School absence trajectories and their consequences for achievement

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Conflict of Interest
None.

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Abstract

In this study, we examined the joint trajectories of authorised and unauthorised absences from first year of primary to the end of secondary school, and their consequence for educational achievement. Our sample consisted of linked data from the Millennium Cohort Study and the National Pupil Database in England (*N*=7093). Employing k-medians clustering for longitudinal data, we identified seven distinct absence trajectories. Five of these clusters had very low levels of unauthorised absences but different levels and dynamics of authorised absences (constantly low, constantly moderate, decreasing, slightly increasing, dramatically increasing), while two clusters were characterised by moderately and dramatically increasing unauthorised absences in the last years. Next, using a regression-with-residuals approach to adjust for time-varying confounders, we found that absence trajectories had significant consequences for pupils' achievement, with a large effect size. The largest disadvantages appear for pupils with dramatically increasing unauthorised absences followed by dramatically increasing authorised, and moderately increasing unauthorised absence trajectories. These pupils were between 25 and 40 percentage points less likely to obtain 5 GCSEs. Even low to moderate absence trajectories were significantly detrimental to achievement. Our findings suggest a need to pay equal attention to all forms and levels of absences throughout the educational life course.

Keywords: school absences, school attendance, truancy, excused, unexcused, academic achievement, cluster analysis

1. Introduction

There is ample evidence of the harmful consequences of school absences for children's academic achievement (e.g., Aucejo & Romano, 2016; Gottfried, 2010, 2011; Gottfried & Kirksey, 2017; Kirksey, 2019; Morrissey et al., 2014), suggesting that a child's achievement is determined by cumulative exposure to schooling over time (Bronfenbrenner & Morris, 2006; Shonkoff & Phillips, 2000). However, school absence is a dynamic and multi-dimensional phenomenon, which must be addressed when analysing its effects.

First, school absences are not a static phenomenon but change as children progress through their education. The trajectory of absence may matter for children's achievement as it captures the extent, timing, and variability of exposure to school-based learning. However, the school absenteeism literature has not consistently examined the dynamic nature of school absences and their impact on student achievement. The majority of previous studies measured absences in one year or averaged absences up to three school years (e.g., Gottfried, 2014; Morrissey et al., 2014; Ready, 2010; Smerillo et al., 2018). This restriction may mask important differences between students and likely underestimates the effect of absences on student achievement (Liu & Lee, 2022). The few studies that have examined absence trajectories and achievement (Anderson & Romm, 2020; Chen et al., 2016; Schoeneberger, 2012; Simon et al., 2020) have primarily focused on elementary and middle school students. None of these studies have considered absence trajectories throughout a student's entire school career.

Second, absences can be caused by authorised (e.g., sickness) or unauthorised reasons (e.g., truancy), which can change throughout a child's educational career and have varying effects on achievement. For instance, unauthorised absences are much more prevalent in later school stages (Department for Education, 2011) and seem to be more detrimental to school performance than authorised absences (Gershenson, et al., 2017; Gottfried, 2009). However, previous studies on absence trajectories and achievement have focused on absences as a whole (Anderson & Romm, 2020; Simon et al., 2020), and thus have been unable to determine the intersecting role of reason and temporal variation of absences in relation to achievement outcomes. We argue that examining the joint trajectories of authorised and unauthorised absences on achievement is crucial, given that they likely interact and vary in frequency over time.

Our study contributes to the literature by addressing the following research questions:

1. What joint authorised-unauthorised absence trajectories emerge across entire school careers?
2. To what extent do these absence trajectories affect student achievement?

We answered these questions using linked administrative data on absences and standardised achievement tests from the National Pupil Database (NPD) in England, along with survey data from the Millennium Cohort Study (MCS) to answer these questions. These data allowed us to identify the joint trajectories of authorised and unauthorised absences throughout the entire mandatory school career in England (Years 1 to 11) while simultaneously conditioning on a rich set of baseline and time-varying confounders of the association between absence trajectories and achievement.

2. Absence trajectories and achievement

The Faucet theory suggests that students improve their skills through frequent exposure to schooling, and they cease making educational gains when their exposure to school is cut off (Alexander et al., 2001). Consequently, students who receive fewer hours of instruction during the school year are disadvantaged in their learning, receive lower grades, perform worse on exams, and are more likely to drop out of school (Morrissey et al., 2014). This argument aligns well with empirical evidence demonstrating a link between classroom instruction time and academic achievement (Bodovski & Farkas, 2007; Fitzpatrick et al., 2011; Heatly et al., 2015; Marcotte & Hemelt, 2008). In addition, students who are frequently absent from school may feel less connected to their classmates and struggle to participate in classroom activities and interactions with teachers and peers, which is detrimental to their academic development (Korpershoek et al., 2020).

While there is abundant evidence on the negative consequences of school absences for children's school achievement (e.g., Aucejo & Romano, 2016; Gottfried, 2010, 2011; Gottfried & Kirksey, 2017; Kirksey, 2019; Morrissey et al., 2014), these studies did not consider that absences may be differently associated with achievement depending on their temporal sequencing and their reasons over time. The pattern of absences during early, middle, and high school may vary over time and for different students across their school life span. The detrimental effects of school absences may not manifest until after prolonged exposure (Bronfenbrenner & Morris, 2006). While the literature on school absences focuses on measures of chronic absenteeism (typically 10% or more days) over the course of a given school year, it accounts less for the persistence of absences over multiple school years. Absences from school in one year may not be sufficient to significantly disrupt children's learning, so that snapshot measures may underestimate the cumulative effect of school absences on later achievement. This requires a holistic measurement of school absences via clustering of individual trajectories.

Studies examining absence trajectories have uncovered a variety of temporal patterns. For example, Anderson and Room (2020) described absence changes using intercept and slope and found a significant decline in attendance from pre-kindergarten to second grade for students from an urban school district. However, neither the number of days attended in pre-Kindergarten nor the decline in attendance were associated with math or reading achievement in the third grade. The analysis assumes that all students exhibit the same trajectory of attendance over the period under consideration, which is a limitation. Other studies examining whether different groups of students vary in their absence trajectories during specific school stages (e.g., kindergarten to elementary; middle; or high school) have commonly found between four and seven clusters of absence trajectories (Benner & Wang, 2014; Chen et al., 2016;

Schoeneberger, 2012; Simon et al., 2020). Only Simon et al. (2020) investigated the relationship between elementary school absence trajectories and student achievement. Based on data from the Early Childhood Longitudinal Study – Kindergarten Class of 1998-1999, they identified four latent absence trajectories for kindergarten through fifth grade: a low absenteeism group (46%), a decreasing absenteeism group (24%), an increasing absenteeism group (22%) and a high absenteeism group (8%). Students in the low absence group performed the best in maths and reading, while those in the high absence group performed the worst. The group with increasing absences performed marginally better in reading and marginally worse in mathematics than the group with decreasing absences. However, there was no statistically significant difference between the absence groups that are increasing and those that are decreasing.

Absences may have varying consequences for achievement depending on the reason for absence. Teachers may view unauthorised absences negatively, resulting in increased student-teacher conflict, decreased student-teacher closeness, and increased teacher irritation and frustration towards students who miss school unauthorised (Roorda & Koomen, 2021; Wilson, et al., 2008). As a result, teachers may be less willing to support students who miss school due to unauthorised absences in catching up on missed lessons. On the other hand, if students missed lessons for an excused reason, teachers and parents may be more willing to assist them in catching up on lesson content. Some studies examining the impact of various absence reasons have found that unauthorised absences were more harmful for achievement than authorised absences (Aucejo & Romano, 2016; Gershenson et al., 2017; Gottfried, 2009; Hancock et al., 2013). For Scotland, Klein et al. (2022) found that excused absences due to sickness and exceptional domestic circumstances (e.g., bereavement) were just as damaging to achievement as unauthorised absences.

The temporal dynamics of both authorised and unauthorised absences must therefore be considered concurrently. However, previous studies have either explored different trajectories for overall absences (Benner & Wang, 2014; Simon et al., 2020) or unauthorised absences such as truancy (Schoeneberger, 2012). Only one study has examined the joint trajectory of authorised and unauthorised absences over a single high school year, assuming a single trajectory for all participants (Liu & Lee, 2022). For all students, unauthorised absences increased while authorised absences decreased. It remains unclear whether multiple joint trajectories exist for distinct groups across the school life span and the extent to which these trajectories are associated with achievement.

We advance this literature in several meaningful ways. First, we examine latent absence trajectories throughout students' entire school career and study their impact on achievement at the end of compulsory schooling. Second, beyond the modelling of overall absences, we investigate profiles of joint trajectories of authorised and unauthorised absences and their consequences. Third, in contrast to previous research, our linked school administrative and survey data allow us to control for a comprehensive set of risk factors of school absences (Gubbels et al, 2019) and achievement, including time-varying confounders such as early cognitive ability, student behaviour and attitude towards school.

3. Data and Methods

3.1 Data

For the analysis, we used data from the UK Millennium Cohort Study (MCS, Joshi & Fitzsimons, 2016) linked with the National Pupil Database (NPD, Jay et al., 2019), a register dataset of all pupils in state schools in England. The MCS is a large-scale longitudinal study of children born in 2000 or 2001 and living in the UK. 19,244 families were recruited and first surveyed when children were 9 months old. Follow-up assessment took place at age 3 (sweep 2), age 5 (sweep 3), age 7 (sweep 4), age 11 (sweep 5), age 14 (sweep 6), and age 17 (sweep 7).

