The school to work transition for young people who experience custody

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Abstract:

We use individual-level population data to characterise the pathways followed by young people in England who experience custody. We identify a typology of pathways up to age 18 and a separate typology covering ages 19-22. Our results confirm the generally poor prospects among this group, showing 80 per cent to be firmly established as not in employment, education or training (NEET) by age 22. Despite the high level of deprivation in the population considered, prospects are still found to vary with specific markers of disadvantage. Managing to avoid NEET when 16-18 is an important part of the strategy for avoiding NEET when older. This suggests the importance of policy interventions aimed at re-engagement of those who experience custody as a young person.

Key words:

School-to-work transition, labour market, young people, custody, sequence analysis

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Introduction

This paper examines the nature of the school to work transition in England for individuals who experience custody.[1] Young people who experience custody are overwhelmingly from the most disadvantaged backgrounds (Williams et al., 2012; Taylor, 2016; Bowyer et al., 2021). Early exposure to custody is a strong predictor of poor outcomes later in life. Once young people have come into contact with the justice system, they are likely to do so again and, longer term, to struggle in the labour market (Youth Justice Board, 2006). This may be partly explicable by low employability and skills but the experience of being in prison may in itself make it more difficult to find work, thereby compounding initial disadvantage. An understanding of the typical pathways as such individuals move beyond school-leaving age therefore offers the possibility of developing better-informed policy and more effective support.

Numerous studies have sought to document the typical pathways that make up the school to work transition in the population as a whole. McVicar and Anyadike-Danes (2010), Dorsett and Lucchino (2014) and Holmes et al. (2022), are examples of British studies, while Brzinsky-Fay (2007), Quintini and Manfredi (2009), Brzinsky-Fay and Solga (2016) and Schoon and Bynner (2019) provide international evidence. The continued interest arises from a recognition of the importance of this life phase, in particular that adverse circumstances or experiences when young can have lasting consequences. Supporting this, empirical evidence points to the scarring effects of youth unemployment on employment and earnings (Arulampalam, 2001; Gregg, 2001; Gregg and Tominey, 2005; Schmillen and Umkehrer, 2017), while Dorsett and Lucchino (2018) and Andersson et al.

[1] The terms `custody', 'imprisonment' and 'incarceration' are used interchangeably in this paper.

(2018) provide evidence of the negative impact of being NEET (not in education, employment or training), particularly where this is prolonged.

However, there is very little evidence on the trajectories followed by young people who experience custody. A practical reason behind this is that the custody population is too small to be observed in the survey datasets typically used for this type of analysis. We overcome this obstacle by using newly-available administrative data on the full population of English children in state-funded education. From this population, we use as our sample for analysis all those observed to experience custody between the ages of 13 and 18 or who were observed to by studying while in prison between the ages of 19 and 22. The use of administrative data for analysis of this type is quite rare; Achatz et al. (2022) provides a notable example for the case of Germany.

The data used in this paper links education, participation and tax records to provide month-by-month histories from the age of 13 until 22 for individuals in England born between September 1994 and August 1995. A major advantage to using administrative data is that the full population is observed. A limitation relative to survey data is that it does not allow as rich a characterisation of economic activity at a given point in time. Up to age 18 (secondary school age), we identify typical patterns of transitions between four possible states: education, employment, custody and NEET (the residual category). From age 19 onwards (young adults), the data only allows partial identification of custody, so the analysis is based on three states: education, employment and NEET. Again, NEET is a residual category although, unlike with the younger group, it now includes custody. Using these three states, we identify typical patterns of transition among 19-22 year-olds and examine how individuals' patterns when younger compare to their outcomes when older. Doing this allows an assessment of the extent to which the patterns seen in these early years predict longer-term outcomes. Finding a high degree of correlation would suggest that those likely to face ongoing difficulties in the labour market are often identifiable at a very early stage and would point to the importance of early transitions.

Our expectation is that NEET status will dominate activity histories for the custody population. This expectation is based on the low levels of employability among this group but also the penalty imposed by custody itself. Although the analysis does not engage with the question of causality, there are theoretical reasons why custody may affect labour market prospects. Broadly, such an effect might arise through two channels (Aizer and Doyle, 2015). First is the behavioural channel. Being imprisoned might alter children's characteristics and behaviour in a way that has downstream impacts on education and labour market outcomes. Most obviously, incarceration interrupts education and may result in children being 'left behind'. Equally, incarcerated children may be negatively influenced by their peers within the correctional facility (Bayer et al., 2009). Incarceration may also harm children's mental health and reinforce their view of themselves as criminals (Forrest et al., 2000). Second is the labelling channel. Individuals who have experienced custody might be stigmatised by schools and employers and experience discrimination as a result (Bernburg and Krohn, 2003). They may also be treated differently by police and, if charged, by courts. Again, such treatment risks further reinforcing their criminal identity.

Methodologically, the empirical approach uses sequence analysis combined with cluster analysis to identify groups of young people following broadly similar pathways (see Schoon et al., 2001, for an early example of this). A strength of sequence analysis in this case is that it incorporates full information on the dynamics around young people who experience custody, including the order in which events occur, the number of spells of different types and the duration of spells. As such, the paper takes a life-course perspective (O'Rand, 1998). Rather than investigate transitions alone, it recognises the importance of patterns of transitions over an extended period and the cumulative evolution of outcomes.

Our results suggest that for young people who experience custody, their early cluster is predictive of their later cluster. The majority will not manage a successful entry into the labour market over the period considered. Those most likely to do so are those who, between the ages of 16 and 18, engaged in employment or educational activity of some kind.

The justice system for children and young people in England

The modern youth justice system was established by the Crime and Disorder Act 1998. Under the Act, young people charged with a criminal offence have their cases heard, at least initially, in the youth court; a type of magistrates' court for young people aged between 10 (the age of criminal responsibility) and 17. Serious crimes are passed to the Crown Court. For other crimes, the youth court can pass a range of custodial and non-custodial sentences.

