Funding for preventative Children's Services and rates of children becoming looked after: a natural experiment using longitudinal area-level data in England

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Contributorship statement

DB is lead author and guarantor. DT-R and BB are joint senior author. DB, DT-R and BB conceived of and designed the study; AA, KM and DB acquired the data; DB conducted the analysis, with input from all co-authors; DB led the drafting and revision of the manuscript; all authors reviewed and revised drafts and approved the final version for submission. We confirm that authors have no conflicts of interest to disclose.

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ABSTRACT

Background: Children in care face adverse health outcomes, throughout the life-course, relative to the general population. In England, over the last decade, the rate of children entering care has increased. The rate of change differs markedly for older and younger children, who may also experience different preventative services. These services have been subject to inequitable spending reductions due to fiscal policies trailing the 2008 recession.

Objective: To assess the impact of cuts to prevention on rates of preschool children and adolescents entering care between 2012 and 2019.

Participants and Setting: Children aged 1-4 and 16-17 years, across 150 English upper-tier local authorities.

Methods: Our outcomes were annual rates of children entering care, aged 1-4 and 16-17. Our exposures were Children's Services prevention spend per child under 5, and per child over 12. Regression models were used to quantify, within areas, associations between trends in prevention spend and trends in rates of children entering care, controlling for employment and child poverty rates.

Results: We found no association between changes in prevention spend per child under 5 and changes in care entry for 1-4-year-olds. However, spending reductions per child over 12 were associated with rising rates of 16-17-year-olds entering care. Every £10 per child decrease in prevention spend was associated with an estimated additional 1.9 per 100,000 children aged 16-17 entering care the following year (95% CI 0.7 to 2.9), equivalent to 1 in 25 care entries in this age group between 2012 and 2019.

Conclusion: This study offers evidence that rising rates of older children entering care has partly been driven by cuts to prevention services catering to their needs. Policies to tackle

adverse trends should promote reinvestment in youth services, placing ordinary help on a robust statutory footing.

Keywords: Public health; Prevention; Longitudinal analysis; Child welfare; Out-of-home care

INTRODUCTION

Between 2011 and 2019, there was a precipitous rise in the rate of children entering state care in England, from 23 to 27 per 10,000 children (Department for Education, 2011a, 2012a, 2021). The absolute rise has been greater in poorer areas, increasing inequalities (Bennett et al., 2020). It has also been particularly pronounced among children aged 16-17 years. Rates for these children more than doubled, from 26 to 53 children per 10,000 – a greater relative and absolute rise than for any other age group. In contrast, among children aged 1-4, rates remained relatively stable, decreasing slightly from 22 to 20 children per 10,000 (Author's analysis of DfE, 2021).

International research into experiences of adversity in childhood has exposed their lifelong health and social consequences and significant contribution to the global burden of disease (Hughes et al., 2017; Rod et al., 2020). Ample research has shown that adverse socioeconomic conditions are important, modifiable risk factors for child maltreatment and care entry (Bywaters et al., 2016; Conrad-Hiebner & Byram, 2020). Children in care, also referred to in England as Children Looked After by the local authority (see textbox 1), are particularly vulnerable to these consequences, having endured adversity sufficiently severe for the State to intervene in their upbringing (Font & Maguire-Jack, 2020; Meltzer et al., 2003; Viner & Taylor, 2005). In England, a recent study shows that, up to 42 years after initial care assessment, care-experienced adults have a higher mortality risk, with a higher risk for more recent assessments, than adults with no experience of care (Murray et al., 2020).

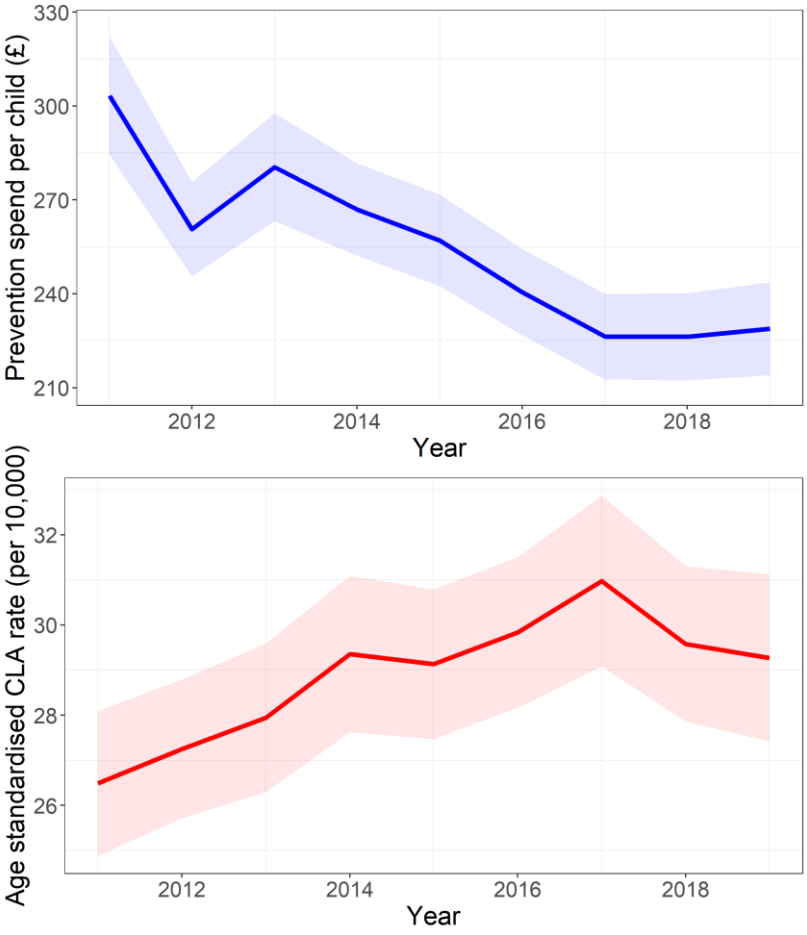
Textbox 1. Definition of a Child Looked After

> In England, a 'Child Looked After' designation refers to a child whose care has been transferred to the local authority, usually from their birth parents following a child protection investigation. These children are typically accommodated in foster or group homes. If a child goes on to be adopted, they are no longer considered 'looked-after'; if they return home, they may cease to be 'looked-after'.

Preventative services have undergone significant upheaval over the past decade. The UK government's policy response to the 2008 recession severely constrained local government.