All participants residing in England during sweeps 3-5 (N=9,047) were asked for consent to link their data to the NPD. 8,489 provided consent and 8,438 were successfully matched to the NPD database. We restrict our analysis sample to participants who agreed to data linkage and were linked in sweep 4 (N=8,206), which enables us to use the MCS survey weights. In addition, for our analysis, we excluded all students for whom we lacked information on absences for a full academic year or key stage four achievement measures. This resulted in N=7,093 cases for the analysis.

We used the MCS weights for participation in England in sweep 4. We multiplied these weights with the inverse of the probability that participants gave consent to data linkage, have been successfully linked, and have complete absence and achievement data to account for selection effects (Hernan & Robins, 2020). We estimate the probability of participation with a logistic regression using socio-demographic characteristics of the families and characteristics of the child as our predictors (see Appendix F). By weighting the analysis with these weights, we created a pseudo-population with the same characteristics as the initial MCS sample of children living in England.

We imputed missing values on covariates using multiple imputation based on Categorization and Regression Trees (CART, Burgette & Reiter, 2010). We created 5 imputed datasets and applied Rubin's rules to obtain standard errors.

3.2 Variables

School absences

In the comprehensive school system of England, students attend primary school for 6 years (key stages 1 and 2) from ages 5/6 and compulsory secondary school for 5 years (key stages 3 and 4) from ages 11/12. Accordingly, the NPD contains information regarding the number of possible school days, the number of days missed due to authorised absences, and the number missed due to unauthorised absences in the autumn, spring, and first half of the summer term for each year of compulsory schooling, from year 1 (ages 5 to 6) to year 11 (ages 15 to 16). After the 2012/13 academic year, data on absences for the second half of the summer term were also collected (Department for Education, 2019). To maintain consistency in our measurement of students' absences over time, we combine data from the fall, spring, and summer terms into annual absence data.

Authorised absences are defined as absences with permission from a teacher or other authorised school representatives, which is only granted if a satisfactory explanation for the absence, such as illness, has been provided. Unauthorised absences are absences for which the school has not granted permission. We calculated the percentage of days missed due to authorised or unauthorised absences because the number of possible days varies between years and between students within the same year. Average absences per year are presented in Appendix A.

Achievement outcomes

After two years of instruction in key stage 4 (year 10 to 11), students sit for their GCSE (General Certificate of Secondary Education) exams at the end of year 11. GCSE exams are taken by all students and are consequential for future education and labour market outcomes (Hodge et al., 2021). On average, students take nine GCSE subjects. English, mathematics, and science are "core subjects" and thus compulsory. In each subject, grades range from 1 (worst) to 9 (best). Students pass these examinations if they earn at least the grade 4. Students who do not meet a minimum standard in a subject receive an "ungraded" score.

We considered three outcomes from these key stage 4 examinations. First, we consider English and maths grades (0-9). We coded "ungraded" as a zero. Our sample's English GPA is 4.7 (SD = 2.0) and its Maths GPA is 4.6 (SD = 2.1). In addition, we used a binary measure whether students passed (achieving grades 4-9) five or more exams, including English and maths. Almost 60 percent of the students in our sample achieved this threshold (see Appendix B).

Covariates

The MCS enables us to control known risk factors of school absenteeism identified in the literature (Gubbels et al., 2019) that may also influence children's achievement. Table 1 displays all covariates included in the analysis, as well as their measurement timings. We included multiple measures of socioeconomic status, child and family demographics, birth conditions, occurrence of disruptive events, parental involvement, educational motivation and aspirations, pupil's health, pupil's cognitive abilities and earlier measures of achievement, pupil's behavioural problems, and school characteristics. A detailed description of all variables is provided in Appendix C. The measurement of latent control variables is described in Appendix D.

Table 1. Control variables

Dimension	Variable	Age 1 Sweep 1	Age 3 Sweep 2	Age 5 Sweep 3	Age 7 Sweep 4	Age 11 Sweep 5	Age 14 Sweep 6
SES	Highest parental education – NVQ			**B**			
	Highest NSSEC 7			**B**			
	Household income			**B**			
	Housing tenure			**B**			
	Neighbourhood deprivation decile			**B**			
Demographics	Ethnicity	**B**					
	Date of birth	**B**					
	Gender	**B**					
	Family structure			**B**			
	Household size			**B**			
	Region within England				**B**		
	Number of children in household			**B**			
Cognitive Abilities / Achievement	BAS vocabulary + Bracken		**B**				
	BAS vocabulary + BAS pattern + BAS picture			**R**			
	Math + BAS reading + BAS pattern				**R**		
	Verbal similarities					**R**	
	Vocabulary						**R**
	Key stage English				**R**	**R**	
	Key stage Math				**R**	**R**	
Attitude towards school	CMs attitude towards school				**R**	**R**	**R**
	CMs attitude towards school (reported by parents)			**R**			
	CMs educational aspirations						**R**
	Parents educational aspirations				**R**	**R**	
Child behaviour	SDQ internalising		**B**	**R**	**R**	**R**	**R**
	SDQ externalising		**B**	**R**	**R**	**R**	**R**
Child Health	Child has longstanding illness			**B**			
	General health			**B**			
Birth conditions	Birthweight	**B**					
	Was in special care unit	**B**					
	Mother smoked during pregnancy	**B**					
	Mother's alcohol consumption during pregnancy	**B**					

Parental involvement	Parents had meeting with teacher	**R**	**R**	**R**	**R**
	Joint learning-related activities – sum score	**R**	**R**		
School characteristics	Stream		**R**	**R**	
	Set (English and Math)		**R**	**R**	
	School fees	**R**	**R**	**R**	**R**
Disruptive events	Parents mental health problems	**B**			
	Changed school	**R**	**R**	**R**	**R**
	Moved residence	**B**			

Note: B indicates that the variable is included as a baseline confounder, R indicates that the variable is included as a residualised confounder.

3.3 Methods

Identifying absence trajectories

We applied k-medians for longitudinal data (KML) to identify clusters with similar joint trajectories on authorised and unauthorised absences from year 1 to 11, using the R package kml3d (Genolini et al., 2013, 2015). We used k-medians instead of k-means to handle the skewed absence distribution. KML enables us to find trajectories that do not follow polynomial curves, which may remain hidden with parametric methods (Genolini & Falissard, 2010), such as a peaks after the transition to secondary school. KML has also been demonstrated to work especially well in exploratory contexts such as ours (Teuling et al., 2021).

The optimal number of clusters is unknown and cannot be deduced from current research. Existing research has identified between four and seven distinct absence trajectory clusters, which are based solely on total absences or unauthorised absences (Benner & Wang, 2014; Schoeneberger, 2012; Simon et al., 2020). We tested cluster solutions with two to ten clusters, using 100 distinct starting points for the initial clusters and selected the preferred cluster solution based on fit indices – AIC/BIC and the Calinski-Harabasz index (for more details on the fit indices see Genolini et al., 2015), predictive validity, and interpretability.

Identifying effects of absence trajectories on achievement

To model the effect of absence trajectories on achievement, we accounted for important risk factors including time-varying covariates, such as early cognitive ability, educational motivation, and behavioural issues, which may be both consequences of earlier absences and confounders for the effect of later absences on achievement (Panayiotou et al., 2021). Consequently, controlling for these time-varying confounders may result in overcontrol bias and collider bias. This issue is referred to as confounder feedback bias (Hernan & Robins, 2020). To address this problem, we employed a regression-with-residuals approach (Wodtke & Almirall, 2017). In a first step, we regress each time-varying confounder on baseline-confounders, all earlier measures of absences and all earlier measures of time-varying confounders and obtain the residuals, of these regressions. In the second step, we regress achievement on absence trajectories, baseline confounders, and the residualised time-varying confounders. The residualised risk factors that could be both the consequence of earlier absences and the cause of later absences are indicated by an “R” in Table 1 (e.g., cognitive abilities), while baseline risk factors which are not affected by absences are indicated by a “B” in Table 1.

Under the assumption that there is no unmeasured confounding, positivity, and correct model specification, the RWR estimates for absence trajectories on our achievement outcomes can be interpreted as average causal effects. We believe a causal assumption to be reasonable given that our covariates set contains longitudinal and high-quality risk antecedents of school absence.

4. Results

4.1 Absence trajectories

The different fit indices suggested different optimal number of clusters. The AIC and BIC suggested using as many clusters as possible (i.e., 10) whereas the Calinski-Harabasz index suggested using as few clusters as possible (i.e., 2). Moreover, we considered the predictive validity regarding our outcomes of interest and explained variance in authorised and unauthorised absences in deciding on the best number of clusters. Solutions with fewer clusters produced a very large groups with relatively low levels of absences obscuring heterogeneity within the groups. Regarding predictive validity, there was a significant increase in predictability when the number of clusters were increased from 2 to 4, with further improvement when considering 7 or 8 clusters. Solutions with more than 8 clusters were difficult to interpret (see Appendix E). The 7-cluster solution was chosen because it provides the most detailed description of absence trajectories while still representing meaningful groups.

