Title	The Dynamics of Multidimensional Poverty in a Cohort of Irish Children
Authors(s)	Madden, David (David Patrick)
Publication date	2021-08
Series	UCD Centre for Economic Research Working Paper Series; WP2021/17
Publisher	University College Dublin. School of Economics
Item record/more information	http://hdl.handle.net/10197/12558

UCD CENTRE FOR ECONOMIC RESEARCH

WORKING PAPER SERIES

2021

The Dynamics of Multidimensional Poverty in a Cohort of Irish Children

David Madden, University College Dublin

WP21/17

August 2021

UCD SCHOOL OF ECONOMICS
UNIVERSITY COLLEGE DUBLIN
BELFIELD DUBLIN 4

The Dynamics of Multidimensional Poverty in a Cohort of Irish Children

David Madden

(University College Dublin)

August 2021

Abstract: This paper examines multidimensional poverty for three waves of a cohort of Irish children ranging from ages 9 to 17. Poverty is measured over the dimensions of health, education and family resources and both unidimensional and multidimensional poverty is examined. Both show a clear gradient with respect to maternal education. The dynamics of both unidimensional and multidimensional poverty is also analysed. The greatest degree of mobility is observed with respect to family resources. Mobility also is higher for children whose mothers have lower levels of education, with net movements into rather than out of poverty.

Keywords: Poverty, multidimensional, mobility, dynamics

JEL Codes: I31, I32, J13, I14.

Corresponding Author: David Madden,

School of Economics,

University College Dublin,

Belfield,

Dublin 4,

Ireland.

Phone: 353-1-7168396

E-Mail: david.madden@ucd.ie

Funding: This project was not funded by any specific grant.

Conflict of Interest: The author declares that he has no conflict of interest.

Acknowledgements: I gratefully acknowledge helpful comments from colleagues at University College Dublin, particularly Orla Doyle and Chris Whelan. I remain responsible for any errors.

The Dynamics of Multidimensional Poverty in a Cohort of Irish Children

1. Introduction

This paper examines multidimensional deprivation for a cohort of Irish children using the landmark *Growing Up in Ireland* (GUI) survey which follows two cohorts of children from ages ranging from nine months to seventeen years: the Infant cohort born in the period December 2007-June 2008 and the Child Cohort born in the period November 1997-October 1998 (see Thornton et al, 2013 and Williams et al, 2009). Our analysis in this paper focuses on the Child cohort, for which there are three waves of data, with information on the cohort aged 9, 13 and 17 years respectively.

The motivation for studying child poverty is clear. Child poverty can have long term consequences lasting into adolescence and adulthood in areas such as health, education and the labour market (Brooks-Gunn and Duncan, 1997, Dickerson and Popli, 2018). Much analysis of poverty and deprivation focusses upon one dimension, usually income or expenditure or some other measure of resources and in the case of children the analysis typically looks at children in poor families (e.g. Thévenon et al, 2018). [1]

However there are a number of drawbacks with this approach. First, it has long been acknowledged that poverty can occur in dimensions other than monetary/material ones, for example in areas such as health and education. Hence in recent years there have been a number of attempts to examine poverty across a number of dimensions (for recent surveys see Alkire et al, 2015 and the special edition of the Journal of Economic Inequality in 2011). In some cases analysts have examined the marginal distributions of individual dimensions and then looked at correlations across these dimensions (Madden, 2015). Another approach has been to construct aggregate indices which themselves incorporate measures of correlation across dimensions (Bourguignon and Chakravarty, 1999). An approach which has gained considerable popularity is the dual cut-off method of Alkire and Foster (2011). This approach breaks down the identification of the poor into two parts: first of all those who are deprived in

[1] Note, in this paper we will use the terms "being poor in a dimension" and "being deprived in a dimension" interchangeably.

each individual dimension are identified. Then there is a second round of identification whereby those who have a (weighted) number of deprivations above a certain threshold are deemed to be multidimensionally poor. Once the poor have been identified there are then a number of measures which aggregate this information into an overall index.

The second drawback with what we label the "traditional" approach is that by focussing on children in poor households the issue of within household distribution is not addressed (this is not meant as a criticism of this approach as data on within household distribution is typically very difficult to acquire). [2] However, there is evidence particularly from research in developing countries that within households certain members (typically women and children) can experience systematic discrimination (Jayachandran 2015 and Jayachandran and Pande, 2017). It might also be the case that when a family transitions into poverty adults choose to protect children so that while overall household resources are less, they are reallocated towards children. Thus, data permitting, analysis should try to focus on outcomes specific to the child herself.

Finally, and again reflecting the availability of data, much analysis of child poverty has provided a static picture of poverty at a given point in time. This is clearly valuable information to have but it is also important to supplement this information with knowledge regarding the dynamics of poverty. Is poverty a transient or a persistent phenomenon for children? Is there much "churning" in the sense of children moving in and out of poverty? And, in the case of multidimensional poverty is there much transitioning between different dimensions of poverty or do transitions mainly happen within the same dimensions?

The contribution of this paper is to address, to some degree at least, these drawbacks of the traditional approach. Using the breadth of information available in GUI we examine poverty across a number of dimensions including outcomes which directly pertain to the children themselves. The longitudinal nature of the data also permits analysis of mobility and dynamics. We choose to focus upon three dimensions of child welfare and to examine deprivation in these measures. The three dimensions are education, health and family income/resources.[3] The first

[2] Whelan and Maitre (2012) explore the distinction between children who directly experience deprivation and children who live in households where basic deprivation is present.

[3] These dimensions are also the foundation of the Global Multidimensional Poverty Index (Alkire et al. 2015).

two of these are direct measures of outcomes for the children.[4] In the case of education we employ a measure based upon educational tests which the children undergo. The health measure is based upon obesity as defined by body mass index with the threshold adjusted for age and gender. The final measure which is based upon family resources is not a direct outcome measure of the children. Instead it is the response to a question addressed to the principal carer (in almost all cases the biological mother of the child) concerning how difficult it is for the family to make ends meet. This is not a direct outcome measure for the child since, as outlined above, within household allocation of resources could in principle work in favour, or against, the child. Alas, this is an issue which bedevils the vast majority of measures of household income/resources which typically lack the detail which enable the analysis of within household distribution. Nevertheless, we feel it is still vital that some measure of resources be included and that without it any picture of child poverty would be incomplete.[5]

A further contribution of this paper is that apart from just analysing transitions into and out of multidimensional poverty, we also examine transitions across specific deprivations e.g. is there more churning in education poverty compared to health poverty? Are there many transitions across different dimensions of poverty? We are able to analyse these issues in some detail.

Finally, unlike much of the existing research in this area applying to Ireland, this paper covers not just the entry into the Great Recession (which started around 2008-2009) but also Ireland's subsequent recovery, which can be dated from around 2013-14. The timing of the three waves of GUI serendipitously coincide with a period just before the Great Recession, a period during the Great Recession and a final period when recovery from the Recession was under way.

As we outline in more detail in our data section, the breadth of information in GUI implies that other possible dimensions of poverty are available for inclusion. While it is possible to aggregate information across dimensions into overall measures of multidimensional poverty (and we carry out such analysis below), we are also anxious to look at correlations between dimensions and also movements into and across different dimensions. We wish to exploit the

[4] This is consistent with the UNICEF Multidimensional Overlapping Deprivation Analysis (MODA) framework as outlined in Hjelm et al (2016), whereby the child is the unit of analysis, where possible.

[5] Recent research has investigated the allocation of resources within households and the fraction going to children (e.g. Dunbar et al, 2013). However this analysis requires detailed data on household spending patterns which is not available in GUI.

panel nature of the data and given that we have three dimensions and three waves of data the view taken was that the inclusion of extra dimensions would run the risk of falling foul of a version of the curse of dimensionality, whereby there is so much information that it becomes difficult to distil it into a coherent picture.[6]

In the next section we review some of the evidence on multidimensional deprivation, paying particular attention to work carried out for Ireland. We also briefly review work on the dynamics of poverty as opposed to snapshots at a moment in time. We then discuss our data and our choice of deprivation indicators in some detail. In section 4 we calculate uni-dimensional and multidimensional measures of poverty for three waves of the GUI dataset. In section 5 we then examine movements into and out of multidimensional poverty, while section 6 looks at dynamics for specific dimensions of poverty. Section 7 provides discussion and concluding comments.

2. A Review of Evidence Concerning Multidimensional Poverty Amongst Children

As outlined in the introduction, two of the principal innovations of this paper are to examine child poverty across multiple dimensions and also to specifically analyse the dynamics of transitions into and out of these dimensions. We now briefly review evidence on both these issues for Ireland and elsewhere.

One paper close to ours is Williams et al (2014) who apply the Alkire-Foster methodology to examine multidimensional deprivation using wave 1 of the child cohort of GUI. They use ten indicators of deprivation which cover seven domains: material well-bring, housing and environment, education, health, risk behaviours, quality of school life and emotional well-being. They choose three as their second threshold (i.e. someone has to be deprived in three or more of the ten dimensions to be regarded as multidimensionally poor) and calculate a poverty rate of 29.4%. They also stratify their analysis along a number of dimensions including social class and find that for professional and managerial classes deprivations tend to be in the areas of behaviour, overweight and bullying (being a victim of) whereas for lower skilled and unskilled classes deprivations are more concentrated in education and material resources. They

[6] For example, with *n* dimensions of poverty the transition matrix between successive waves is of dimension $2^n x 2^n$. n=3 is probably about the limit of manageability.

also observe a gradient for the total number of deprivations by social class and maternal education.

Chzhen et al (2018) examine child multidimensional poverty across a range of countries using EU-SILC data. They look at seven different dimensions of poverty: nutrition, clothing, educational resources, leisure activities, social activities, information access and housing (these are taken from the UNICEF Convention on Rights for the Child). They apply the Alkire-Foster methodology using two or more deprivations as their second cut-off. Ireland is at the lower end of European countries for nearly all individual dimensions and also for multidimensional poverty. The Irish raw headcount rate is just over 20 per cent, compared to the country with the lowest rate, Norway, with a rate of around 5 per cent. Despite the onset of the Great Recession, the Irish rate also shows relatively little change between 2009 and 2014.

An earlier paper in the spirit of our work is that of Nolan, Maitre and Watson (2001). They look not just at income poverty dynamics for children but also at dynamics for other indicators of material deprivation using data from the 1993 and 1994 waves of the Irish part of the European Community Household Panel Survey (ECHP). They identified a number of dimensions of deprivation (basic, secondary and housing) and examined households with both low incomes (below a typical poverty line of say a fixed fraction of average income) and enforced basic deprivation (i.e.the absence of items such as food, clothing, heating). The authors point out though, that similar to much other work in the area, they are lacking in measures of direct outcomes for children. Data is typically available at household level and little is known about within household sharing. A summary deprivation index is constructed and shows a correlation with income of around -0.43. The correlation of individual deprivations with income ranges from about -0.5 for housing to around -0.3 for basic and secondary items, correlations which are qualitatively similar to correlations across deprivations which we find in this paper. They find that about 10 per cent of children stay in high deprivation households (as indicated by the summary indication score) over the two waves of ECHP. However, they do not examine deprivation specific transitions. They also show reasonably high levels of mobility for households who had very low incomes, suggesting that identifying very poor households solely from single snaps of cross-sectional data can be misleading.

Nolan and Maitre (2017) examine how children fared during the Great Recession in Ireland. They point out that at the start of the recession many family/child related payments in Ireland were high compared to the rest of Europe which provided something of a cushion when those payments were cut. What changes were made to social supports over the crisis were also progressive so the system as a whole did a reasonable job of protecting the worst off during what was one of the most severe fiscal crises in Europe. Inevitably however, the number of children in poor households in Ireland increased, particularly when a fixed poverty line is used. Families with children also fared relatively worse than pensioner families, a finding also echoed below in the next set of papers we review.

The papers by Whelan et al (2015) and Watson et al (2017) examine the first two waves of GUI data specifically focussing upon the impact of the Great Recession which began just after the first wave of GUI was surveyed. They use a measure which they term economic vulnerability which encompasses a low level of income, household joblessness and economic stress. They note that families with children were badly hit by the Great Recession, particularly compared to the elderly. In terms of a child specific outcome, they choose to focus upon the emotional health and problem behaviours of children as measured by responses to the Strength and Difficulties Questionnaire (SDQ). A high value of the SDQ score, indicating the presence of emotional health problems, is associated with their vulnerability measure, in particular if the family experienced persistent vulnerability i.e. vulnerable in both waves 1 and 2 of GUI. Persistent economic vulnerability was the case for 10 per cent of families, while 15 per cent of families became vulnerable during the recession and 5 per cent escaped out of vulnerability. They also note that the profile of families entering vulnerability in the second wave of GUI was different from those whose experiencing permanent vulnerability in terms of characteristics such as lone parenthood and maternal education. Our results below will cast further light on dynamics into and out of our measure of income based poverty, bearing in mind that it is a narrower measure than employed in these two papers.

In a more recent paper Grotti et al (2017) examine poverty transitions in Ireland using Irish EU-SILC data, the successor to the ECHP. Their focus is not specifically on families with children but they do look at transitions for different demographic groups. Their data covered the period 2004-2015, thus considerably overlapping with the span of the data we use. Their stratification of the sample differs from ours but they still find socioeconomic gradients in persistent as well as transient poverty. They also find what they term a "…relatively high level of movement into and out of income poverty and deprivation". However, with the exception perhaps of the results for income and resources the findings of this paper are not directly comparable since our deprivations refer more to child outcomes rather than the presence or absence of household necessities.

Reinhard et al (2018) examine the effect of the Great Recession in Ireland on some specific child health outcomes, this time using the Infant Cohort of GUI. They analyse the effect of what could be termed various recession related outcomes or indicators (such as job loss, reduction in income or welfare benefits, reduction in working hours, falling behind on bills etc) on reported child health problems in general and also specifically on atopy and asthma. They find significant effects of the recession on these health outcomes and note a key role for welfare payments.

Briefly turning to international evidence, one of the papers closest to ours is that of Dickerson and Popli (2018), who examine multidimensional poverty in the UK, using the Millenium Cohort Study, a dataset quite similar to GUI, and who also examine poverty dynamics. They use the Alkire-Foster methodology to look at poverty over five dimensions: financial constraints, material deprivation, parental involvement, housing environment and neighbourhood. In line with most of the work in this area they find that multidimensional poverty overlaps to a significant degree, but far from perfectly, with traditional income poverty. They also find that similar demographic characteristics such as workless households and ethnicity are associated with both types of poverty and also that persistence across time for both types of poverty is comparable. One area however where their approach differs from ours is that they do not examine transitions between specific dimensions of poverty.

To summarise these diverse papers, we see that poverty measured in just one dimension (most usually family income or expenditure) does not capture fully the degree of poverty experienced. Other measures of deprivation show strong but not perfect correlation with income. Snapshot measures of poverty can be misleading with families moving both into and out of poverty. The papers also note the role of the Great Recession, especially in terms of transitions into poverty. Overall, the results from these papers support the idea that a measure of multidimensional child deprivation, which incorporates child-based outcomes and is available on a panel basis for the same children over a number of years would be a very useful addition to the analysis of child poverty. In the next section we provide more detail on our chosen measure of multidimensional poverty.

3. Measuring Multidimensional Poverty

As outlined in the introduction, historically research into poverty concentrated on monetary measures such as income or expenditure, despite the acknowledgement that poverty can occur in dimensions other than monetary ones, such as health, education, housing etc. Hence the attempts in recent years to set the measurement of multidimensional poverty on a more rigorous footing (for recent surveys see Alkire et al, 2015 and the special edition of the Journal of Economic Inequality in 2011). The approach which has probably gained most support is the dual cut-off method of Alkire and Foster (2011, henceforth AF). This breaks down the identification of the poor into two parts: first of all those who are deprived in each individual dimension are identified. Then there is a second round of identification whereby those who have a (weighted) number of deprivations above a certain threshold are deemed to be poor. As we will see below, once the poor have been identified there are then a number of measures which aggregate this information into an overall index. These measures take account of not just the number of people who are deemed multidimensionally poor but also the number of dimensions in which they are deprived.

More formally, suppose there are N individuals and there are $D \geq 2$ deprivation indicators (these would be in dimensions such as income, health, education, housing etc.). Y is the DxN matrix whose i,jth entry y_{ij} denotes the level of indicator j for person i. For each indicator, j, there is a deprivation cutoff, z_j, whereby if a person's level of that indicator is below this cutoff, they are deemed to be deprived in this dimension and hence we have a $1xD$ vector of cutoffs $z=(z_1 , z_2, \ldots, z_D)$.[7]

In some cases it might be desirable to assign a different weighting to deprivation in different dimensions (e.g. being deprived in health is seen as somehow "worse" than being deprived in income). Thus we also have a $1xD$ vector of weights $w=(w_1 , w_2 , ,,. w_D)$ with $0 < w_j < 1$ and

[7] In some instances it might be the case that a person is deprived if they are *above* a certain threshold e.g. the BMI cutoff of 30 for obesity. In this case we simply work with the negative of the dimension, so $-BMI_i < -30$ indicates that person i is deprived in this dimension.

$\sum_{j=1}^{D} w_j = 1$. Most applications of this approach however make the simplifying assumption of assigning the same weight to all dimensions, and we follow that practice here.

We can define a matrix g^0 which summarises deprivations across all dimensions such that $g_{ij}^0 = 1$ whenever $y_{ij} < z_j$ and $g_{ij}^0 = 0$ otherwise. The measure of deprivation in each dimension is then calculated to obtain a weighted deprivation score for each individual $c_i = \sum_{j=1}^{D} w_j g_{ij}^0, 0 < c_i < D$.

Given the deprivation score for each individual we then identify the multidimensionally poor via the indicator $MP_i^{(k)}$ such that $MP_i^{(k)} = I(c_i \geq k), 0 < k \leq D$, and k is the poverty cut-off. The poverty cut-off k is then applied to the matrix g^0 to obtain the censored deprivation matrix $g^0(k)$ whose *ij*th element is $g_{ij}^0(k) = g_{ij}^0 \times MP_i^{(k)}$. This then gives the censored deprivation score for each observation as $c_i^{(k)} = \sum_{j=1}^{D} w_j \, g_{ij}^0(k), 0 < c_i^{(k)} < D$, where $c_i^{(k)} = c_i$ when $c_i \geq k$ and zero otherwise.

Given individual deprivation scores we can calculate the population average deprivation score, $M_0 = \frac{1}{N}\sum_{i=1}^{N} c_i^{(k)}$. This measure can be usefully expressed as $M_0 = H \times A$ where $H = \frac{q}{N}$ where q is the number of people who are multidimensionally poor and $A = \frac{\sum_{i=1}^{N} c_i^{(k)}}{qD}$ is the intensity of multidimensional poverty amongst the poor. M_0 is referred to as the "adjusted headcount ratio" and it has the desirable property that it is sensitive to both the number of people who are multidimensionally poor and also to the number of dimensions in which they are poor. Note that it is not sensitive to the intensity of poverty *within* a given dimension e.g. how far below, say, the income poverty line an individual is.

The choice of k is clearly up to the discretion of the analyst but it is worth pointing out two limiting cases. If $k = 1$ then we have what is known as the *union* approach whereby being poor in just one dimension identifies you as multidimensionally poor. If $k = D$ then we have the *intersection* approach whereby you must be poor in all dimensions to qualify as multidimensionally poor.

One of the attractive properties of the AF dual cut-off approach is that the index can be decomposed in two very useful ways. First of all, for an index defined over, say, three dimensions it is possible to calculate the contribution of each dimension to multidimensional poverty. Thus if $h_j(k)$ is the censored headcount ratio for dimension j i.e. the fraction of the population both multidimensionally poor *and* deprived in that dimension, then $M_0 = \sum_{j=1}^{d} w_j h_j(k)$, where d is the total number of dimensions and w_j is the weight assigned to dimension j in multidimensional poverty.

Secondly, if we break down the overall population into mutually exclusive and exhaustive groups (say in our case by maternal education) then it is possible to calculate how much of overall multidimensional poverty is accounted for by each group. Thus, if we index each sub-group by h then the overall adjusted headcount ratio can be expressed as $M_0 = \sum_{h=1}^{m} \ell^h M_0^h$ where M_0^h is the adjusted headcount for group h, and we have m groups and $\ell^h = \frac{N^h}{N}$ is the fraction of population accounted for by group h.

We now turn to discuss our data and the particular dimensions of poverty we choose to analyse.

4. Data

Our data comes from the first three waves of the Growing Up in Ireland (GUI) 9 year old cohort. This tracks the development of a cohort of children born in Ireland in the period November 1997-October 1998 (see Williams et al, 2009). The sampling frame of the data was the national primary school system, with 910 randomly selected schools participating in the study. The field work for wave 1 was carried out between August 2007 and May 2008, that for wave 2 between August 2011 and March 2012 and that for wave 3 between April 2015 and August 2016.

As we explain in more detail below, we analyse multidimensional poverty over three dimensions: health, education and a measure of family resources. We work with a complete case balanced panel, consisting of only those children who were sampled in each of the three waves and dropping observations where the underlying health, educational or family resource data are missing and also where the primary caregiver changes between waves. Thus given an original sample in wave 1 of 8568 children, this leaves us with an ultimate sample of 5117 (2614 female and 2503 male). Naturally in making these adjustments the issue of attrition arises. Attrition in surveys such as GUI is rarely random and this is confirmed in Murphy et al (2018) who show that attrition tends to be higher for those with lower maternal education. Correspondingly the data are re-weighted so that the sampling weight in the balanced panel which we analyse is the product of the original sampling weight for wave 1 and the attrition weights which take account of non-random attrition in subsequent waves.[8] We now turn to discuss the measures we use in the dimensions of health, education and family resources.