Custodial sentences usually take the form of a Detention and Training Order (DTO) and last between 4 months and 2 years; the first half served in custody, the second in the community. The custodial period may be served at a young offender institution (YOI), a secure training centre (STC) or a secure children's home (SCH). Despite only serving boys aged 15–17, YOI's account for most of the youth custody population; 73% in 2018/19, compared to 17% in STC and 10% in SCH. YOIs mainly hold children considered to be more resilient. STCs are smaller and accommodate more vulnerable children. SCHs are smaller still and designed for especially vulnerable children.

Non-custodial sentences include Referral Orders (whereby the offender agrees a contract with restorative commitments lasting 3-12 months which aim to make up for harm caused by their offending and support the child towards living a safe and crime-free life) and Youth Rehabilitation Orders which specify requirements the offender must comply with for up to three years (such as curfew, electronic tagging, voluntary work). The courts can also use Liaison and Diversion services to divert vulnerable offenders to the appropriate places of treatment at sentencing.

From age 18, young people are regarded as adults by the law. However, those sentenced to custody will not go to an adult prison but instead be sent to a facility for 18 to 25-year-olds.

Figure 1 shows the trend in numbers of under-18s in custody since 2000 (Youth Custody Service, 2021). Since 2008 there has been a marked and steady reduction. This reflects both a fall in the number of proven offences by children[2] but also an increased tendency to divert children from entering the youth justice system; the respective role of these two factors is unclear (National Audit Office, 2022). With less challenging individuals diverted away from the courts, young people entering custody increasingly constitute a 'hard core' with complex needs.

Figure 1 here

Also shown in Figure 1 is the number of children in care (Department for Education, 2021). Our analysis distinguishes such look-after children from other children due to their over-representation among those in custody. The degree of over-representation is substantial; those in care account for less than 1% of all children but approximately half of all children in custody (Laming, 2016). Figure 1 shown a steady growth in their numbers since 2000.

Methodology

We identify a typology of young people's transitions into and out of custody using a combination of sequence analysis and cluster analysis. Sequence analysis techniques are used to construct a measure of dissimilarity between each pair of sequences (Abbot and Forrest, 1986; Sankoff and Kruskal, 1983). Cluster analysis is applied to these measures of dissimilarity, allowing similar sequences to be grouped together.

Sequence analysis begins by representing each individual's history over a period of time as a series of values, with each value representing the state an individual occupies at that point in time. With our data (see next section), each sequence consists of 115 months, running from academic ages 13 to 22. As noted already, the sequences are split into two periods, an early period covering up to the

[2] Less serious or first-time offences may be dealt with by the police without involving a court, using cautions or community resolutions (an informal resolution agreed with the victim of the crime).

academic age 18 and a later period covering academic ages 19 to 22. This division is prompted by the fact that, in the available data, custody is fully observed up to age 18 but only partially beyond that point. Specifically, between ages 19-22, custody is inferred from education records showing that an individual participates in a course of study that is delivered in a prison. Our analysis is based on all individuals *observed* to experience custody. This maximises the number of individuals whose transitions can be considered. Since it excludes individuals who only experienced prison when aged between 19 and 22 and who did not participated in a course during that time, the analysis is representative of all those who experienced youth custody or who participated in training or education when in prison aged 19-22.

In the early period (ages 13-18), the possible states we consider are: education while looked after, education while not looked after, employment, NEET, custody and missing (unobserved). The need for this latter state reflects issues with data collection and quality in the underlying systems. In particular, school summer holidays are less well-recorded so there is sometimes a break at this time in individuals' observed histories. Other possible reasons for individuals having missing observations for some months include moving to England after the age of 13 or spending some time in independent schools. In the later period (ages 19-22), the possible states are reduced to education, employment and NEET, where NEET now implicitly includes those in custody.

The sequence analysis algorithm compares each young person's sequence with that of each other person and derives a measure of dissimilarity. For each such pairwise comparison, this measure is calculated on the basis of the number and type of changes required to the second sequence to make it identical to the first sequence. The type of change we allow is the substitution of one state for a different state. We do not allow insertions of states into the sequence nor deletions. The reason for this is that the academic year features prominently in young people's lives, with transition points such as school holidays and national examinations happening at the same time for everyone. These key points are important to the profile of young people's pathways and allowing insertions/deletions would disrupt this timeline.

To implement sequence analysis, a cost matrix is required. The intuition behind this is that a higher cost should indicate a change that is `bigger' in the sense of resulting in a state that is more different from the current state. Rather than arbitrarily specify this, we use a data-driven approach whereby the cost for a particular transformation is inversely related to how often a transition of that type is seen in the data. Furthermore, these costs are allowed to vary over time, reflecting the fact that particular types of transformation are more common at particular stages in the life-course. This is the Dynamic Hamming distance, defined as the inverse of the conditional transition probability at the specific point in the sequence.

Cluster analysis is conducted on the measures of dissimilarity to group similar sequences together. Deciding the clustering algorithm and the number of groups requires careful consideration. The Partitioning Around Medoids algorithm (Kaufman and Rousseeuw, 1990) which minimises the sum of dissimilarities between each sequence and its group's medoid was used due to its robustness to outliers. Alternative clustering methods were found to produce broadly similar results, suggesting the findings were not particularly sensitive to this choice.

The specified number of clusters was allowed to vary between 2 and 20. The preferred number was in part guided by a comparison of statistical indices of fit, in particular the average Silhouette width (Rousseeuw, 1987). However, the presence of missing periods in the data coupled with the relative rarity of custody means that the clustering algorithms may not always suggest the most informative number of clusters. We therefore also relied on visual inspection of the main patterns in the resulting clusters as captured by index plots in order to decide on the number of clusters. Ultimately, a combination of a local maximum for the silhouette score and visual inspection of the index plots leads to 5 clusters being selected in each period (13-18 and 19-22).

The combination of sequence analysis with cluster analysis is a powerful technique that can synthesise large amounts of information from complex sequences and categorise these into relatively homogenous groups. The strength of sequence analysis lies in its holistic nature, as its algorithm draws on information from the full set of elements in a sequence. It therefore overcomes limitations of other commonly used statistics, which generally summarise outcomes at a point in time or over a specified period, discarding important information on dynamics. Instead, sequence analysis allows histories to be compared in their full dynamic richness, including the type, length, order and timing of spells.

