulative deprivation as those whose maximal position falls below a given threshold. For instance, we could establish that those individuals with a maximal position no higher than 0.25 are cumulatively deprived. This means that one individual is considered to suffer from cumulative deprivation if he/she is simultaneously in the first quartile in all dimensions considered. Hence, to study the socio-economic gradient and dynamics of cumulative deprivation, we can also use non-linear models in which the dependent variable is a binary variable taking the value 1 if the individual suffers from cumulative deprivation and 0 otherwise.

3. DATA AND DEFINITION OF VARIABLES

We use the 2007-2021 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a micro panel survey representative of the Australian population. With a yearly structure, each wave covers approximately 8,000 households drawn from 13 regions of the country and includes approximately 20,000 individuals. After dropping observations with item non-response, the estimation sample includes 108,290 observations from 16,481 individuals across 14 years.

For each year, we calculate the individuals' ranking in the three domains of welfare, namely income, health and energy. Table 1 summarizes the metrics used in each domain. Income is defined as net disposable income by household equivalent unit. Health condition is given by an overall health score based on the SF-36 health questionnaire included in HILDA. This questionnaire is based on 36 questions and gives rise to four mental-wellbeing scores (Vitality, Social Functioning, Role-Emotional and Mental Health) and four physical health scores (Physical Functioning. Role-Physical, Bodily Pain, General Health). These scores are summed up and standardized to an overall health scores which ranges from 0 to 100, with higher scores indicating better health. Finally, energy deprivation is based on five different facets of energy deprivation. Specifically, we employ three expenditure-based measures according to which a household is classified as energy deprived if i) its share of income spent on energy is greater than twice the national median (the *2M* indicator), ii) its share of income spent on energy exceeds 10% (the Ten Percent Rule, *TPR*), or iii) its actual energy expenditures are above the national median and, at the same time, their income net of energy costs is below the official national income poverty line (the Low Income High Costs indicator, *LIHC*). We also consider two self-assessed indicators based on the household's inability to pay to heat their home because of a shortage of money (*Heat*) and pay electricity, gas, or telephone bills on time (*Arrears*). These criteria have been validated by a myriad of papers (Awan et al., 2022; Fry et al., 2022; Spandagos et al., 2023).

- Insert Table 1 here -

Noting that energy poverty is multifaceted, the MEPI used in the paper is based on the aforementioned items. Let *J* be a set of poverty indicators with element j, $j \in J, m = card(J)$. Let *I* be a set of individuals, with element i, $i \in I$, and EP_{ij} denote the status of the *i*th individual in the *j*th indicator. If an individual i is poor under indicator *j*, then EP_{ij} takes the value of one, and zero otherwise. Following the family of indexes typically described in the literature on material deprivation (Dhongde et al., 2019), individual *i*'s weighted poverty score is given by

$$MEPI_i = \left(\sum_{j \in J} w_j EP_{ij}\right) \quad \forall i \in I \tag{6}$$

where w_j denotes the weight assigned to the poverty indicator *j*, with $\sum_{j \in J} w_j = 1$. Hence, MEPI ranges from 0 to 1 and captures the percentage of dimensions in which the individual is deprived.[3] While it is common to assign equal weights to the indicators, we emphasise the indicators where deprivation is less common, the so-called frequency-based weighting approach (Decancq & Lugo, 2013). The weight given to an indicator is proportional to the percentage of individuals *not*

[3] When two individuals have identical MEPI; we rank them according to the percentage of income spent on energy.

classified as poor under that specific indicator within a particular state. In other words, $w_j = \frac{(1-n_j)}{\sum_{j\in J}(1-n_j)}$ where n_j is the proportion of poor individuals in dimension j. This choice is motivated by the idea that not having access to common items should be a more relevant determinant of deprivation than less common items. Additionally, the weights are based on the distribution of achievements in society without considering any value judgement about what the trade-offs between items should be. For greater granularity and accuracy, the weights are calculated separately for each wave. There are two advantages to using this approach. Firstly, it allows the poverty of a given individual to increase if their conditions do not change and the conditions of all others improve. Secondly, it adapts automatically over time, considering economic conditions and social and cultural preferences when accessing items.

3.1 Cumulative deprivation

We employ two binary indicators to measure cumulative deprivation (*CD*). The first indicator equals one if the individual's highest position across three dimensions—income, health, and energy—is below the median. This criterion, which applies to 17.6% of the sample, is referred to as *mild* cumulative deprivation. The second indicator uses the first quartile of the distribution as an alternative threshold, capturing individuals whose highest position is within the bottom 25%. This stricter condition affects 5.9% of the sample and is termed *severe* cumulative deprivation. Additionally, we define a third indicator based on the maximum position occupied by the individual across the different dimensions.

4 ECONOMETRIC APPROACH

We employ a CMLE model, inspired by Wooldridge (2005), to analyze binary dependent variables (mild and severe cumulative deprivation), specified as follows:

$$CD_{it} = \mathbf{1}\ \boldsymbol{if}\ (\rho CD_{it-1} + X'_{it}\beta + c_i + u_{it} > 0) \qquad (7)$$

$(i = 1, \dots, N)$; $(t = 2, \dots, T)$, where CD_{it} is the cumulative deprivation dummy variable, X_{it} is the set of covariates, c_i denotes the unobserved individual-specific time-invariant effect; and u_{it} is assumed to be a normally distributed error term $N(0, \sigma_u^2)$. In the regression stage, standard errors are clustered at the individual level.

We deal with the initial condition problem (i.e., the possibility that energy poverty at the start of the observation period is endogenously determined by the individual's past history) we follow Skrondal & Rabe-Hesketh (2014) and define an auxiliary distribution of the unobserved individual effect which is conditioned on the initial value CD_{i1}, the initial values X_{i1} of the time-varying covariates and the within-means of the time-variant explanatory variables, $\bar{X}_{.i}$,

$$c_i|CD_{i1},\ X_{it} \sim N\left(\vartheta_0 + \vartheta_1 CD_{i1} + \bar{X}_i'\vartheta_3, \sigma_\xi^2\right) \qquad (8)$$
$$c_i = \vartheta_0 + \vartheta_1 CD_{i1} + \bar{X}_i'\vartheta_3 + \xi_i$$

with $\xi_i \sim N\left(0, \sigma_\xi^2\right)$. The reliability of this approach in solving the initial conditions problem is well-grounded on experimental analyses and Monte-Carlo simulations (Akay, 2012). The auxiliary distributional assumption on the individual-specific effects allows the model to address two concerns, namely the potential correlation between i) the unobserved heterogeneity and the regressors, i.e., $E(X_{it}\, c_i) \neq 0$; and ii) the unobserved heterogeneity and the initial value of the dependent variable, i.e., $E(CD_{i1}\, c_i) \neq 0$.