Between 2011 and 2018, across England, central government funding for local authorities fell by 49.1% (National Audit Office, 2018), with no corresponding reductions in local authorities' statutory responsibilities. Despite ongoing emphasis on prevention and early help for long-term cost savings in health and social care (Department of Health and Social Care, 2018), and widespread recognition that a failure to do so means 'storing up trouble' for the future (All Party Parliamentary Group for Children, 2018), non-statutory, preventative services have inevitably borne the brunt of reduced public spending (C. J. R. Webb & Bywaters, 2018). Deprived areas with a smaller tax base, less able to raise funds locally, have been worst affected. The introduction of the business rate retention scheme in 2013, whereby local authorities may retain half of business rates growth, further compounded funding inequalities, watering down the needs-based component of the formula used to determine resource allocation (Alexiou et al., 2021). Children's Services were not spared (figure 1). Between 2011 and 2019, as rates of children in care increased, total spending on preventative services for children and families fell by about 25% in real terms (figure 2), with deeper cuts in more deprived areas (appendix 1 figure 1). 'Prevention spend' refers here to any spend not associated with either the running of social services, or children in care.

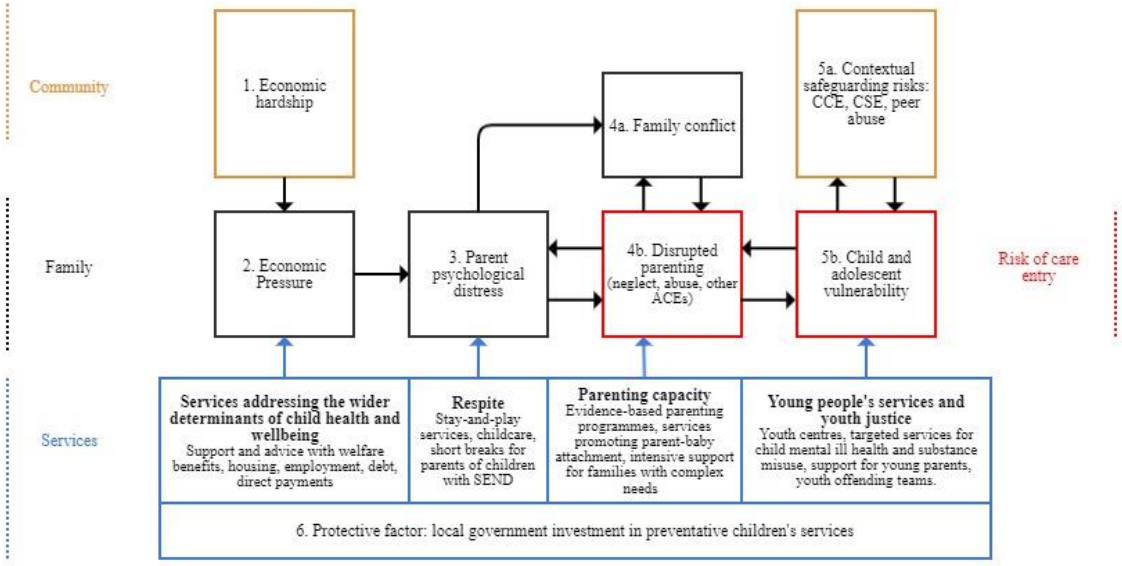
Figure 1. Trends in total prevention spend, and age standardised rate of children starting to be looked after, across local authorities in England (2011-19)



Children's Services preventative spending may influence the risk of children becoming looked after through a variety of plausible mechanisms (figure 2). In England, under Section 17 of the Children Act 1989, local authority Children's Services are tasked with delivering prevention and 'early help' to children and families who would benefit from support due to their health and development needs, but do not meet thresholds for statutory child protection intervention. Local authorities are expected to provide evidence-based services attuned to local need (HM Government, 2018). A broad range of services may be delivered, including: Sure Start Children's Centres – community-based spaces intended to offer integrated care and services to young children and their families, inspired by the US Head Start programme (Purcell, 2020); intensive, targeted support for families with multiple and complex needs;

contributions to community-based initiatives such as the Family Nurse Partnership; universal recreational and educational services for children over the age of 12; targeted support for adolescents; broader strategies aiming to reduce under 18's conception; counselling services for children and families; and youth justice services supporting children who have been in trouble with the law (Education Funding Agency, 2014). For further detail see appendix 2. While different services may have differing objectives and theorised mechanisms (figure 2), all seek to promote children's welfare, alleviate family stress, and forestall poor outcomes for children, including those that would warrant care entry.

Figure 2. Logic model of mechanisms for the impact of Children's Services prevention spend on the risk of children becoming looked after, adapted from Masarik and Conger's family stress model (Masarik & Conger, 2017). (CCE - Child Criminal Exploitation; CSE - Child Sexual Exploitation; ACEs – Adverse Childhood Experiences; SEND – Special Educational Needs and Disabilities)



There is a patchwork of evidence on the prevention of child maltreatment, from evaluations of complex policy-driven interventions such as Sure Start Children's Centres and the Family Nurse Partnership (National Evaluation of Sure Start (NESS) Team, 2012; Robling et al., 2016), to randomised controlled trials of more rigidly defined programmes (Miller &

Harrison, 2015). A 2009 systematic review of reviews of child maltreatment prevention identified home-visiting, parent education, abusive head trauma prevention and multi-component interventions as promising, but lamented the scarcity of methodologically rigorous research (Mikton & Butchart, 2009). In England, high profile reviews including the Allen reports (Allen, 2011), and work by the Early Intervention Foundation (*Early Intervention Foundation*, n.d.), have led to widespread institutional support for early intervention into the lives of very young children, usually under two-years old. A greater emphasis on early intervention and securing a permanent, stable home environment has emerged, recalibrating the relationship between the family and the State (Featherstone et al., 2014; White et al., 2014). One consequence of the strong research focus on young children has been a relative paucity of evidence for the impact of early help on older children who come to the attention of Children's Services (Wastell & White, 2012). Adolescents tend to require long-term, whole-family and contextual early support (Thoburn et al., 2013); many experience acute risks beyond the family home, in the community, from peers and child criminal and sexual exploitation. Their complexity presents challenges for research, and the absence of a good evidence base increases their vulnerability to spending cuts relative to early years services (W. Mason, 2015; White et al., 2014).