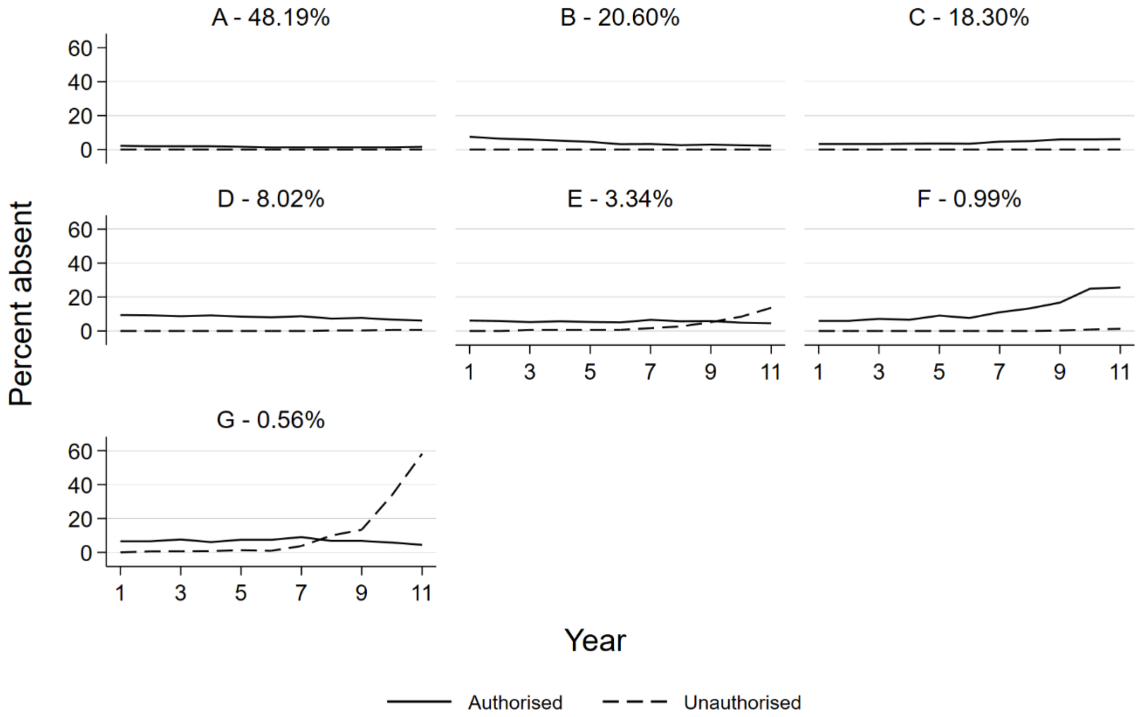
Figure 1 depicts the median authorised and unauthorised absences for the 7-absence trajectory cluster from Year 1 to Year 11. Most students (48.2%, *n*=3418) fall into absence trajectory A, which is characterised by consistently low unauthorised and very low authorised absences throughout their school career. We defined this cluster as the *very low absence* trajectory.

Furthermore, we found two clusters with very low unauthorised absences but higher authorised absences than the first. In terms of the evolution of authorised absences over time, these clusters differ. Cluster B is distinguished by moderate levels of authorised absences in the first years and lower levels of authorised absences in subsequent years. This cluster contains 20.6% of students (*n*=1461) and was defined as the *moderately decreasing authorised absence* trajectory. Students in Cluster C, on the other hand, have low authorised absences in the first years, which increase in the later years. This group was named the *moderately increasing authorised absence* trajectory, which includes 18.6% of all students (*n*=1229).

Cluster D is characterised by a *constantly moderate authorised absence* trajectory. The 8.0% of students (*n*=569) had on average 8.9% authorised absences per year but similarly low rates of unauthorised absences as the previous three clusters. Cluster E is the first to have moderate levels of unauthorised absences in later years (8.4% in Year 10, 13.6% in Year 11), combined with moderate levels of authorised absences throughout (on average 6.7%). We defined this cluster as *moderately increasing unauthorised absence* trajectory (3.3% of students, *n*=237).

The last two clusters are distinguished by dramatically increasing absences in recent years, but they only describe the patterns of 1.0% (*n*=70) and 0.6% (*n*=40) of students, respectively. Cluster F is distinguished by *dramatically increasing authorised absences* over time, reaching more than 20% in the last two years. Finally, cluster G is distinguished by *dramatically increasing unauthorised absences* over time, reaching more than 30% in the last two years.

Fig 1. Median authorised and unauthorised absences over time by absence trajectory cluster. Linked MCS-NPD data, N=7,093, unweighted.



4.2 Consequences for achievement

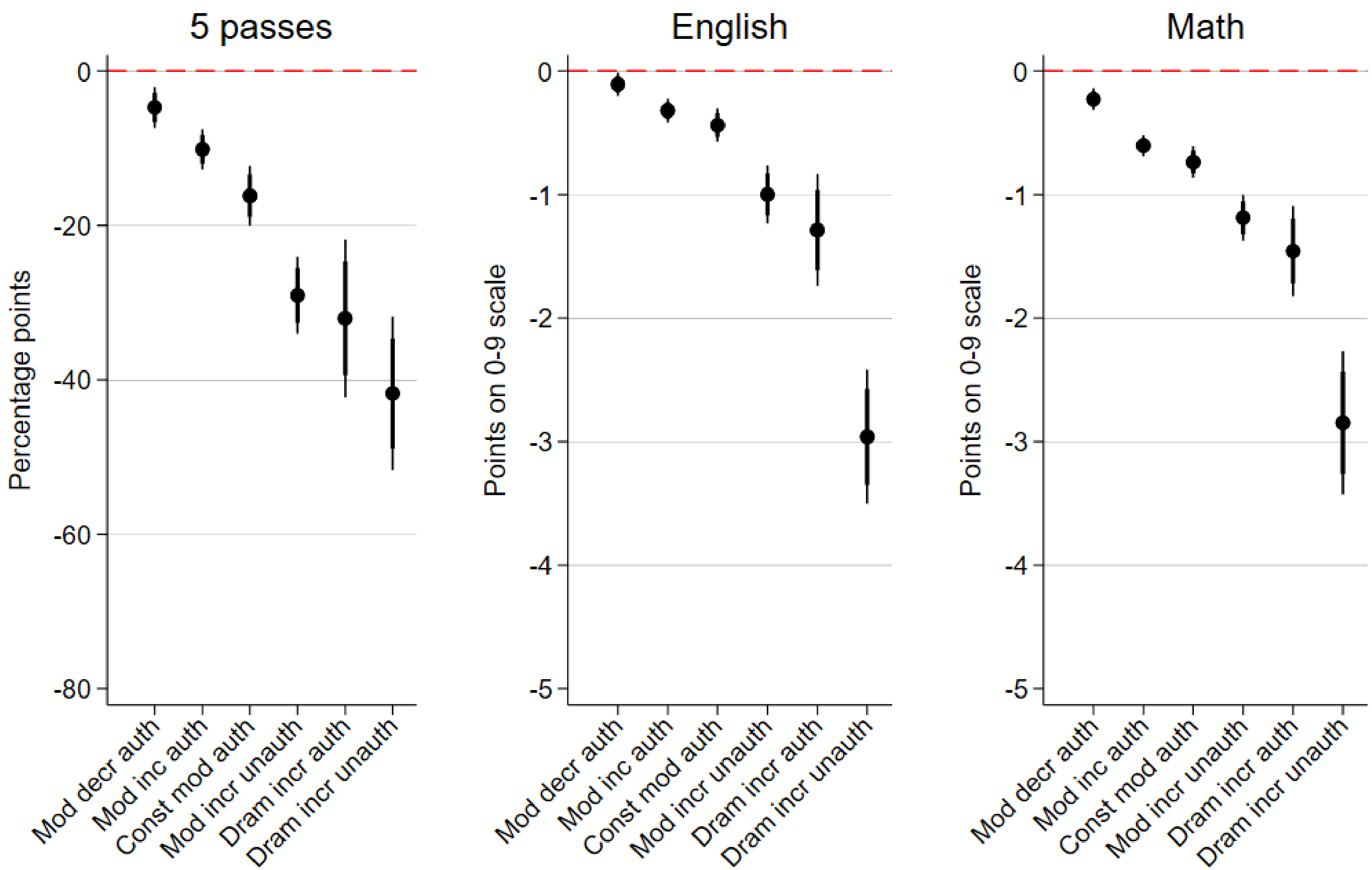
Figure 2 shows the differences in achievement by absence trajectories after adjusting for school absenteeism risk factors, both baseline and time-varying risk factors (Results without any control variables and with baseline-controls only are available in Appendix G). Figure 2 compares the effect of having a specific absence trajectory (on the x-axis) to the very low absence trajectory (indicated by the dashed red line). The left side of Figure 2 shows the effects of absence trajectories on passing 5 or more GCSEs, including English and Math. The impact of absence trajectories on English and Maths grades is shown in the middle and right sections. The thick vertical lines represent the estimates' 83% confidence interval, which roughly allows us to judge whether the effects of absence trajectories are significantly different from other absence trajectories, whereas the thin vertical lines represent the 95% confidence interval when comparing estimates to the reference absence trajectory.

Even after controlling for all risk factors for school absences, large differences in pupil achievement persist across absence trajectories. Significant differences emerge not only when comparing pupils with very low and very high absence trajectories, but also in almost all pairwise comparisons of absence trajectories. For all three outcomes, we see a similar ranking of absence trajectories in terms of their consequences for achievement. Children with *very low absence* trajectories outperform those with *moderately decreasing authorised absences*, *moderately increasing authorised absences*, *constantly moderate authorised absences*, *moderately increasing unauthorised absences*, and *dramatically* *increasing authorised absences*. Pupils with *dramatically increasing unauthorised absence* trajectories fare the worst in terms of academic achievement.