For the maximal position occupied by the individual across dimensions (a continuous variable) we employ a GMM estimation procedure. An additional characteristic of this setting is that it deals with the unobserved heterogeneity with less restrictive assumptions than those stated in Eq. (2). We start by taking first differences of a linear version of Eq. (1) to purge the individual-specific effect from the model:

$$\Delta CD_{it} = \rho \Delta CD_{it-1} + \Delta X'_{it}\beta + \Delta u_{it} \qquad (9)$$

Noting that in the resulting model there is still correlation between the differenced lagged variable and the disturbance process (the former contains CD_{it-1} and the latter contains u_{it}), we instrument ΔCD_{it-1} with all lags of CD_{it-j}, for $j \geq 2$ (Arellano and Bover, 1995). We employ a two-step GMM approach, incorporating a second-order transformation known as 'forward orthogonal deviations'. This technique involves subtracting the average of all future available observations from the current value of a variable, as opposed to subtracting the previous observations. By utilizing the two-step GMM model, we mitigate unnecessary data loss. The two-step GMM estimator is unbiased and consistent under the assumption of no second-order serial correlation in the error term, $E(CD_{it-j}\Delta u_{it}) = 0\ \forall j \geq 2,$ a moment condition that can be tested. Strictly exogenous regressors are assumed to be uncorrelated with u_{it} and are used as instruments for themselves. It is possible that some regressors are weakly exogenous, that is, they are correlated with past errors, $(x_{it+s}u_{it}) \neq 0$ for $s > 0$, but uncorrelated with contemporaneous and future errors, $E(x_{it+s}u_{it}) = 0$ for $s \leq 0$. If a regressor is presumed to be correlated with the contemporaneous error, it is considered endogenous. In such instances, only lagged values can be employed as valid instruments.

We employ standard instruments for strictly exogenous regressors, collapsed instruments for the remaining regressors, and Windmeijer-corrected robust standard errors (Windmeijer, 2005). To mitigate the efficiency loss associated with instrument proliferation—an issue that can result in overfitting endogenous variables without adequately addressing their endogenous components—we collapse the instruments and restrict the maximum lags to three periods, as detailed by Kripfganz & Schwarz (2019). The optimal combination of exogenous and endogenous regressors was selected based on an extensive series of sensitivity checks, primarily guided by tests for serial correlation in first-differenced errors and Hansen's J-test for overidentifying restrictions. The most robust combination assumed that income, employment and schooling are weakly exogenous, while the remaining variables are strictly exogenous.

4.1 Covariates

Vector X includes socioeconomic factors that are standard when accounting for individual economic outcomes. These include gender, schooling, age, marital status, labour status, parenthood and having disabled household members. We also include controls for remoteness, region of residence (the six states and two territories of Australia, reference: New South Wales), time fixed effects and variables to control for macroeconomic conditions at the regional level. The economic cycle affects the chance to find and keep jobs, and it also impacts the likelihood of having a stable income source. We include controls for the regional unemployment rate, per capita GDP, and GDP growth. We also include the regional participation rate to capture competition effects in the labour market and the labour force share of part-time workers to control for the fact that areas with a larger proportion of temporary and/or part-time workers generally have more flexibility to adapt to labour market disequilibria.

Vector X also includes energy prices, given their potential impact on energy poverty and perhaps indirectly on cumulative deprivation. We use annual electricity and gas prices at the state level drawn from the Australian Bureau of Statistics (ABS, 2024). The average price of gas and electricity over the sample period was \$0.014 and \$0.275 per kWh, respectively. To avoid variable proliferation, in the regression stage we introduce just one control for energy prices, defined as the weighted average between the price of gas and electricity.[4] Since energy prices are not available monthly, we construct a 12-month rolling average, $\bar{p}_{it}^{12} = k_{it} \times p_t + (1 - k_{it})p_{t-1}$, where $k_i t$ is the proportion of months elapsed from January 1 to individual's i date of the interview in year t and p_t is the energy price in year t. Thus, we do not only exploit variation in energy prices across states, but also over time and across individuals. We standardize this variable to have zero mean and one standard deviation.

5. RESULTS

5.1 The incidence of cumulative deprivation in Australia

In this section, we study the extent and evolution of cumulative deprivation in Australia using the diagonal section of the copula introduced in Section 2.2. Figure 2 shows the estimated diagonal section for the years 2005 (in black), 2010 (in blue), 2015 (in red) and 2020 (in green), together with 95% confidence intervals calculated via bootstrap with 1000 replicates. There exists cumulative deprivation in income, energy and health in Australia, since for all years the estimated diagonal sections of the copula are clearly above that of the independence case. Furthermore, the curves are very close together, which indicates that cumulative deprivation in Australia has remained rather stable over the years.

- Insert Figure 2 here –

To get a further insight into this evolution, Figure 3 shows the evolution of the proportion of individuals suffering from cumulative deprivation in the three dimensions (income, energy and health) using different thresholds to identify them. In particular, the graph shows in red the evolution of $\hat{\delta}_{C,n}(0.25)$, that is, the proportion of individuals that are simultaneously in the first quartile in income, energy conditions and health. Similarly, the evolution of $\hat{\delta}_{C,n}(0.1)$ is displayed in green and that of $\hat{\delta}_{C,n}(0.5)$ in blue. Regardless of the threshold used, the level of cumulative deprivation in Australia has remained stable over the years. For instance, the percentage of individuals that are simultaneously in the first quartile in the three dimensions has remained stable around 6%. This percentage has been around 1.5% if we consider the first decile as the threshold.

[4] An average Australian household spends about twice as much on electricity as on gas (ABS, 2024). Accordingly, we assign a weight of 0.66 to electricity prices and 0.33 to gas prices. Alternative linear combinations yielded comparable results, and including separate controls for electricity and gas prices did not significantly improve the models' goodness of fit.

Finally, the percentage of individuals who are simultaneously below the median in the three dimensions has remained stable around 20%.