The difficulty of generating evidence for complex interventions through traditional experimental designs (Meadows, 2007; Stewart-Brown, 2012; Stewart-Brown et al., 2011) has led to renewed interest in natural policy experiments for evaluating the broader ecology of public services (Craig et al., 2018; Ogilvie et al., 2019; C. Webb, n.d.). Natural policy experiments are defined here as policies "not under the control of the researchers, but (…) amenable to research which uses the variation in exposure that they generate to analyse their impact" (Craig et al., 2012). They are considered a promising alternative to experimental designs, particularly where there is a limited evidence base for policy intervention (Hu et al.,

2017; Petticrew et al., 2005; Roe & Just, 2009). They have been used to assess the impact of spending cuts in a variety of contexts (Alexiou et al., 2021; McCartney et al., 2020; Reeves et al., 2016). In England, each local authority has responded differently to central government cuts, depending on the depth of the cuts, local strategies, and political priorities. Previous research has highlighted that the unequal reduction in funding for prevention may have contributed to the uneven rise in children becoming looked after across England (Bennett et al., 2020; Bywaters et al., 2018), opening up the potential for evaluating the impact of this variation in spending as a natural policy experiment.

In this study, therefore, we exploit the natural policy experiment borne of the differential impact of reduced central government funding across local authority Children's Services in England, to assess the relationship between changing investment in preventative services and changing rates of children becoming looked after. Given the divergent approaches to early help for young children and young people, we examined outcomes for children at different extremes of the age spectrum, children aged 1-4, and, separately, children aged 16-17. The two age groups present the best possible match to the spend data available, allowing for the clearest possible delineation of age-specific service funding. Both groups of children are old enough to have directly benefited from services; they are not subject to England's primary and secondary compulsory school age, and so may be more likely to depend on Children's Services support.

METHODS

Data sources

We conducted a longitudinal study at local authority level in England using panel data from 150 English upper-tier local authorities between 2011 and 2019. Two local authorities, the City of London and the Isles of Scilly, were excluded due to their small population size.

Our primary outcome was the annual rate of children starting to be looked after by local authorities in England (CLA rate), stratified by age. We investigated outcomes for children aged 1-4, and young people aged 16-17. For the younger age group, count data were drawn from the 'children looked after data return', submitted by local authorities to the Department for Education annually. Data for 2013-2019 are published on a dedicated website (Department for Education, 2021). Data for earlier years are available from the National Archives (Department for Education, 2011a, 2012a). For the older age group, a Freedom of Information request yielded count data excluding unaccompanied children seeking asylum, who are likely to be older, and whose care status is unlikely to be related to changes in local authority prevention spend, our exposure of interest (Department for Education, 2020).

We defined two age-specific measures of prevention spend, relevant to our two outcome measures: '*prevention spend per child aged under 5'*, and '*prevention spend per child aged over 12*'. Spend data for every local authority in England were taken from Section 251 expenditure statements, published by the UK Ministry of Housing, Communities & Local Government, and compiled for years 2011-2019 in the place-based longitudinal data resource (Place-based Longitudinal Data Resource, 2019). These data capture spending across a range of broad categories, allowing for some limited specificity in relation to age. For categories relating to preventative services, the widest possible age range of intended beneficiaries was identified based on 2013 guidance to local authorities, in which age-ranges for key categories were first made explicit (Department for Education, 2013), and used to derive a spend-per-child estimate.

The population of children of the relevant age-range, sourced from Office for National Statistics (ONS) mid-year population estimates, formed the denominator (Office for National Statistics, 2020). We then summed age-relevant spend-per-child estimates, defining our two age-specific measures. Both measures encompass spend in the categories 'family support'

and ‘other children and family services’, which may benefit children of any age. The measure ‘prevention spend per child aged under 5’ includes spend in the category ‘Sure start children’s centres and early years’. The measure ‘prevention spend per child aged over 12’ includes spend in the categories ‘services for young people’, and ‘youth justice’. For further details of the categories, and how the age-specific measures were defined, see appendix 2. All spend figures were adjusted for inflation to 2019 prices using the consumer price index deflator (Office for National Statistics, 2021). We refer to the financial year by the latter year throughout.

In all models, we controlled for local economic trends that may confound the association between prevention spend and care entry rates. These trends may be monitored by local authorities attempting to gauge need and forecast spend; they may also affect care entry rates via their impact on family stress and parental behaviours. We controlled for: trends in employment, using Labour Force Survey data on employment rates for the working age population (Office for National Statistics, 2019), a commonly used measure of economic participation (Department for Business Innovation and Skills & Department for Communities and Local, 2010; UK Commission for Employment and Skills, 2014); and trends in regional child poverty rates, using Households Below Average Income (HBAI) statistics on the proportion of children living in households with less than 60% of contemporary household median income, after housing costs (Department for Work and Pensions, 2020).

Statistical analyses

Using age-stratified scatter plots, we first visually explored the unadjusted association between changes in prevention spend and changes in the CLA rate, across local authorities. For each local authority, we took the absolute difference in prevention spend and CLA rates

between two time points, 2011 and 2018. We plotted change in CLA rates on the y-axis against change in prevention spend on the x-axis.

We then used within-between regression models (Allison, 2009) to estimate, across the whole time period, the association between trends in prevention spend and trends in CLA rates. These models allowed us to control for time-invariant differences between areas and national trends affecting all areas equally, as in a fixed-effects regression approach, while also allowing us to estimate random intercepts to account for the correlation of observations within local authorities. They make use of the between-local authority variation in responses to budgets cuts to tease out the contribution of those cuts to rising CLA rates. We stratified analyses by age, examining CLA rates for 1–4-year-olds in relation to prevention spend per child under 5, and CLA rates for 16–17-year-olds in relation to prevention spend per child over 12. The allocation of resources within Children's Services may be informed by changing levels of anticipated need in an area. We therefore controlled for local area employment rates, and regional child poverty rates, both potential confounders. Since we would not expect a change in the exposure and control variables to have an immediate effect on CLA rates, these variables were lagged by one year. The resulting models were used to estimate the contribution of changing prevention spend for children and families to rising CLA rates (for full details, see appendix 3).

Using these models, and in order to contextualise our findings, we estimated the marginal difference between observed trends, and trends that might have been expected had prevention spend remained constant, in effect the total number of care entries linked to the cuts. For each local authority in each year, we took the difference between model estimates under observed conditions, and model estimates under the counterfactual scenario of constant prevention spend from 2011, summing these differences across all years, 2011-2018. We repeated this for 1,000 random draws from the sampling distribution of model parameters to derive

confidence intervals for our estimate. Random error was assumed to be comparable under these two scenarios. All models were estimated using the "panelr" package (Long, 2020), in R version 3.6.3.