The magnitude of the consequences of absence trajectories is of large effect size, especially when comparing the *very low* to the *dramatically increasing unauthorised* absence trajectory. The latter absence trajectory reduces pupils' likelihood of passing 5 or more GCSEs by 42 percentage points and nearly 3 grade points on the English and Maths score (equivalent to more than 1.3 standard deviations). Students with *dramatically increasing unauthorised* absence trajectories still score more than 1.5 grade points lower in English and Math than the second worst performing pupils, those with *dramatically increasing authorised* absence trajectories.

It is important to note that 95% of pupils in our sample fall into one of four trajectory clusters: very low, moderately decreasing authorised, moderately increasing authorised, and constantly moderate authorised absences trajectories. However, even within these trajectories, the majority of pairwise differences are statistically significant and of substantial magnitude. For instance, having a *moderately decreasing authorised absence* trajectory reduces pupils' likelihood of gaining 5 or more GCSEs by 4.7 percentage points compared to following a *very low absence* trajectory. Yet, pupils with a *moderately decreasing authorised* absence trajectory are 5.4 percentage points more likely to obtain 5 GCSEs compared to pupils with *moderately increasing authorised* absences and 11.4 percentage points more likely compared to pupils with a *constantly moderate absence* trajectory.

Fig 2. Differences in achievement by absence cluster – adjusted for baseline and time-varying risk factors. Linked MCS-NPD data, N=7,093, weighted. Reference trajectory: *Very low* absence trajectory. Thick vertical lines indicate the 83%-Confidence Interval, thin vertical lines the 95%-Confidence Interval.



5. Conclusion

This study examined both authorised and unauthorised absence trajectories throughout a child's mandatory school career for a sample of children born in 2000/2001 in England, and the consequences for academic achievement at the end of compulsory secondary schooling. Using k-median clustering, we identified seven distinct absence trajectories, each with its own set of levels and dynamics of authorised and unauthorised absences. Only 48% of the students belonged to a very low absence group. About 39% fell into one of two low to moderate authorised absences trajectories (moderately decreasing or increasing authorised absences over time). 13% of students were on various trajectories with moderate to high absences (constantly moderate authorised, moderately increasing unauthorised, dramatically increasing authorised, dramatically increasing unauthorised).

In our analyses on achievement, we conditioned on pupil characteristics that influence both absences and achievement but have been previously unmeasured such as educational motivation (e.g., Hancock et al., 2013). When compared to the very low absence trajectory, all absence trajectories have a significantly lower achievement outcomes (5 or more GCSE passes, English, and Math GPA). This suggests that regular school attendance is beneficial across all school years. In line with existing studies on elementary school-aged children in the US (e.g., Ansari and Pianta; Gottfried, 2011, 2014), we find larger effects of absence trajectories on achievement in Math than on achievement in English. However, this only holds when comparing students with moderate levels of absenteeism to students with low levels of absenteeism. In contrast, for students with dramatically increasing absences, effects on Math and English are of similar magnitude.

Furthermore, almost all pairwise comparisons of trajectories show statistically significant achievement differences. By far the worst performers are the small proportion of students on the dramatically increasing unauthorised trajectory, who are more than 40 percentage points less likely to obtain 5 or more GCSEs and have a GPA in English and Maths that is nearly three grade points lower than the reference group. This group's achievement is lower than that of students with dramatically increased authorised absences, supporting the evidence that while all absences are consequential for achievement (Klein et al., 2022), unauthorised absences are more harmful than authorised absences (Gottfried, 2009; Gershenson et al., 2017). Unlike Simon et al. (2020), who identified no significant differences between decreasing and increasing absence trajectories on elementary school achievement, we found that moderately increasing authorised absences are more detrimental to secondary achievement that moderately decreasing authorised absences.

While timing matters, cumulative exposure is important, too. Pupils with consistently moderate authorised absences have a lower achievement than pupils with increasing or decreasing authorised absences. Consistent attendance over multiple years ensures that students receive the necessary instruction and support to master new concepts and skills. In addition, it provides opportunities for students to develop positive peer networks and relationships with teachers that are long-lasting. Any transition to more frequent absences may derail these gains and have long-term consequences for academic performance. These findings emphasize the importance of examining entire trajectories of absenteeism and its associations with academic outcomes.

Our findings have implications for interventions aimed at reducing absenteeism to improve academic achievement. Given that any form and level of absence during the educational life course is detrimental to achievement, intervention should aim to address the root causes of school absences and mitigate its effect throughout the period of schooling. While increased unauthorised trajectories are more harmful, a narrow focus on those with persistent unauthorised absences will miss a large group of students. Although most students only miss a small number of days, it has long-term consequences for achievement that require an equal level of attention.

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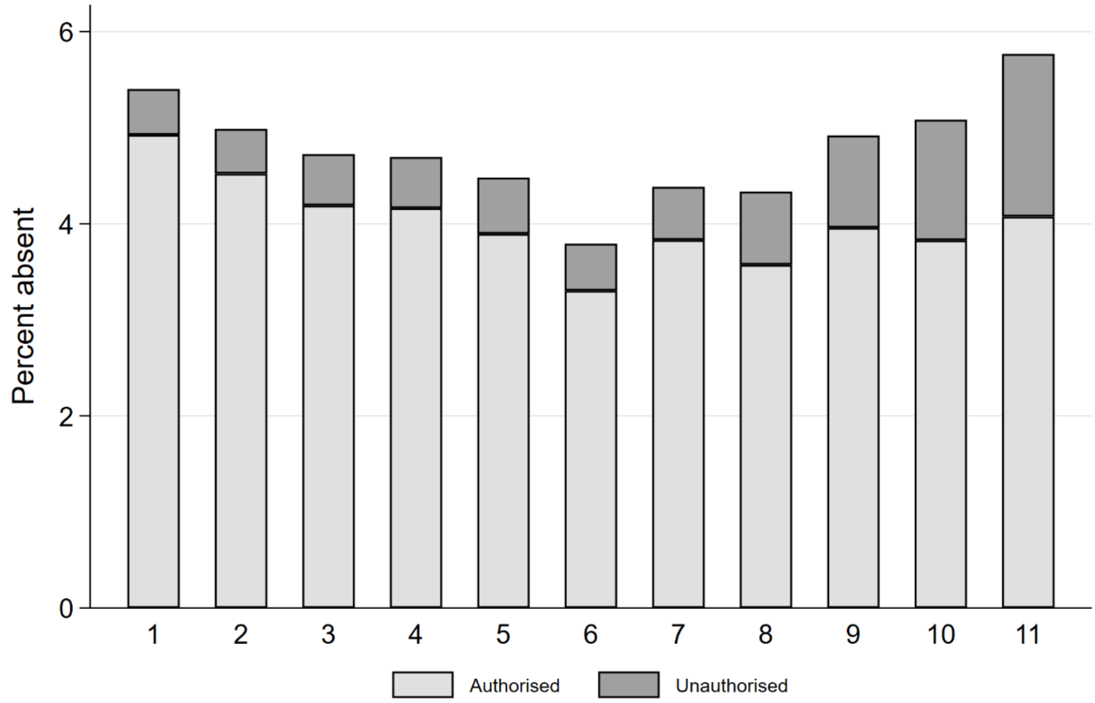
Appendix

A. Distribution of absences

Fig A1. Average authorised and unauthorised absences by year. Linked MCS-NPD data, N=7,093, unweighted.



B. Distribution of outcomes

Tab B1. Distribution of outcomes. N=7,093.

	Mean	SD	Min	Max
Passed 5 GCSEs	.594	-	.000	1.000
GCSE English	4.671	1.955	.000	9.000
GCSE Math	4.647	2.119	.000	9.000

Tab B2. Correlations between outcomes. N=7,093.

	Passed 5 GCSEs	GCSE English
GCSE English	.89	
GCSE Math	.89	.72

C. Distribution of confounders

Table C1. Distribution of confounders before and after multiple imputation

	Before imputation		After imputation
	Mean	N	Mean
Date of Birth	493.463	7093	493.463
Boy	1.499	7093	1.499
HH size	4.372	6796	4.373
Children in HH	2.427	6796	2.426
Neighborhood Deprivation	4.920	6796	4.895
HH income	341.176	6750	340.543
Residential Moves	.114	7092	.114
Birthweight	3.321	6713	3.320
Alcohol during pregnancy	9.421	6716	9.424
Smoking during pregnancy	.194	6573	.197
Parental depression	3.332	6468	3.390
Child general health	1.743	6770	1.748
Bracken (Age 3)	103.721	5860	102.929
BAS vocabulary (Age 3)	48.824	6175	48.092
Externalising (Age 3)	6.831	6104	6.902
Internalising (Age 3)	2.995	6115	3.087
Ethnicity			
White	.776	7038	.776
Mixed	.034	7038	.034
Indian	.036	7038	.036
Pakistani/Bangladeshi	.091	7038	.091
Black	.044	7038	.044
Other	.019	7038	.019
Family structure			
Two natural parents	.769	6795	.769
Step-family	.047	6795	.047
Single parent	.181	6795	.181
Other	.004	6795	.004
Parental education			
None	.123	6766	.123
NVQ 1	.061	6766	.061
NVQ 2	.265	6766	.265
NVQ 3	.152	6766	.152
NVQ 4	.341	6766	.341
NVQ 5	.058	6766	.058
Parents' social class			
NSSEC 1	.135	6418	.135
NSSEC 2	.298	6418	.298
NSSEC 3	.151	6418	.151
NSSEC 4	.087	6418	.087
NSSEC 5	.088	6418	.088