In the area of health we were anxious to employ a measure which was clearly an outcome, as opposed to an input measure (e.g. usage of medical resources). Consequently we use obesity as measured by body mass index (BMI, which is defined as weight in kilos divided by height in metres squared).[9] Weight was measured to the nearest 0.5 kg using a medically approved flat mechanical scales and children were advised to wear light clothing. Height was measured to the nearest mm using a height measuring stick. We make an additional adjustment to the data which facilitates our analysis. As the obesity threshold for BMI differs by age and gender a simple comparison of BMI can be misleading. Consequently, we analyse *normalized* BMI figures, where BMI is divided by the appropriate obesity threshold which varies by age and gender (we take these thresholds from Cole at al, 2000). Thus a normalized BMI of 1.1 indicates that the child had a BMI which was 1.1 times the relevant threshold for their age and gender. This facilitates comparisons across age and gender where these thresholds differ. Naturally, as our threshold for this measure we use a normalized BMI figure of 1.0. Thus anyone with a normalized BMI greater than or equal to unity is deemed "health poor".

As our education measure we again use an outcome rather than an input, in this case a measure based upon child scores in cognitive tests. The first set of tests administered to the children were the curriculum based Drumcondra Reading and Maths Tests administered by teachers in the classroom in wave 1 when the children were for the most part aged 9 (very small numbers were aged 8 and 10). In wave 2 of the Child Cohort the tests administered were the Drumcondra Numerical and Verbal Ability tests and the children were aged 11. It should be noted that unlike the Drumcondra Reading and Maths tests, these are not curriculum based tests. In wave 3 of the cohort three tests were carried out: a Cognitive Naming Test, a Cognitive Maths Test and Cognitive Vocabulary Test (details in Williams et al (2019)). More details are available in appendix 2, and table 3 in that appendix also provides the rank correlations across the different subscales and components within each cohort. In most cases these correlations

[8] Appendix 1 gives detail of sample design and weighting.

[9] Lindberg et al (2020) show that childhood obesity can be associated with higher risk of all cause mortality in early adulthood.

are at least 0.3 and in some cases as high as 0.7, correlations which are comparable to those obtained by Feinstein (2003) in his influential study of the socioeconomic gradient of tests scores in the UK. The children were all of similar ages and hence for the most part at the same educational grade. However, there was some differentiation and so it was necessary to standardise the results. Hence the data we use are the logit scores which were obtained from the original raw data using the principles of Item Response Theory (see Lord, 1980).

Given the wide range of cognitive test scores, we follow Feinstein (2003) in using all the information available for each wave to construct a general measure via principal components analysis (PCA). PCA is the eigenvalue decomposition of the correlation matrix R of the different individual test score measures available in each wave. If we have, say, n measures, $x_1 \dots x_n$ then the first principal component, y_1 is given by

$$y_1 = a_{11}x_1 + a_{12}x_2 \dots + a_{1n}x_n$$

where a_{1i} are the weights which are chosen to maximise the variance of y_1 and must also satisfy the normalising constraint $\sum_{i=1}^{n} a_{1i}^2 = 1$.

Using the first principal component has the advantage of combining information from the different cognitive tests. As noted above, the rank correlations across the different measures seem to be sufficiently high to be confident that we are picking up a similar underlying process.

In appendix 2 we show the scree plots for the PCA. Using the rule of thumb that components where the eigen value exceeds unity should be selected we see that in nearly all cases it is only the first principal component which satisfies this condition. Table 4 in appendix 2 also shows the fraction of variance explained by the first principal component. Where we have only two measures entering into the PCA then the first component explains about 75-80% of variance. When there are more measures then the fraction of variance explained falls to 40-50%. In all instances the value of Kaiser-Meyer-Olkin test statistic for sampling adequacy for PCA meets the rule of thumb threshold of 0.5, though in some cases only barely. Then, in terms of identifying who is "education poor" we use a z score of the first principal component of -1.5 or lower.

The final dimension we include in our measure of multidimensional poverty is one of family resources. Probably the most obvious measure to use is a measure of equivalised after-tax disposable family income and such a measure is available in GUI. However, there is an issue with the use of such a measure. Child income poverty is typically defined as being in a family whose income is below a threshold such as 50% (or sometimes 60%) of median equivalised disposable income. Calculating such a poverty line for GUI is problematic as the sample from which median income is drawn will be a sample of those households where a child was born in the period September 1997-October 1998 and this sample will not be nationally representative. In addition, the use of a relative poverty line can be problematic when there is a discrete fall in income (as happened between wave 1 and wave 2). If the poverty line itself falls, then even though many if not most families have experienced a decline in living standards, poverty (as measured by a purely relative poverty line) may remain unchanged or even fall.

An additional problem with the GUI data in waves 2 and 3 is that the income data is rounded off to the nearest €1000, which creates measurement error when identifying people below a poverty threshold.

Given these issues with the income data, an alternative is to use a *subjective* measure of family resources. In each wave of GUI the principal carer (almost always the biological mother of the child) is asked the question: *Concerning your household's total monthly or weekly income, with which degree of ease or difficulty is the household able to make ends meet?* The available answers range from "very easily" to "with great difficulty". We use as our threshold the following responses: "with great difficulty" or "with difficulty".[10] We retain the term "income poor" however for the families that fall on or below this threshold.

In the next section we present our results, commencing with information on uni-dimensional poverty across our three dimensions.

5. Results

Unidimensional Poverty

We now present results, concentrating first of all on uni-dimensional poverty and then moving on to multidimensional poverty. For the present we also focus on what we could term a static view of the issue, merely looking at each cross-section and not examining dynamics which we

[10] Schenck-Fontaine and Panico (2019) review different measures of income poverty, material deprivation and family financial stress in terms of their impact upon child behavioural problems and conclude that other measures, apart from income poverty, can have independent effects on such behaviours.

postpone until later. We also stratify the results by maternal education in line with previous, similar, work using this dataset (Madden, 2020a, 2020b).[11]

Table 1 shows the incidence of uni-dimensional poverty across the three dimensions with the results stratified by maternal education. We employ four categories of education: (1) completion of lower secondary schooling (2) completion of secondary schooling (3) obtaining a post-secondary school diploma or cert and (4) completion of third level education. We choose to present these results by maternal education level in wave 1. While there is some change in maternal education levels between waves 1, 2 and 3, it is relatively minimal and by fixing on wave 1 maternal level we ensure that it is the same sample of observations in each category for each wave.

It perhaps is more instructive to look at the trends and socioeconomic gradients in unidimensional poverty rather than the actual levels, as the levels will be sensitive to precise cutoffs. Health poverty, as defined by obesity shows little change between wave 1 and wave 2 but then increases to nearly 7 per cent in wave 3. The gradient by maternal education is clear. Obesity levels where the mother has lower secondary education are four to five times higher than where the mother has third level education. Where the mother has completed secondary education or has a post-school diploma/cert levels are intermediate and differ very little from each other. There are some signs that the gradient may be getting slightly steeper over time and this is explored in more depth in Madden (2017).

In terms of education poverty, while the absolute level is higher than in the case of obesity, it shows little sign of changing over time. Again a gradient by maternal education is visible and this gradient shows a clear sign of becoming steeper over time. In wave 1 children whose mother had lower secondary education were about four to five times more likely to suffer from education poverty compared to children whose mothers had third level education. By wave 3 they were over nine times more likely to be education poor. This phenomenon is driven by an improvement in the situation of children whose mothers have third level education. Their relative performance in wave 3 is considerably better than in wave 1 and it is this which lies behind the steepening of the gradient.

[11] Bjorkegren et al (2020) find a significant role for parental education in the adult health outcomes for children in a large Swedish dataset.

The most dramatic change in unidimensional poverty is observed in resource poverty where the headcount rate increases from just under 6 per cent in wave 1 to 20 per cent in wave 2 and then falls back slightly to around 17 per cent in wave 3. This is not unexpected as the Great Recession occurs in between waves 1 and 2 and this clearly has a major impact upon families perceived ability to make ends meet. It is interesting to note that the gradient by maternal education is not as steep here as in the case of health and education. This may reflect the fact that the measure we use for resource poverty is self-assessed and subjective rather than objectively measured.

Before moving on to measures of multidimensional poverty it is useful to look at the correlations between the different measures of unidimensional poverty (this follows the spirit of the dashboard approach outlined by Ferreira and Lugo, 2013). In table 2 we show the tetrachoric correlations between each dimension of poverty for each wave. Concentrating first of all on correlations for a given dimension over time, we see that correlations for education are in the region of 0.6-0.7, those for health around 0.75-0.85 and those for income around 0.5-0.55. This suggests quite a high level of persistence within unidimensional poverty, and persistence appears to be increasing since in general the wave 2-wave 3 correlations are higher than the wave 1-wave 2 correlations, and persistence also appears to be higher for health.

Turning now to within wave correlations between the different dimensions, we see wave 1 correlations ranging from 0.16-0.24, correlations in wave 2 from 0.15-0.19 and correlations in wave 3 around 0.16-0.18. Thus, not surprisingly, correlations between dimensions in a given wave are considerably lower than correlations for the same dimension over time. There is also no clear trend in terms of inter-dimension correlation over time, nor in terms of higher correlations between any two particular dimensions.

Multidimensional Poverty

Figures 1-2 provide graphical evidence of the extent of multidimensional poverty across the three waves, though not taking account of correlations between different dimensions of poverty. Figure 1 shows the breakdown of the total number of uni-dimensional poverty spells (or deprivations) experienced by children. We see that in total about 53% of the children experience no deprivations over the three waves and just over 22% of them experience only one deprivation. Thus multiple deprivation, in terms of either experiencing different deprivations or the same deprivation more than once, is experienced by about one quarter of the children. Figure 2 shows the gradient by maternal education. As is the case for most of our results, the pattern is for a clear difference between highest and lowest levels of maternal education, with the two intermediate levels showing little difference between each other. For example, only one third of children with the lowest level of maternal education experience no deprivations, while the corresponding ratio for children with the highest level of maternal education is around 70 per cent. Correspondingly, multiple (i.e. two or more deprivations) is experienced by only about 10 per cent of children with the highest maternal education but by over 40 per cent of those with lowest maternal education.

Table 3 presents results for multidimensional poverty for the whole sample, while table 4 presents the results by maternal education. The first column presents the adjusted headcount ratio and the second column the raw headcount ratio. Column 3 provides the deprivation intensity while column 4 gives the average number of deprivations for each person identified as multidimensionally poor. The results are also presented for different levels of k, the dimension cut-off. As might be expected, trends in multidimensional poverty reflect trends in the individual dimensions, in particular the increase in resource poverty after wave 1. There is very little change in either the deprivation intensity or in the average number of deprivations per poor person.

The gradient by maternal education is also very similar to those for the individual dimensions. Taking the union approach to multidimensional poverty (k=1), poverty rates for the lowest level of maternal education are about three times that of the highest level. The two intermediate levels of maternal education lie in between and have very similar rates of multidimensional poverty.

The gradient does get steeper for values of k in excess of 1, but the cell sizes here are very small. Even if we look at the total sample and not by maternal education we see that the raw headcounts for when k=3, the intersection approach, are all less than 1 per cent, even in waves 2 and 3 following the increase in income poverty. Even for the lowest level of maternal education and in the "worst" wave (wave 2), the fraction of children experiencing all three deprivations is 0.013.

In tables 5a-5e we present a different form of decomposition, this time in terms of the relative contribution of each dimension, for the sample as a whole and by maternal education. It is important to remember that this table gives the *share* of each dimension in multidimensional poverty over time and also by maternal education. For the case of k=1, we are simply dealing with the presence of poverty in any dimension, and hence correlations between dimensions do not play a role. Education plays the greatest relative role in wave 1 but following the onset of the Great Recession in waves 2 and 3, we see the dominant role being taken by resources. For the case of k=2, then inter-dimensional correlation can play a role and we see a greater convergence in the contributions. This reflects the fact that to be multidimensionally poor requires being poor in at least two dimensions and hence the role of any individual dimension is diluted somewhat.

Looking at the results by maternal education, we note that the relative importance of resources increases for higher levels of maternal education, especially in waves 2 and 3. This simply reflects the fact that for higher levels of maternal education there is comparatively very little health or education poverty and especially in later waves it is resource poverty which is most important.

In summary, the "static" results for multidimensional poverty show that about one quarter of the children experience more than one deprivation over the three waves and about 12% experience more than two. However, this includes children who experience the same deprivation in different waves. In terms of children experiencing multiple deprivations within a given wave, rates of multidimensional poverty appear low, not even exceeding 5 per cent in wave 2, when the Great Recession was at its peak. Much of this reflects the fact that while resource poverty increases between waves 1 and 2, there is little change in health poverty and education poverty falls slightly. The rise in health poverty in wave 3 is offset by a fall in resource poverty and thus the fraction of children experiencing more than one deprivation within a given wave does not exceed 5 per cent.

Multidimensional Poverty Dynamics

In this part of the paper we exploit the panel nature of the data to examine the dynamics of multidimensional poverty. We first of all examine the overall degree of persistence: how many children are poor in one or more than one dimension of poverty over time. We then examine transitions into and out of poverty, again for uni-dimensional and multi-dimensional poverty and calculate indices of mobility into and out of poverty between waves. As in previous sections we stratify the analysis by maternal education. We do not explicitly model the factors affecting transitions into and out of poverty, though that is an issue we hope to return to in future research.

What about the total amount of "churning" over the three waves? Figure 3 shows the total number of "moves" made by children over the three waves. A move is defined as a change in the number of deprivations experienced by a child from wave to wave. Thus if a child has no deprivations in wave 1 but has one deprivation in wave 2, that counts as one move. If they had no deprivations in wave 1 and two deprivations in wave 2 that counts as two moves. The histogram in figure 3 not surprisingly is similar to that in figure 1. If you have never had a deprivation then clearly you will not move, though those in figure 3 with zero moves also includes that small number of children (nearly 4 per cent) who are deprived in at least one dimension and who remain in that situation over the three waves. Figure 4 shows these histograms by maternal education. Once again a clear social gradient can be observed. Children whose mothers have not completed second level education experience more transitions, while the lowest number of transitions are experienced by those who's mothers have third level education.

We now look more explicitly at transitions between waves and critically in which direct they go. In figures 5a-5b we present what are effectively transition matrices, with each cell entry a form of histogram. In figure 5a, the column shows how many deprivations are experienced in the original wave (wave 1) and the row shows how many are experienced in the subsequent wave (wave 2). Thus for example, reading across the first row of figure 5a we see that 62.5% of children experienced no deprivations in waves 1 or 2, 16.6% went from zero deprivations in wave 1 to one deprivation in wave 2, 1.4% went from zero deprivations to two deprivations etc.

In terms of rough rules of thumb of how to interpret these matrices, low mobility will be reflected in large entries along the main diagonal i.e. people experience no change in their number of deprivations. In terms of off-diagonal entries, then large fractions to the north east of the main diagonal indicate a position where children are acquiring deprivations (i.e. moving into poverty), while large fractions to the south west of the main diagonal indicate a situation where children are shedding deprivations.

In terms of a welfare perspective, then assuming we prefer less deprivations to more and that we prefer to see children moving out of rather than into deprivations, then what we ideally want to see is the greatest amount of mass in the top left hand corner i.e. no deprivations in either wave. After that we prefer mass to the left of the main diagonal and preferably higher up i.e. moving from a low number of deprivations towards zero.

In terms of comparing the degree of mobility by simply eye-balling the transition matrix it is typical to look at entries on the main diagonal. High values along the main diagonal imply that a greater fraction stayed with the same number of deprivations. Thus comparing figure 5a and figure 5b we see in general higher entries along the main diagonal in figure 5b. This would seem to indicate greater persistence (or less mobility) between waves 2 and 3 compared to between waves 1 and 2. However care must also be taken to look at movements off the main diagonal, in particular the size of transitions between different categories.

In terms of looking at total deprivations rather than distinguishing between specific deprivations, which we do later, we see in Figure 5a that most of the mobility (the off diagonal cells) are to the right of the main diagonal i.e. children acquiring deprivations rather than shedding them. However, we do see 7.5% of children moving from one deprivation to zero, so there is movement in both directions. Another striking feature of figure 5a is that most of the mass is in cells towards the north west, reflecting the fact that very few children experience more than one deprivation.

Turning to figure 5b and transitions between waves 2 and 3, we see that overall mobility looks very similar, the fractions along the main diagonal being almost identical. Note however that the off-diagonal elements pretty much cancel each other out, with 11.5% going from zero to one deprivation but 12.1% moving in the opposite direction.

In appendix 3 we present these results by maternal education. We note the greatest mobility (in the sense of lower fractions along the main diagonal) for children with the lowest level of maternal education between waves 1 and 2. The relatively greater mass to the north east of the main diagonal reflects the acquisition rather than the shedding of deprivations with children moving into income poverty following the Great Recession. Eyeballing of the data also suggest that what we might regard as "good" mobility i.e. that located in the south-west of the matrix is more observed at higher education levels. Turning now to mobility patterns between waves 2 and 3, again we see more mobility at lower levels of maternal education in the sense that there is less mass along the main diagonal, but for all levels of maternal education we see that the off-diagonal cells on either side of the main diagonal pretty much cancel each other out.

However simply eyeballing the data may not always be reliable and it is helpful to have a statistic which summarises the degree of mobility. The measure which we use is the Bartholomew average jump index. Thus we have four categories, from zero up to three deprivations and if a child moves from say zero to one deprivation between waves 1 and 2 that counts as one jump or transition. If they move from zero to two deprivations that counts as two transitions etc. We then add together the total number of transitions in either direction and take the average over the population.[12] We also calculate the number of transitions up (an increase in the number of deprivations) minus the number of transitions down, which we term "net transitions" and this captures the welfare dimension referred to earlier.

Table 6 provides data on the average number of absolute and net transitions per child. A positive value for average net transitions indicates a situation where on balance more children acquired rather than shed extra deprivations.

Overall, we can see that these results confirm the results from the graphical transition matrices. Average mobility in terms of the absolute number of transitions is pretty much unchanged between waves 1 to 2 and waves 2 to 3. However looking at net transitions we see that from wave 1 to wave 2 children were on average acquiring deprivations whereas between waves 2 and 3, deprivations were essentially unchanged. We also observe cross sectional difference by maternal education. Children whose mothers have the lowest level of education show much greater absolute mobility between waves 1 and 2, with an average of almost half a transition per child. Bear in mind though that not all these transitions involve acquiring a deprivation, though the average net transition is positive and statistically significant. Looking at transitions between waves 2 and 3 we again see a higher absolute number of transitions for this category but the net effect is effectively zero.

For the other levels of maternal education we see the lowest level of mobility for those cases with the highest level of education, and intermediate levels of mobility for maternal education levels 2 and 3. Net moves are positive for these categories between waves 1 and 2, indicating that on balance children in these categories acquired deprivations, with the lowest rate of acquisition for those whose mothers had third level education. Similar to children with

[12] We chose not to use the Shorrocks index based on the transition matrix as this index assumes that the proportions in each category (i.e. row/column) is the same, as would be the case if the matrix was based upon quintiles. In our case here however proportions are clearly not the same across categories.

maternal education level 1, on balance there is no net acquisition of deprivations between waves 2 and 3.

So far we have examined transitions only in an overall sense i.e. we have not concerned ourselves with which particular deprivations are acquired or shed. We address this issue in the next sub section.

Dimension Specific Dynamics

In figure 6a-6b we reproduce the transition matrices in histogram form which we used above to analyse transitions in terms of total deprivations. Now we have a separate row and column for each possible combinations of deprivations. As before, if we observe heavily populated cells along the main diagonal then we have a situation of low mobility. Observe also that the top left hand cell (where a child has no deprivations in either wave) is the same regardless of whether we are looking at total or specific deprivations. Again in terms of the off-diagonal patterns we generally wish to see greater mass towards the south-west, indicating that children are shedding deprivations, as opposed to the north east, where children are acquiring them. Of course what is of greatest interest in these diagrams is precisely *which* cells off the diagonal have the greatest mass, since that indicates which deprivations show the most movement into and out of.

Figure 6a shows deprivation specific transitions for the whole sample between waves 1 and 2. As in figure 5a, about 63% of the sample experience no deprivations in either wave. The off diagonal cell with the highest percentage in it (12%) is for those who had no deprivations at all in wave 1 and who became income deprived in wave 2. Most other off-diagonal cells have very low percentages except perhaps for those who had been education deprived in wave 1 but moved back to no deprivations in wave 2 (4%). Cells in the south east quadrant have very low percentages indicating that thankfully very few children have multiple deprivations.

Figure 6b presents the same data except this time between waves 2 and 3. The fraction who have no deprivations in either wave is slightly lower, at just over 58%. We also see nearly 6% of children who are resource poor for both waves 2 and 3. The two biggest off-diagonal cells are 6.4% for children who have no deprivations in wave 2 but are resource poor in wave 3 and 8.3% for children who were resource poor in wave 2 but transit back to no deprivations in wave

3. We also observe around 3% moving between no deprivations and education poverty only but it seems to fair to say that most of the mobility between deprivations involve resources.