Robustness tests

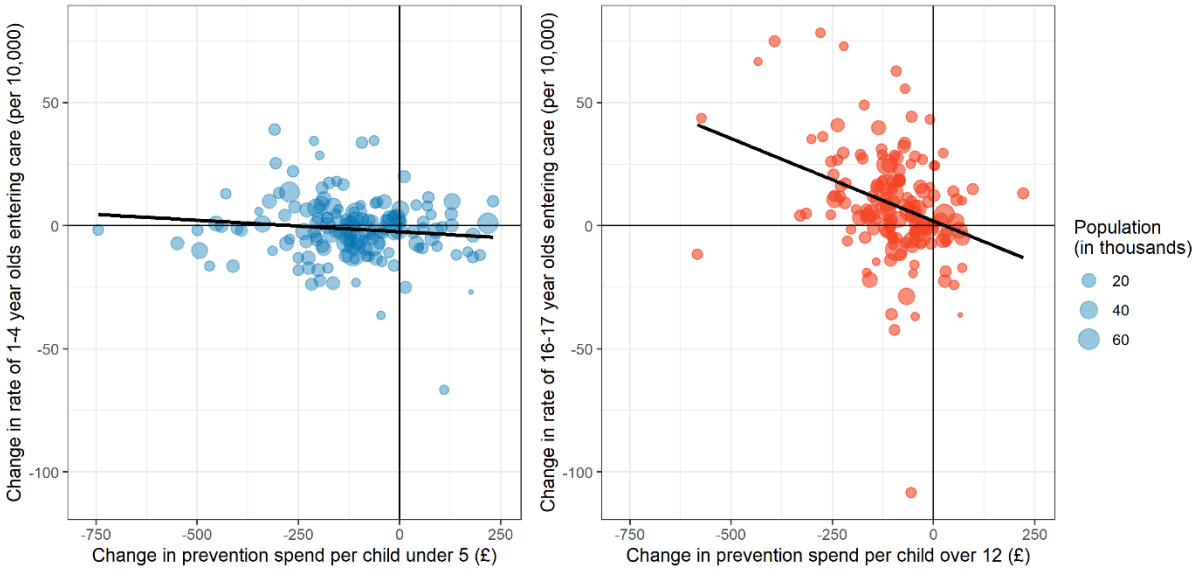
We undertook several robustness tests. First, to test whether associations identified in our main analysis were likely due to unmeasured confounding, we conducted negative control analyses (Lipsitch et al., 2010; K. E. Mason et al., 2021). We repeated our main analyses, using age-inappropriate categories of spend as negative control exposures: expenditure on 'Sure Start Children's Centres and early years' for children aged 16-17; and expenditure on 'services for young people' for children aged 1-4. Any observed association between these negative control exposures and the outcomes would be non-causal, indicating likely residual confounding in our primary analyses. If no association is observed, a causal interpretation of the primary associations is more plausible. Second, since reliable child poverty data for the time period were only available at regional and not local authority level, and to explore outcomes when more effectively controlling for this potential confounder, we fit our main models aggregating all data to regional level. Third, due to potential variation in expenditure recording practices between areas, and within areas longitudinally, we fit models for both age groups to alternative specifications, using total prevention spend per child as the exposure, rather than age-relevant spend. Fourth, to address possible bias due to mathematical coupling that could result from both our exposure and outcome measures sharing the same denominators (i.e., the population), we fit Poisson regression models with the log of the population as an offset rather than modelling CLA rates directly (Berrie, 2019). Fifth, we excluded from our analyses any notable outliers. Finally, we excluded from our analyses all London local authorities, to ensure that findings were not due to the capital's idiosyncrasies (Allan et al., 2017).

RESULTS

Main results

Summary statistics are presented in appendix 4 tables 1-3. Our exploratory scatter plots show negative associations, particularly for older children, between the change in prevention spend per child and the change in CLA rate, between 2011 and 2018, in each local authority (figure 3).

Figure 3. Age-stratified scatter plots showing associations between changes in prevention spend and changes in the rate of children starting to be looked after, between 2011 and 2018, in each local authority



Our modelling results tell a similar story. While the model for children aged 1-4 shows no association between changing prevention spend and rates of young children becoming looked after, our model for children aged 16-17 shows that, between 2011 and 2018, across English local authorities, and after controlling for local economic trends and regional child poverty, a £10 per child cut to prevention spend was associated with 1.9 per 100,000 additional 16-17 year olds becoming looked after the following year (95% CI 1 to 3). Table 1 summarises the output of our models (for full model output see appendix 5). We estimate that 1,077 additional adolescents became looked after between 2012 and 2019 than would have been

expected had 2011 levels of funding been sustained (95% CI 414 to 1,772), equivalent to 3.9% of total care entrants in this age group. Approximately 1 in 25 care entries over the period, in this 16-17 age group, were linked to the cuts.

Table 1: Annual change in the rate of children starting to be looked after the following year (per 100,000 children) for a £10 per child reduction in prevention spend, after controlling for local economic trends and regional child poverty

Age group	Effect estimate	95% CI, lower	95% CI, upper
1-4	-0.04	-0.51	0.43
16-17	1.87	0.67	2.94
Sample size**: 1,200 observations nested within 150 local authorities, across 8 timepoints**			

Robustness tests results

Results of the robustness tests are shown in appendix 6. The negative control analyses reveal no association between negative controls and CLA rates, strengthening the causal case for the impact of age-relevant prevention spend on rates of 16–17-year-olds entering care. The regional level models show some slight differences. Most notably, in the regional model for 1–4-year-olds, a £10 cut to prevention spend was associated with an additional 2 per 100,000 young children entering care, though with confidence intervals spanning the null (95% CI 0 to 4). The regional model for 16–17-year-olds also showed a larger effect of prevention spend compared to the local authority level model. Controlling more effectively for child poverty may more clearly reveal the protective impact of prevention spend. However, aggregating up to the regional level may also introduce bias due to ecologic variation in the distribution of local authority effects, or compound the effect of unknown time-variant factors that vary markedly by region, for example social work culture or practice. Due to a small sample size, the regional-level models may also be underpowered to reliably estimate a small but important population effect (Button et al., 2013).

The model using total prevention spend per child as the exposure, intended to address the possible effects of differential expenditure recording practices, yielded similar findings: no apparent effect on younger children and a protective effect for the adolescents, though with a smaller estimated effect size. Given that a large proportion of the change in total prevention spend will have affected early years services, this is as expected. The Poisson regression models corroborate our main findings of an association between changing spend and outcomes for older children aged 16-17, with no discernible effect of spend on younger children. Models excluding outliers or London local authorities show a slightly increased protective effect of prevention spend for older children.