However, there is a risk that a mechanical application of purely statistical techniques may lack sociological meaning (Levine, 2000; Morgan and Ray, 1995; Wu, 2000) and of being determined by arbitrary choices of the researcher (Everitt, Landau, Leese and Stahl, 2011; Wu, 2000). This motivates the inspection of index plots to ensure that the resulting clusters make intuitive sense. Nevertheless, whether the resulting typology does in fact have an objective socioeconomic significance, or the extent to which this meaning may be attributed subjectively ex-post by the researcher remain open questions. This element of subjectivity is recognised and therefore the reader is cautioned from taking descriptions of the groups identified as absolute.

Using the identified clusters, a simple transition matrix of early cluster to later cluster provides an indication of the extent to which childhood pathways relate to those of early adulthood. We examine this in more detail using multinomial logit regression to estimate the probability of each of the late period clusters, allowing for the influence of both childhood cluster and personal characteristics.

Data

Analysis is based on a linked administrative dataset, NPD-LEO (Jay et al, 2019; Anderson and Nelson, 2021), which is maintained by the Department for Education, the ministry responsible for education in England. This provides individual-level data on the full population of pupils in state-funded education.

The respective components of NPD-LEO are outlined below:

- The National Pupil Database (NPD) provides a history of enrolments, attainment, attendance and exclusions while in the state-funded school system. Personal information such as special educational needs, eligibility for free school meals (a measure of disadvantage) and area of residence is also included. Several other government datasets are included within the NPD. Of particular relevance to this study is the information on whether children are in care (children looked after) or receiving social services (children in need). Monthly activities in the two to three years following compulsory schooling originate from the National Client Caseload Information System (NCCIS), which forms part of the NPD.[3] Essential to this study, the NCCIS records those months spent in custody.[4] Within NPD, individuals are indexed by a common identifier (PMR).
- The Longitudinal Educational Outcomes (LEO) data is drawn from other government sources and provides data on labour market and education outcomes beyond school-leaving age. These include enrolments and achievements in further and higher education (colleges and universities), spells in employment, spells in receipt of state benefits and earnings in employment. Within LEO, individuals observed in the component datasets are linked using

[3] A feature of the NCCIS activity histories is that some months are recorded as not known. For such gaps, monthly status was imputed. If the status before the gap was the same as after, the missing months were imputed to that same status. If the status before and after differed, the transition from the initial to the later state was assumed to occur at a randomly selected month within the gap.

[4] Analysis reported in Bowyer et al. (2021) shows that custody levels taken from NCCIS compare quite closely with official statistics, although there is some evidence of under-reporting.

pattern matching (names, addresses, date of birth etc.) and assigned an identifier which is then matched to the NPD identifier.

The analysis in this paper is based on a dataset made up of all individuals born between September 1994 and August 1995 who are observed in the National Pupil Database between the years 2001 and 2014. This covers nearly the full cohort of individuals born in the 1994/95 academic year who either remained in England or moved to England. For this group of individuals, the available data covers up until 2018, by which time the cohort was age 22.

We use NPD-LEO to track the education, social care, custody and employment histories of the cohort. We derive a monthly activity indicator for each individual. Up to age 18, we consider the following states: education; employment; NEET; custody. Adopting the terminology 'CLA' (child looked after), we separate education while CLA from education while not CLA. Beyond age 18, we distinguish between three states: education, employment and NEET. We no longer distinguish education while in care from education while not in care since this distinction is not generally applicable beyond age 18. Furthermore, custody is only observed beyond age 18 where an individual participates in education or training while imprisoned. In view of it only being partially observed, we do not include custody as a distinct state beyond age 18 bur instead regard those in prison at this age as NEET. Hence, NEET status among the older group is different from NEET status among the younger group.

We highlight that, unlike the other statuses considered in this paper, NEET status is not observed but is instead defined as not being in one of the other states. Essentially, it is a residual category and, as a consequence, it is very heterogenous. Levels et al. (2022) highlights the lack of a coherent sociological interpretation of NEET and provide an overview of the multiple theoretical reasons why some young people become NEET. Nevertheless, the policy relevance of NEET as a status for young people aged 16-18 gained prominence following publication by the UK government of its *Bridging the Gap* report (Social Exclusion Unit, 1999), which argued that that this phase in a young person's development was pivotal to longer-term life chances and represented a point where policy could play an effective role. Over time the relevance of NEET beyond age 18 has become recognised and UK statistics now cover ages 16-24.[5] This age range more closely aligns with the definitions used by most other EU countries (Eurofound, 2012).

From this overall population, we select the subgroup of individuals who experienced custody by age 18 (identified from data fields available for looked after children and from the NCCIS) and those who are observed in prison beyond this age (mainly identified from those enrolled in a course of study that is delivered in prison). Around 7,500 individuals from the cohort are retained in this group.

Other than its large size, a particular strength of administrative data is that it avoids the standard problems that beset survey data such as non-response bias and recall error. Typically, the drawback is that administrative data is less rich, a consequence of not having been expressly designed for research purposes. While the data used in this study is rich by administrative data standards, it remains the case that some potentially informative variables are not observed. Nevertheless, the variables needed to capture transitions are there in full and provide the definitive basis for such an analysis.

Results

Table 1 provides some basic descriptive statistics for the cohort as a whole and for the custody subgroup. A first point to note is the highly selected nature of the custody subgroup. Only about 1 per cent of the cohort experiences custody at some point. From this, the need to restrict the estimation sample to the custody cohort is evident. Since the proportion with experience of custody is so small, their experiences would be lost in an analysis on the full cohort. A consequence of this is that the analysis is not able to contrast young people who experience custody with those who do

[5] https://www.gov.uk/government/statistics/neet-age-16-to-24-2021

not, all the young people in the estimation sample experience custody at some point. Instead, we look at the different pathways followed by those who experience custody.