Appendix 4 shows these transition matrix histograms by maternal education. Briefly, as already discussed we see more mobility at lower levels of maternal education. For the lowest level of maternal education, between wave 1 and 2 the biggest transition is again for children who had no deprivation in wave 1 becoming resource poor in wave 2 (14.3%). For this group again we see some mobility in and out of education poverty (4.7% in and 6.6% out) and relatively little mobility elsewhere. The same pattern can be observed as maternal education levels increase, except that absolute levels of mobility are lower. The one (minor) exception to this is for the highest level of maternal education where we see some mobility out of resource poverty deprivation in wave 1 to no deprivations at all in wave 2 (2.9%).

Looking at the wave 2 to wave 3 transitions and again focusing on the lowest level of maternal education, we again observe a magnified version of what is happening to the complete sample. Just under 55% show no mobility (though 7.5% of that 55% stay resource poor), most mobility is into and out of resource poverty (6.5% in and 10% out) and again there is some mobility into and out of education but relatively little with respect to health. Similar to the wave 1-wave 2 transitions we see less absolute mobility with higher levels of maternal education. It is interesting to note however that for the highest level of maternal education we see quite high levels of mobility into and out of resource poverty (6% into and 8% out of). These figures indicate that for this group mobility with respect to resource poverty is similar to other levels of maternal education. This is not true for mobility in education and health where mobility for children whose mothers have the highest level of maternal education is a scaled down version of mobility for the rest of the sample.

Overall though, what is probably most notable about the pattern of mobility by maternal education level is that qualitatively it does not differ greatly. Lower levels of maternal education generally observe higher levels of mobility but for the most part it is a scaled up version of what happens elsewhere. Or to put it another way, in terms of transitions children with lower maternal education are not poor in a different way, they are just more poor in the same way.

Again, it is useful to go beyond eye-balling the transition matrices and to see if we can more formally examine the different transition patterns. Given two transition matrices T_1 and T_2

what we are essentially looking for is some measure of how similar or alike these matrices are. The approach we choose is to calculate the matrix T_1-T_2 and then to calculate the infinity norm of this matrix. The infinity norm of an nxn matrix A can be defined as follows (assuming a_{ij} is the element in the ith row and jth column): $\|A\|_\infty = max_{i=1:n} \sum_{j=1}^{n} \lceil a_{ij} \rceil$ i.e. the maximal row sum of the matrix. Intuitively the norm of a matrix gives an idea of the magnitude of a matrix and hence the norm of the matrix T_1-T_2 gives a sense of the magnitude of the difference between the transition matrices i.e. how different they are.

In table 7 we present the values of the infinity norms for all possible T_i-T_j combinations where we include the transition matrix for the sample as a whole and for each level of education.[13] The absolute values of the norms are of little interest, what matters most is the relative magnitude. Thus if we look at how each maternal education level differs from the total sample, we see that it is the lowest and the highest levels which show the most difference. These levels also show the biggest pairwise difference with maternal education levels 2 and 3 relatively close to the total sample and also close to each other. Transition patterns for maternal education levels 2 and 3 are also considerably closer to maternal education level 4 than to maternal education level 1.

Finally, in our comparison of these transitions matrices we return to the question of whether the difference between matrices (e.g. between maternal education levels 1 and 4) arises from the fact that there are simply more transitions for education level 1 or whether the patterns of transitions differ between the education levels. Are transition levels for maternal education level 1 simply a scaled up version of those for maternal education level 4, or do we also observe a qualitative difference in the transitions?

To investigate this we need to scale transition matrices so that in some sense the total degree of transitions have been controlled for and what we pick up is merely the difference in the pattern of transitions. We take overall transitions as our base and let the transition matrix for the whole sample be T. Then, suppose we wish to normalize the transition matrix for maternal education level 1, T_1, so that its overall rate of transition has been normalized to that of T, we multiply the elements along the main diagonal of T_1 by the ratio of the trace of matrix T and

---

[13] We also calculated the norm of these matrices based upon maximal column sums (the "L1" norm) and the results were qualitatively very similar. Results available on request.

the trace of T_1. This reflects the fact that overall transitions in the transition matrix can be captured by the trace, which tells us the fraction of observations which do not change between waves. The off-diagonal elements are scaled by the reciprocal of this measure, reflecting the fact that a low trace indicates a high fraction of off-diagonal elements and hence greater mobility. Thus the re-scaled matrix for T_1, which we label T_1^s has elements $a_{ii}^s = a_{ii}\frac{Tr(T)}{Tr(T_1)}$ $i = 1, \dots, n$ and elements $a_{ij}^s = a_{ij}\frac{Tr(T_i)}{Tr(T)}, i \neq j$. We then calculate the infinity norm for the matrices $T_1^s - T_2^s$ etc. This approach, while admittedly ad hoc, does provide some idea of the differing pattern of transition while controlling for its overall level. Results for the infinity norms for the difference between these scaled transitions matrices is provided in tables 8a-8b.

Comparing the results of tables 7a-7b and 8a-8b we see that the distance between the transition matrices has fallen considerably, in many cases by a factor of well over 50%. This is consistent with the impression provided by eye-balling the transition matrices that the pattern of poverty transitions by maternal education does not differ too much, rather it is the overall scale which is key.

6. Discussion and Conclusion

This paper has analysed unidimensional and multidimensional poverty for three waves of a cohort of Irish children aged between 9 and 17 years of age. The study has, as much as possible, concentrated on direct child outcomes and also examines mobility across the waves. The focus is less on the levels of poverty but more on their development over time, the degree to which there is a gradient with respect to maternal education and also the correlations across the different dimensions of poverty. We now discuss the results in detail and also any policy implications which may arise. Our discussion of policy implications is quite broad-brushed and we do not investigate the effectiveness of specific policy interventions.

Education and health poverty show relatively little change over time, with just a slight increase in health poverty as children move from age 13 to age 17. This increase in health poverty however is not observed for children with the highest level of maternal education and thus we see a steepening of the gradient here. It is also noticeable that while the overall level of educational poverty as we define it is unchanged over time, again there is a steepening of the gradient with respect to maternal education. Educational poverty for those with the lowest level of maternal education is nearly 4 times that for those with the highest level when children are aged 9. By the time children are aged 17, this ratio has nearly trebled to over 11. This change in the gradient arises because of a reduction in educational poverty for children with the highest level of maternal education. This suggests that these families are able to identify and act upon educational deficiencies to a much greater extent than families with low levels of maternal education. These results provide more support for early interventions to prevent children becoming left behind in education. Previous work for Ireland and elsewhere has stressed that the socioeconomic gradient for education (across the whole of the distribution and not just below the educational "poverty line") can set in as early as three years of age (Dearden et al, 2011, Madden, 2020). The results here certainly suggest that in terms of educational poverty, children with higher maternal education are better equipped to escape from such poverty.

The greatest change in unidimensional poverty over the three waves is with respect to resource poverty, specifically the difficulties families have in making ends meet, going from when children were aged 9 to when children were aged 13. Of course, this captures the start of the Great Recession and regardless of maternal education, there was on average a threefold increase in poverty rates for this measure. This measure of poverty however showed a decline then between waves 2 and 3 when the children aged from 13 to 17. Changes in the overall gradient with respect to maternal education are more complex here. The highest and lowest levels of maternal education showed smaller increases between waves 1 and 2 and bigger decreases between waves 2 and 3 than was the case for the intermediate levels of maternal education. It is difficult to think of an obvious reason why this should be so.

Turning now to poverty in a multidimensional setting we first of all note that the correlations across the different dimensions show signs of a slight decrease and this arises owing to a slight decoupling of resource poverty from health and education poverty. Correlations between resource poverty and the other two dimensions both fall and the biggest decrease is for the education-resources correlation which goes from 0.245 to 0.169. This seems to arise from a combination of educational poverty becoming relatively more concentrated amongst those with lowest maternal education while resource poverty becomes (relatively) more concentrated amongst those with intermediate maternal education.

Turning now to the multidimensional poverty indices, regardless of the choice for the second AF cut-off, the AF index for the sample as a whole increases between waves 1 and 2 and then falls back slightly in wave 3. These changes are very much driven by changes in resource poverty. It is also interesting to note that changes in the index arise mainly from changes in the headcount ratios of those who are multidimensionally poor, rather than from an increase in the intensity of multidimensional poverty (which is not entirely unexpected when we have "only" three dimensions of poverty).

Analysis of the AF indices by maternal education reveal complex patterns depending upon where we set the second cut-off. If we take the ratio of the indices for lowest and highest level of maternal education as a rough proxy for the social gradient then table 4 shows that when the cut-off is one i.e. being poor in any dimension of poverty qualifies you as multidimensionally poor, this ratio stays pretty much unchanged between waves 1 and 3, with a value of around 3. However, with a second cut-off of two, the ratio increases from around 7 in wave 1 to around 16 in wave 3. This dramatic change in the gradient partially reflects the reassuring fact that absolute numbers are small and so small changes can lead to exaggerated changes in the ratio. However, examining the part of the AF index accounted for by the headcount ratio, we see that the reduction in education poverty for the highest level of maternal education means that even though overall multidimensional poverty levels increase between waves 1 and 3, the number of children from the highest level of maternal education who experience poverty in more than one dimensions falls.

Turning now to the results for mobility, we see that mobility changes little when comparing wave 1-wave 2 transitions with wave 2-wave 3 transitions. What is different is the direction of transition with a balance of movement into poverty (by this we mean entering into poverty in a specific dimension) between waves 1 and 2 (very much associated with the increase in resource poverty following the Great Recession), whereas between waves 2 and 3 movements into and out of poverty pretty much cancel each other out. Mobility is inversely related to the level of maternal education, with highest mobility observed for children with the lowest level of maternal education. This is true at all ages but it is reassuring to see that there is mobility out of resource poverty, even for the lowest level of maternal education.

The different mobility patterns by dimension are noteworthy. Family resource poverty shows the highest level of mobility suggesting that escape from this type of poverty is possible. The much lower levels of mobility for health and education indicate that while movement into these types of poverty is more rare than for resources, escape is also much more difficult (one exception to this seems to be escape from education poverty for the highest level of maternal education). These poverties (health and education) seem to be more deep-rooted and structural suggesting that care needs to be taken in formulating policies in this area. Given the difficulties in escaping from poverty in these dimensions, prevention may be a better policy than cure.

With the exception of the aforementioned higher rates of escape from education poverty by those with the highest level of maternal education, the pattern of dimension specific mobility by maternal education does not seem that varied (following adjustment for the overall level of poverty). What this suggests is that the nature of poverty mobility (in terms of movements into and out of specific dimensions) does not differ too much by maternal education. It is more the case that there is simply more net mobility into poverty for lower levels of maternal education, rather than that the pattern is different. A tentative policy conclusion which could be drawn from this is that broad based policies could be effective rather than interventions tailored to specific parts of the socioeconomic gradient.

Table 1: Uni-Dimensional Poverty Rates

	Wave 1	Wave 2	Wave 3
Health Poor			
Total	**0.054**	**0.052**	**0.068**
Lower Secondary	0.084	0.100	0.110
Complete Secondary	0.049	0.038	0.061
Diploma/Cert	0.046	0.033	0.059
Third Level	0.023	0.024	0.026
Education Poor			
Total	**0.106**	**0.096**	**0.095**
Lower Secondary	0.188	0.164	0.182
Complete Secondary	0.085	0.086	0.077
Diploma/Cert	0.086	0.083	0.078
Third Level	0.039	0.021	0.016
Resources Poor			
Total	**0.058**	**0.200**	**0.173**
Lower Secondary	0.096	0.282	0.229
Complete Secondary	0.038	0.176	0.163
Diploma/Cert	0.052	0.188	0.167
Third Level	0.048	0.136	0.114

Table 2: Tetrachoric Correlations across Uni-dimensional Poverty

	E w1	H w1	R w1	E w2	H w2	R w2	E w3	H w3	R w3
E w1	1								
H w1	0.1605	1							
R w1	0.2450	0.2254	1						
E w2	0.6144	0.1124	0.1361	1					
H w2	0.1985	0.8281	0.2464	0.1555	1				
R w2	0.1754	0.1632	0.5520	0.1993	0.1662	1			
E w3	0.6079	0.1460	0.2316	0.6967	0.1974	0.2099	1		
H w3	0.1300	0.7487	0.2313	0.1441	0.8449	0.1467	0.1608	1	
R w3	0.1238	0.1298	0.4706	0.1507	0.1759	0.5670	0.1689	0.1782	1

Table 3: Multidimensional Poverty

	Wave 1				Wave 2				Wave 3			
	M=HA	H	A	AD	M=HA	H	A	AD	M=HA	H	A	AD
k=1	0.072	0.193	0.37	1.16	0.117	0.297	0.39	1.20	0.113	0.289	0.39	1.19
k=2	0.015	0.022	0.68	2.21	0.032	0.046	0.70	2.17	0.031	0.045	0.69	2.11
k=3	0.002	0.002	1.00	3.00	0.005	0.005	1.00	3.00	0.003	0.003	1.00	3.00

Table 4: Multidimensional Poverty by Maternal Education

	Wave 1				Wave 2				Wave 3			
	M=HA	H	A	AD	M=HA	H	A	AD	M=HA	H	A	AD
Lower Secondary												
k=1	0.123	0.312	0.39	1.18	0.183	0.437	0.42	1.15	0.174	0.420	0.41	1.24
k=2	0.035	0.048	0.73	2.17	0.069	0.096	0.72	2.14	0.064	0.091	0.70	2.11
k=3	0.008	0.008	1.00	3.00	0.013	0.013	1.00	3.00	0.010	0.010	1.00	3.00
Completed Secondary												
k=1	0.057	0.160	0.36	1.07	0.101	0.267	0.38	1.12	0.101	0.267	0.38	1.28
k=2	0.008	0.013	0.62	2.00	0.021	0.031	0.68	2.06	0.023	0.033	0.70	2.02
k=3	0.000	0.000	1.00	3.00	0.002	0.002	1.00	3.00	0.001	0.001	1.00	3.00
Diploma/Cert												
k=1	0.061	0.167	0.36	1.10	0.102	0.264	0.39	1.15	0.102	0.271	0.38	1.12
k=2	0.011	0.016	0.69	2.03	0.026	0.039	0.67	2.04	0.022	0.033	0.67	2.00
k=3	0.001	0.001	1.00	3.00	0.001	0.001	1.00	3.00	0.000	0.000	1.00	3.00
Third Level												
k=1	0.037	0.103	0.36	1.07	0.061	0.174	0.35	1.04	0.053	0.150	0.35	1.04
k=2	0.005	0.007	0.71	2.00	0.005	0.007	0.71	2.00	0.004	0.006	0.67	2.00
k=3	0.000	0.000	1.00	3.00	0.000	0.000	1.00	3.00	0.000	0.000	1.00	3.00

Table 5a: Relative Contribution to Multidimensional Poverty

	Wave 1	Wave 2	Wave 3
k=1			
Health	0.244	0.147	0.199
Education	0.482	0.271	0.279
Resources	0.274	0.583	0.522
k=2			
Health	0.250	0.215	0.270
Education	0.404	0.352	0.322
Resources	0.306	0.433	0.408

Table 5b: Relative Contribution to Multidimensional Poverty, Educ=1

	Wave 1	Wave 2	Wave 3
k=1			
Health	0.227	0.181	0.209
Education	0.506	0.296	0.344
Resources	0.267	0.523	0.447
k=2			
Health	0.242	0.239	0.290
Education	0.432	0.349	0.341
Resources	0.327	0.411	0.369

Table 5c: Relative Contribution to Multidimensional Poverty, Educ=2

	Wave 1	Wave 2	Wave 3
k=1			
Health	0.281	0.124	0.200
Education	0.491	0.282	0.251
Resources	0.229	0.594	0.549
k=2			
Health	0.332	0.203	0.253
Education	0.313	0.347	0.285
Resources	0.355	0.451	0.462

Table 5d: Relative Contribution to Multidimensional Poverty, Educ=3

	Wave 1	Wave 2	Wave 3
k=1			
Health	0.248	0.108	0.191
Education	0.464	0.266	0.252
Resources	0.288	0.626	0.558
k=2			
Health	0.209	0.137	0.237
Education	0.407	0.385	0.304
Resources	0.384	0.479	0.459

Table 5e: Relative Contribution to Multidimensional Poverty, Educ=4

	Wave 1	Wave 2	Wave 3
k=1			
Health	0.207	0.131	0.161
Education	0.351	0.115	0.101
Resources	0.442	0.754	0.738
k=2			
Health	0.116	0.207	0.145
Education	0.425	0.285	0.392
Resources	0.459	0.508	0.463

Table 6: Mobility Indices

	Wave 1 to Wave 2				
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**
Average Transitions	0.318 (0.010)	0.490 (0.027)	0.273 (0.014)	0.265 (0.018)	0.194 (0.017)
Up-Down	0.130 (0.012)	0.178 (0.034)	0.127 (0.016)	0.121 (0.020)	0.071 (0.019)
	Wave 2 to Wave 3				
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**
Average Transitions	0.316 (0.010)	0.451 (0.027)	0.293 (0.014)	0.273 (0.018)	0.194 (0.016)
Up-Down	-0.010 (0.012)	-0.025 (0.033)	0.002 (0.017)	-0.000 (0.020)	-0.025 (0.018)

Table 7a: Infinity Norm of Difference between Transition Matrices – Wave 1 to Wave 2

Total					
Mat Ed=1	0.243				
Mat Ed=2	0.058	0.296			
Mat Ed=3	0.067	0.310	0.023		
Mat Ed=4	0.201	0.444	0.148	0.134	
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**

Table 7b: Infinity Norm of Difference between Transition Matrices – Wave 2 to Wave 3

Total					
Mat Ed=1	0.209				
Mat Ed=2	0.040	0.247			
Mat Ed=3	0.055	0.258	0.027		
Mat Ed=4	0.211	0.419	0.178	0.168	
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**

Table 8a: Infinity Norm of Difference between Scaled Transition Matrices – Wave 1 to Wave 2

Total					
Mat Ed=1	0.089				
Mat Ed=2	0.025	0.059			
Mat Ed=3	0.016	0.102	0.022		
Mat Ed=4	0.077	0.163	0.064	0.063	
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**

Table 8b: Infinity Norm of Difference between Scaled Transition Matrices – Wave 2 to Wave 3

Total					
Mat Ed=1	0.111				
Mat Ed=2	0.027	0.138			
Mat Ed=3	0.015	0.126	0.034		
Mat Ed=4	0.096	0.205	0.069	0.097	
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**