DISCUSSION

Using data for the whole of England, this study exploits a natural policy experiment to investigate the association between changing spend and changing rates of children becoming looked after within local authorities. We found that between 2011 and 2019, across England, areas that experienced deeper cuts to prevention services for adolescents saw a greater increase in 16–17-year-olds becoming looked after the following year. We estimate that an additional 1,077 children aged 16-17 became looked after than would otherwise have been expected had 2011 levels of spend been sustained, at great cost to local authorities. In addition to causing avoidable harm to children and families, the cuts are unlikely to have represented a meaningful cost saving. Altogether, in the short-run, cuts to preventative services for adolescents totalling £57.7 million potentially resulted in corporate parenting costs of £60.2 million (95% CI 23.1 to 99.0). This estimate is based on local authorities' annual Children Looked After spend per child in care on 31st March, adjusted for inflation. It does not consider the higher cost of residential placements for many adolescents or the cost to Children's Services of supporting adolescents up to and beyond the age of 18, let alone the wider societal costs (HM Government, 2016). We found no association between changing

prevention spend and children aged 1-4 becoming looked after in our main local authority-level model.

Our finding of an association between cuts to services for adolescents and a rise in the rate of 16–17-year-olds becoming looked after is as expected. The withdrawal or hollowing out of services designed to promote young people's personal and social development, in a safe environment, within their communities, may increase vulnerability. The effects may be immediate, through sudden increased exposure to family or community risks; or gradual, through foregone opportunities: to develop trusting relationships with peers and adults; to use facilities and resources that may not otherwise be available to them; and to build confidence and resilience, life skills, hope for the future, and a positive sense of belonging (Chaskin, 2009; Davies, 2019). The loss of more targeted services, for young people with substance misuse or acute mental health issues, or who, through child criminal or sexual exploitation, have come into contact with the youth justice system, may increase the need for statutory intervention. Reduced service provision for young people may also affect the wider family, increasing family stress and so heightening young people's vulnerability through myriad pathways, including parental mental ill health, substance misuse and conflict. Older adolescents may be particularly vulnerable to cuts to prevention spend in Children's Services, given their direct and cumulative exposure to other austerity effects: at the level of the household due to welfare changes and high youth unemployment (Tucker, 2017); in schools, through the loss of pastoral support for vulnerable students; in the health system, with Child and Adolescent Mental Health Services at capacity (Hood et al., 2020); and in the community as a result of a shrinking voluntary sector (Jones et al., 2016). Our findings accord with a literature documenting concerning trends for adolescents in recent years, including rising rates of school absence, exclusion, violent youth crime, and lower educational attainment, particularly among the most deprived (Marmot et al., 2020; Wallace & Khazbak, 2020). They

parallel findings of an association between changing prevention spend at local area level and a less acute child welfare outcome - children beginning an episode of need (C. Webb, n.d.). They are also consistent with a wider public health literature on the potential health and inequalities gains of reinvestment in public services (Alexiou et al., 2021; Antonakakis & Collins, 2015; Barr et al., 2015). Reinvestment in prevention services for adolescents, after a decade of cuts disproportionately affecting more deprived areas, has the potential to prevent costly State interventions into the lives of 16-17 year olds that may go on to impair their health and wellbeing throughout adulthood (Meltzer et al., 2003; Viner & Taylor, 2005), while tackling increasingly dramatic inequalities in adolescents starting to be looked after (Bennett et al., 2020; C. J. R. Webb & Bywaters, 2018).

We did not detect an association between cuts to prevention services for families with young children and rates of these children becoming looked after. There are several possible explanations. At the service level, a preventative service may serve a dual protective function with divergent effects on our outcome of interest: on the one hand, preventing need from escalating, so contributing to lower CLA rates; and on the other, identifying acute child protection concerns, potentially increasing CLA rates – a recent study of the impact of enhanced early years services shows that, in less deprived areas, they are associated with higher intervention rates (Scourfield et al., 2021; C. Webb et al., 2020). At local authority level, therefore, the supply of early years services may only meaningfully affect CLA rates beyond a certain threshold of investment, when major barriers to access have been overcome, and unmet need has come to light. This threshold may not have been reached. Our regional-level robustness test, in which we aggregate all data up to the regional level so as to more appropriately control for child poverty, lends some credence to the theory that rising need may be outstripping the supply of services. These robustness tests point to a greater protective impact of prevention spend, suggesting that the local authority level analysis may

not sufficiently account for local trends in socioeconomic conditions: high need associated with changing socioeconomic conditions may overwhelm the effect of spend in our main model. A further possibility is that, after years of spending cuts, surviving services are less effective, perhaps in some cases ineffective. Under conditions of resource scarcity, the quality of provision may suffer. Local authorities may be most likely to consolidate services, raising barriers to access, including travel time and costs. They may also be more likely to cut services offering 'ordinary help' for families getting by (practical relational or material support) (Featherstone et al., 2018; C. Webb, n.d.; White et al., 2014), in favour of more targeted services for families with complex and entrenched needs (behavioural, including therapeutic interventions). Families with young children may be less likely to engage with community services if they are seen as inviting scrutiny, surveillance, and social care involvement. Moreover, by their nature, increasingly targeted services may be less successful in stemming the flow of children into LA care: so-called 'early' help may come too late (Hood et al., 2020). While short-term, targeted interventions that adopt an individualised medical or psychiatric model of health may evince improved child or parental health outcomes, particularly under experimental conditions, in practice this may not translate into reduced care entry (Thoburn et al., 2013), and may in fact impede family engagement and coping (Featherstone et al., 2014; White et al., 2014). This may result in counterproductive public health outcomes. Finally, the one-year time lag may be insufficient for detecting an impact of early years services on such an acute outcome.

In the longer term, there is abundant evidence that investment in high quality early years services, following a proportionate universalist approach, is likely to yield benefits throughout the life course (Cattan & Farquharson, 2019; Marmot et al., 2020; Sim et al., 2018; Waldfogel, 2004). Commissioning strategies for younger children could assume the more holistic social model of early help espoused in the social work literature (Featherstone

et al., 2018), and, given our finding of a protective effect of services for adolescents, may look to the principles and practices of youth work with adolescents. This may require a shift in how we generate evidence of effective service design. Moving away from a singular reliance on randomised controlled trials, for example by leveraging natural experiments using local area data, as in this study, may strengthen the evidence base for a broader range of interventions. Natural policy experiments are increasingly used in the US to evaluate the impact of a variety of policies, including those aiming to provide support services to children and families (Cancian et al., 2013, 2017; McLaughlin, 2017, 2018; Raissian & Bullinger, 2017; Spencer et al., 2021). These methods may be usefully deployed in other contexts.