NSSEC 6	.147	6418	.147
NSSEC 7	.094	6418	.094
Housing tenure			
Owned outright	.047	6765	.047
Owned with mortgage	.616	6765	.616
Rent - Local authority	.144	6765	.144
Rent - Housing association or private	.167	6765	.167
Other	.027	6765	.027
Long standing illness			
No	.808	6764	.808
Yes, but at most a little bit affected	.139	6764	.139
Yes, strongly affected	.053	6764	.053
Region			
North East	.050	7093	.050
North West	.131	7093	.131
Yorkshire and the Humber	.120	7093	.120
East Midlands	.088	7093	.088
West Midlands	.116	7093	.116
East of England	.115	7093	.115
London	.144	7093	.144
South East	.150	7093	.150
South West	.086	7093	.086
Complications at birth			
No complications	.549	6715	.549
Complications, not in special care	.365	6715	.365
Complications, in special care	.086	6715	.086
BAS picture (Age 5)	55.187	6781	55.132
BAS vocabulary (Age 5)	53.426	6796	53.298
BAS pattern (Age 5)	50.425	6793	50.326
Externalising (Age 5)	4.706	5831	4.788
Internalising (Age 5)	2.589	6524	2.642
Educational motivation (Age 5, reported by parents)	1.574	6727	1.577
Parents met teacher (Age 5)	.877	7093	.924
Joint activities (Age 5)	4.287	6765	4.282
School Fees (Age 5)	.994	6730	.994
School change (Age 5)	.025	6730	.025
BAS reading (Age 7)	112.884	7043	112.814
BAS pattern (Age 7)	52.516	7013	52.473
NFER math (Age 7)	97.559	7049	97.511
Externalising (Age 5)	4.696	6070	4.752
Internalising (Age 5)	2.847	6872	2.869
Educational motivation (Age 7)	2.361	6617	2.359
Parents met teacher (Age 7)	.949	7093	.952
Reading - Writing score in KS 1	3.060	7073	3.059
Math score in KS 1	3.162	7073	3.163
Parents' educational aspiration (Age 7)	.981	6845	.981

Joint activities (Age 7)	3.903	7074	3.903
School Fees (Age 7)	.999	7078	.999
School change (Age 7)	.097	6719	.100
Top Stream (Age 7)	.049	7093	.075
Top English set (Age 7)	.082	7093	.126
Top Math set (Age 7)	.102	7093	.158
Bottom Stream (Age 7)	.026	7093	.042
Bottom English set (Age 7)	.043	7093	.072
Bottom Math set (Age 7)	.050	7093	.083
Verbal similarities (Age 11)	58.634	6262	58.401
Externalising (Age 11)	6.457	5270	6.496
Internalising (Age 11)	6.601	5678	6.655
Educational motivation (Age 11)	3.211	6105	3.207
Parents met teacher (Age 11)	.852	7093	.958
Reading score in KS 2	4.277	7092	4.277
Math score in KS 2	4.339	7092	4.338
Parents' educational aspiration (Age 11)	.893	6231	.892
School Fees (Age 11)	.999	6259	.997
School change (Age 11)	.199	6298	.202
Top Stream (Age 11)	.064	7093	.104
Top English set (Age 11)	.142	7093	.207
Top Math set (Age 11)	.217	7093	.317
Bottom Stream (Age 11)	.020	7093	.036
Bottom English set (Age 11)	.054	7093	.090
Bottom Math set (Age 11)	.086	7093	.139
Vocabulary (Age 14)	7.089	5355	6.991
Externalising (Age 14)	4.245	4948	4.370
Internalising (Age 14)	3.714	5583	3.758
Educational motivation (Age 14)	2.922	5614	2.915
Parents met teacher (Age 14)	.724	7093	.904
Parents' educational aspiration (Age 14)	87.661	5583	87.017
School Fees (Age 14)	.999	5682	.992
School change (Age 14)	.053	5682	.059

D. Measurement of latent factors

Table D1. Measurement of latent factors not provided by the MCS.

Construct	Items	Method
Attitude towards school Reported by parents Sweep 3	Whether CM enjoys school How often CM talks about school How often reluctant to go to school	Sum score Cronbachs alpha=0.49
Attitude towards school Reported by CM Sweep 4	How often do you try to do your best at school? How often is school interesting? How often do you feel unhappy at school? How often do you get tired at school? How often do you get fed up at school?	Sum score Cronbachs alpha=0.56
Attitude towards school Reported by CM Sweep 5	How often do you try your best at school? How often do you find school interesting? How often do you feel unhappy at school? How often do you get tired at school? How often do you feel school is a waste of time?	Sum score Cronbachs alpha=0.71
Attitude towards school Reported by CM Sweep 6	How often do you try your best at school? How often do you find school interesting? How often do you feel unhappy at school? How often do you get tired at school? How often do you feel school is a waste of time? How often difficult to keep mind on work at school?	Sum score Cronbachs alpha=0.75
Joint Activities Sweep 3	How often do you read to CM? How often tells stories to CM? How often does musical activities with CM? How often does CM paint/draw at home?	Sum score Cronbachs alpha=0.58
Joint Activities Sweep 4	How often do you read to CM? How often tells stories to CM? How often does musical activities with CM? How often does CM paint/draw at home?	Sum score Cronbachs alpha=0.57