Figure 1: Total Number of Deprivations over 3 waves

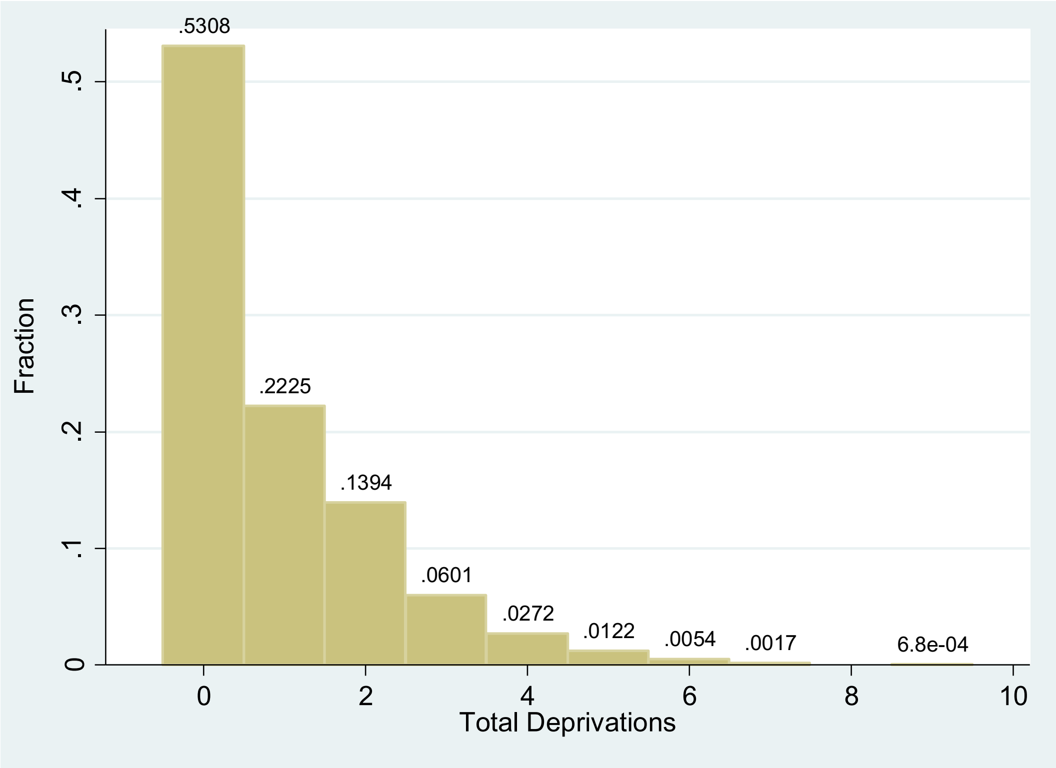


Figure 2: Total Number of Deprivations over 3 waves by Maternal Education

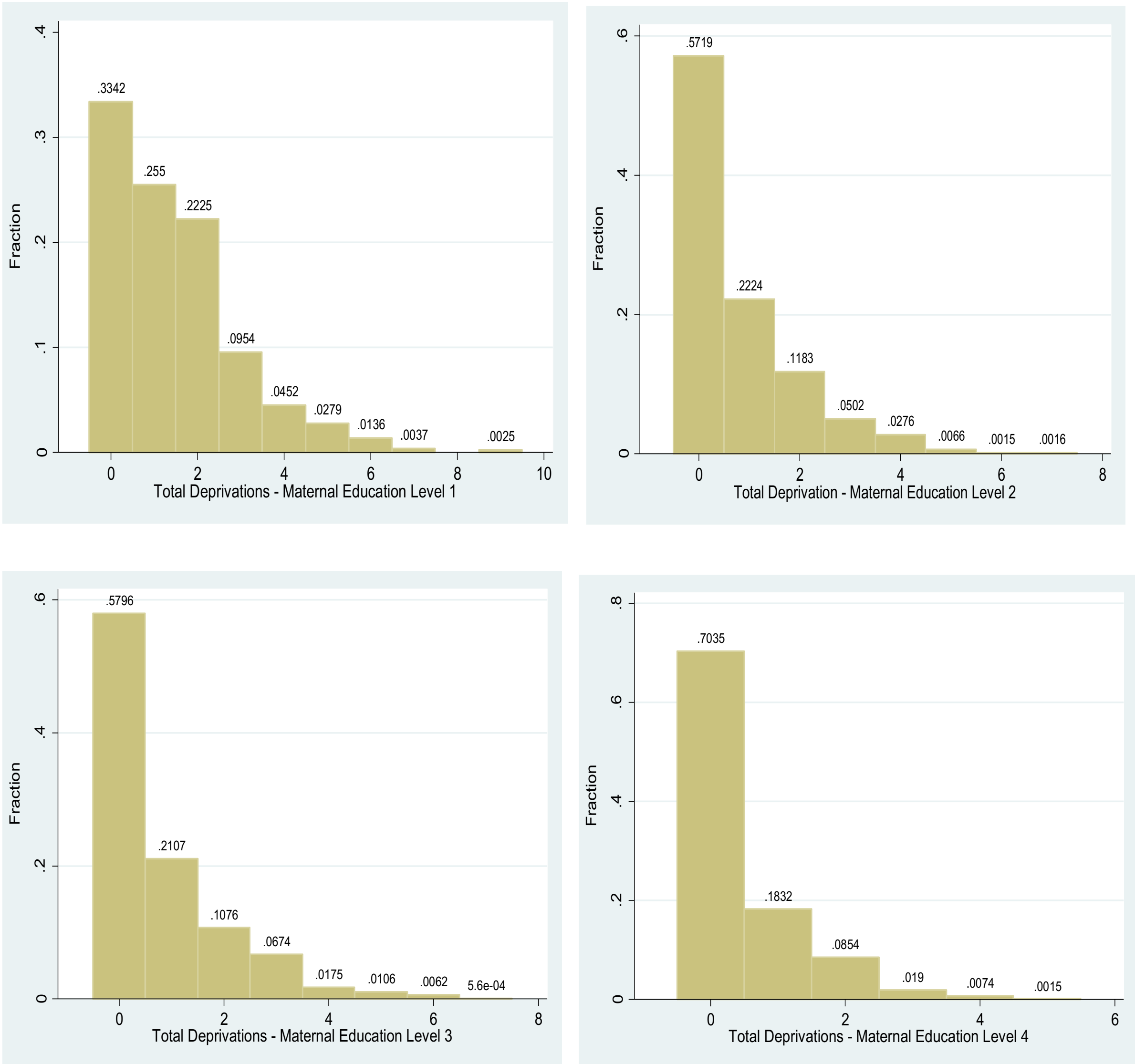


Figure 3: Total Number of Moves over 3 waves

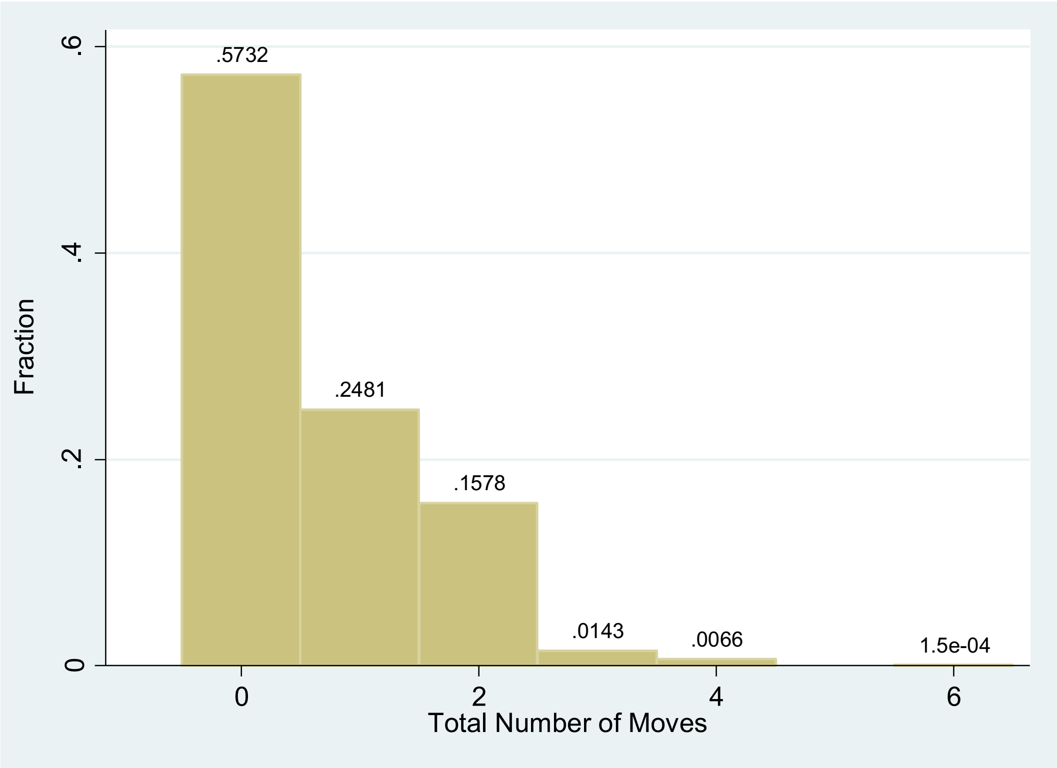


Figure 4: Total Number of Moves over 3 waves by Maternal Education

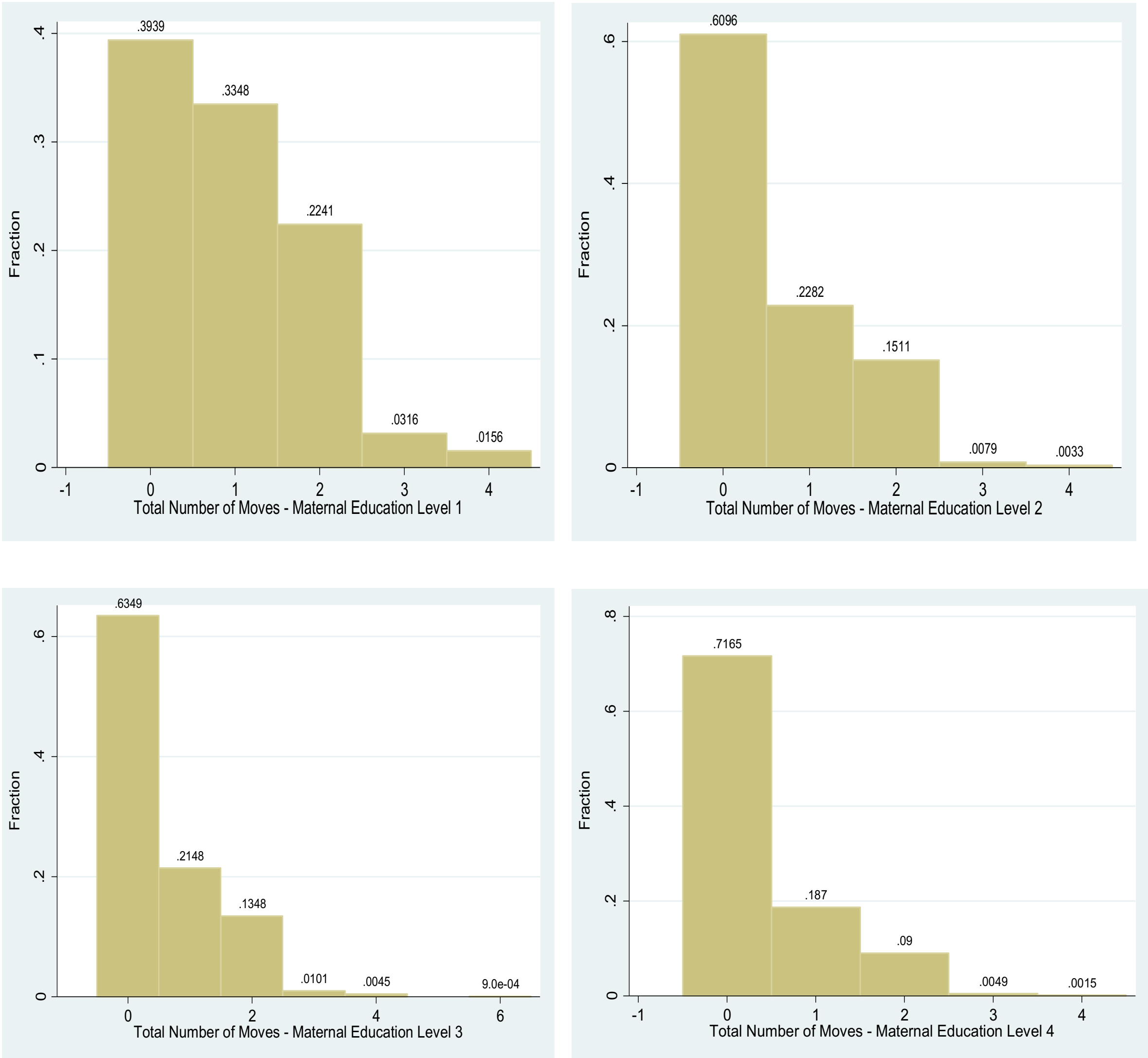


Figure 5a: Transition Matrix, Wave 1 to Wave 2

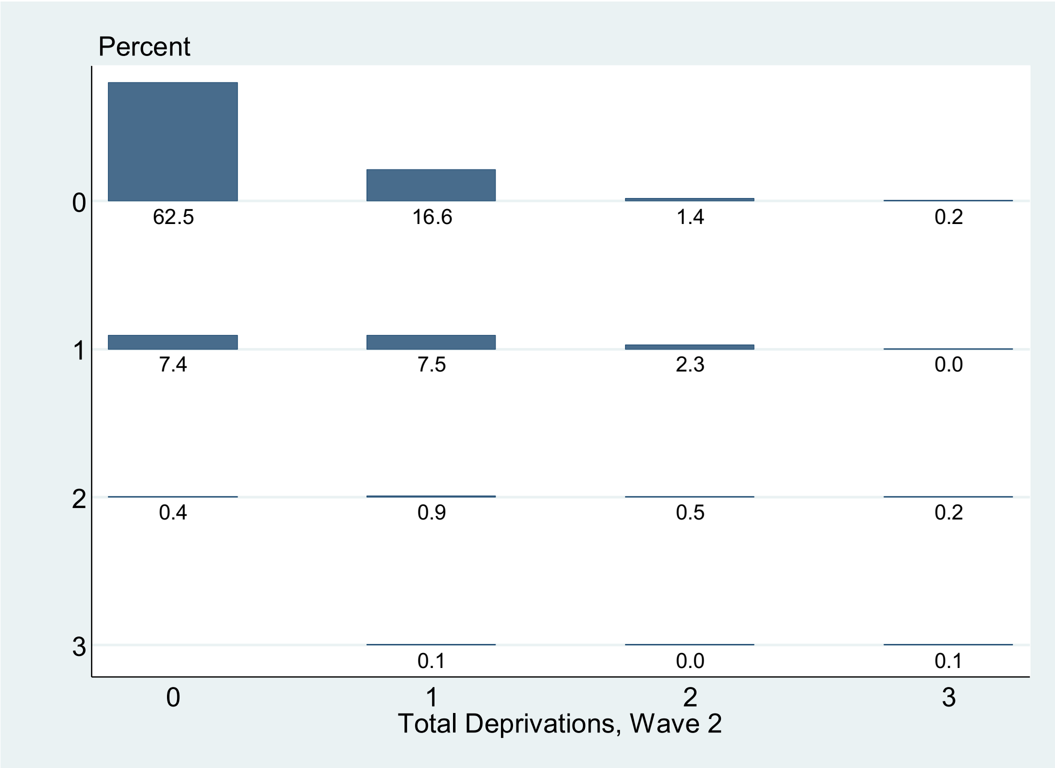


Figure 5b: Transition Matrix, Wave 2 to Wave 3

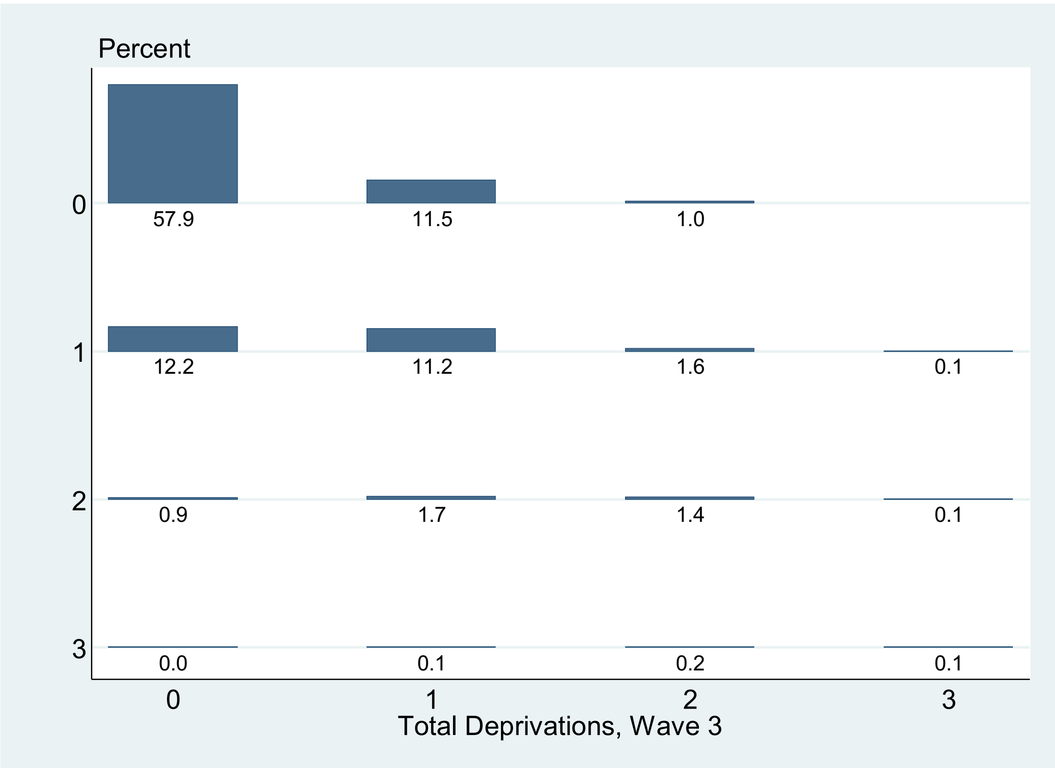


Figure 6a: Deprivation Specific Transition Matrix, Wave 1 to Wave 2

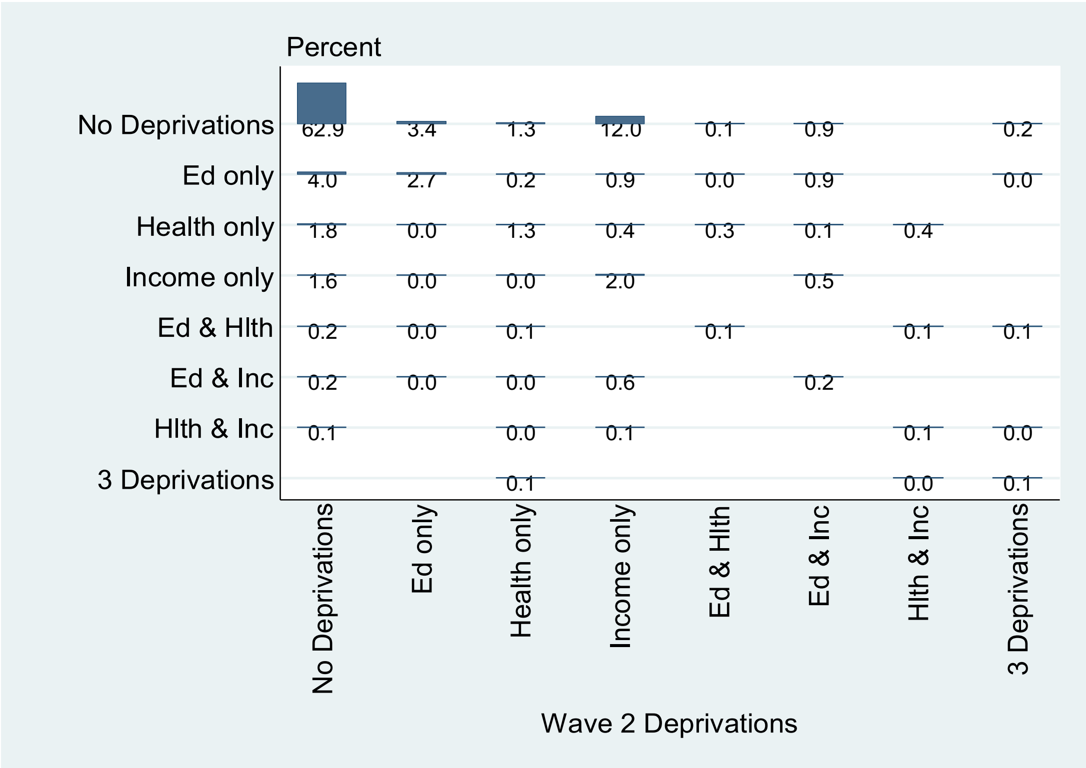
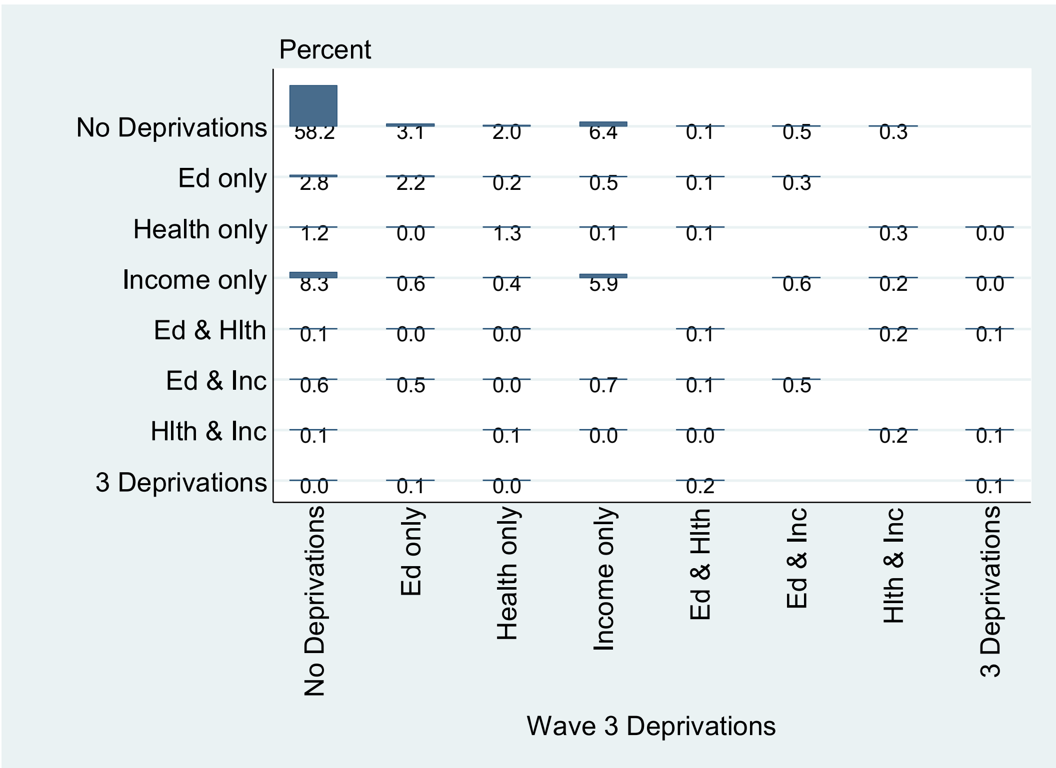


Figure 6b: Deprivation Specific Transition Matrix, Wave 2 to Wave 3



References:

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of public economics*, *95*(7), 476-487.

Alkire, S., Foster, J., Seth, S., Roche, J. M., & Santos, M. E. (2015). *Multidimensional poverty measurement and analysis*. Oxford University Press, USA.

Bedük, Selçuk. "Understanding material deprivation for 25 EU countries: risk and level perspectives, and distinctiveness of zeros." *European Sociological Review* 34, no. 2 (2018): 121-137.