- Insert Figure 3 here –

To assess whether cumulative deprivation tends to be a permanent phenomenon for the affected individuals or, by the contrary, it is a transient state that affects changing layers of the population, in Table 1 we calculate the average duration of cumulative deprivation in our sample and the average entry and exit rates. To provide a more nuanced view, the table also contains the corresponding figure for domain-specific deprivation. The majority of individuals were never mildly deprived (53.6%), while an even larger proportion (82.2%) were never severely deprived. Cumulative deprivation appears to be far from a permanent state. In fact, only 1.0% of individuals experienced mild cumulative deprivation for more than twelve waves, while most of those who reported an episode of cumulative deprivation remained in that state for three waves or less. In contrast, domain-specific deprivation tends to be more persistent than cumulative deprivation. For instance, approximately 7% of the sample experienced health deprivation for more than twelve waves. The last three columns of the table show that the average duration (4.2 waves) and the average entry rate (10.4%) into mild cumulative deprivation is sensitively below the corresponding figures for either income, health and energy deprivation. While an average of 40.5% of the respondents who were cumulative deprived in a previous period manage to scape from cumulative deprivation in the next period, the share of respondents doing so for income deprivation falls to 17.3. The figures for severe deprivation, shown in the bottom panel of Table 2, are broadly supportive of these patterns. To what extent the observed persistence is associated with the persistence of causal variables or, by the contrary, is due to a cumulative deprivation inertia is a question that the next section addresses through dynamic econometric regression.

- Insert Table 2 here -

5.2. Cumulative deprivation state dependence

Table 3 reports the CMLE results for mild and severe cumulative deprivation and the GMM estimates for the maximal position occupied by the individual. We find evidence of a significant cumulative deprivation persistence among individuals in Australia, even after controlling for a large set of socio-economic determinants. Specifically, the reference individual is 9.3 pp more likely to be mildly cumulative deprived if he/she was deprived at t-1. The effect is well determined and represents a 34.6% increase in the sample average hazard of having a maximal position below the median of the distribution (17.6 pp). In the next column, the effect of lagged severe cumulative deprivation is relatively lower (2.4 pp), but it represents again a sizeable increase (35.3%) relative to the sample hazard of being severely cumulative deprived (4.4 pp).

The inclusion of initial cumulative deprivation in the regressions (CD_0) is crucial to examine whether individuals who were better positioned at the beginning of the observation period are more likely to be currently better off. The estimated coefficient is particularly relevant, as it captures how individual-level conditions prior to the start of the data collection in HILDA might affect different trajectories of deprivation in the subsequent T periods. The significant effect of CD_0 on contemporaneous deprivation is suggestive of a true estate dependence effect. The estimates from the GMM model are consistent with the state dependence effects found in the CMLE setting, suggesting that a previous high maximal position raises, ceteris paribus, the contemporaneous maximal position of the individual. In the lower section of Table 3, we report the diagnostic tests for the GMM model, including the test for serial correlation in the first-differenced errors and Hansen's J-test of overidentifying restrictions. The results indicate no evidence of second-order serial correlation, supporting the validity of the lagged instruments used in the model, as their relevance depends on the error term not being serially correlated beyond the first order. Additionally, Hansen's J-test fails to reject the null hypothesis that the instruments are uncorrelated with the error term, confirming their appropriateness. These diagnostics suggest that the model satisfies the key assumptions underpinning GMM estimation, ensuring that the estimates are not biased by instrument invalidity or misspecified error structures.

5.3 The socio-economic gradient of cumulative deprivation

Although current deprivation is strongly determined by the individual's recent history of deprivation, the results also document the existence of effects stemming from contemporaneous variations in the individual's socio-economic characteristics. Gender is not significantly related to deprivation. In contrast, formal education prevents cumulative deprivation in our sample, possibly owing to high education levels influencing households' labour, health and energy efficiency-related decisions. Age shows an inverted U-shaped relationship with cumulative deprivation in the CMLE specification, with those in their late 30s being more likely to experience cumulative deprivation than the very young or old.[5] This pattern suggests that young individuals tend to accumulate resources and social capital, which reduces their probability of falling into economic strain at later ages (Dogan et al, 2021). Married individuals are less likely to experience deprivation, likely due to household resource pooling and economies of scale. In contrast, having children or household members with disabilities significantly increases the risk of deprivation,

[5] Taking the first derivative, $0.36 - 2\text{age}\times 0.005 = 0$, which yields age = 36.0 for mild deprivation

possibly due to higher household expenditures and reduced time available for market-based productive activities. Labour market dynamics also play a significant role, as employed individuals are less likely to be deprived. Compared to an inactive individual, an employed person is 3.0 percentage points less likely to experience mild deprivation. Employment also substantially reduces the likelihood of severe deprivation by 1.6 percentage points. Overall, these findings qualitatively align with previous studies on deprivation in non-dynamic settings, including research on income deprivation (Mussida and Sciulli, 2022), material deprivation (Fabrizi and Mussida, 2020; Fabrizi et al., 2023), and cumulative deprivation (Decancq, 2023; Scarchilli, 2024).

One particularly notable estimate is the positive effect of energy prices on the likelihood of mild cumulative deprivation, suggesting that energy costs may be a relevant driver of deprivation across various domains. However, the non-significant effect of energy prices on severe deprivation (as shown in the second column of the table) suggests that more extreme forms of deprivation are driven by factors beyond energy costs. Finally, we identify clear geographical patterns: individuals living in remote regional Australia are less likely to be deprived compared to those in major cities or inner and outer regional areas. Moreover, the macroeconomic variables included in the model tend to be non-significant, likely because the region and year fixed effects in the regressions account for between-region differences and annual fluctuations in aggregate indicators.