E. Cluster solution with 2 to 10 clusters

Fig E1. Median absences by year with 2 cluster solution

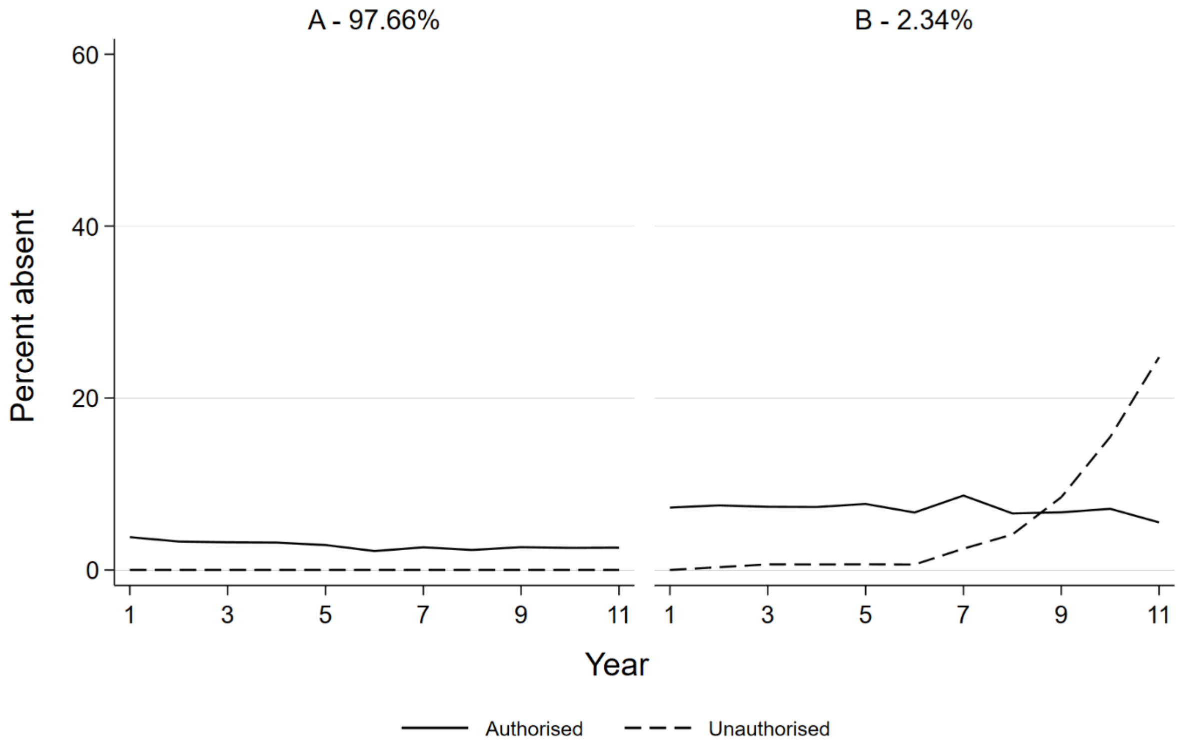


Fig E2. Median absences by year with 3 cluster solution

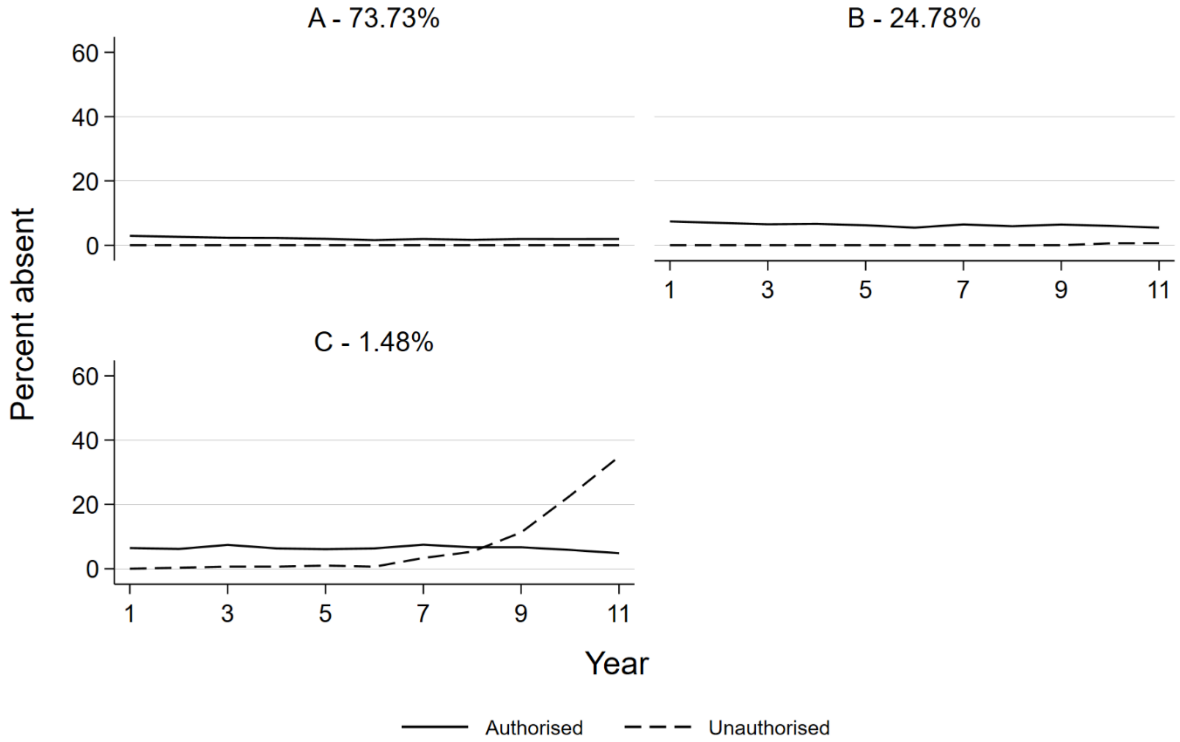


Fig E3. Median absences by year with 4 cluster solution

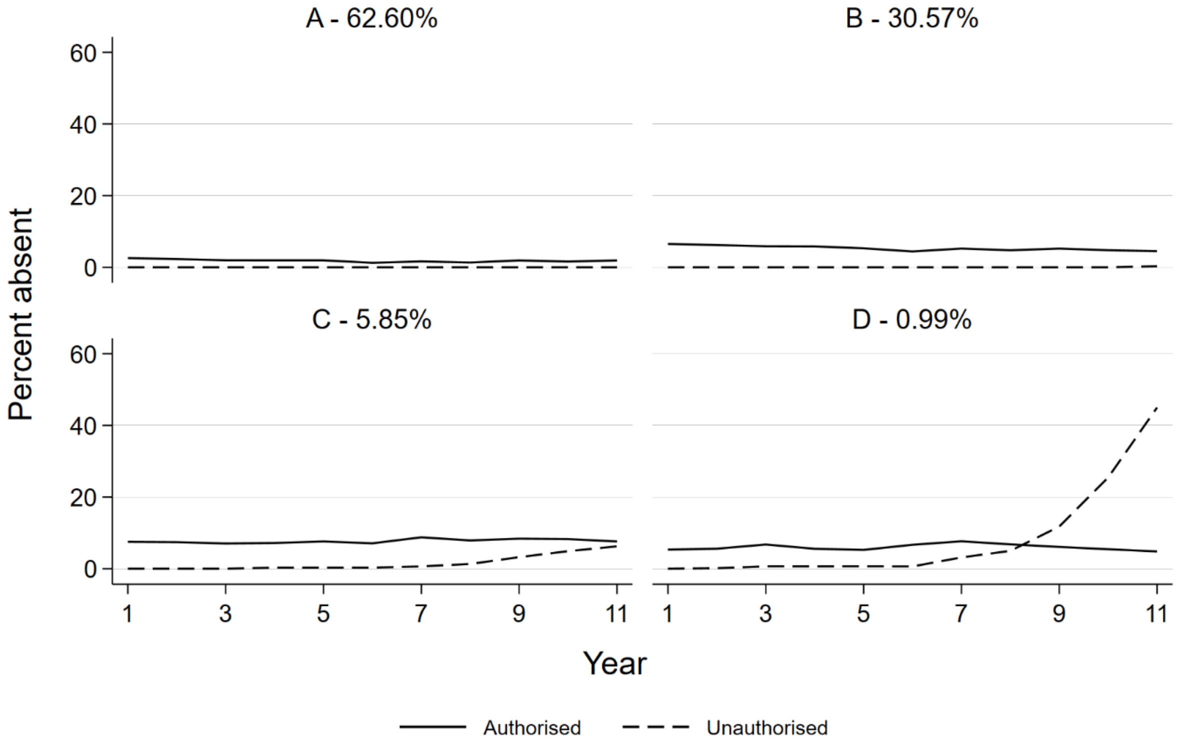


Fig E4. Median absences by year with 5 cluster solution