Bjorkegren, E., M. Lindahl, M.Palme and E. Simeonova (2020): Selection and Causation in the Parental Education Gradient in Health: Lessons from a Large Sample of Adoptees. *NBER Working Paper 28214.*

Bourguignon, Francois, and Satya R. Chakravarty. "A family of multidimensional poverty measures." In *Advances in econometrics, income distribution and scientific methodology*, pp. 331-344. Physica-Verlag HD, 1999.

Brooks-Gunn, Jeanne, and Greg J. Duncan. "The effects of poverty on children." *The future of children* (1997): 55-71.

Burkhauser, R. And J. Cawley (2008): Beyond BMI: The value of more accurate measures of fatness and obesity in social science research. *Journal of Health Economics*, vol. 27, pp. 519-529.

Chzhen, Yekaterina, Zlata Bruckauf, and Emilia Toczydlowska. "Monitoring progress towards sustainable development: multidimensional child poverty in the European Union." *Journal of Poverty and Social Justice* 26, no. 2 (2018): 129-150.

Cole, T., M. Bellizzi, K. Flegal and W. Dietz (2000): Establishing a Standard Definition for Child Overweight and Obesity Worldwide: International Survey, *British Medical Journal*, Vol. 320, pp. 1-6.

Deary, I. J., S. Strand, P. Smith, and C. Fernandes (2007). Intelligence and educational achievement. *Intelligence*, Vol. 35(1), pp. 13-21. doi:http://dx.doi.org/10.1016/j.intell.2006.02.

Dearden, Lorraine, Luke Sibieta, and Kathy Sylva (2011). *The socio-economic gradient in early child outcomes: evidence from the Millennium Cohort Study*. No. 11, 03. IFS working papers.

Desmarais, Bruce A., and Jeffrey J. Harden. "Testing for zero inflation in count models: Bias correction for the Vuong test." *The Stata Journal* 13, no. 4 (2013): 810-835.

Dunbar, Geoffrey R., Arthur Lewbel, and Krishna Pendakur. "Children's resources in collective households: identification, estimation, and an application to child poverty in Malawi." *American Economic Review* 103, no. 1 (2013): 438-71.

Feinstein, L. (2003): Inequality in the Early Cognitive Development of British Children in the 1970 Cohort. *Economica*. Vol. 70, pp. 73-97.

Ferreira, Francisco HG, and Maria Ana Lugo. "Multidimensional poverty analysis: Looking for a middle ground." *The World Bank Research Observer* 28, no. 2 (2013): 220-235.

Gomulka, J (1994), "Grossing up: a note on calculating household weights from family composition totals." *University of Cambridge, Department of Economics, Microsimulation Unit Research Note MU/RN/4*.

Grotti, R., B. Maître, D. Watson, and C. Whelan. "Poverty Transitions in Ireland: An Analysis of the longitudinal Central Statistics Office (CSO) Survey on Income and Living Conditions (SILC), 2004-2015." *Social Inclusion Technical Paper* 8 (2017).

Hannan, D., E. Smyth, J. McCullagh, R. O'Leary and D. McMahon (1996). *Coeducation and Gender Equality: Exam Performance, Stress and Personal Development*. Dublin: Oak Tree Press.

Hjelm, Lisa, Lucia Ferrone, Sudhanshu Handa, and Yekaterina Chzhen. "Comparing approaches to the measurement of multidimensional child poverty." (2016).

Howe, L.D., D. Lawlor, and C. Propper, (2013). Trajectories of socioeconomic inequalities in health, behaviours and academic achievement across childhood and adolescence. *Journal of Epidemiology and Community Health*, pp.jech-2012.

Jacob, B. and Rothstein, J., (2016). The measurement of student ability in modern assessment systems. *Journal of Economic Perspectives*, Vol. 30, pp.85-108.

Jayachandran, Seema. "The roots of gender inequality in developing countries." *Annual Review of Economics* 7, no. 1 (2015): 63-88.

Jayachandran, Seema, and Rohini Pande. "Why are Indian children so short? The role of birth order and son preference." *American Economic Review* 107, no. 9 (2017): 2600-2629.

Lindberg, Louise, Pernilla Danielsson, Martina Persson, Claude Marcus, and Emilia Hagman. "Association of childhood obesity with risk of early all-cause and cause-specific mortality: A Swedish prospective cohort study." *PLoS medicine* 17, no. 3 (2020): e1003078.

Lord, F. M. (1980). *Applications of Item Response Theory to Practical Testing Problems.* Hillsdale, NJ: Lawrence Erlbaum.

Madden, David. "Health and wealth on the roller-coaster: Ireland, 2003–2011." *Social Indicators Research* 121, no. 2 (2015): 387-412.

Madden, David. "Childhood obesity and maternal education in Ireland." *Economics & Human Biology* 27 (2017): 114-125.

Madden, David. "BMI Mobility and Obesity Transitions Among Children in Ireland." *Economics & Human Biology* (2020a): 100896.

Madden, David. “The Socioeconomic Gradient of Cognitive Test Scores: Evidence from Two Cohorts of Irish Children.”, UCD School of Economics, Working Paper (2020). WP/20/20.

Murray, A., C. McCrory, M. Thornton, J. Williams, A, Quail, L. Swords et al (2011). *Growing Up in Ireland: National Longitudinal Study of Children: Design, Implementation and Procedure for the Child Cohort.* Dublin: Office of the Minister for Children and Youth Affairs.

Nolan, Brian, and Bertrand Maître. "Children of the Celtic tiger during the Economic Crisis: Ireland." *Children of Austerity. Impact of the Great Recession on Child Poverty in Rich Countries* (2017): 146-169.

Nolan, Brian, Bertrand Maître, and Dorothy Watson. "Child income poverty and deprivation dynamics in Ireland." In *The dynamics of child poverty in industrialised countries* (2001): 196-214.

Quail, A., J. Williams, M. Thornton and A. Murray (2014): *A Summary Guide to Wave 2 of the Child Cohort (at 13 Years) of Growing Up in Ireland.* ESRI. Dublin.

Schenck-Fontaine, Anika, and Lidia Panico. "Many kinds of poverty: Three dimensions of economic hardship, their combinations, and children’s behavior problems." *Demography* 56, no. 6 (2019): 2279-2305.

Shorrocks, Anthony F. "The measurement of mobility." *Econometrica: Journal of the Econometric Society* (1978): 1013-1024.

Thévenon, Olivier, Thomas Manfredi, Yajna Govind, and Ilya Klauzner. "Child poverty in the OECD: Trends, determinants and policies to tackle it." OECD. Paris. (2018).

Thornton, M., J. Williams, C.McCrory, A. Murray, A., and A. Quail, (2016). *Growing Up in Ireland: Design, Instrumentation and Procedures for the Child Cohort at Wave 2 (13 Years)*. Dublin: Department of Children and Youth Affairs.

Watson, Dorothy, Bertrand Maitre, Christopher Whelan, and James Williams. "Child poverty in a period of austerity." Heffernan, Emma; McHale, John and Moore-Cherry, Niamh (eds.) (2017).

Whelan, Christopher T., and Bertrand Maitre. "Identifying Childhood Deprivation: How Well Do National Indicators of Poverty and Social Exclusion in Ireland Perform?." *The Economic and Social Review* 43, no. 2, Summer (2012): 251-272.

Whelan, Christopher T., Dorothy Watson, Bertrand Maitre, and James Williams. "Family economic vulnerability & the Great Recession: An analysis of the first two waves of the Growing Up in Ireland study." *Longitudinal and Life Course Studies* 6, no. 3 (2015): 230-244.

Williams, J., S. Greene, E. Doyle et al (2009): *The Lives of 9 Year Olds: Growing Up in Ireland, National Longitudinal Study of Children (Report 1 of the Child Cohort).* Dublin; The Stationery Office.

Williams, James, Aisling Murray, and Christopher T. Whelan. "Multi-dimensional deprivation among 9-year-olds in Ireland: an analysis of the growing up in Ireland survey." *Child Indicators Research* 7, no. 2 (2014): 279-300.

Williams, J., A. Murray, D. O Mahony, A. Quail, C. O'Reilly, M. Thornton and M. Neary (2019). Growing Up in Ireland. National Longitudinal Study of Children. Technical Series Number 2019-7.

Appendix 1: Sample Design and Construction of Sampling Weights

The choice of sampling frame for the Child cohort of GUI was the National School System. A comprehensive list of all primary schools in the country was obtained from the Department of Education and Science. This list provided information on enrolment by age and gender and in addition details on the characteristics of the school such as region, disadvantaged status, size, school type, denominational status and gender mix. This information was used for pre-stratification prior to sample selection.

The sampling for the Child cohort was two-stage with the school being the primary sampling unit (PSU) and the child the secondary unit. As explained in Murray et al (2011) the primary schools had many of the features suited to being PSUs. A comparison of the number of children in the school system (as reported by the Department of Education and Science) and the number of children for the relevant age group as reported in the nearest census shows that the discrepancy is very small (e.g. some children are home-schooled).

Since non-response in a survey such as GUI is rarely random, the eventual sample obtained had to be re-weighted in order to ensure that it aligned with the population from which it is sampled. These weights were constructed by comparing the distribution of various dimensions in the sample with the distribution derived from tables provided by the Central Statistics Office (CSO) and drawn from the census of population. Given the two-stage sampling procedure (at school and then child level) two weights had to be constructed and this was carried out via the procedure described in Gomulka (1994). The school based weight was constructed on the basis of the number of nine-year olds in the school, the type and region of the school, whether the school was designated with disadvantaged status, the religious denomination of the school and finally its co-educational status. The second stage weight was then constructed on the basis of the study child's sex, family structure, maternal age, maternal PES, paternal PES, maternal education, maternal and paternal social class, household social class and tenure and maternal ethnicity. The second stage weights were also based upon some school dimensions used in the construction of the first stage weights viz. the number of nine year olds in school, the type and region of the school and whether it had disadvantaged status.

Between wave to wave attrition is not random and so re-weighting of the data each wave is necessary. The original sample in wave 1 consisted of 8568 children. Allowing for attrition due to migration etc the relevant target for wave 2 was 8465 children of whom 7525 responded, giving a response rate of around 89%. Attrition was associated with primary caregiver education, family structure, household social class and income. Re-weighting was then carried out on the basis of child's sex, family structure, maternal age, maternal PES, paternal PES, maternal and paternal social class, household social class and tenure and maternal ethnicity. Following analysis of non-response patterns in wave 2 the following dimensions were also used as a basis for constructing the attrition weight: maternal smoking and alcohol consumption, size of location of household, whether primary caregiver had experienced depression, family income and finally, willingness to complete the "sensitive" questionnaire (seen as an indication of commitment to the survey).

In wave 3 of the study the response rate was 81% of those who took part in wave 2 and in total just over 70% of the original 8568 children participated in all three waves. It is also important to remember that a much higher fraction of the responses in wave 3 of the survey were provided by the study child themselves, as opposed to the primary caregiver. Attrition nevertheless was associated with the same dimensions as in wave 2. In addition, higher rates of attrition were observed amongst study children who performed poorly in the wave 2 reasoning test and this may reflect engagement with the survey. The wave 2-wave 3 re-weighting was then based upon maternal education, family structure, family income, family social class, gender of study child and performance of study child in reasoning test in wave 2.

Appendix 2: Measure and Construction of Educational Outcomes

Wave 1	Test in reading and maths administered by the GUI fieldworkers at school. Known in Ireland as the Drumcondra tests and a feature of the Irish educational system for a number of years and linked to the national curriculum. Logit scores from test are used, obtained via Item Response Theory.
Wave 2	Shortened versions of the Drumcondra Reasoning Test focussing on items related to numerical ability and verbal reasoning. These are measures of cognitive ability or aptitude rather than performance in school or academic achievement and the content of the test is not related to the school curriculum. Logit scores from test are used, obtained via Item Response Theory.
Wave 3	Cognitive Naming Test, Cognitive Maths Test and Cognitive Vocabulary Test, details in Williams et al (2019).

Table 1: Rank Correlations Across Different Subscales/Components

Wave 1 – aged 9 years

	Drumcondra Maths	**Drumcondra Reading**
Drumcondra Maths	1.000	
Drumcondra Reading	0.5851	1.000

Wave 2 – aged 13 years

	Drumcondra Numerical	**Drumcondra Verbal**
Drumcondra Numerical	1.000	
Drumcondra Verbal	0.5496	1.000

Wave 3 – aged 17 years

	Cognitive Naming	**Cognitive Maths**	**Cognitive Vocab**
Cognitive Naming	1.000		
Cognitive Maths	0.2357	1.000	
Cognitive Vocab	0.2969	0.3709	1.000

Table 2: Rank Correlation of Composite Measure Across Waves

	Wave 1	**Wave 2**	**Wave 3**
Wave 1	1.000		
Wave 2	0.682	1.000	
Wave 3	0.569	0.692	1.000

Table 3: Rank Correlations between components of Education Measure

	Mathsls	Rdgls	Nals	Vrls	CogNam	CogMath	CogVoc
Mathsls	1.000						
Rdgls	0.582	1.000					
Nals	0.547	0.449	1.000				
Vrls	0.477	0.674	0.546	1.000			
CogNam	0.198	0.283	0.254	0.318	1.000		
CogMath	0.439	0.363	0.542	0.432	0.236	1.000	
CogVoc	0.368	0.543	0.421	0.656	0.295	0.368	1.000

Table 4: Fraction of Variance of Composite Measure Explained by 1st Principal Component

	Infant Cohort			**Child Cohort**		
	Wave 1	**Wave 2**	**Wave 3**	**Wave 1**	**Wave 2**	**Wave 3**
Fraction of variance	0.420	0.703	0.478	0.798	0.773	0.551
KMO	0.742	0.500	0.794	0.500	0.500	0.6234

We now discuss these tests in more detail.

Wave 1

In wave 1 of the child cohort the vast majority of the children were aged 9 and part of the survey consisted of tests in mathematics and reading which were administered by the GUI fieldworkers at school. These tests are known in Ireland as the Drumcondra tests and have been a feature of the Irish educational system for a number of years and are linked to the national curriculum. These are administered on an annual basis to all children in the primary school system. However, the particular tests for the GUI survey had not been seen by schools, teachers or pupils in advance of their use in GUI, thus it seems unlikely that students would have been intensively prepared for these tests, although they would have had some familiarity with tests of this kind from previous years.[14] It should be noted that the Drumcondra tests have no implications for further progression in the school system. The particular cohort of nine year olds in the GUI survey were spread over three different school grades (2nd, 3rd and 4th class) and three different levels of the test were administered, with the majority of the children in 3rd class (roughly equivalent to grade 3 in the US).

The test scores used for this wave are the results from these tests in maths and reading. As the tests were administered at three different levels it was necessary to standardise the results, hence the data we use are the logit scores which were obtained from the original raw data using the principles of Item Response Theory (see Lord, 1980). Results from tests at this age (and earlier) have been shown to have predictive power for subsequent later-life outcomes in areas such as education and health (Feinstein, 2003). It is important to note that the tests administered in wave 1 are *achievement* tests, based on the existing Irish primary school curriculum and essentially measures the amount the child would have learned at school up to then.

Wave 2

In wave 2 the children were now mostly aged 13 and the vast majority had entered the secondary school system. The secondary school system (which lasts from the ages of about 12-13 to 18) is more diverse in terms of curriculum and students have choice regarding what subjects they take (though practically every student will take Mathematics and English). The tests administered in wave 2 of GUI were shortened versions of the Drumcondra Reasoning Test focussing on items related to numerical ability and verbal reasoning. Thus critically they are measures of *cognitive ability or aptitude* rather than performance in school or academic achievement and the content of the test was *not* related to the school curriculum. As with wave 1, the scores which formed the basis of the composite measure are the logit scores from the test again obtained via Item Response Theory.

It must be stressed that ability/aptitude and achievement tests differ (see Jacob and Rothstein, 2016, and Williams et al 2018). Aptitude tests refer to scholastic ability not related to the school curriculum. Since they do reflect the acquisition of certain skills it is highly likely that

[14] For more details on these tests see Murray et al (2011).

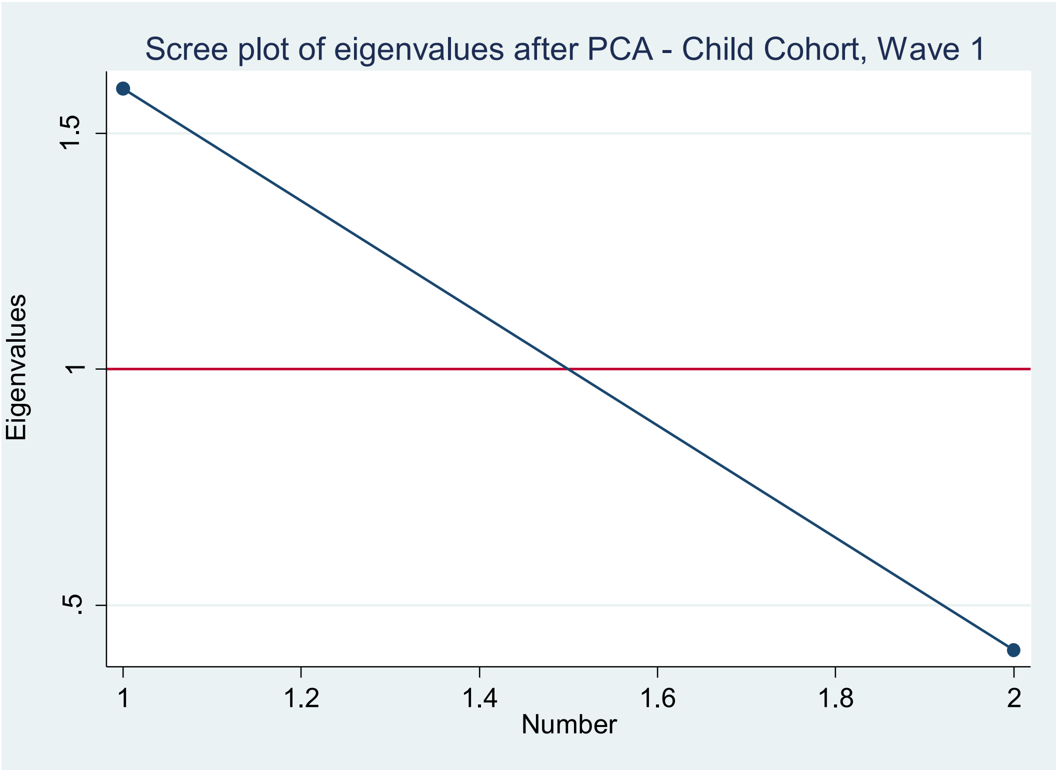
they will be influenced by the environment (school and home) where these skills are acquired but they are not specifically linked to the school curriculum. Achievement tests however measure performance and will be strongly influenced by school and home factors. The two measures are generally agreed to be quite strongly correlated (see Deary, 2007) and Hannan (1996) finds that verbal and numerical performance in the Differential Aptitude Test was highly predictive of subsequent achievement in the Junior Certificate. The Drumcondra Reasoning Tests were also chosen on the basis that they would provide some comparability across the waves of GUI (Thornton et al, 2016). However it is important to bear in mind the warning of Williams et al (2018): *"Although the 13 year old's results on the Drumcondra Reasoning Tests may be correlated with their academic achievement or school performance, it is important to emphasise the conceptual difference between the cognitive measure of ability captured by the DRT and a measure of school achievement or performance."*