5.4 Dynamics by socio-economic groups

The estimates can be used to infer relevant steady state characteristics of cumulative deprivation. We focus on transition rates into and out of deprivation, expected spell duration and the steady state probability, defined as the probability of cumulative deprived at time *t* conditional on having been deprived at time *t-1*. The entry and exit probability are given by Pr $(CD_{\mathrm{it}} = 1|CD_{\mathrm{it-1}} = 0, ,\bar{X}_i)$ and Pr $(CD_{\mathrm{it}} = 0|CD_{\mathrm{it-1}} = 1, \bar{X}_i)$, respectively. It can be shown (Grotti and Cutuli, 2018, for details) that individual's *i* steady state probability (SSP) of cumulative deprivation and average duration of cumulative deprivation (ADP) are given, respectively, by:

$$\mathrm{SSP} = \Pr\,(CD_{\mathrm{it}} = 1|CD_{it-1} = 1,\ \bar{X}_i) \tag{10}$$

and

$$\mathrm{ADP} = \frac{\Pr\left(CD_{it} = 1\middle|CD_{it-1} = 0, \bar{X}_i\right)}{\Pr\left(CD_{it} = 1\middle|CD_{it-1} = 0,\ \bar{X}_i\right)+\Pr\left(CD_{it} = 0\middle|CD_{it-1} = 0, \bar{X}_i\right)} \tag{11}$$

In Table 4 we split the sample into gender, marital status, employment status, parenthood and disability categories to show how the dynamics of deprivation differ among individuals with different characteristics. Three main conclusions emerge. First, irrespective of the group considered, severe deprivation is a more transient and less durable phenomenon than mild deprivation. For instance, considering the whole sample, the probability of entry into deprivation decreases from 10.6 to 2.3 pp when switching from a mild to a severe definition of deprivation, while the exit probability raises from 78.1 to 94.8 pp. Similarly, the duration of a mild deprivation episode is longer than that of severe deprivation. Second, entry and exit rates are significantly influenced by specific characteristics. Ceteris paribus, married individuals are nearly 5 pp less likely to enter mild deprivation compared to non-married individuals and approximately 8 pp more likely to exit a deprivation spell. This gap is even wider when comparing parents to non-parents and slightly smaller when focusing on employment status. Thirdly, the role of individual characteristics in shaping deprivation dynamics depends on the intensity of deprivation considered. For instance, the dynamics of mild deprivation are remarkably driven by the presence of children at home, as the entry risk (13.9% versus 6.0%), the projected steady-state probability (16.1% versus 6.5%) and the expected mean duration of poverty spells (1.38 versus 1.16 waves) are substantially higher among individuals with children at home than among childless individuals. However, the corresponding figures do not differ that much, even in relative terms, when we focus on severe deprivation. The pattern is different when we consider employment status, which is relatively more relevant to account for severe forms of deprivation. For instance, the risk of entry into severe deprivation and its steady state probability it is practically halved when the individual is employed, while the exit probability gap between the employed and the non-employed is even larger for severe deprivation.

---Insert Table 4 here ----

5.5 Differences across domains

Since individuals are not deprived equally in all dimensions, the results presented so far may be seen as an average across heterogeneous deprivation profiles. That would be so if the dynamics of cumulative deprivation and the associated socio-economic gradient are domain-specific. To address this issue, we modified our models by re-estimating them and taking as dependent variable a binary indicator, D_i, that equals one if individual i is considered deprived based on criterion j (income, health, energy).

The estimates in Table 5 document the state dependence effects and the socio-economic gradient of various forms of deprivation. Firstly, the self-perpetuating nature of deprivation applies to all domains, specially for income. In the health equation, an initial health condition at the beginning of the sample period is relatively more relevant to account for current health status than lagged health, an observation that is consistent with the notion that individuals with ill health have a history of poor health. It is worth noting that the domain-specific inertia effects reported in Table 5 are relative larger than those found for cumulative deprivation. This should not come as a surprise, insofar as being persistently deprived in various dimensions simultaneously is less likely than remaining deprived in just one dimension. Table 6 presents the GMM estimates for the determinants of an individual's position within each domain. The results largely align with the CMLE model, confirming that persistence is strongest in income-related deprivation and weakest in health-related deprivation.

Some variables exert a differential effect on the various forms of deprivation. Table 5 shows a clear gender dimension when assessing the social gradient of deprivation. Although women are less likely than men to experience income deprivation, they are more likely to face poorer health outcomes and are similarly affected by energy deprivation. Similarly, education is a key determinant of income and energy deprivation but does not have a significant effect on health deprivation. Moreover, age exhibits an inverted U-shaped relationship with most forms of deprivation. However, severe income deprivation decreases steadily with age, an observation that suggests that the young are particularly exposed to income poverty. A candidate explanation is that older people can benefit from better networks of support, due to pensions, accumulated assets and social assistance programs. Finally, the estimates underscore the importance of employment when accounting for the relative position of the individual in all three distributions, particularly in the case of severe deprivation. A similar pattern is found for parenthood, which is a major determinant of mild and severe forms of domains-specific deprivation.

The CMLE results are also suggestive of regional differences, with individuals living in inner regional and outer regional Australia being more likely to be deprived that individuals living either in a major city or very remote locations. Moreover, there are macroeconomic effects in all three dimensions. The unemployment rate is negatively related to mild energy deprivation and income deprivation, while GDP growth significantly reduces the risk of health and energy deprivation. Individuals living in richer regions are less likely to be mildly income deprived, but are significantly more likely to be severely energy deprived. This is consistent with the larger housing affordability and cost of living pressures in capital cities than in regional areas. Moreover, among the eight Australian capital cities, Sydney, Melbourne, and Brisbane rank at least in the top four by number of affordability measures, including the proportion of household income required to afford a median mortgage and the dwelling price to income ratio (CoreLogic Australia, 2018).

Finally, the estimates in Table 5 suggest that energy prices are a key determinant of mild energy deprivation. The coefficient is significant and implies that a one-standard deviation increase in the energy price is associated with a 1.8 pp decrease in the probability of mild energy deprivation. This result is in line with earlier findings for Australia based on HILDA data, which show a neatly significant association between energy poverty and energy prices (Renner et al., 2019). In contrast, the last column of Table 5 indicates that energy prices cannot account for severe forms of deprivation. This observation suggests that long-term economic conditions (embedded in lagged deprivation) and the individual socio-economic profile (employment, parenthood and marital status, mainly) are more relevant than short-term fluctuations in energy prices when accounting for severe forms of deprivation among the Australian population. As an alternative explanation for our findings, it may be hypothesised that for vulnerable individuals energy costs may better represented by the price of cheap and less efficient energy sources, such as firewood and LPG, rather than by mains gas and electricity prices. Nevertheless, the proportion of households using fuelwood or LPG for space heating and cooking in the bottom quintile of the Australian income distribution is below 15%, and only in Tasmania is the share relatively large (30%) (Saddler, 2018). Although there is consensus that energy poverty rates are particularly sensitive to electricity prices, in computations not reported here we extended the specification to separately include the price of electricity and the price of "gas and other household fuels" (which includes firewood and LPG) as provided by the ABS (2017).[6] The estimates in failed to be statistically significant.