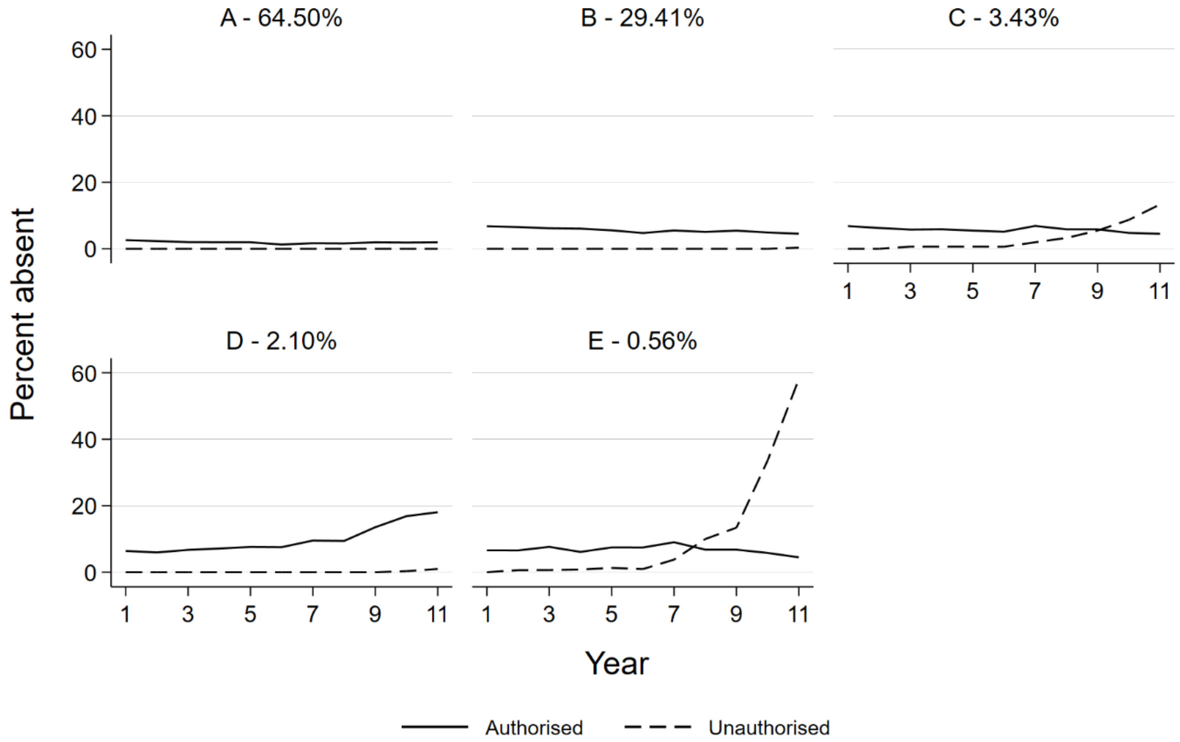


Fig E5. Median absences by year with 6 cluster solution

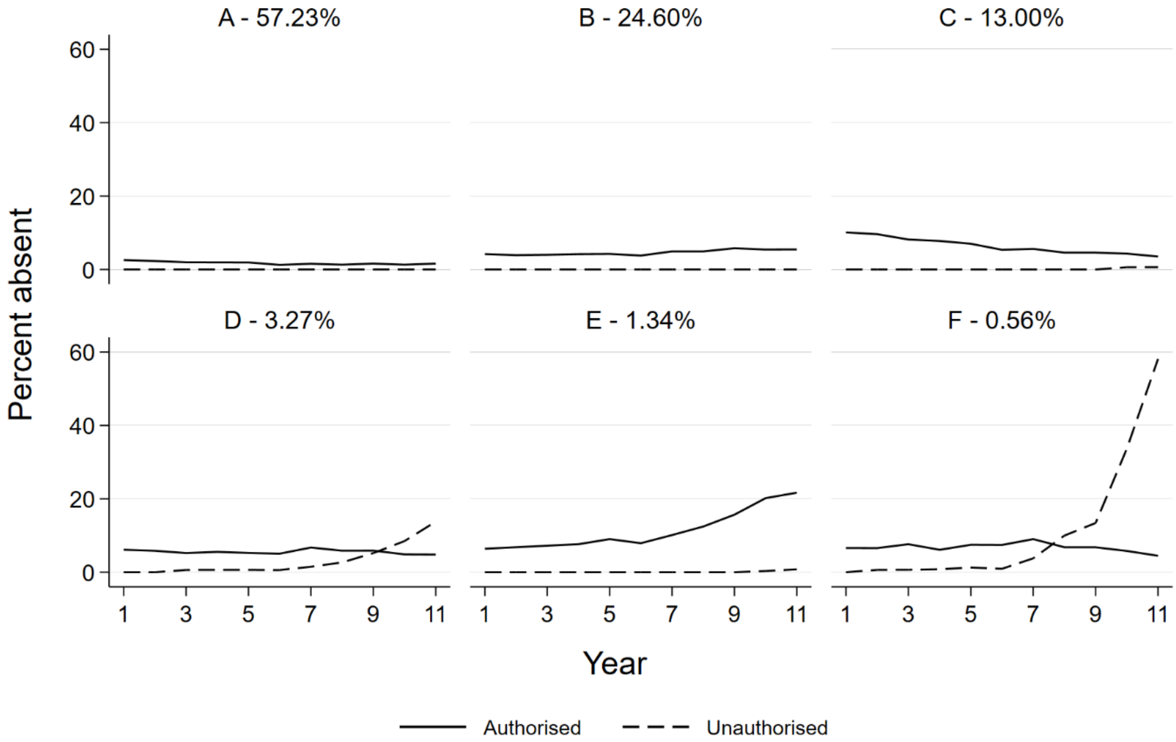


Fig E6. Median absences by year with 8 cluster solution

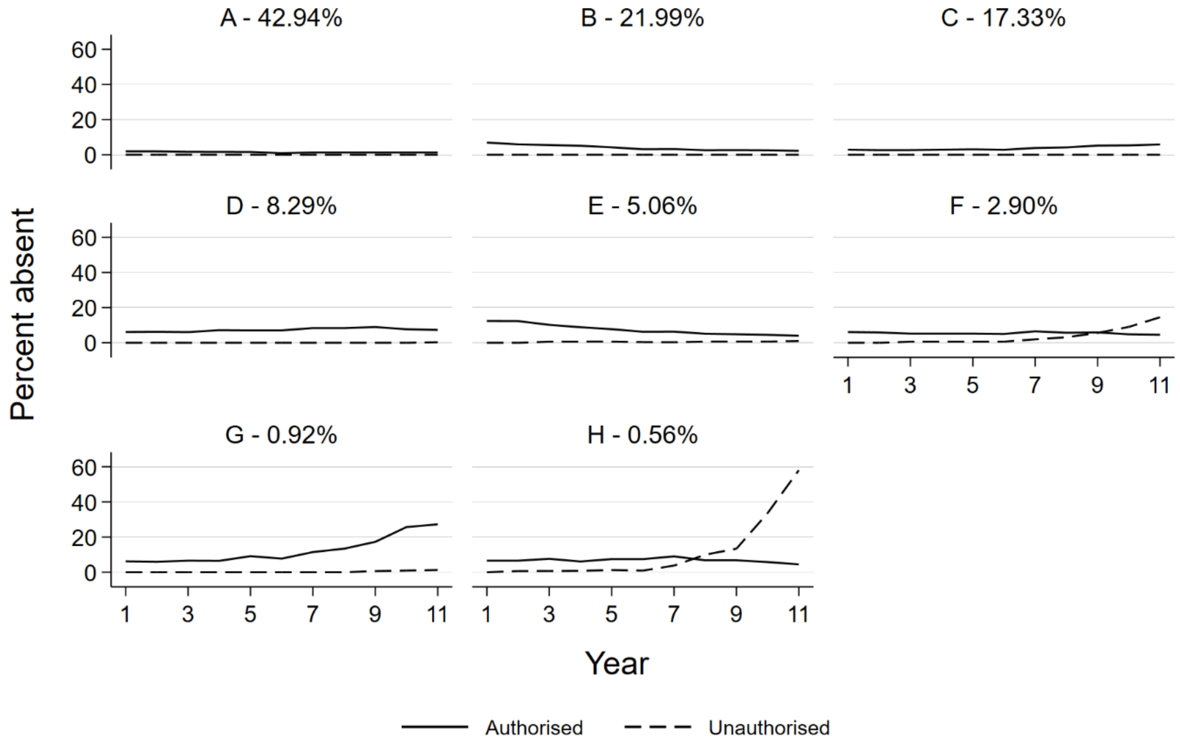


Fig E7. Median absences by year with 9 cluster solution

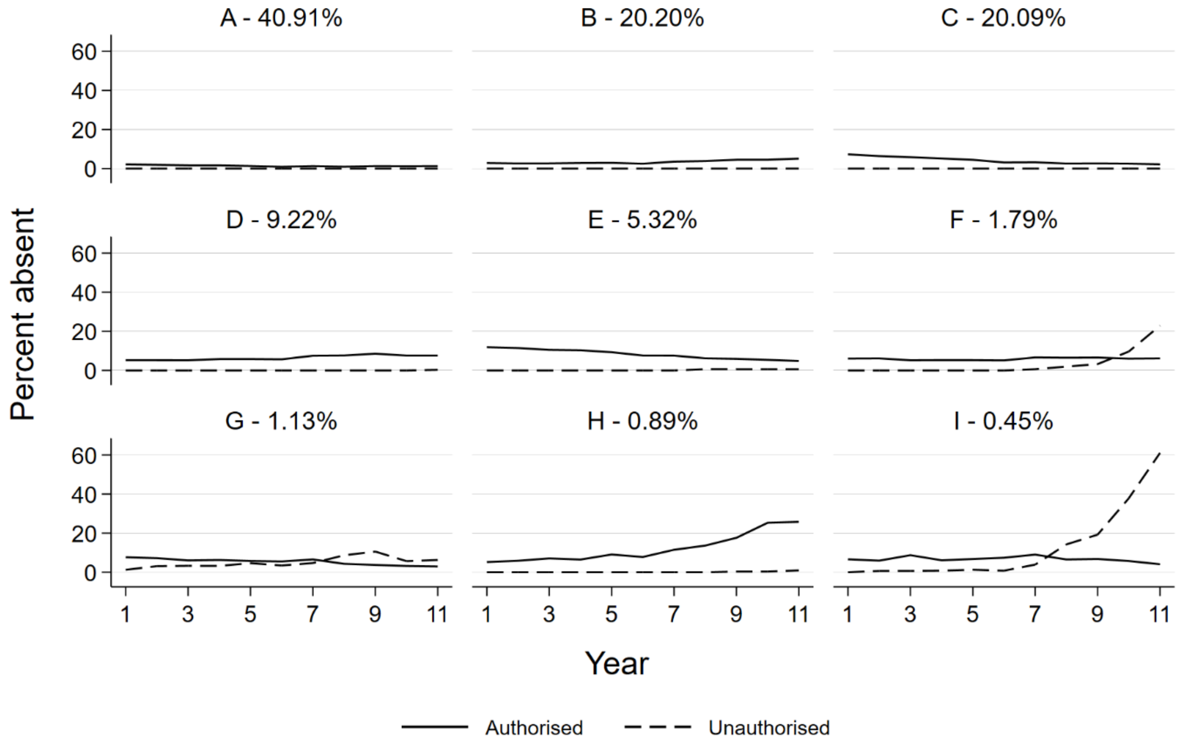
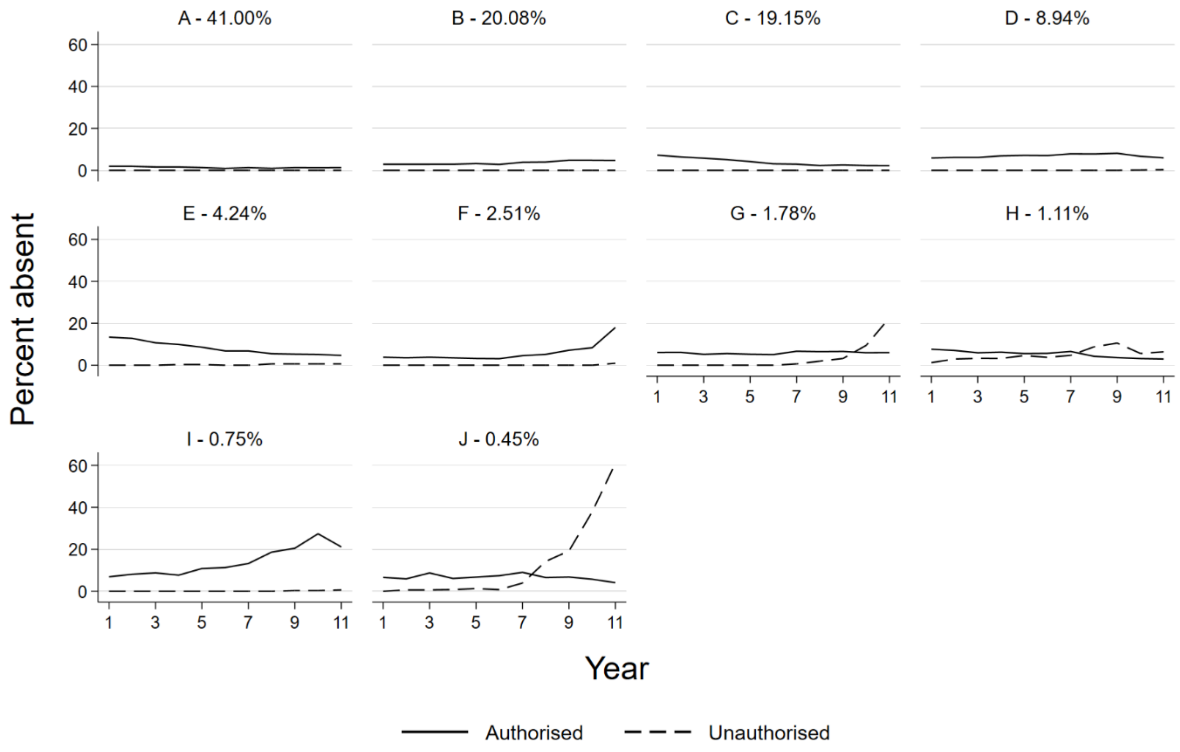