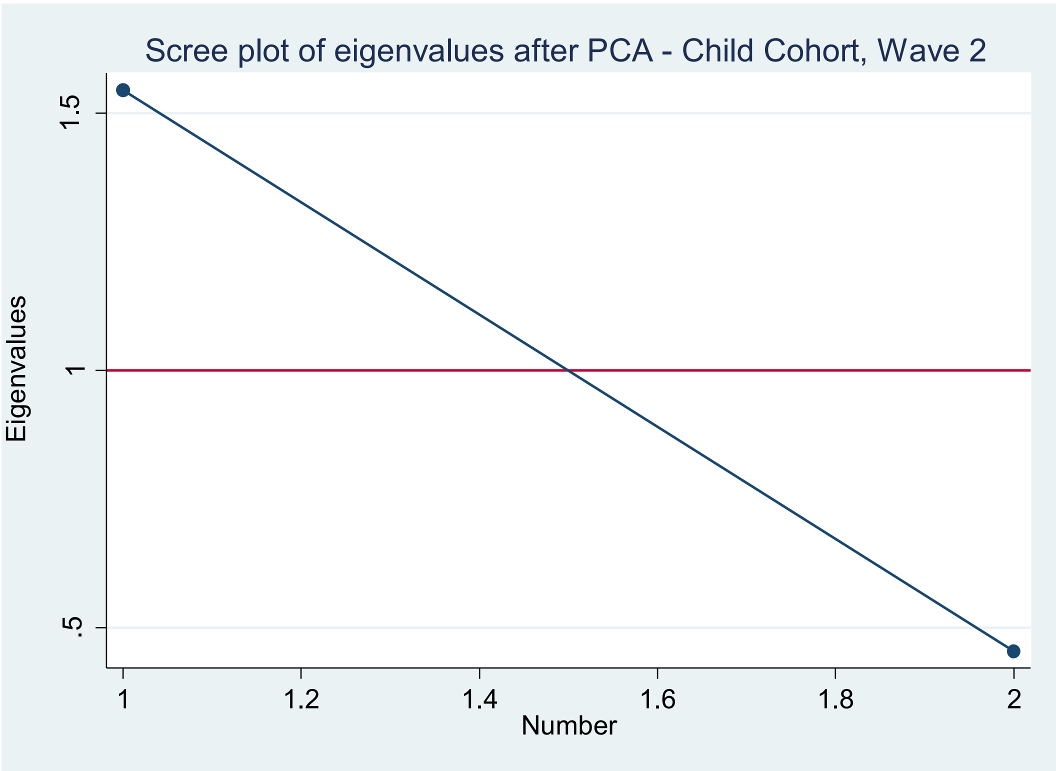
Wave 3

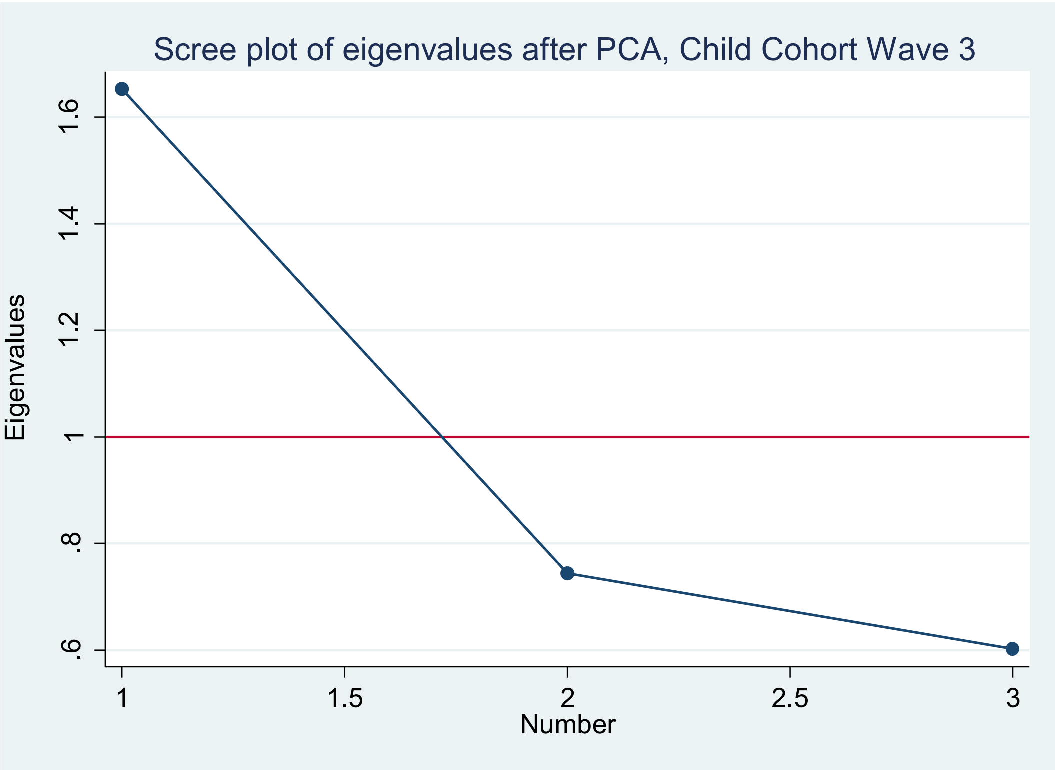
Wave 3 of GUI Child Cohort has outcomes from three cognitive tests. These are the Cognitive Naming Tasks, Cognitive Maths Score and Cognitive Vocabulary Test.

The Naming Task, also known as the Semantic Fluency Test involved the participant naming as many animals as they could think of in one minute and draws on general knowledge in long term memory. The Maths test involved three short questions aimed at testing the participant's ability to perform simple mathematical calculations and they also test financial literacy. The Vocabulary test consists of 20 words sharply increasing in difficulty. Each word is accompanied by five other words and the participant has to choose the word closest in meaning to the target word. Further details of the tests are available in Williams et al (2019).

Scree Plots for PCA

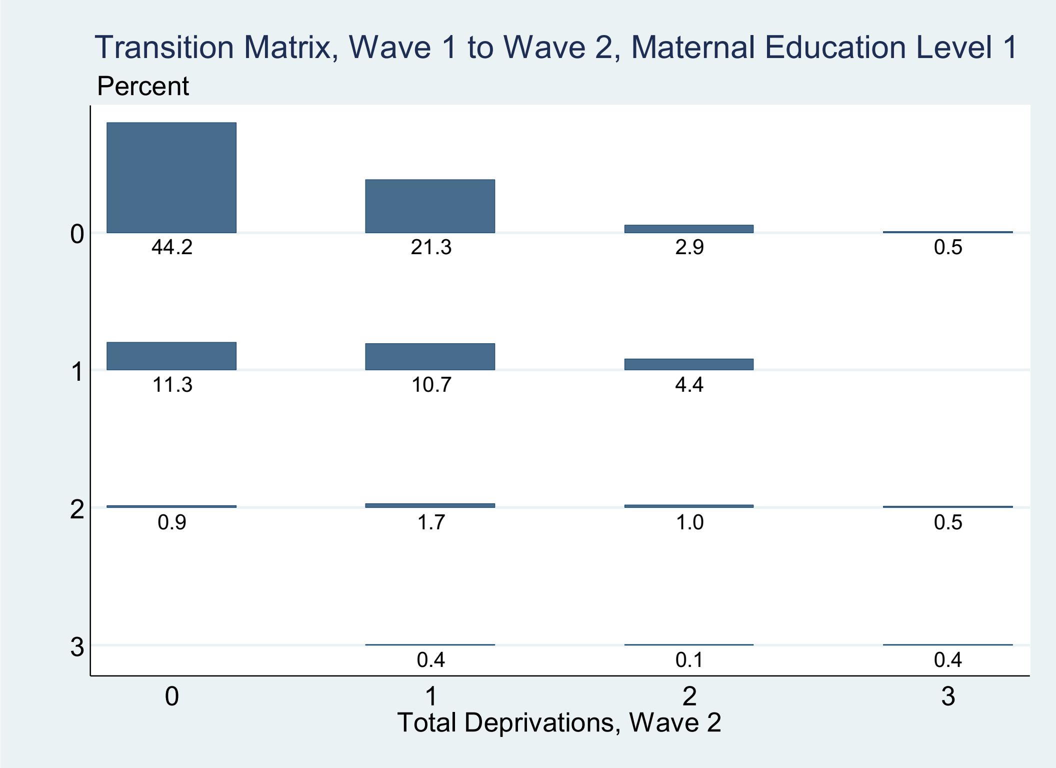


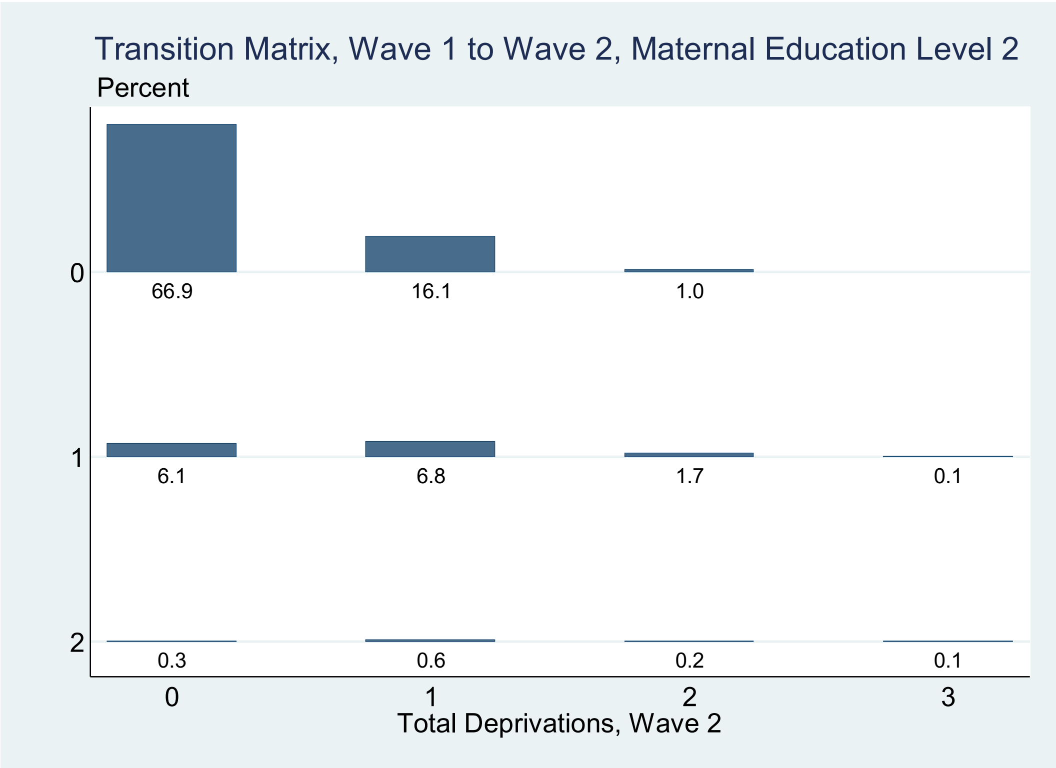


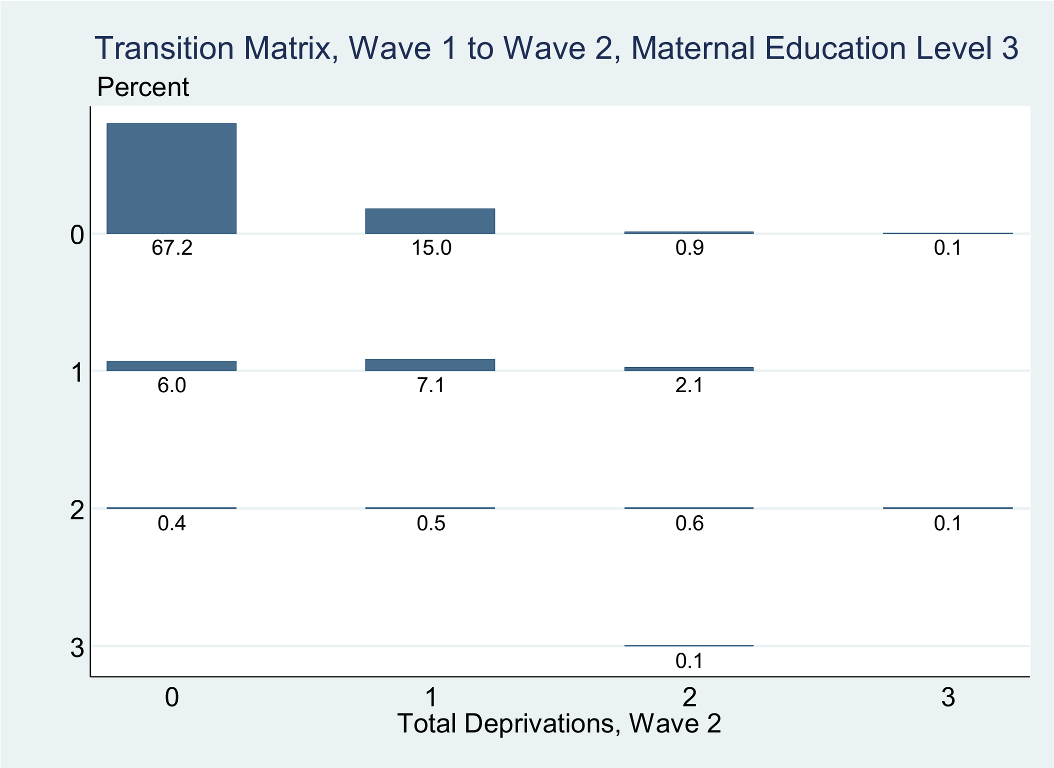


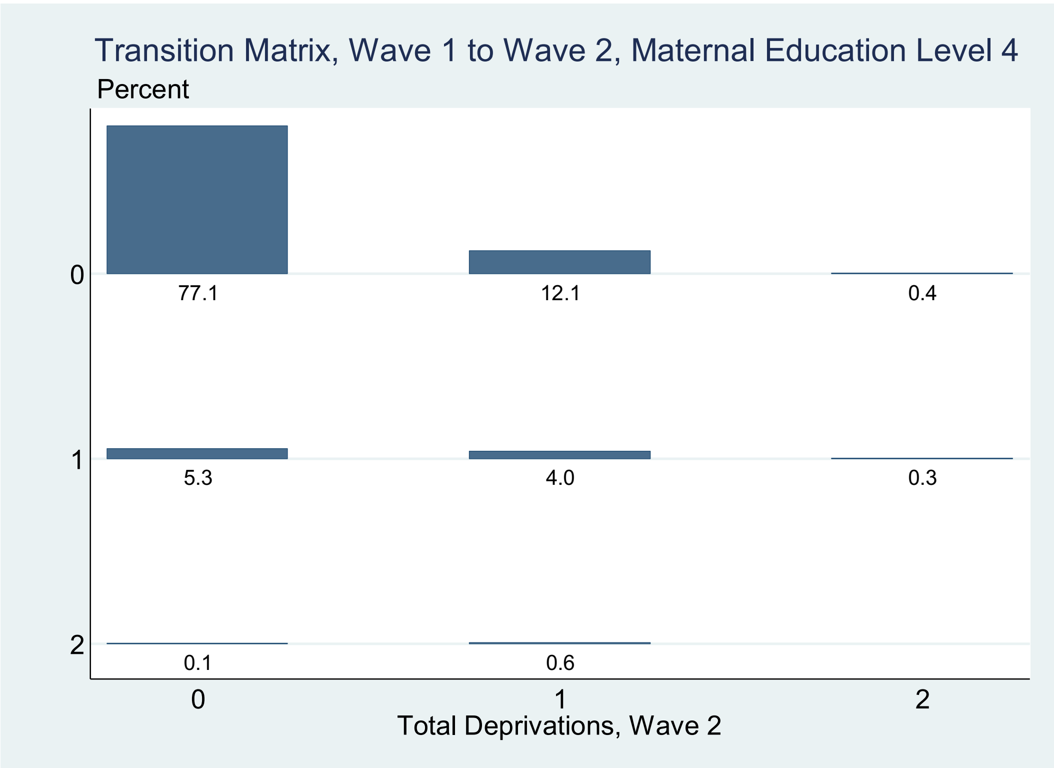
Scree plot of eigenvalues after PCA, Child Cohort Wave 3
Eigenvalues
.6
.8
1
1.2
1.4
1.6
1
1.5
2
2.5
3
Number

Appendix 3: Transition Matrices by Maternal Education Wave 1 to Wave 2

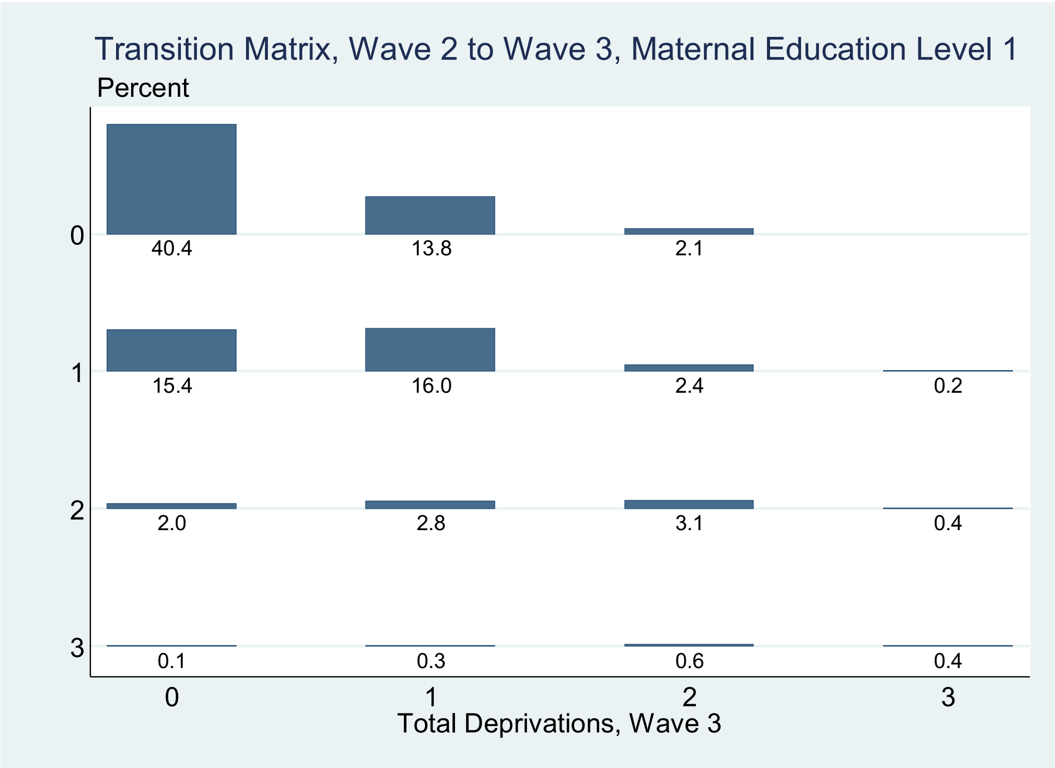


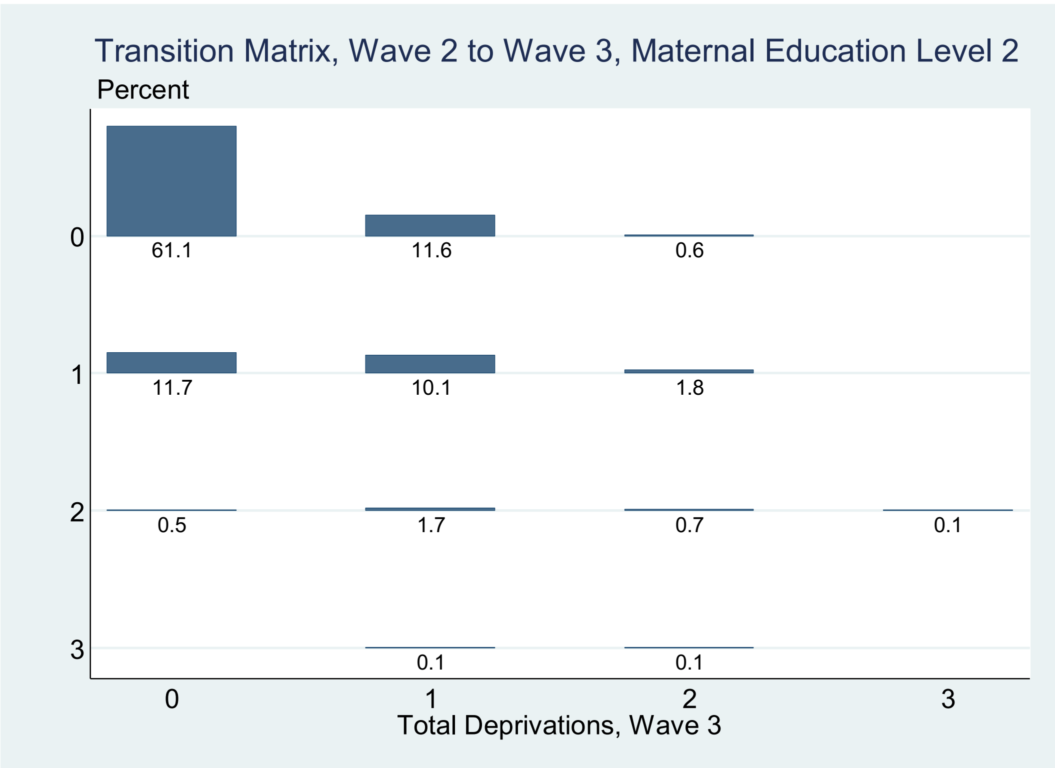


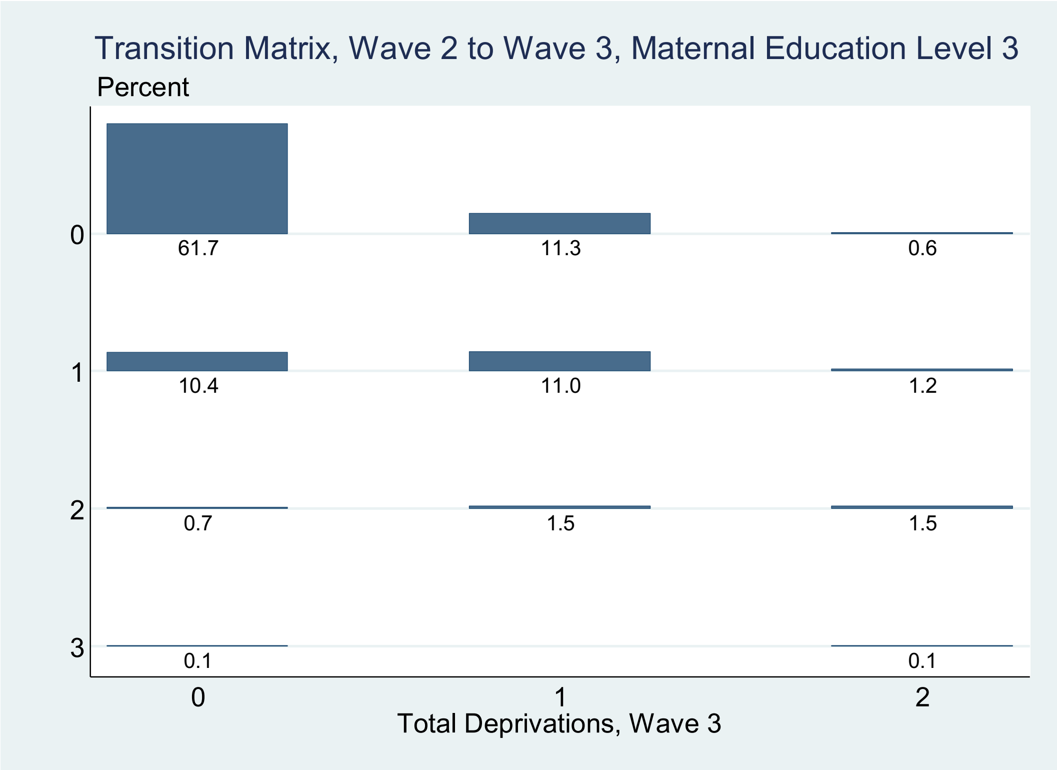

Transition Matrix, Wave 1 to Wave 2, Maternal Education Level 3
Percent
0
1
2
3
67.2
15.0
0.9
0.1
6.0
7.1
2.1
0.4
0.5
0.6
0.1
0.1
0
1
2
3
Total Deprivations, Wave 2