This subgroup has quite different characteristics from the population as a whole. Individuals who experience custody are much more likely to be male and non-white, to have been identified as having special educational needs, to have been on the Children in Need register, have been the subject of a Child Protection Plan, or have been looked after by the state[6]. They are also likely to have resided in more deprived areas -- as captured by the IDACI (Income Deprivation Affecting Children Index) measure -- and to have scored less well at Key Stage 4 exams.

Table 1 here

Using the monthly histories to perform sequence analysis and cluster analysis resulted in the identification of five clusters over ages 13-18 and five clusters over ages 19-22. The silhouette score for the younger age group was rather low (0.23), although it compares favourably with 0.21 for four clusters and 0.19 for six clusters. While this silhouette score is helpful in choosing the preferred number of clusters, we do not take its low value as the sole determinant of the success of the procedure. Instead, as mentioned earlier, it is important to consider whether the resulting clusters make intuitive sense in the extent to which they tend to group together children following recognisably similar pathways. This applies also to the older age group, although here the silhouette score is higher (0.52) so there is not such a concern about the statistical justification of the clusters.

The clusters are depicted through index plots that show, in full detail, the individual histories of each member of the cluster. Each history is represented as a horizontal series, colour-coded according to status in a particular month. Stacking the series for all individuals in each group creates the index plot, which gives an immediate visualisation of the general dynamics characterising that cluster.

[6] Within NPD, data on children looked after has been collected since the 2005/06 academic year and data on children in need since 2008/09. This means we only partially observe being in care, being in need and being subject to a child protection plan. For the cohort studied, we observe CLA status from age 11 and CIN status from age 13.

The index plots for the five age 13-18 clusters are presented in Figure 2. An immediate impression is of the clusters being well-differentiated and for there to be some discernible commonality across histories within each cluster. Labelling these 'early' clusters E1-E5, we suggest the following characterisation:

E1 Children in care who become NEET after age 16

E2 Mostly missing / not observed

E3 Non-CLA children who become NEET after age 16

E4 Non-CLA children who enter employment sometime by age 18

E5 Non-CLA children who remaining in education post 16.

As an initial comment, the results offer some support for the approach taken to handling missing data. Those about whom we know relatively little have been grouped into a single cluster (E2) and so can effectively be 'quarantined' when considering how membership of one of other clusters is associated with later transitions. Furthermore, we note all other clusters are characterised by a period of missingness at the time of school-leaving age. This suggests that the absence of information on activity at that life-stage does little to affect the ability of the analysis to cluster individuals into meaningful groups.[7]

The largest cluster is E3. When combined with E1, it is clear that roughly half those with experience of custody are mostly NEET after school-leaving age. It is notable that E1 is the only cluster in which looked-after children feature. The fact that NEET is the dominant E1 outcome is indicative of the challenges faced by members of this group. More positively, roughly the same number of young people are in E4 and E5. These are young people who appear to have successfully entered the labour market or at least remain engaged in study beyond school-leaving age.

[7] An alternative would be to impute status in months where it is unknown. As noted above, we did this in the case of the NCCIS activity histories. While this approach could have been applied more generally in order to remove any instances of missing status, doing so risks distorting the data in an unknown way. The coherence of the achieved clusters suggests that retaining a 'missing' category does not hinder identification of meaningful groups.

It is important to bear in mind that these descriptives do not provide any indication of causality. While it may be plausible to assume that the experience of custody affects subsequent outcomes, it is notable from the index plots that in many cases custody happens after school-leaving age when the child is already NEET.

The index plots for the five age 19-22 clusters are presented in Figure 3. Labelling these 'late' clusters L1-L5, we suggest the following characterisation:

L1 Young people mostly staying in education

L2 Young people mostly staying in employment

L3 Young people initially in employment, then transitioning to NEET

L4 Young people mostly NEET

L5 Young people moving from NEET into employment around age 20-21

Of these, L1, L2 and L5 are the most positive groups in the sense of being made up of young people who mostly seem to avoid being NEET over this age range (although there is some suggestion with L1 of the NEET rate increasing towards the end of this period). Nevertheless, even when combined, these groups are small in number relative to the L4 'NEET' group.

Figure 2 here

Figure 3 here

Table 2 provides detail on the size of each cluster and the number of young people who experience each pairwise combination of early and late cluster. From this, it is clear that the most common transition is from E3 to L4. Individuals with this combination of clusters essentially have a post-school pathway that is dominated by NEET.

Table 2 here

The bottom panel of Table 2 shows this same information as row percentages. This makes more visible the dominance of L4 across all early clusters. For example, 85.6% of young people in cluster

E1 (CLA into NEET) transition into cluster L4 (NEET). L4 is the most likely destination regardless of which early cluster a young person is in. However, being in clusters E4 (Education into employment) or E5 (Continued education) seems to offer the best chance of avoiding L4. E4 members are relatively over-represented in L2 (Employment) or L3 (Employment then NEET) while E5 members are relatively over-represented in L1 (Mostly education). A visual impression of these flows is provided in Figure 4.

Figure 4 here

Table 3 presents the results of a multinomial logistic regression estimation of the probability of late cluster membership. The value of this is that it allows the influence of other characteristics to be included. These are of interest in their own right but it is also informative to examine whether the relationship between early and late cluster remains once we control for other sources of variation. The results are shown in the form of marginal effects which capture the extent to which a change in each variable affects the probability of membership of each group. The results also indicate the statistical significance of the association.

With regard to personal characteristics, being female is associated with an increase of 10 percentage points (ppts) in the probability of being in L4 (NEET) and a smaller increase (3 ppts) in the probability of being in L1 (Education). Partially offsetting this is the 9 ppts reduction in the probability of being in L3 (Employment then NEET). Being non-white similarly increases the probability of being in L4 (6 ppts) or L1 but the biggest reduction is in the probability of L2 (Employment), 4 ppts. We can also see that, in general, SEN reduces the probability of being in L2 (Employment), by 4 ppts or 8 ppts when statemented. Statemented children are also 10 ppts more likely than non-statemented children to be in L4 (10 ppts). The type of special educational need is relatively less important. Behavioural, Emotional and Social Difficulties (BESD) increases L4 probability by 3 ppts, Specific Learning Difficulty (SPLD) reduces L2 by 4 ppts. The level of local deprivation is captured by the IDACI index. This is a ranking, with more deprived areas having a lower rank. The results in Table 3 therefore indicate that the probability of being in the L4 (NEET) group is higher for more deprived areas. Lastly, we see the importance of qualifications. Having more KS4 points is associated with a reduced probability of being L4 (NEET) and a higher probability of being in any of the other groups but particularly L1 (Education).