6. CONCLUSIONS

Identifying populations at risk of deprivation is crucial for developing effective policy interventions. While substantial research has been conducted on this issue, most studies tend to focus on domain-specific deprivation, such as income or material conditions. However, deprivation often spans multiple domains, having a cumulative nature.

In this paper, we analyzed the incidence, dynamics, and socio-economic gradient of cumulative deprivation in Australia. Our findings provide strong evidence of state dependence, indicating that individuals experiencing multiple simultaneous disadvantages—such as in income, health, and energy—face significant challenges in breaking free from deprivation. The results remain

[6] Since the ABS series do not allow for comparisons between states, we conducted separate regressions by Australian states.

robust across various sensitivity checks, including alternative definitions of deprivation (mild vs. severe, continuous vs. dichotomized measures) and different estimation approaches (CMLE vs. GMM). This suggests that past experiences of deprivation significantly heighten the risk of future deprivation, even after accounting for other factors. The persistence of cumulative deprivation underscores the need for policies that address both immediate hardships and long-term structural barriers to well-being. Additionally, our analysis highlights the protective role of employment, which lowers the risk of deprivation, while factors such as disability and parenthood increase vulnerability.

From a policy perspective, the pronounced persistence of deprivation suggests that interventions focused solely on alleviating current deprivation must be complemented by strategies addressing its root causes. Structural improvements—such as removing systemic barriers to employment, monitoring family dynamics, supporting parenthood, and enhancing energy infrastructure—may be essential in breaking the cycle of energy poverty in these populations. Programs that integrate income support with measures to strengthen health and energy security are likely to be more effective in reducing deprivation. Additionally, targeted policies are crucial for vulnerable groups, such as individuals with disabilities or single-parent families, who face heightened risks of persistent deprivation.

This study has several limitations that warrant further investigation. The findings emphasize the importance of understanding the origins of deprivation inertia, suggesting the need for future research to investigate the structural, institutional, and economic factors perpetuating this persistence. Although these factors were not explicitly analyzed, they likely play a critical role in shaping outcomes. Another promising avenue is conducting separate analyses by distinct population segments. While most research on deprivation focuses on socio-demographic determinants at the aggregate level, the evidence on how these factors influence specific population clusters is practically non-existent. Furthermore, the study abstracts from the financial strategies and economic behaviors households may employ to mitigate the impact of adverse life events, despite evidence that variables such as income and employment significantly influence how individuals navigate material deprivation challenges (Burlinson et al., 2024). Future research could bridge these gaps by incorporating structural and idiosyncratic factors, offering a more nuanced understanding of the mechanisms driving cumulative deprivation.

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Data Availability

We have used data from the HILDA Survey, which are not publicly available. The HILDA (Household, Income and Labour Dynamics in Australia) dataset is a longitudinal study that tracks Australian households annually. It collects data on income, employment, health, education, and family relationships. Access is granted through the Australian Data Archive (ADA) at the Australian National University (ANU). Researchers must register on the ADA Dataverse (https://dataverse.ada.edu.au/), locate the HILDA dataset, and submit a Data Access Request. Once access is granted, the dataset can be downloaded from the ADA portal or received via a secured USB device. It is available in Stata, SAS, and SPSS formats. For further details, researchers can visit the HILDA Survey official page at https://melbourneinstitute.unimelb.edu.au/hilda or contact the HILDA team at hilda-inquiries@unimelb.edu.au.

ABS energy prices are freely available at the Australian Bureau of Statistics (ABS) website: https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/consumer-price-index-australia/mar-quarter-2024#data-downloads

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Tables

Table 1. Ranking variables for each dimension

Dimension	**Ranking variables**
Income	Net disposable income by household equivalent unit
Health	Derived from the SF-36 survey. It is the average across eight dimensions: role physical, bodily pain, physical functioning, general health, social functioning, role emotional, vitality, and mental health.
Energy	Multidimensional Energy Poverty Index (MEPI). When two individuals have identical MEPI; we rank them according to the percentage of income spent on energy.

Table 2 - The prevalence and duration of deprivation

	Never	1-3waves	4-6 waves	7-9 waves	10-12 waves	>12 waves	Av. duration	Av. entry rate	Av. exit rate
Mild deprivation (maximal position < 50%)									
Cumulative	**53.6**	**30.6**	**8.6**	**4.2**	**2.0**	**1.0**	**4.2**	**10.4**	**40.5**
Deprived in income	24.4	35.6	15.8	10.7	7.2	6.3	6.9	17.2	17.3
Deprived in health	21.3	39.8	15.7	9.8	6.5	6.9	6.7	22.6	22.4
Deprived in energy	19.7	38.4	18.2	11.8	7.3	4.6	6.5	30.5	29.7
Severe deprivation (maximal position < 25%)									
Cumulative	**82.2**	**13.7**	**2.6**	**1.0**	**0.3**	**0.2**	**3.1**	**3.3**	**50.8**
Deprived in income	49.2	31.0	9.8	5.3	2.9	1.8	4.8	9.5	28.0
Deprived in health	48.0	33.2	9.1	4.8	2.6	2.3	4.7	11.4	33.0
Deprived in energy	40.9	39.6	10.9	5.5	2.2	0.9	4.1	14.6	43.9