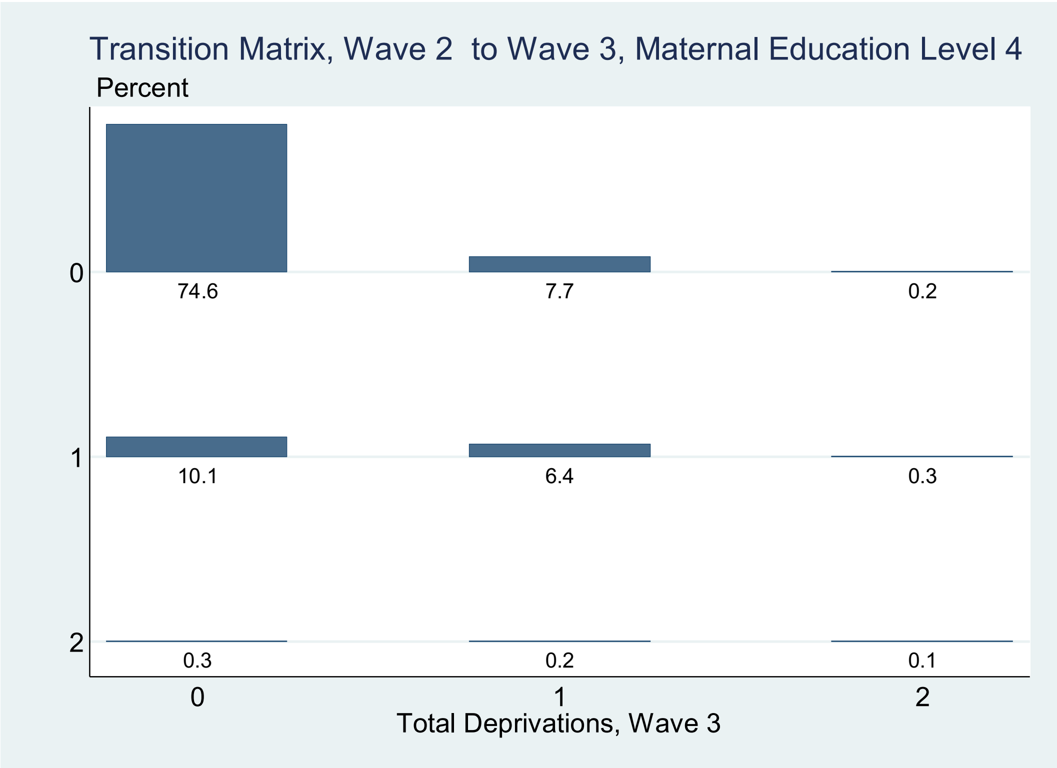

Transition Matrix, Wave 1 to Wave 2, Maternal Education Level 4
Percent
0
1
2
77.1
12.1
0.4
5.3
4.0
0.3
0.1
0.6
0
1
2
Total Deprivations, Wave 2

Transition Matrices by Maternal Education Wave 2 to Wave 3

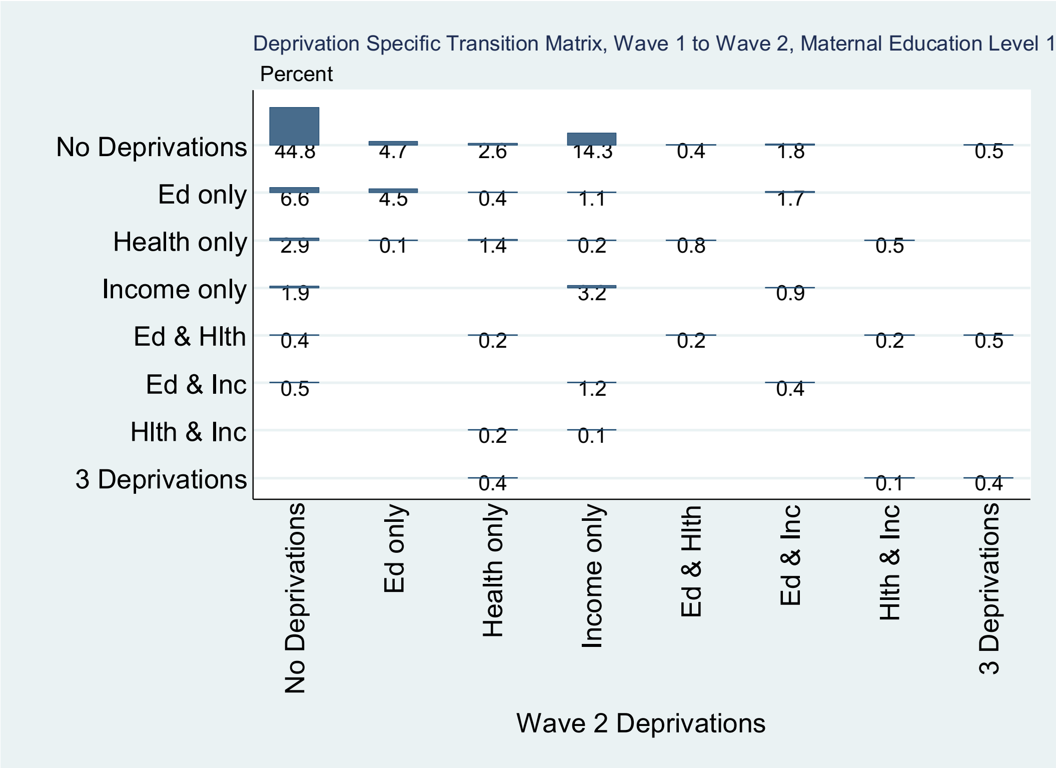


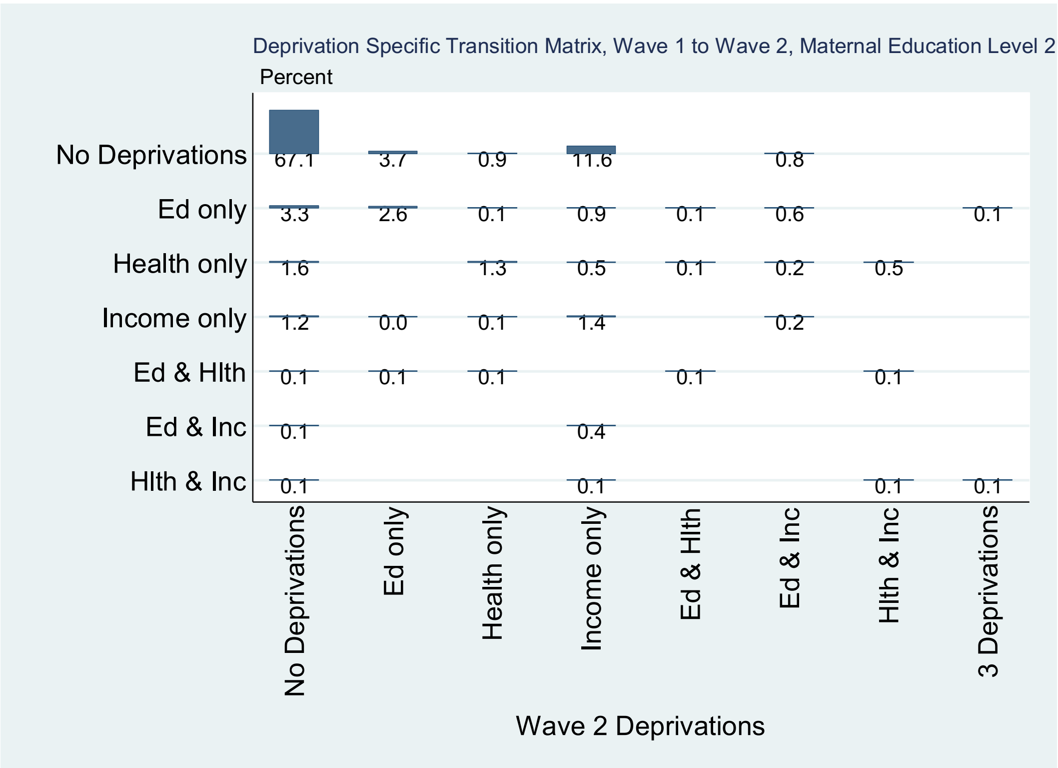


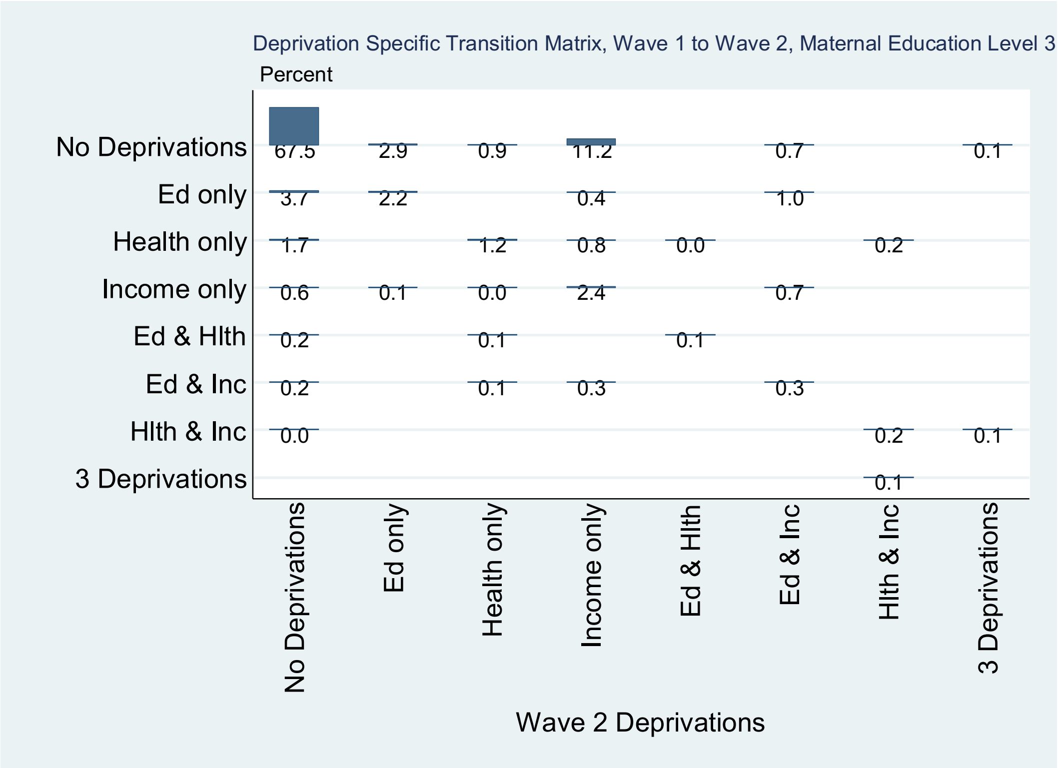

Transition Matrix, Wave 2 to Wave 3, Maternal Education Level 3
Percent
0
1
2
3
61.7
11.3
0.6
10.4
11.0
1.2
0.7
1.5
1.5
0.1
0.1
0
1
2
Total Deprivations, Wave 3

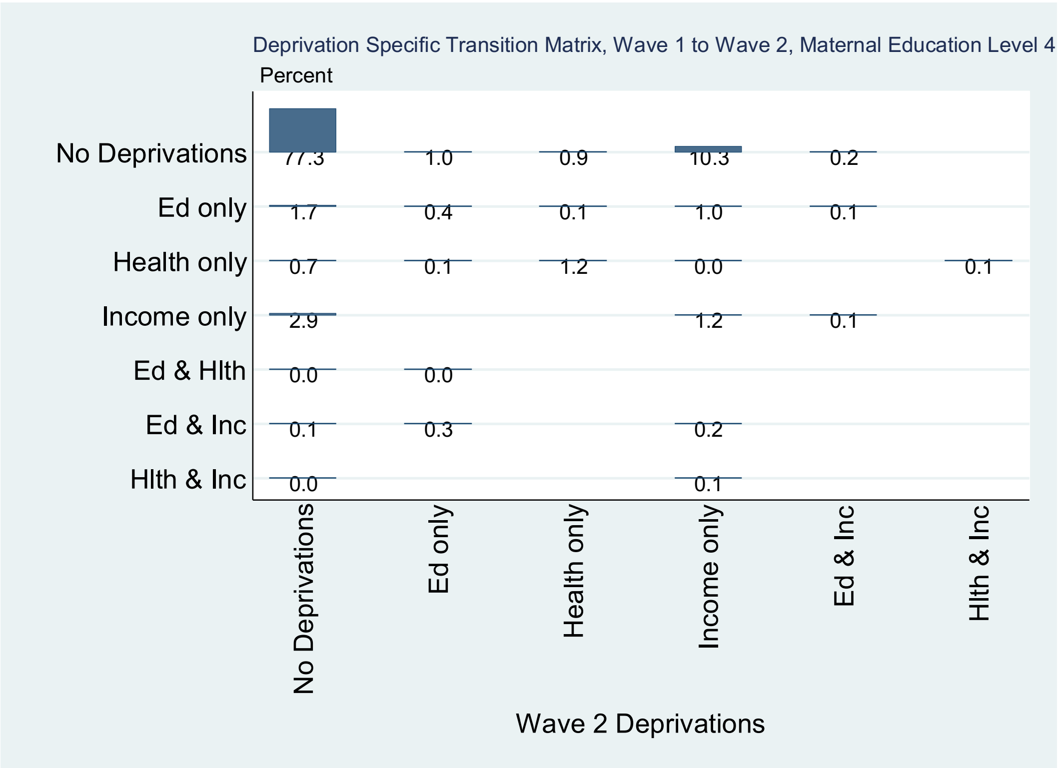

Transition Matrix, Wave 2 to Wave 3, Maternal Education Level 4
Percent
0
1
2
74.6
7.7
0.2
10.1
6.4
0.3
0.3
0.2
0.1
0
1
2
Total Deprivations, Wave 3

Appendix 4: Deprivation Specific Transition Matrices by Maternal Education, Wave 1 to Wave 2

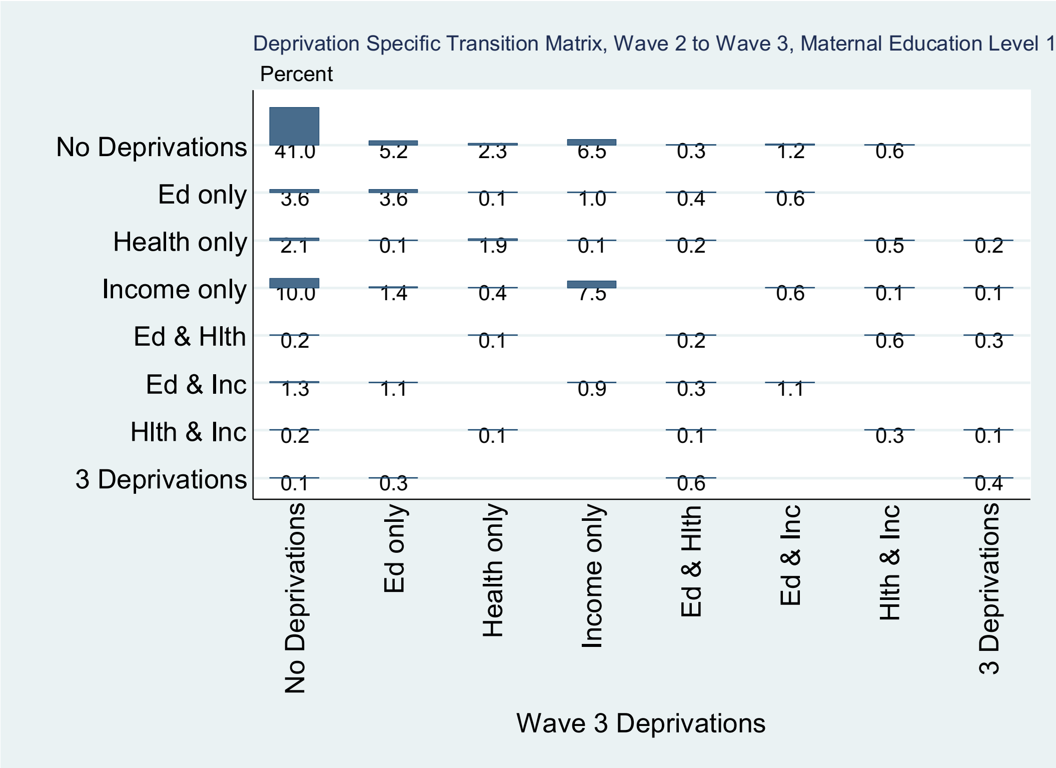


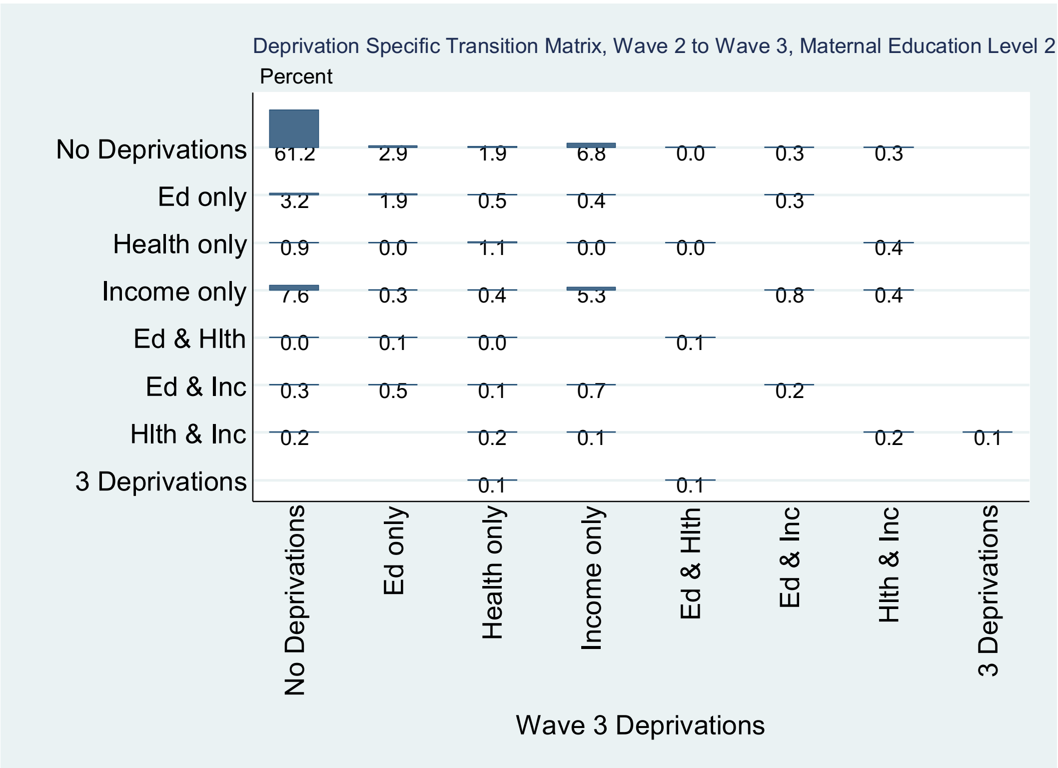


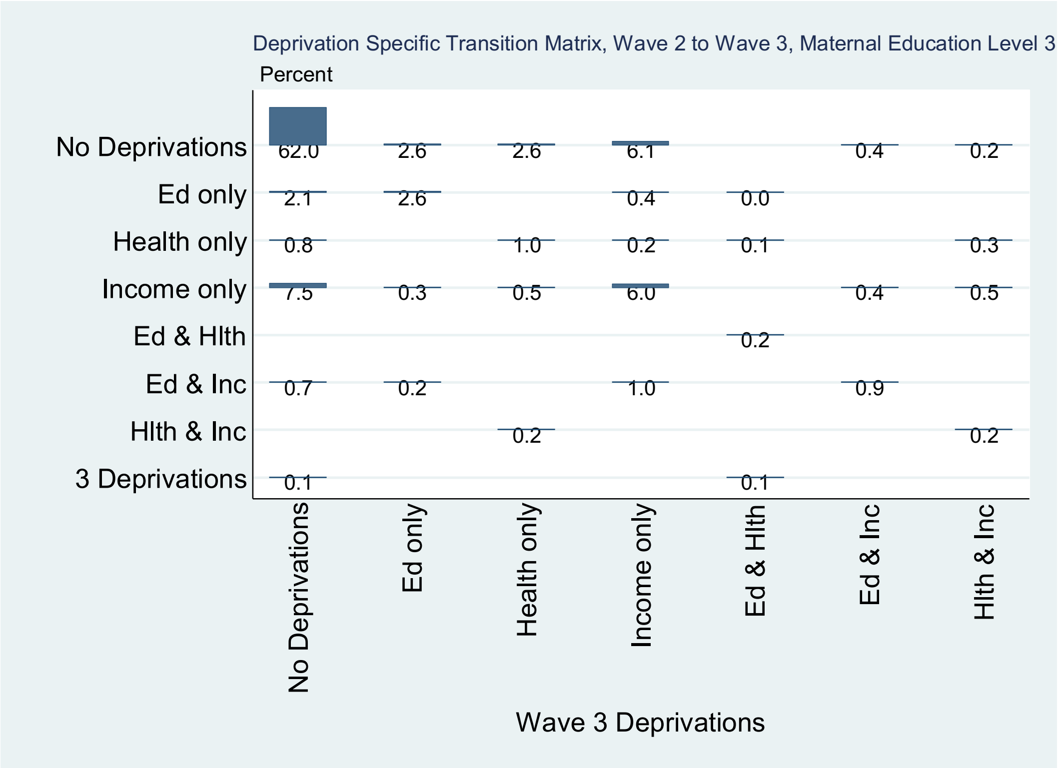

Deprivation Specific Transition Matrix, Wave 1 to Wave 2, Maternal Education Level 3
Percent
No Deprivations
Ed only
Health only
Income only
Ed & Hlth
Ed & Inc
Hlth & Inc
3 Deprivations
67.5
2.9
0.9
11.2
0.7
0.1
3.7
2.2
0.4
1.0
1.7
1.2
0.8
0.0
0.2
0.6
0.1
0.0
2.4
0.7
0.2
0.1
0.1
0.2
0.1
0.3
0.3
0.0
0.2
0.1
0.1
Wave 2 Deprivations