Fig E8. Median absences by year with 10 cluster solution



F. Sample selection and inverse probability of attrition weights

Table F1. Distribution of baseline covariates in initial and analysis sample

	Initial sample	Analysis sample
Date of Birth	493.457	493.463
Boy	.506	.499
HH size	4.383	4.373
Children in HH	2.427	2.426
Neighborhood Depriv.	4.961	4.895
HH income	356.570	340.543
Residential Moves	.121	.114
Birthweight	3.318	3.320
Alcohol during pregnancy	6.404	6.424
Smoking during pregnancy	.195	.197
Parental depression	3.392	3.390
Child general health	1.748	1.748
Bracken (Age 3)	102.886	102.929
BAS vocabulary (Age 3)	47.901	48.092
Externalising (Age 3)	6.881	6.902
Internalising (Age 3)	3.083	3.087
Ethnicity		
White	.759	.776
Mixed	.039	.034
Indian	.038	.036
Pakistani/Bangladeshi	.095	.091
Black	.050	.044
Other	.019	.019
Family structure		
Two natural parents	.767	.769
Step-family	.046	.047
Single parent	.184	.181
Other	.004	.004
Parental education		
None	.126	.123
NVQ 1	.059	.061
NVQ 2	.245	.265
NVQ 3	.145	.152
NVQ 4	.351	.341
NVQ 5	.074	.058
Parents' social class		
NSSEC 1	.163	.135
NSSEC 2	.294	.298
NSSEC 3	.140	.151
NSSEC 4	.086	.087
NSSEC 5	.081	.088
NSSEC 6	.145	.147
NSSEC 7	.092	.094
Housing tenure		

Owned outright	.052	.047
Owned with mortgage	.607	.616
Rent - Local authority	.142	.144
Rent - Housing association or private	.173	.167
Other	.027	.027
Long standing illness		
No	.804	.808
Yes, but at most a little bit affected	.137	.139
Yes, strongly affected	.059	.053
Region		
North East	.045	.050
North West	.127	.131
Yorkshire and the Humber	.114	.120
East Midlands	.083	.088
West Midlands	.115	.116
East of England	.114	.115
London	.159	.144
South East	.155	.150
South West	.087	.086
No complications	.545	.549
Complications, not in special care	.367	.365
Complications, in special care	.088	.086
Observations	8,986	7,093

Table F2. Logit coefficients of regressing analysis sample participation on baseline covariates

	Coefficient	SE
Date of Birth	0.00652	(0.00776)
Boy	-0.104*	(0.0554)
Ethnicity		
Mixed	-0.515***	(0.129)
Indian	-0.284*	(0.153)
Pakistani/Bangladeshi	-0.585***	(0.121)
Black	-0.524***	(0.129)
Other	-0.0748	(0.201)
Family structure		
Two natural parents	-0.0585	(0.148)
Step-family	-0.337***	(0.0956)
Single parent	-0.684*	(0.387)
Household size	-0.0730	(0.0507)
Number of children	0.0432	(0.0588)
Parental education		
NVQ 1	0.129	(0.143)
NVQ 2	0.286***	(0.105)
NVQ 3	0.0639	(0.120)
NVQ 4	-0.0780	(0.110)
NVQ 5	-0.430***	(0.141)
Parents' social class		
NSSEC 2	0.424***	(0.0857)
NSSEC 3	0.597***	(0.126)
NSSEC 4	0.232*	(0.130)
NSSEC 5	0.510***	(0.143)

NSSEC 6	0.252**	(0.126)
NSSEC 7	0.341**	(0.140)
Neighborhood depriv.	-0.0114	(0.0130)
Housing tenure		
Owned with mortgage	0.472***	(0.119)
Rent - Local authority	0.113	(0.152)
Rent - Housing association or private	-0.0480	(0.136)
Other	0.248	(0.217)
Income	-0.00174***	(0.000181)
Region		
North West	-0.304*	(0.172)
Yorkshire and the Humber	-0.233	(0.176)
East Midlands	-0.228	(0.184)
West Midlands	-0.365**	(0.173)
East of England	-0.282	(0.176)
London	-0.569***	(0.171)
South East	-0.488***	(0.170)
South West	-0.471***	(0.179)
Residential Moves	-0.268***	(0.0801)
Birthweight	-0.0123	(0.0515)
Complications, not in special care	-0.0537	(0.0597)
Complications, in special care	-0.0662	(0.106)
Alcohol during pregnancy	0.0444*	(0.0264)
Smoking during pregnancy	-0.167**	(0.0847)
Parental depression	-0.00355	(0.00944)
General health	0.0195	(0.0356)
Yes, but at most a little bit affected	-0.0214	(0.0830)
Yes, strongly affected	-0.538***	(0.117)
Bracken (Age 3)	0.00333	(0.00220)
BAS vocabulary (Age 3)	0.00519	(0.00348)
Externalising (Age 3)	6.37e-06	(0.00901)
Internalising (Age 3)	-0.00182	(0.0128)
Constant	-1.691	(3.859)

N=8,986. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

G. Differences in achievement when ignoring time-varying confounders

Fig G1. Differences in achievement by absence cluster. N=7,093. Reference trajectory: Very low absences.

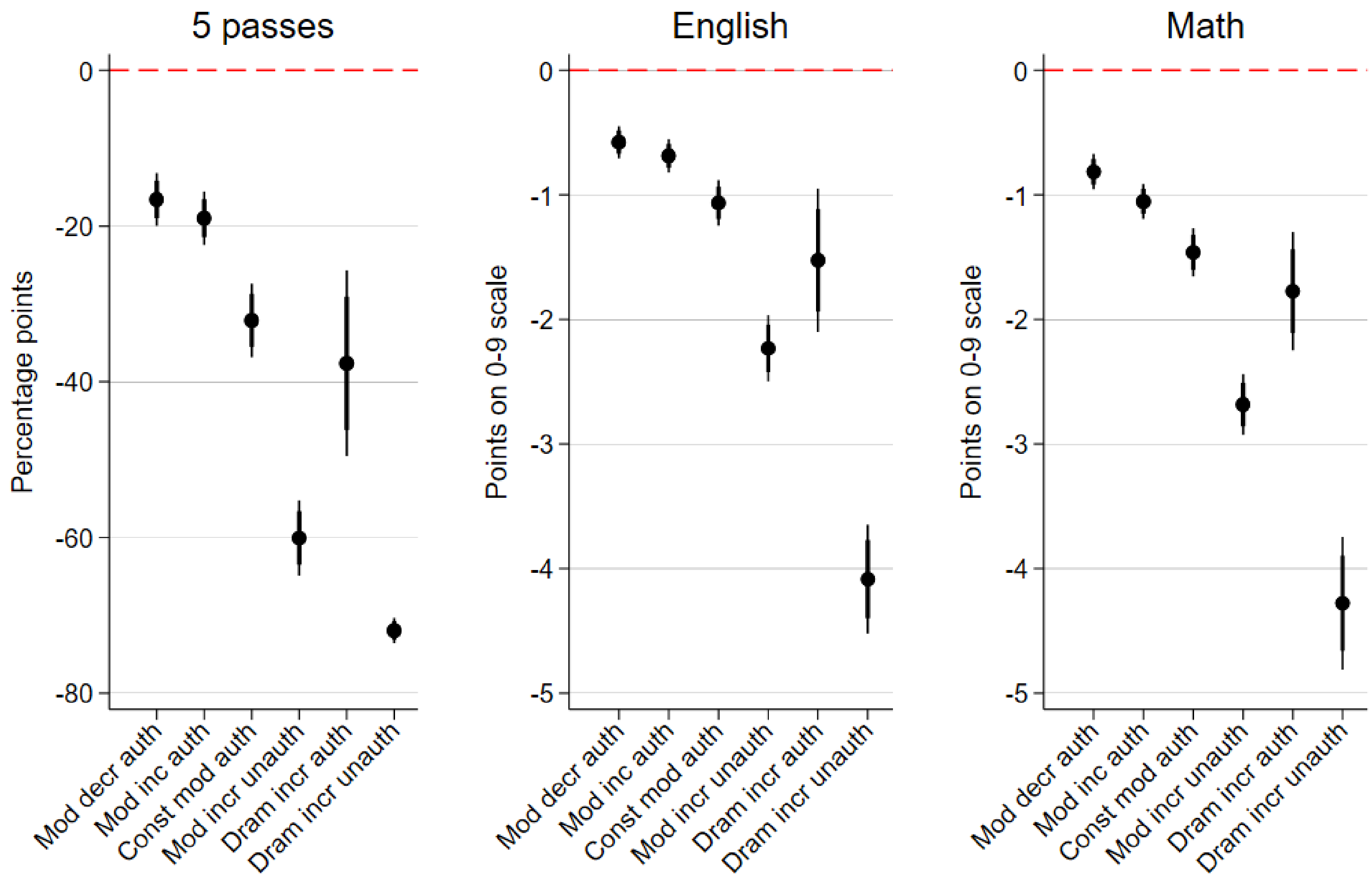


Fig G2. Differences in achievement by absence cluster – adjusted for baseline risk factors. N=7,093. Reference trajectory: Very low absences.