Table 3

Our main interest is in the predictive power of the early clusters. Table 3 shows that the most significant differences are associated with E4 (Entering employment) and E5 (Education). In both cases there is a substantial reduction in the probability of being L4 (NEET). To show this more clearly, Figure 5 plots the probability of being in each of the late period clusters conditional on membership of each early period cluster. E4 particularly stands out; its members are 12 ppts more likely than the base category (E3) to be in L2 (Employment) and 17 ppts more likely to be in L3 (Employment then NEET). Their probability of being in L4 (NEET) is 30 ppts lower. To some extent children in E4 appear to have better labour market prospects, although it is questionable the extent to which L3 is consistent with this interpretation. E5 members are also less likely to be L4 (14 ppts). Instead, they are more likely to be in L1, L2 or L3; about 4-5 ppts in each case. Interpreting L1 and L2 as the most positive trajectories, E5 members can also be seen to have better labour market prospects than average.

Figure 5

Conclusion

The analysis in this paper contributes new evidence on the school to work transition of those who experience custody as a young person. The results confirm the generally poor prospects facing many such individuals. Roughly 80 per cent appear established as NEET by age 22. For comparison, the level in the population as a whole has been found in other studies to be 10 per cent.

Many of young people who experience custody are from disadvantaged backgrounds and might be expected to have poor outcomes regardless. Given the focus on such a deprived group it is notable that, as with previous studies for the population as a whole, the results still find that labour market prospects vary with personal characteristics and circumstances in a familiar way. For instance, the probability of being NEET throughout the later (19-22) period is higher among females, non-whites, those with special educational needs, those with lower attainment and those in more deprived areas. Evidently, it would be wrong to regard those who experience custody when young as undifferentiated; some will fare better than others and the results presented in this paper suggest that the predictors familiar from population-wide studies are also relevant here. Custody almost certainly compounds the effect of early disadvantage.

The results suggest that managing to avoid NEET when 16-18 is an important part of the strategy for avoiding NEET when older. In view of this, policy interventions aimed at engagement and re-engagement have a clear role. Promoting education and training and providing support for employment can help steer young people towards the pathways shown in this paper to be associated with more promising outcomes. While education and employment programmes exist, it is important that they are sufficiently tailored to the specific needs of young people with experience of custody who, in addition to disadvantage, face the challenge on release of re-adjusting from a highly-structured environment. Previous explorations (Youth Justice Board 2008) have identified a shortage of research into effective engagement with young people. There is therefore an argument for strengthening the evidence base in this regard.

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Figure 1 Trends in youth custody and care

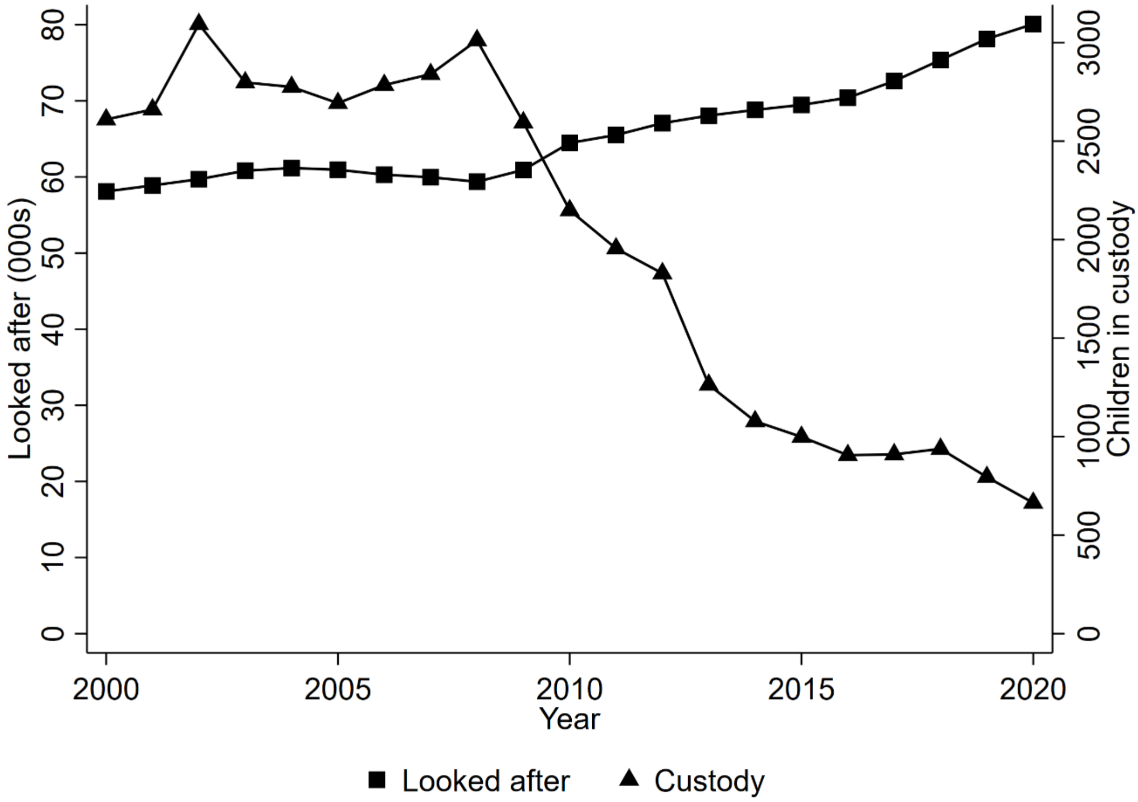

Figure 2 Early clusters (ages 13-18)