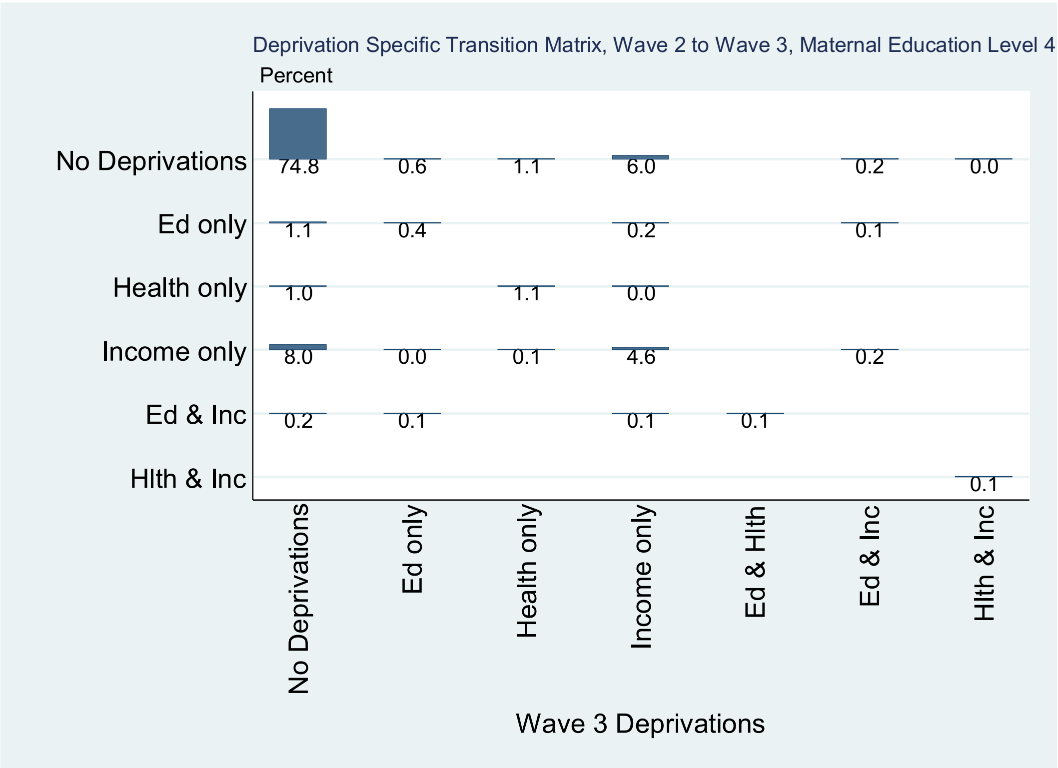

Deprivation Specific Transition Matrix, Wave 1 to Wave 2, Maternal Education Level 4
Percent
No Deprivations
Ed only
Health only
Income only
Ed & Hlth
Ed & Inc
Hlth & Inc
77.3
1.0
0.9
10.3
0.2
1.7
0.4
0.1
1.0
0.1
0.7
0.1
1.2
0.0
0.1
2.9
1.2
0.1
0.0
0.0
0.1
0.3
0.2
0.0
0.1
Wave 2 Deprivations

Deprivation Specific Transition Matrices by Maternal Education, Wave 2 to Wave 3






Deprivation Specific Transition Matrix, Wave 2 to Wave 3, Maternal Education Level 3
Percent
No Deprivations
Ed only
Health only
Income only
Ed & Hlth
Ed & Inc
Hlth & Inc
3 Deprivations
62.0
2.6
2.6
6.1
0.4
0.2
2.1
2.6
0.4
0.0
0.8
1.0
0.2
0.1
0.3
7.5
0.3
0.5
6.0
0.4
0.5
0.2
0.7
0.2
1.0
0.9
0.2
0.2
0.1
0.1
No Deprivations
Ed only
Health only
Income only
Ed & Hlth
Ed & Inc
Hlth & Inc
Wave 3 Deprivations


Deprivation Specific Transition Matrix, Wave 2 to Wave 3, Maternal Education Level 4
Percent
No Deprivations
Ed only
Health only
Income only
Ed & Inc
Hlth & Inc
74.8
0.6
1.1
6.0
0.2
0.0
1.1
0.4
0.2
0.1
1.0
1.1
0.0
8.0
0.0
0.1
4.6
0.2
0.2
0.1
0.1
0.1
0.1
No Deprivations
Ed only
Health only
Income only
Ed & Hlth
Ed & Inc
Hlth & Inc
Wave 3 Deprivations

Appendix: Is Multidimensional Deprivation Qualitatively Different?

In this appendix we explore the extent to which multidimensional poverty may be qualitatively different from unidimensional poverty. Is it the case that children who are poor in more than one dimension are qualitatively similar to those who are poor in one dimension but just have "extra" poverty? Or can we observe a qualitative difference?

To analyse this we adopt the approach of Beduk (2018), with a slight modification. We estimate a zero inflated count model of the number of deprivations which each child suffers. The zero inflated model allows for a mixture of data generation processes, with one process modelling zero versus non-zero outcomes (e.g. a logit or probit) and the other process modelling the number of non-zero integers or counts (e.g. a Poisson or negative binomial). Unlike the hurdle models which Beduk (2018) employed, with zero inflated models the count model applies to all observations, not just the truncated sample of non-zero counts. Thus zero is also a possible outcome for the count model, which is not the case for the hurdle models.

To test for the possibility that multiple deprivations are systematically different from single deprivations we examine the corrected Vuong statistic (Desmarais and Harden, 2013). A high value of the statistic indicates the presence of a zero-inflated component i.e. multiple deprivations are qualitatively different from single deprivations.

As an alternative approach to exploring this issue we also estimate multinomial probit and logit models.[15] Here we allow for three different outcomes: no deprivation, a single deprivation and more than one deprivation.[16] To save space we just present the results for the multinomial logit and for the Vuong test for the zero inflated model. Results for other models are qualitative very similar and available on request (although the three outcome multivariate probit did not converge for waves 2 and 3).

We choose as covariates maternal age (allowing for a non-linear effect), maternal education, equivalised family income (log) and maternal health.

[15] I am very grateful to John Mullahy for this suggestion and for discussion on this point.

[16] We also estimated multivariate probit and logit models over all possible combinations of deprivation outcomes (eight). However the multivariate probit model did not converge and the qualitative result for the multinomial logit was similar to the three outcome model so we do not present these results here.

Examining first of all the results from the multinomial model we see that comparing the model for one versus for many deprivations that the signs of the coefficients and the significance levels are the same in nearly every case. What is also noticeable is that the absolute size of the coefficients for many deprivations is always greater than for a single deprivation. Our interpretation of this is that for a variable such as "mother completed secondary school" this acts as a protection against having one deprivation and an even greater protection against having more than one deprivation. In other words, children with many deprivations are qualitatively similar to those with only one deprivation, except "more so".

The Vuong test also adds support to this. Unfortunately the zero inflated model only converged for the Poisson version in wave 1. However, when the Vuong test is corrected by either Aikake or Bayesian Information Criterion, the test statistic is low and not significant at conventional levels.

Overall then, the results of the analysis are not supportive of the idea that the factors associated with multiple deprivations are qualitatively different from those associated with single deprivations.

Appendix Table X: Voung Test Statistic

Wave 1	**Voung**	**AIC Corrected**	**BIC Corrected**
Zero Inflated Poisson	2.21	0.74	-4.08

Appendix Table X: Multinomial Logit, Number of Deprivations

	Wave 1 (N=5117)		Wave 2 (N=5117)		Wave 3 (N=5117)	
	Many Deps	**One Dep**	**Many Deps**	**One Dep**	**Many Deps**	**One Dep**
Maternal Age	-0.134 (0.249)	-0.256*** (0.092)	-0.521*** (0.161)	-0.230*** (0.081)	-0.347** (0.167)	-0.234*** (0.081)
Maternal Age^2	0.001 (0.003)	0.003** (0.001)	0.006*** (0.002)	0.002** (0.001)	0.004* (0.002)	0.003** (0.001)
Complete Secondary	-1.254*** (0.320)	-0.486*** (0.120)	-0.872*** (0.208)	-0.239** (0.107)	-0.770*** (0.207)	-0.289*** (0.107)
Diploma Cert	-0.769** (0.318)	-0.549*** (0.131)	-0.887*** (0.231)	-0.293*** (0.114)	-0.779*** (0.232)	-0.254** (0.114)
3rd Lev	-1.426*** (0.422)	-0.758*** (0.146)	-1.639*** (0.333)	-0.415*** (0.122)	-1.790*** (0.373)	-0.543*** (0.123)
Income	-1.438*** (0.224)	-0.842*** (0.100)	-1.904*** (0.207)	-1.231*** (0.085)	-2.329*** (0.212)	-1.166*** (0.086)
Mum Healthy	-0.597 (0.378)	-0.505*** (0.161)	-0.892*** (0.261)	-0.884*** (0.136)	-0.655** (0.262)	-0.455*** (0.147)
Constant	14.203*** (5.135)	13.156*** (1.921)	27.913*** (3.540)	16.947*** (1.731)	27.855*** (3.595)	15.557*** (1.718)

Appendix 2: Results using different definition of health poverty

In this section of the appendix we reproduce tables 1-8 and also figures 1-8 using a different definition of health poverty.

Table 1: Uni-Dimensional Poverty Rates

	Wave 1	Wave 2	Wave 3
Health Poor			
Total	**0.250**	**0.252**	**0.265**
Lower Secondary	0.307	0.318	0.331
Complete Secondary	0.246	0.253	0.268
Diploma/Cert	0.236	0.211	0.231
Third Level	0.184	0.187	0.187
Education Poor			
Total	**0.106**	**0.096**	**0.095**
Lower Secondary	0.188	0.164	0.182
Complete Secondary	0.085	0.086	0.077
Diploma/Cert	0.086	0.083	0.078
Third Level	0.039	0.021	0.016
Resources Poor			
Total	**0.058**	**0.200**	**0.173**
Lower Secondary	0.096	0.282	0.229
Complete Secondary	0.038	0.176	0.163
Diploma/Cert	0.052	0.188	0.167
Third Level	0.048	0.136	0.114

Table 2: Tetrachoric Correlations across Uni-dimensional Poverty

	E w1	H w1	R w1	E w2	H w2	R w2	E w3	H w3	R w3
E w1	1								
H w1	0.0340	1							
R w1	0.2450	0.2254	1						
E w2	0.6144	0.1124	0.1361	1					
H w2	0.0883	0.8275	0.1143	0.0811	1				
R w2	0.1754	0.1632	0.5520	0.1993	0.1662	1			
E w3	0.6079	0.1460	0.2316	0.6967	0.1974	0.2099	1		
H w3	0.0614	0.6978	0.0623	0.0731	0.7851	0.1232	0.0421	1	
R w3	0.1238	0.1298	0.4706	0.1507	0.1759	0.5670	0.1689	0.1782	1

Table 3: Multidimensional Poverty

	Wave 1				Wave 2				Wave 3			
	M=HA	H	A	AD	M=HA	H	A	AD	M=HA	H	A	AD
k=1	0.137	0.363	0.377	1.14	0.183	0.437	0.419	1.25	0.178	0.439	0.405	1.21
k=2	0.033	0.048	0.688	2.06	0.070	0.098	0.714	2.13	0.062	0.090	0.689	2.05
k=3	0.003	0.003	1.000	3.00	0.013	0.013	1.000	3.00	0.005	0.005	1.000	3.00

Table 4: Multidimensional Poverty by Maternal Education

	Wave 1				Wave 2				Wave 3			
	M= HA	H	A	AD	M= HA	H	A	AD	M= HA	H	A	AD
Lower Secondary												
k=1	0.196	0.497	0.394	1.19	0.255	0.580	0.440	1.32	0.247	0.576	0.429	1.29
k=2	0.059	0.083	0.711	2.13	0.113	0.154	0.734	2.20	0.107	0.154	0.695	2.08
k=3	0.011	0.011	1.000	3.00	0.031	0.031	1.000	3.00	0.012	0.012	1.000	3.00
Completed Secondary												
k=1	0.122	0.335	0.364	1.10	0.172	0.422	0.406	1.22	0.169	0.424	0.399	1.20
k=2	0.023	0.035	0.657	2.00	0.060	0.086	0.700	2.08	0.055	0.081	0.679	2.03
k=3	0.000	0.000	1.000	3.00	0.007	0.007	1.000	3.00	0.003	0.003	1.000	3.00
Diploma/Cert												
k=1	0.124	0.328	0.378	1.14	0.161	0.394	0.409	1.22	0.159	0.400	0.398	1.19
k=2	0.030	0.045	0.667	2.03	0.056	0.079	0.709	2.12	0.050	0.075	0.667	2.04
k=3	0.001	0.001	1.000	3.00	0.009	0.009	1.000	3.00	0.003	0.003	1.000	3.00
Third Level												
k=1	0.090	0.245	0.367	1.11	0.155	0.298	0.520	1.19	0.106	0.296	0.358	1.08
k=2	0.017	0.025	0.680	2.05	0.036	0.054	0.667	2.01	0.015	0.021	0.652	2.00
k=3	0.001	0.001	1.000	3.00	0.001	0.001	1.000	3.00	0.000	0.000	1.000	3.00

Table 5: Relative Contribution to Multidimensional Poverty

	Wave 1	Wave 2	Wave 3
k=1			
Health	60.17	45.56	49.15
Education	25.80	17.26	17.69
Resources	14.45	37.18	33.16
k=2			
Health	38.71	38.40	38.74
Education	35.77	22.10	23.55
Resources	25.52	39.50	37.71

Table 6: Mobility Indices

	Wave 1 to Wave 2				
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**
Average Transitions	0.383 (0.011)	0.503 (0.027)	0.354 (0.016)	0.353 (0.021)	0.285 (0.021)
Up-Down	0.134 (0.013)	0.174 (0.013)	0.145 (0.019)	0.108 (0.024)	0.072 (0.024)
	Wave 2 to Wave 3				
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**
Average Transitions	0.404 (0.011)	0.497 (0.026)	0.408 (0.016)	0.353 (0.020)	0.382 (0.018)
Up-Down	-0.014 (0.013)	-0.014 (0.013)	-0.007 (0.029)	-0.005 (0.023)	-0.025 (0.022)

Table 7a: Infinity Norm of Difference between Transition Matrices – Wave 1 to Wave 2

Total					
Mat Ed=1	0.199				
Mat Ed=2	0.041	0.232			
Mat Ed=3	0.056	0.248	0.046		
Mat Ed=4	0.205	0.397	0.186	0.150	
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**

Table 7b: Infinity Norm of Difference between Transition Matrices – Wave 2 to Wave 3

Total					
Mat Ed=1	0.194				
Mat Ed=2	0.030	0.222			
Mat Ed=3	0.078	0.272	0.007		
Mat Ed=4	0.203	0.397	0.186	0.153	
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**

Table 8a: Infinity Norm of Difference between Scaled Transition Matrices – Wave 1 to Wave 2

Total					
Mat Ed=1	0.106				
Mat Ed=2	0.021	0.125			
Mat Ed=3	0.313	0.131	0.042		
Mat Ed=4	0.104	0.210	0.105	0.083	
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**

Table 8b: Infinity Norm of Difference between Scaled Transition Matrices – Wave 2 to Wave 3

Total					
Mat Ed=1	0.142				
Mat Ed=2	0.028	0.169			
Mat Ed=3	0.036	0.168	0.049		
Mat Ed=4	0.129	0.269	0.105	0.120	
	Total	**Mat Ed=1**	**Mat Ed=2**	**Mat Ed=3**	**Mat Ed=4**

UCD CENTRE FOR ECONOMIC RESEARCH – RECENT WORKING PAPERS

WP20/23 Morgan Kelly: 'Understanding Persistence' September 2020
WP20/24 Jeff Concannon and Benjamin Elsner: 'Immigration and Redistribution' September 2020
WP20/25 Diego Zambiasi: 'Drugs on the Web, Crime in the Streets - The Impact of Dark Web Marketplaces on Street Crime' September 2020
WP20/26 Paul Hayes, Séin Healy, Tensay Meles, Robert Mooney, Sanghamitra Mukherjee, Lisa Ryan and Lindsay Sharpe: 'Attitudes to Renewable Energy Technologies: Driving Change in Early Adopter Markets' September 2020
WP20/27 Sanghamitra Mukherjee: 'Boosting Renewable Energy Technology Uptake in Ireland: A Machine Learning Approach' September 2020
WP20/28 Ivan Petrov and Lisa Ryan: 'The Landlord-Tenant Problem and Energy Efficiency in the Residential Rental Market' October 2020
WP20/29 Neil Cummins and Cormac Ó Gráda: 'On the Structure of Wealth-holding in Pre-Famine Ireland' November 2020
WP20/30 Tensay Meles and Lisa Ryan: 'Adoption of Renewable Home Heating Systems: An Agent-Based Model of Heat Pump Systems in Ireland' December 2020
WP20/31 Bernardo Buarque, Ronald Davies, Ryan Hynes and Dieter Kogler: 'Hops, Skip & a Jump: The Regional Uniqueness of Beer Styles' December 2020
WP21/01 Kevin Devereux: 'Returns to Teamwork and Professional Networks: Evidence from Economic Research' January 2021
WP21/02 K Peren Arin, Kevin Devereux and Mieszko Mazur: 'Taxes and Firm Investment' January 2021
WP21/03 Judith M Delaney and Paul J Devereux: 'Gender and Educational Achievement: Stylized Facts and Causal Evidence' January 2021
WP21/04 Pierluigi Conzo, Laura K Taylor, Juan S Morales, Margaret Samahita and Andrea Gallice: 'Can ❤s Change Minds? Social Media Endorsements and Policy Preferences' February 2021
WP21/05 Diane Pelly, Michael Daly, Liam Delaney and Orla Doyle: 'Worker Well-being Before and During the COVID-19 Restrictions: A Longitudinal Study in the UK' February 2021
WP21/06 Margaret Samahita and Leonhard K Lades: 'The Unintended Side Effects of Regulating Charities: Donors Penalise Administrative Burden Almost as Much as Overheads' February 2021
WP21/07 Ellen Ryan and Karl Whelan: 'A Model of QE, Reserve Demand and the Money Multiplier' February 2021
WP21/08 Cormac Ó Gráda and Kevin Hjortshøj O'Rourke: 'The Irish Economy During the Century After Partition' April 2021
WP21/09 Ronald B Davies, Dieter F Kogler and Ryan Hynes: 'Patent Boxes and the Success Rate of Applications' April 2021
WP21/10 Benjamin Elsner, Ingo E Isphording and Ulf Zölitz: 'Achievement Rank Affects Performance and Major Choices in College' April 2021
WP21/11 Vincent Hogan and Patrick Massey: 'Soccer Clubs and Diminishing Returns: The Case of Paris Saint-Germain' April 2021
WP21/12 Demid Getik, Marco Islam and Margaret Samahita: 'The Inelastic Demand for Affirmative Action' May 2021
WP21/13 Emmanuel P de Albuquerque: 'The Creation and Diffusion of Knowledge - an Agent Based Modelling Approach' May 2021
WP21/14 Tyler Anbinder, Dylan Connor, Cormac Ó Gráda and Simone Wegge: 'The Problem of False Positives in Automated Census Linking: Evidence from Nineteenth-Century New York's Irish Immigrants' June 2021
WP21/15 Morgan Kelly: 'Devotion or Deprivation: Did Catholicism Retard French Development?' June 2021
WP21/16 Bénédicte Apouey and David Madden: 'Health Poverty' July 2021

UCD Centre for Economic Research
Email economics@ucd.ie