Table 3 – The dynamics and socio-economic gradient of deprivation

	CMLE		GMM
	Mild deprivation	Severe deprivation	Maximal position
CD_{t-1}	0.093 ***	0.024 ***	0.123 ***
	(0.003)	(0.002)	(0.012)
CD_0	0.115 ***	0.020 ***	
	(0.003)	(0.002)	
Female	0.004	0.001	
	(0.002)	(0.001)	
Years of schooling	-0.124 ***	-0.046 ***	0.077 **
	(0.024)	(0.011)	(0.038)
Age	0.360 ***	0.270 ***	-0.005
	(0.010)	(0.005)	(0.004)
Age^2 (x100)	-0.005 ***	-0.004 ***	0.005
	(0.001)	(0.000)	(0.004)
Married (*base category single*)	-0.052 ***	-0.013 ***	0.028 ***
	(0.001)	(0.001)	(0.009)
Divorced	-0.007	0.003	0.014
	(0.005)	(0.002)	(0.012)
Widowed	-0.003	0.006	0.007
	(0.015)	(0.006)	(0.032)
Have children (yes/no)	0.077 ***	0.008 ***	-0.056 ***
	(0.004)	(0.002)	(0.008)
Disability in family (yes/no)	0.057 ***	0.021 ***	0.018 ***
	(0.003)	(0.001)	(0.003)
Employed (*base category inactive*)	-0.030 ***	-0.016 ***	0.006
	(0.003)	(0.002)	(0.005)
Unemployed	0.005	0.000	0.001
	(0.005)	(0.002)	(0.007)
Remoteness (*base major city*)			
Inner Regional Australia	0.016 ***	0.003	0.063
	(0.003)	(0.001)	(0.224)
Outer Regional Australia	0.012 ***	0.001	0.406
	(0.004)	(0.002)	(0.365)
Remote Australia	-0.015	-0.008 **	0.144
	(0.010)	(0.004)	(0.764)
Very Remote Australia	-0.034 **	-0.010	1.255
	(0.018)	(0.007)	(1.438)
Energy price (x10)	0.005 ***	0.001	0.001
	(0.001)	(0.001)	(0.002)
Participation rate	0.001	-0.001	0.004
	(0.001)	(0.001)	(0.004)
Share part-time workers	0.001	0.000	0.001
	(0.001)	(0.001)	(0.004)
Unemployment rate	0.002	0.000	-0.001
	(0.001)	(0.001)	(0.005)
GDP per capita (x10,000)	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)
GDP yearly growth rate	0.000	0.000	-0.001
	(0.001)	(0.001)	(0.002)
Australian regions fixed effects	yes	yes	yes
Time fixed effects	yes	yes	yes
Log likelihood	-34734.9	-9153.5	
No autocorrelation of order 1 (Prob > |z|)			0.000
No autocorrelation of order 2 (Prob > |z|)			0.558
Valid overidentifying restrictions (Prob > chi2)			0.251
No. of observations	108,293	108,293	108,293

Notes: i) *** denotes significant at the 1% level, ** denotes significant at the 5% level; * denotes significant at the 10% level; ii) standard errors shown in parentheses. Source: HILDA 2005–2021 waves.

Table 4 –Deprivation dynamics, by groups

	Entry probability		Exit probability		Steady state prob.		Average duration	
	Mild depr.	Severe depr.	Mild depr.	Severe depr.	Mild depr.	Severe depr.	Mild depr.	Severe depr.
Whole sample	0.106	0.023	0.781	0.948	0.120	0.023	1.280	1.055
Men	0.103	0.023	0.787	0.947	0.115	0.023	1.271	1.055
Women	0.109	0.023	0.777	0.948	0.123	0.023	1.280	1.055
Married	0.091	0.019	0.804	0.953	0.102	0.020	1.243	1.048
Not married	0.140	0.026	0.723	0.939	0.163	0.027	1.384	1.065
Employed	0.097	0.015	0.792	0.961	0.109	0.015	1.263	1.041
Not employed	0.127	0.029	0.742	0.927	0.146	0.031	1.347	1.078
With children	0.139	0.024	0.726	0.946	0.161	0.024	1.378	1.058
Without children	0.060	0.020	0.862	0.953	0.065	0.021	1.161	1.050
Disability at home	0.129	0.027	0.740	0.933	0.148	0.029	1.351	1.071
No disability at home	0.099	0.018	0.790	0.955	0.111	0.018	1.265	1.047

Notes: i) The results are controlling for: lagged deprivation, gender, schooling, marital status, employment, age, children at home, urban vs. rural area, and regional level macroeconomic variables, including labour market participation rate, share of part-time workers, per capita GDP, GDP growth unemployment, energy prices and wave and region fixed-effects. Source: HILDA 2005–2021 waves.

Table 5 – The dynamics and socio-economic gradient of deprivation, by domains – CMLE results

	Income		Health		Energy	
	Mild deprivation	Severe deprivation	Mild deprivation	Severe deprivation	Mild deprivation	Severe deprivation
D_{t-1}	0.262 ***	0.144 ***	0.137 ***	0.088 ***	0.174 ***	0.126 ***
	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)	(0.003)
D_0	0.165 ***	0.096 ***	0.320 ***	0.186 ***	0.150 ***	0.154 ***
	(0.004)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
Female	-0.017 ***	-0.014 ***	0.032 ***	0.025 ***	0.003	0.000
	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)
Years of schooling	-0.358 ***	-0.177 ***	0.040	-0.006	-0.274 ***	-0.151 ***
	(0.032)	(0.022)	(0.037)	(0.026)	(0.040)	(0.031)
Age (×100)	0.463 ***	-0.180 ***	0.340 ***	0.240 ***	1.435 ***	0.355 ***
	(0.130)	(0.933)	(0.164)	(0.109)	(0.165)	(0.124)
Age^2(×100)	-0.012 ***	0.000	-0.002	0.001	-0.002 ***	-0.006 ***
	(0.001)	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)
Married (*base category single*)	-0.113 ***	-0.064 ***	-0.030 ***	-0.015 ***	-0.090 ***	-0.059 ***
	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)
Divorced	-0.014 *	-0.002	0.010	0.010 *	0.006	0.020 ***
	(0.007)	(0.005)	(0.006)	(0.006)	(0.009)	(0.006)
Widowed	-0.028	0.012	0.042	0.026	0.004	0.007
	(0.023)	(0.014)	(0.031)	(0.018)	(0.029)	(0.018)
Have children (yes/no)	0.177 ***	0.066 ***	0.015 ***	0.000	0.143 ***	0.078 ***
	(0.005)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)
Disability in family (yes/no)	0.021 ***	0.014 ***	0.186 ***	0.129 ***	0.043 ***	0.038 ***
	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.004)
Employed (*base category inactive*	-0.072 ***	-0.057 ***	-0.029 ***	-0.048 ***	-0.037 ***	-0.030 ***
	(0.005)	(0.003)	(0.006)	(0.004)	(0.007)	(0.005)
Unemployed	-0.027 ***	0.002	-0.029 ***	-0.026 ***	0.009 ***	0.031 ***
	(0.009)	(0.005)	(0.006)	(0.006)	(0.011)	(0.007)
Remoteness (*base major city*)						
Inner Regional Australia	0.040 ***	0.024 **	-0.007	0.000	0.053 ***	0.029 ***
	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.004)
Outer Regional Australia	0.039 ***	0.030 **	-0.015 *	-0.007	0.059 ***	0.034 ***
	(0.006)	(0.004)	(0.008)	(0.005)	(0.008)	(0.005)
Remote Australia	-0.002	0.020 **	-0.024	-0.007	0.019 ***	0.035 ***
	(0.015)	(0.011)	(0.019)	(0.013)	(0.019)	(0.014)
Very Remote Australia	-0.051 *	0.013	-0.044	-0.021	-0.118 ***	-0.096 ***
	(0.031)	(0.024)	(0.039)	(0.027)	(0.039)	(0.032)
Energy price (×10)	-0.002	-0.002	0.006 *	0.006 ***	0.018 ***	0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Participation rate	0.002 *	-0.001	0.001	-0.003	0.009 ***	-0.003
	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Share part-time workers	0.001	-0.002	-0.005 *	-0.002	0.000	-0.008 ***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)
Unemployment rate	0.011 *	0.005 *	0.000	0.001	0.013 ***	0.003
	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)
GDP per capita (x10,000)	-0.011 **	-0.005	0.005	-0.005	0.003	0.016 ***
	(0.006)	(0.004)	(0.007)	(0.004)	(0.007)	(0.005)
GDP yearly growth rate	-0.001	0.000	-0.002 **	0.001	-0.004 **	-0.002 **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Australian regions fixed effects	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes	yes
Log likelihood	-43214.37	-31816.3	-52436.37	-38105.28	-61801.52	-45292.12
No. of observations	108,293	108,293	108,293	108,293	108,293	108,293