Meanwhile, tackling major drivers of need, such as child poverty, may be the most effective and cost-effective short-term strategy for safely reducing the rate of younger children entering care.

Strengths and limitations

Our study has several limitations. Due to the lack of individual level data, we used an ecological area-level analysis, and cannot identify whether children entering care were directly affected by spending cuts. The association between changing prevention spend and CLA rates in our analysis may be due to trends in unobserved time-varying confounding factors that varied between local authorities. Despite wide variation in changes to prevention spend across local authorities, the allocation mechanism determining exposure status in this natural policy experiment does not approximate a randomization process: residual confounding is therefore possible, tempering causal claims (Vocht et al., 2020). However, the null findings of the negative control analyses offer reassurance that the main results are not biased by residual confounding. The lack of reliable longitudinal child poverty estimates at local area level for the relevant time period was a limitation (Francis-Devine, 2020). We

attempted to partially overcome this limitation by controlling for regional child poverty alongside LA employment, and conducting robustness tests at regional area level.

A further limitation of the analysis is that the main exposure variable may not be strictly exogenous: the CLA rate at one point in time may affect prevention spend in the same year. Local authorities' statutory, corporate parental obligations towards Children Looked After mean that spend on these children is less flexible. If the rate of children entering care in a year largely determines the remaining funding available for prevention services, this may bias the analysis. We lagged exposure and control variables by one year, ensuring that exposure preceded outcome. However, we cannot specify the real-world causal lag with a high degree of certainty, and, since the models used are sensitive to the correct specification of temporal lags (Leszczensky & Wolbring, 2019), some bias may persist. One year is a plausible lag time for the effect of changing spend on preventative services for children and families, and can be accommodated without loss of data and statistical power.

A final limitation relates to the Section 251 returns. Data collected between 2009 and 2010 cannot be reconciled with data from later years and were therefore not considered (Department for Children Schools and Families, 2009; Department for Education, 2010). The restricted time period does not allow for an assessment of the pre-policy period, so precluded the possibility of using more robust methods for causal inference, such as regression discontinuity or difference in difference designs. Our analytic approach nevertheless overcomes the limitation of the restricted time period by exploiting the between-local authority variation in responses to spending cuts following the implementation of austerity policies. The time period is the relevant one for our analysis. Moreover, the plausibility of the protective effect of preventative services, together with the null findings of negative control analyses indicating the specificity of the impact of age-specific spend on particular age groups, are suggestive of a causal effect (Hill, 1965).

Although the financial data are broadly comparable from 2011, quality and consistency issues, particularly in the early years of the returns (Department for Education, 2012b; Freeman & Gill, 2014), led us to use broad categories of spend, rather than more granular data relating to specific services. Nevertheless, the potential for variation in the interpretation of spend categories longitudinally and between local authorities led us to conduct a robustness test using, as the exposure for both age groups, the cruder measure of total prevention spend per child (C. J. R. Webb & Bywaters, 2018). The findings allay concerns about measurement bias. Our age-specific exposures remain broad, and may reflect a range of services, of varying quality. Process evaluations of social interventions and qualitative literature on the lived experiences of children and families foreground the quality of interpersonal relationships with programme staff, local community strengths and services, and good leadership (Meadows, 2007). From the data available, we cannot determine the nature or quality of prevention services within an area, nor trace their change over time. However, these data remain the best available national indicator of local authorities' commitment to delivering upstream support to children and families, and our findings demonstrate their importance for effective public health and children's social care policy. We echo others in urging governments to move towards accurate and comparable expenditure statements (Holmes, 2021). In the meantime, further qualitative work should explore the impact of funding cuts on Children's Services prevention strategies over the past decade, and the implications for quality, accessibility, and type of services available.

A strength of this analysis is the use of longitudinal methods that combine aspects of fixed and random effects models allowing us to control for time-invariant differences between areas and national trends affecting all areas equally. We were also able to control for important confounders, yielding estimates that, in combination with the null findings of the negative control analyses, may approach a causal association. We also investigate outcomes

in relation to specific age groups of children, acknowledging and exploring the different risk environments and prevention services available at different stages of childhood. Ours is the first study to harness these methods to evaluate the natural experiment of changing preventative spend for Children Looked After specifically. Our analytic approach is appropriate to an exploration of this most acute child welfare intervention, as thresholds for statutory intervention are less likely than other child welfare outcomes to vary over time within an area. Other outcomes may require a different modelling approach (C. Webb, n.d.).

IMPLICATIONS FOR POLICY AND PRACTICE

Our study highlights the child welfare costs of the policy response in England to the 2008 recession. In this moment, in the midst of a pandemic and on the brink of another economic downturn, it is imperative that we learn from past decisions. Between 2011 and 2019, regressive cuts to LA funding may have led to more young people becoming looked after, with far-reaching consequences for children and families, and for LA's financial health, in particular the most deprived. While underlying differences in child protection systems and local service delivery may limit the international relevance of this study, the English perspective can offer wider insights. We argue that preventative children's services, delivered by local government, can play a part in reducing rates of children in care. These findings may be of particular relevance in high-income settings where austerity measures have adversely impacted local government and children's services funding.

Prevention is better than cure. It is a tired idiom, but it has the virtue of being true. Strategies to safely and effectively reverse adverse trends in children looked after should mandate greater investment in upstream support for children, young people and their families. The costs of state care are astronomical, and outcomes for these children in adulthood are poor. Further cuts, or a failure to reinvest in preventative services for adolescents, may contribute

to a consolidation of the spiralling costs and child-removal practices in England today. Currently, through determined effort, individual policymakers may choose to 'hold their nerve' on prevention (The Association of Directors of Children's Services Ltd, 2018). But the survival of these services should not depend on individual local policymakers' conviction and resolve. National government policies must bolster, not undermine, local governments' ability to deliver statutory early help and family support – a key recommendation of the 2011 Munro report and a familiar refrain amongst local policymakers, long overlooked (Munro, 2011). A strengthened statutory safety net could lead to a systemic shift in the approach to prevention in Children's Social Care. This would require sustained central government funding of local government Children's Services, proportional to the level of need, and attention to the social determinants of health and child welfare inequalities. The long-term benefits to children, families, and society of these policy measures are likely to be immense.