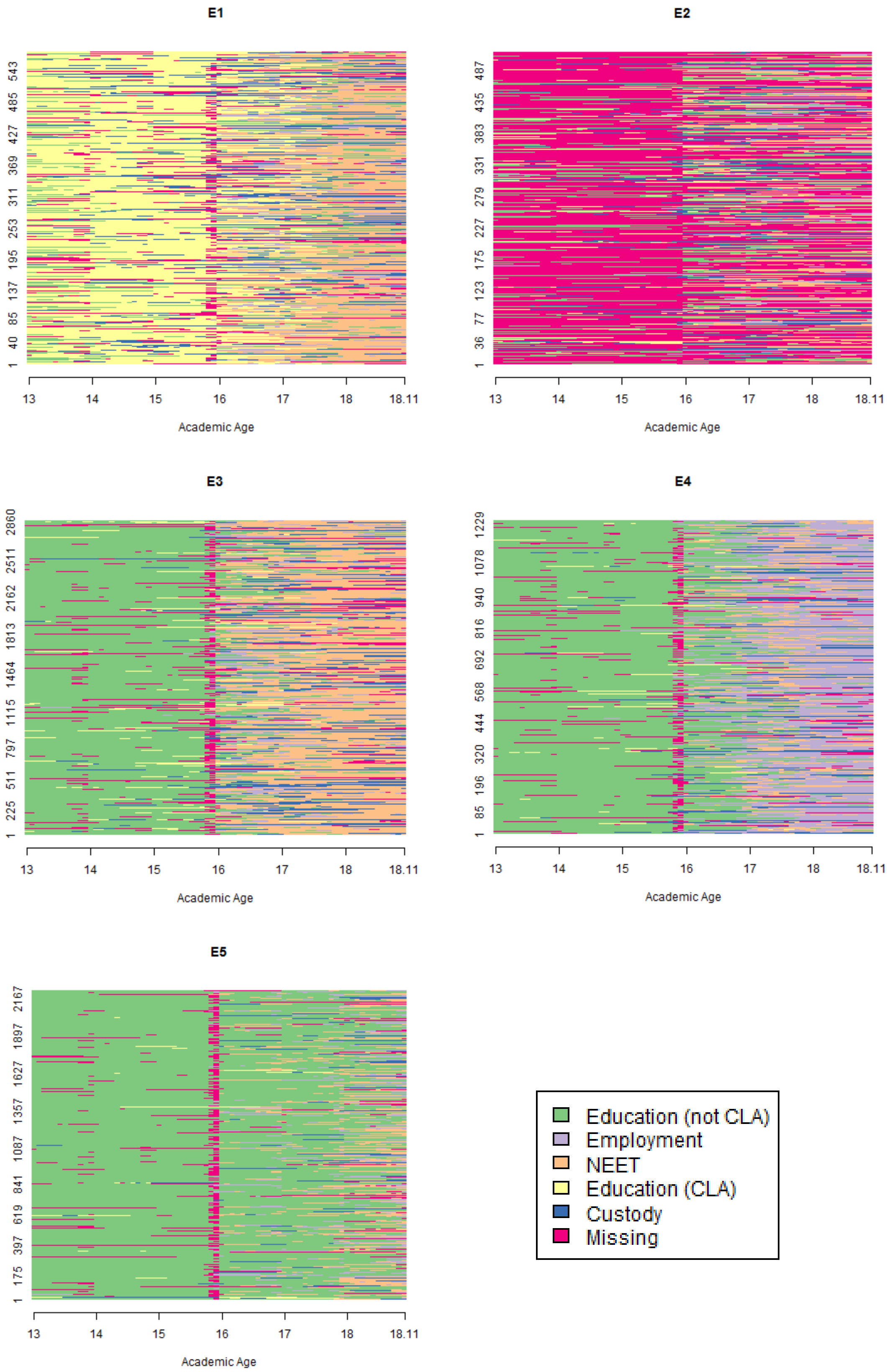

Figure 3 Late clusters (ages 19-22)