Notes: i) *** denotes significant at the 1% level, ** denotes significant at the 5% level; * denotes significant at the 10% level; ii) standard errors shown in parentheses. Source: HILDA 2005–2021 waves.

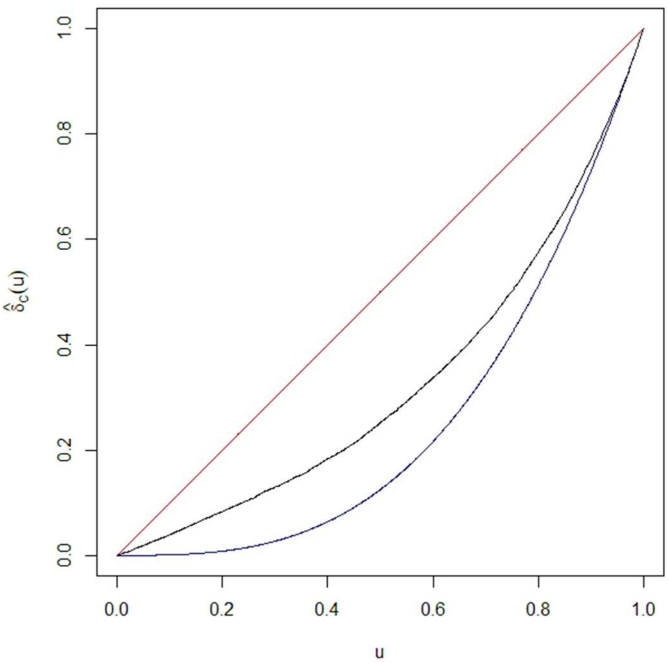
Table 6 – The dynamics and socio-economic gradient of deprivation, by domains – GMM results

	Income	Health	Energy
D_{t-1}	0.282 ***	0.095 ***	0.118 ***
	(0175)	(0.121)	(0.018)
Years of schooling	0.142 **	-0.005	0.194 *
	(0.067)	(0.058)	(0.119)
Age (×100)	0.005	-0.011	-0.008
	(0.006)	(0.007)	(0.013)
Age^2(×100)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Married (*base category single*)	0.042 ***	0.012	0.077 ***
	(0.013)	(0.013)	(0.027)
Divorced	0.004	-0.003	0.078 ***
	(0.020)	(0.016)	(0.037)
Widowed	-0.017	-0.057	0.129 *
	(0.037)	(0.049)	(0.071)
Have children (yes/no)	-0.126 ***	0.017	-0.094 ***
	(0.010)	(0.006)	(0.025)
Disability in family (yes/no)	0.000	0.018 ***	-0.005
	(0.004)	(0.008)	(0.008)
Employed (*base category inactive*)	-0.001	0.004 ***	0.018
	(0.007)	(0.011)	(0.013)
Unemployed	-0.010	-0.049 **	-0.003
	(0.010)	(0.004)	(0.019)
Remoteness			
(*base major city*)			
Inner Regional Australia	0.045	0.193	-0.345
	(0.337)	(0.351)	(0.685)
Outer Regional Australia	-1.048	0.678	-0.723
	(0.663)	(0.580)	(1.410)
Remote Australia	0.535	1.445	-1.831
	(0.930)	(1.083)	(2.338)
Very Remote Australia	2.022	3.897	-1.935
	(1.863)	(2.372)	(3.545)
Energy price (×10)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)
Participation rate	0.273	-0.002	-5.987
	(0.905)	(0.006)	(2.404)
Share part-time workers	0.472	0.009	0.412
	(0.006)	(0.006)	(0.011)
Unemployment rate	-0.001	-0.008	0.020
	(0.006)	(0.007)	(0.015)
GDP per capita (x10,000)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
GDP yearly growth rate	0.002	-0.004	0.006
	(0.004)	(0.004)	(0.008)
No autocorrelation of order 1	0.0000	0.0000	0.0000
No autocorrelation of order 2	0.1126	0.0528	0.0683
Valid overidentifying	0.0245	0.6259	0.9268
No. of observations	108,293	108,293	108,293

Notes: i) *** denotes significant at the 1% level, ** denotes significant at the 5% level; * denotes significant at the 10% level; ii) standard errors shown in parentheses. Source: HILDA 2005–2021 waves