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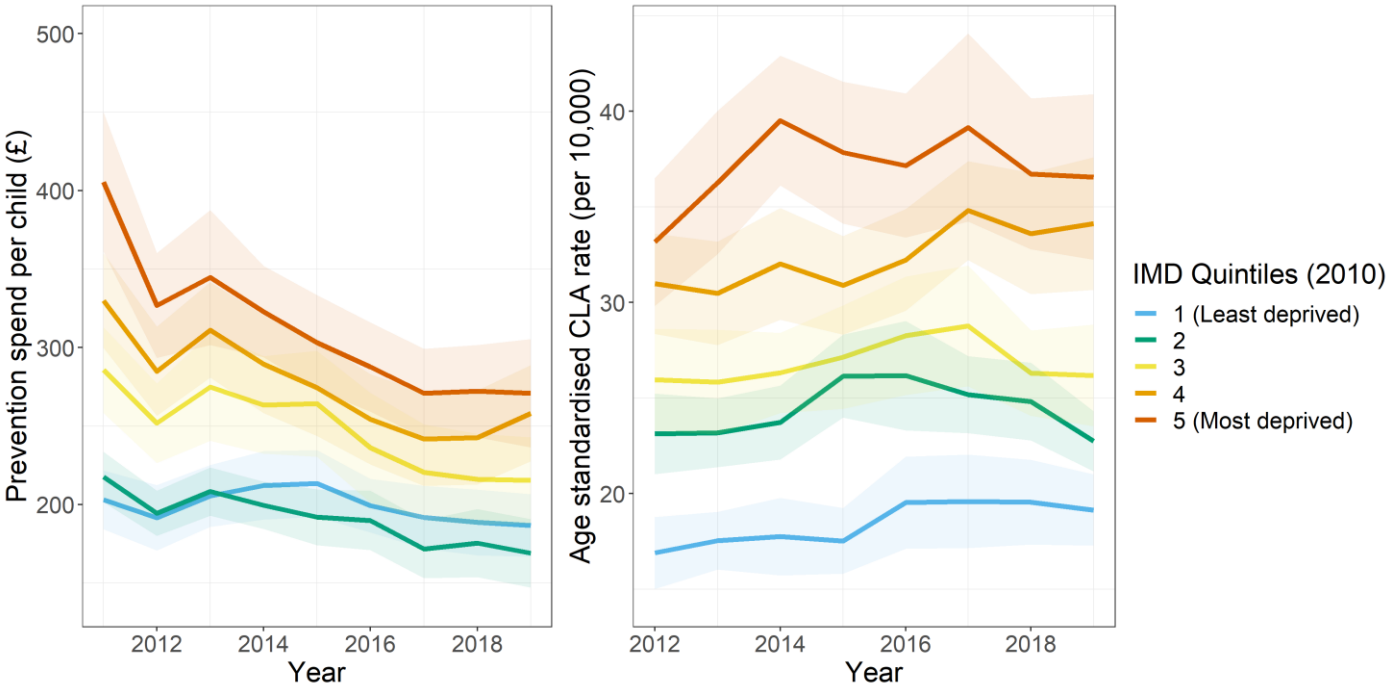
APPENDICES

Appendix 1: trends in inequalities in our exposure and outcome variables

Appendix 1 figure 1: trends in inequalities in total prevention spend (adjusted for inflation to 2018 prices, using the consumer price index deflator), and annual age-standardised rates of children starting to be looked after



Appendix 2:

Summarising categories of prevention spend

Departmental advice for local authorities compiling their budget statement outlines each of the categories of prevention spend included in our analyses (*Youth Offending Teams*, n.d.). The categories are summarised as follows:

- 'Sure start children's centres and early years' may encompass a range of services for families with children under 5 years of age. These often include: parenting programmes; health promotion; prenatal and health visitor services; early learning and links to childcare; and links with employment, welfare, and other forms of parental support. (Goff et al., 2013)

- ‘Services for young people’ are intended for children between the ages of 13 and 19, and encompass: universal services, including youth work, recreational activities, and services that support participation in education or training; and targeted services, such as substance misuse services, services for young parents, and discretionary awards.
- ‘Youth justice’ spend relates to services for children above the age of criminal responsibility, who have been in trouble with the law, including: youth offending teams that work with young people to prevent reoffending (*Youth Offending Teams*, n.d.); community-based services; bail support schemes to ensure that children can remain a home where possible; and in rare cases, spend on secure accommodation for children who pose a risk to themselves or others, or who have been convicted of grave crimes.
- ‘Family Support Services’ cover: support for children with special educational needs and disabilities; universal family support, for examples services that facilitate partnership between parents and schools or peer-to-peer and relationship support; and intensive, targeted support for vulnerable families.
- ‘Other Children and Family Services’ relate to miscellaneous spend on children and their families, such as grants to voluntary organisations, and counselling and other generic support services.

Defining age-based exposures

For the exposure ‘Prevention spend per child aged under 5’, we took the sum of the following:

- ‘Sure start children’s centres and early years’ / Population of children under 5 years of age
- ‘Other children and family Services’ / Population of children under 18

- ‘Family support services’ / Population of children under 18

For the exposure ‘Prevention spend per child over 12’, we took the sum of the following:

- ‘Services for young people’ / Population of children aged 13-19
- ‘Youth justice’ / Population of children aged 10-17
- ‘Other children and family Services’ / Population of children under 18
- ‘Family support services’ / Population of children under 18

Appendix 3: Model formula

$$Y_{ijt} = \beta_0 + \beta_1(x_{1it-1} - \bar{x}_{1i}) + \beta_2(x_{2it-1} - \bar{x}_{2i}) + \beta_3(x_{3jt-1} - \bar{x}_{3j}) + U_i + \delta_t + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

Let:

- Y_{ijt} denote the rate of children taken into care (per 100,000), dependent on LA i (in Region j) and year t
- x_{1it-1} denote exposure lagged prevention spend per child (£10s), dependent on LA i and year t-1
- x_{2it-1} denote the lagged employment rate (%), dependent on LA i and year t-1
- x_{3jt-1} denote the lagged child poverty rate (%), dependent on Region j and year t-1
- U_i denote LA random effects
- δ_t denote a series of dummy variables for each year t
- $\varepsilon_{it} \sim N(0, S_1)$ denote the random error for LA i in year t
- δ_t denote a series of dummy variables for each year t
- The overbar denote time averages