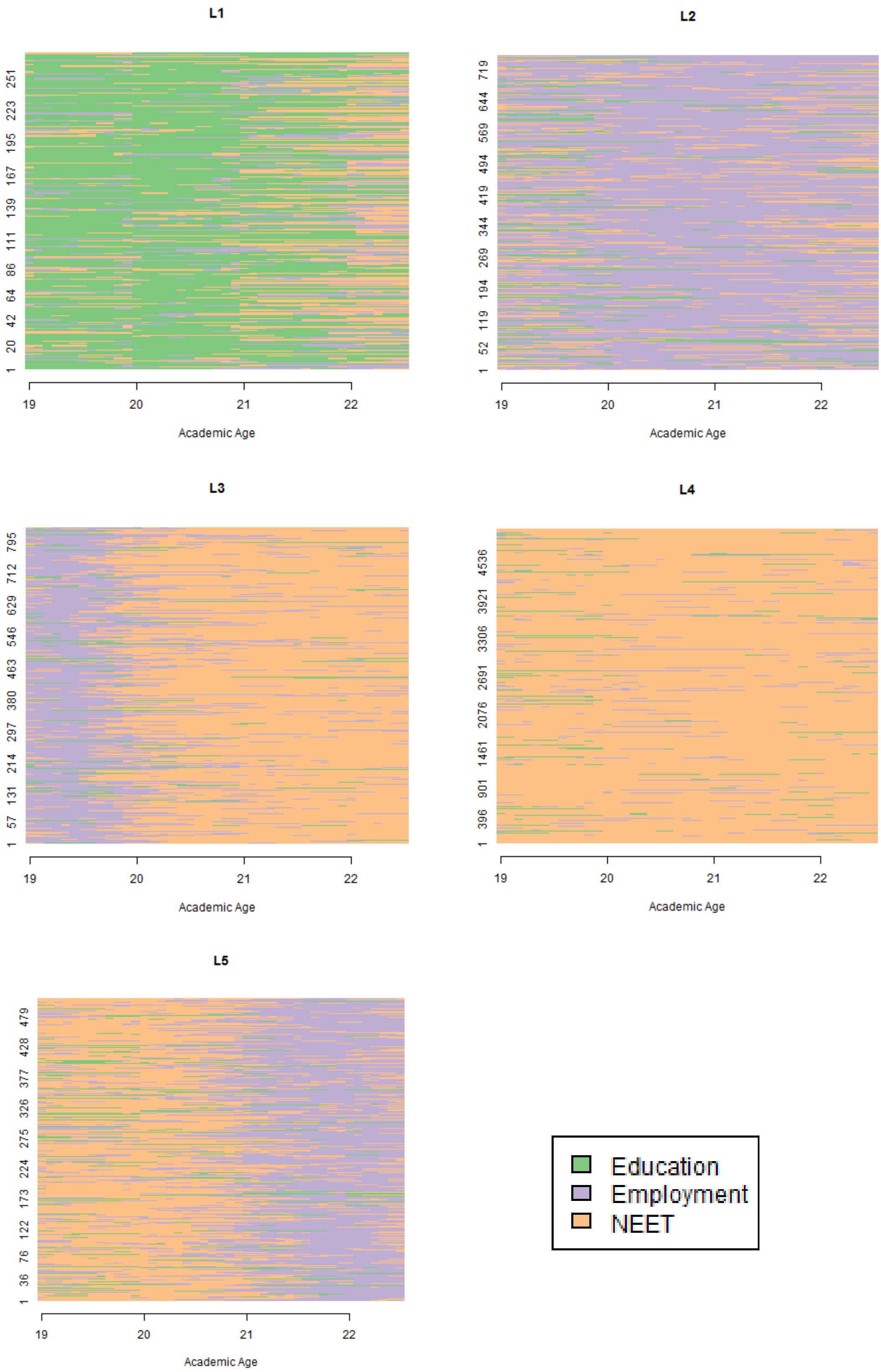

Figure 4 Flows between early and late clusters

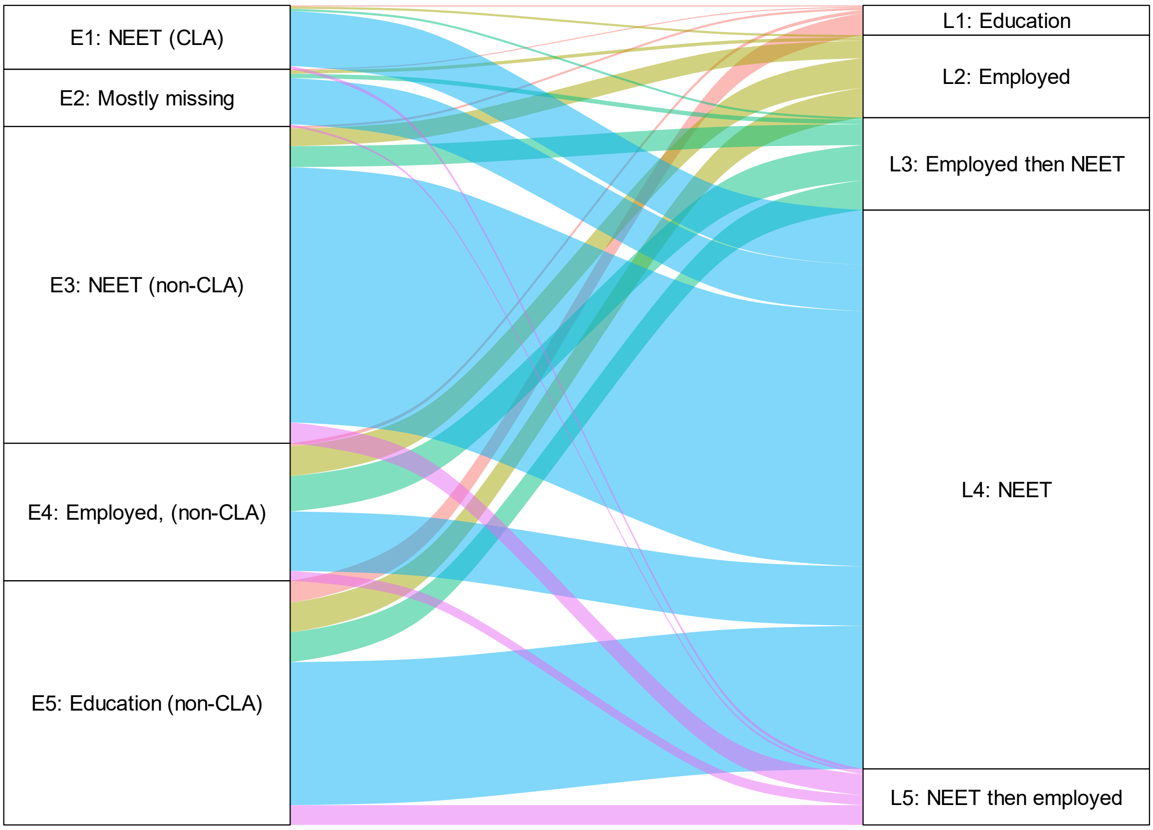

Figure 5: Multinomial Logit, Marginal Effects, probability of being in late period cluster conditional on membership of early period cluster