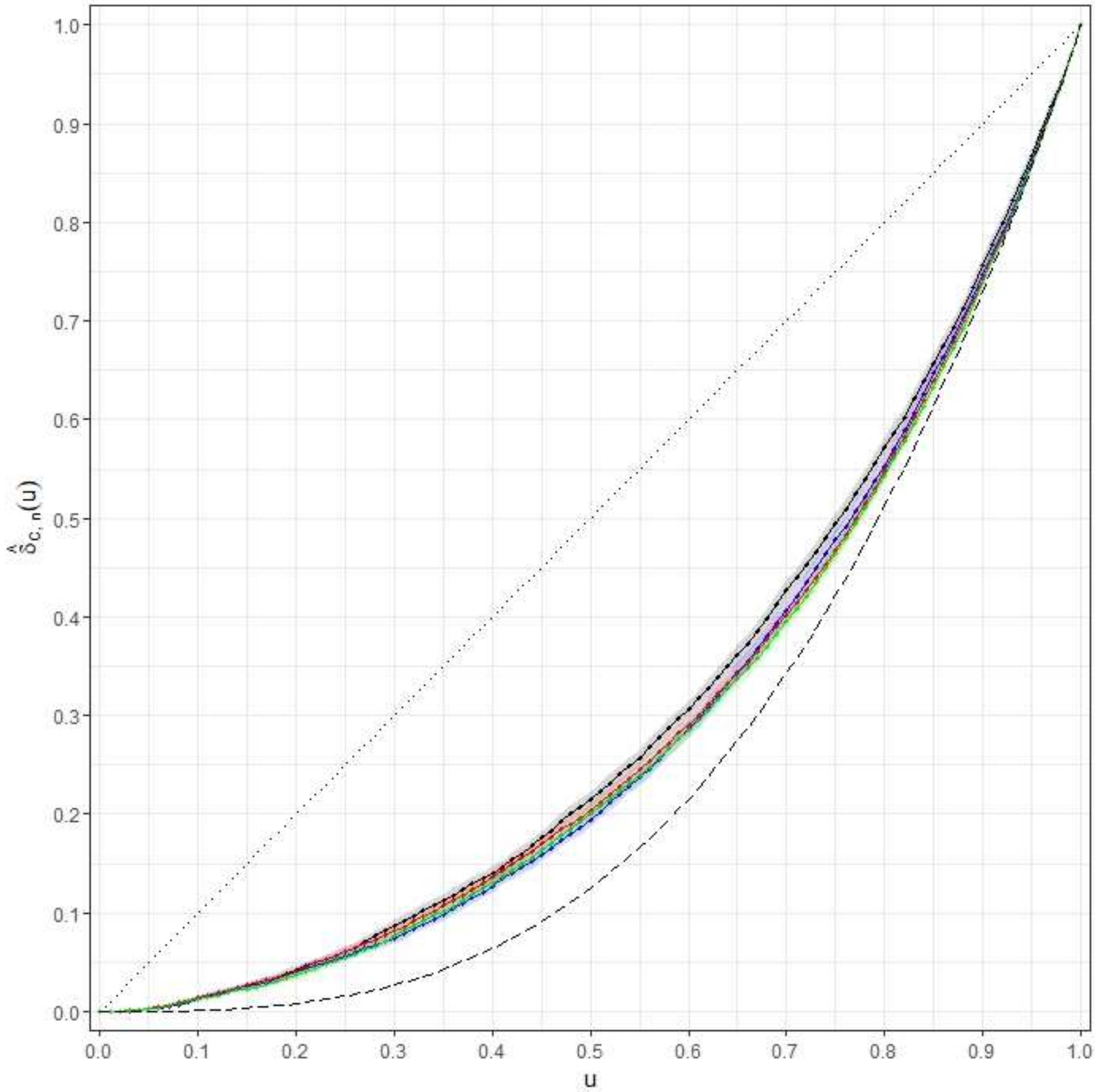
Figures

Fig. 1. Diagonal section of the copula



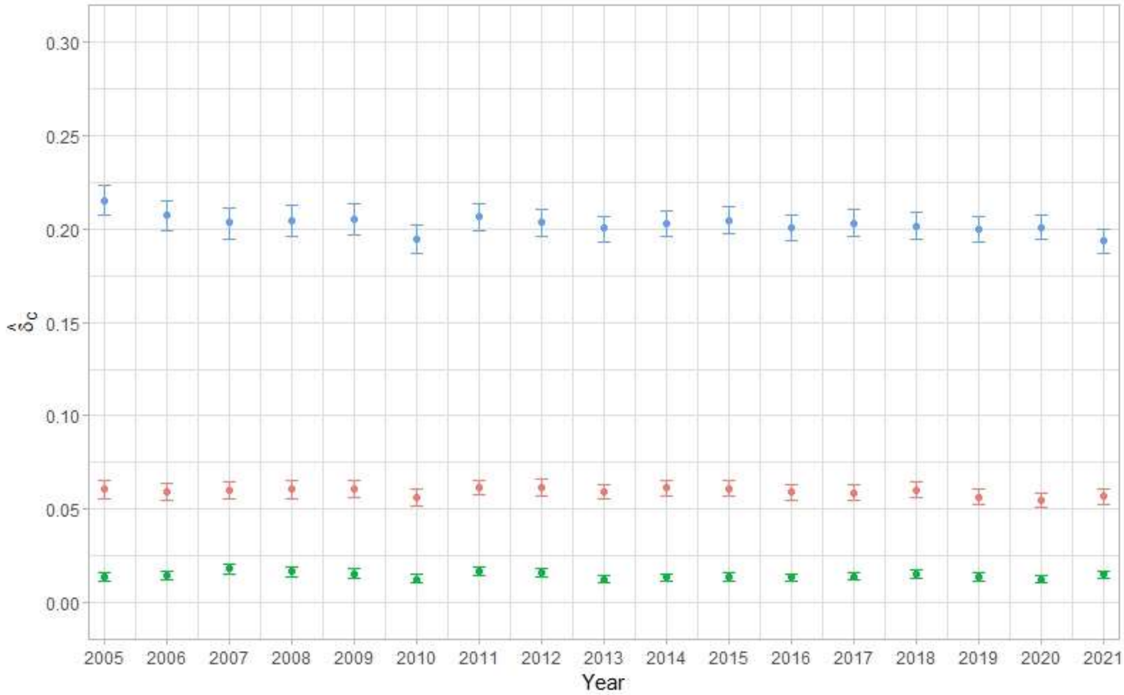
Notes: Diagonal section of the copula of a trivariate distribution (in black). The diagonal section of the comonotonic copula is displayed in red and that of the independent copula in blue.

Fig. 2. Estimated diagonal section of the copula



Notes: Estimated diagonal section of the copula in 2005 (black), 2010 (blue), 2015 (red) and 2020 (green) with 95% bootstrap confidence intervals.

Fig. 3. Evolution of cumulative deprivation in Australia.



Notes: Proportion of individuals suffering from cumulative deprivation in the three dimensions, with the first quartile ($\hat{\delta}_{C,n}(0.25)$ in red), first decile ($\hat{\delta}_{C,n}(0.1)$ in green) and median ($\hat{\delta}_{C,n}(0.5)$ in blue), as thresholds. With 95% bootstrap confidence intervals.