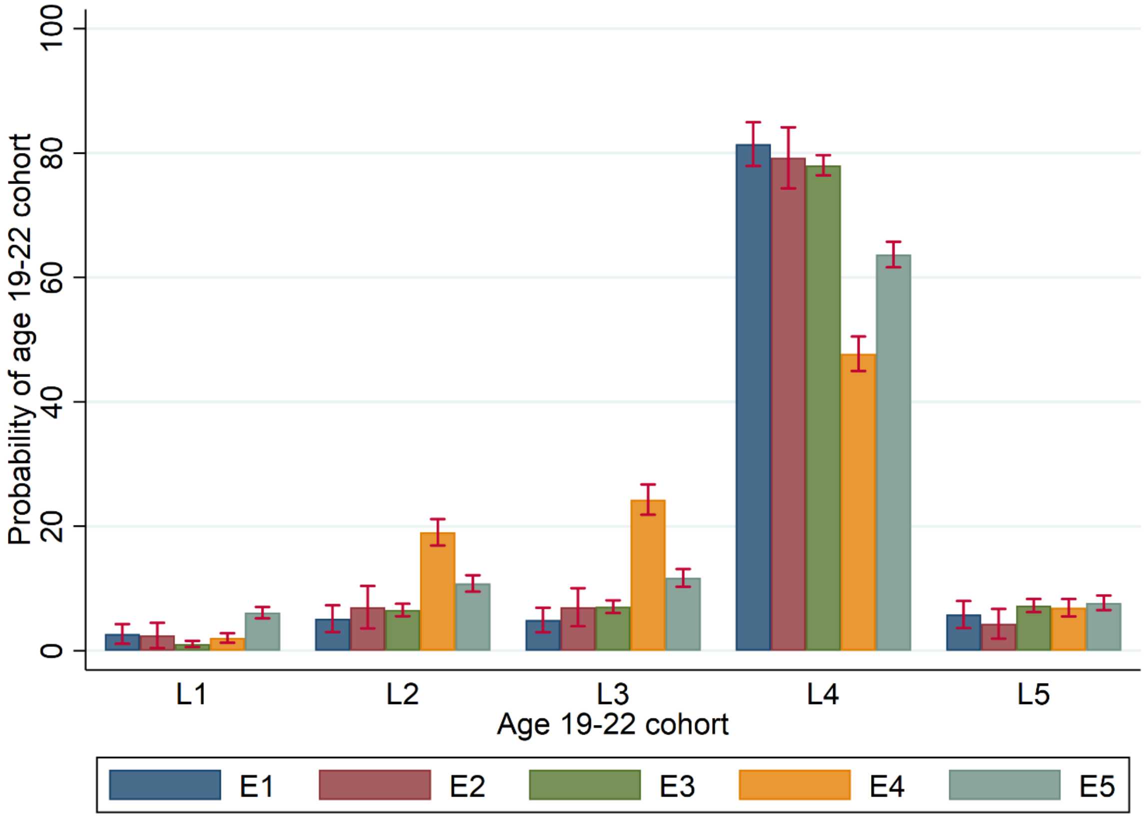

Table 1. Summary statistics comparing the sample with the population

	Full cohort	Custody subgroup
Female	48.7%	7.4%
Non-white	28.9%	40.9%
Special educational needs (ever)	46.8%	87.1%
Child in need (ever)	9.2%	51.1%
Child Protection Plan (ever)	6.8%	37.6%
Child Looked After (ever)	1.9%	25.0%
mean IDACI rank	14,999	7,866
mean KS4 score	38.0	18.0
Total (rounded to nearest 10)	663,330	7,440

Table 2 Transition Matrix, numbers of young people (rounded to the nearest 10)

		Ages 19-22 cluster					
		L1	L2	L3	L4	L5	All
		Numbers of young people (rounded to the nearest 10)					
Ages 13-18 cluster	E1	10	20	20	500	30	580
	E2	10	30	40	420	20	520
	E3	20	160	190	2320	190	2,870
	E4	30	270	320	540	90	1,250
	E5	200	270	270	1300	180	2,230
	All	270	750	830	5,070	510	7,440
		Row percentages					
Ages 13-18 cluster	E1	1.9	3.6	4.2	85.6	4.7	100
	E2	2.3	5.4	6.8	81.4	4.1	100
	E3	0.6	5.6	6.5	80.7	6.6	100
	E4	2.2	21.7	25.4	43.4	7.4	100
	E5	9.2	12.2	12.2	58.4	8.1	100
	All	3.7	10.1	11.2	68.2	6.9	100

Table 3: Marginal effects on the probability of late group membership from multinomial logit estimation (N=7,440 (rounded to nearest 10))

	L1 (Education)	L2 (Employment)	L3 (Emp, NEET)	L4 (NEET)	L5 (NEET, Emp)
Female	3.29***	-2.68*	-9.28***	10.10***	-1.43
	(0.66)	(1.56)	(2.16)	(2.29)	(1.25)
Non-white	1.07**	-4.21***	-1.40*	5.94***	-1.40**
	(0.48)	(0.78)	(0.83)	(1.14)	(0.67)
SEN Level:					
School Action	-1.15*	-3.69***	0.99	2.98	0.87
	(0.61)	(1.28)	(1.30)	(1.88)	(1.03)
School Action Plus	-0.48	-3.82***	-0.06	2.92	1.45
	(0.76)	(1.46)	(1.35)	(1.98)	(1.08)
Statement	-1.22	-7.60***	0.40	10.00***	-1.58
	(1.01)	(1.61)	(1.71)	(2.37)	(1.20)
SEN Type:					
BESD	-0.39	-1.46	-0.43	3.15**	-0.87
	(0.64)	(0.99)	(0.99)	(1.37)	(0.79)
MLD[8]	-1.67**	-1.90*	1.77*	2.34*	-0.54
	(0.78)	(1.02)	(0.96)	(1.39)	(0.81)
SPLD	0.89	-3.75**	-0.95	2.80	1.01
	(0.96)	(1.70)	(1.54)	(2.16)	(1.17)
Deprivation:					
IDACI at age 7 (x100)	0.01**	0.02***	0.01*	-0.05***	0.01***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
IDACI at age 16 (x100)	0.00	0.00	0.01*	-0.02***	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
KS4 points	0.24***	0.10***	0.07**	-0.50***	0.08***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)
Early cohort:					
E1	1.61*	-1.40	-2.14*	3.38*	-1.45
	(0.84)	(1.20)	(1.12)	(1.96)	(1.22)
E2	1.37	0.45	-0.08	1.20	-2.94**
	(1.08)	(1.86)	(1.70)	(2.71)	(1.38)
E4	0.96**	12.48***	17.22***	-30.31***	-0.35
	(0.46)	(1.19)	(1.34)	(1.63)	(0.89)
E5	5.03***	4.27***	4.63***	-14.36***	0.44
	(0.54)	(0.87)	(0.92)	(1.38)	(0.83)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[8] Moderate Learning Difficulties