Appendix 4: Summary statistics

Appendix 4 table 1. Summary statistics for outcome variables

	Outcome variables							
Year	CLA rate 1-4 (per 10,000)				CLA rate 16-17 (per 10,000)			
	Mean	Sd.	Min	Max	Mean	Sd.	Min	Max
2011	237.4	126.3	13.6	709.5	221.7	179.9	0.0	1390.0
2012	237.5	115.8	9.7	697.3	228.6	172.6	0.0	1119.5
2013	239.8	132.4	41.4	841.5	264.1	183.0	19.5	888.0
2014	240.9	121.0	21.3	661.9	326.0	228.6	21.1	1324.5
2015	235.3	126.8	30.5	655.8	321.7	220.3	22.4	1815.8
2016	225.7	117.2	8.9	694.3	321.6	199.3	5.9	1382.1
2017	241.6	136.3	28.5	804.6	313.3	217.2	18.7	1477.8
2018	223.1	132.4	8.8	727.6	306.8	213.8	0.0	1174.6
2019	227.6	143.1	17.4	752.4	314.6	197.0	39.9	1129.6

Appendix 4 table 2. Summary statistics for exposure variables (2019 data not available at the time of writing)

	Exposure variables							
Year	Prevention spend per child <5s (£10s)				Prevention spend per child >12s (£10s)			
	Mean	Sd.	Min	Max	Mean	Sd.	Min	Max
2011	43.2	20.1	3.1	132.9	36.9	14.6	14.7	111.2
2012	36.3	15.4	3.4	108.8	31.6	12.1	5.3	85.6
2013	40.4	18.4	7.9	130.6	33.1	13.8	10.1	93.0
2014	37.9	15.3	4.5	101.7	31.4	11.7	12.8	75.9
2015	36.2	16.2	6.5	112.6	30.2	11.1	11.2	76.7
2016	33.7	16.1	5.6	111.8	28.2	10.1	10.4	67.3
2017	32.0	15.8	4.6	108.3	26.2	11.1	6.9	98.2
2018	31.1	17.0	4.2	108.3	26.5	10.0	5.7	63.9
2019	-	-	-	-	-	-	-	-

Appendix 4 table 3. Summary statistics for control variables

	Control variables							
Year	Employment rate (%)				Child poverty (%)			
	Mean	Sd.	Min	Max	Mean	Sd.	Min	Max
2011	69.6	5.3	53.4	81.5	30.4	5.4	22	38.0
2012	69.3	5.3	56.0	79.1	29.4	5.1	22	37.0
2013	70.3	5.1	57.6	80.9	28.6	5.2	22	37.0
2014	71.2	5.2	59.8	82.4	28.8	5.4	23	38.0
2015	72.3	5.0	60.0	82.9	29.2	4.4	25	37.0
2016	73.4	4.8	60.4	84.2	30.1	4.3	25	37.0
2017	73.8	5.0	60.9	82.3	31.1	4.2	25	37.0
2018	74.6	4.9	58.7	84.4	31.1	4.5	25	37.0
2019	74.9	4.6	61.7	84.3	31.6	5.2	25.0	39.0

Appendix 5: Full main linear regression model output

Appendix 5 table 1. Output of the main regression models estimating absolute change in the rate of children starting to be looked, per 100,000

	Main models			
	Age 1-4		**Age 16-17**	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part				
$\boldsymbol{\beta_0}$ Intercept	233.96	8.87	299.59	13.99
$\boldsymbol{\beta_1}$ Age-relevant prevention spend per child in the corresponding age group	0.04	0.25	-1.87	0.60
$\boldsymbol{\beta_2}$ Employment	-0.41	1.26	3.24	2.05
$\boldsymbol{\beta_3}$ Child poverty	2.87	1.79	0.72	2.91
$\boldsymbol{\delta_t}$ Year	*		*	
Year - Linear	-13.72	9.63	25.45	16.23
Year - Quadratic	-8.06	6.95	-59.52	11.31
Year - Cubic	4.69	6.29	31.66	10.25
Year - Quartic	-1.31	6.09	14.14	9.96
Year - Quintic	4.23	6.01	-14.91	9.76
Year - Sextic	12.08	6.01	15.26	9.79
Year - Septic	7.57	5.99	-9.08	9.76
Parameter	Estimate	Std. Dev.		
Random part: local authority level				
Intercept variance	(β_0 Intercept)	105.5	(β_0 Intercept)	166.1
Random part: observation level				
Residual variance		119.8		119.3
Pseudo-R^2 (fixed effects)	0		0.03	
Pseudo-R^2 (total)	0.68		0.67	
AIC	14105.98		15257.52	
Number of local authorities	150		150	
Number of observations	1200		1200	
* Using the panelr package, orthogonal polynomial coding for trend analysis accounts for the effect of the year dummy variables $\boldsymbol{\delta_t}$. The contrast matrix can be estimated for the 8 time points using the contr.poly function.				

Appendix 6: Robustness tests

1. Negative control analyses

Appendix 6 table 1a. Output of the negative control analysis for 1–4-year-old estimating the absolute change in the rate of children aged 1-4 starting to be looked after, per 100,000

	Negative control analysis for 1–4-year-olds	
Parameter	Estimate	Std. Err.
Fixed part		
$\boldsymbol{\beta_0}$ Intercept	233.96	8.87
$\boldsymbol{\beta_1}$ Spend per 13-19 year old on young people's services	-0.02	0.05
$\boldsymbol{\beta_2}$ Employment	-0.42	1.26
$\boldsymbol{\beta_3}$ Child poverty	2.93	1.78
$\boldsymbol{\delta_t}$ Year	*	
Year - Linear	-15.84	10.50
Year - Quadratic	-7.99	6.95
Year - Cubic	4.66	6.28
Year - Quartic	-0.91	6.07
Year - Quintic	3.95	6.00
Year - Sextic	12.34	6.01
Year - Septic	7.40	5.99
Parameter	Estimate	Std. Dev.
Random part: local authority level		
Intercept variance	(β_0 Intercept)	105.5
Random part: observation level		
Residual variance		73.19
Pseudo-R^2 (fixed effects)	0	
Pseudo-R^2 (total)	0.68	
AIC	14109.28	
Number of local authorities	150	
Number of observations	1200	
* Using the panelr package, orthogonal polynomial coding for trend analysis accounts for the effect of the year dummy variables $\boldsymbol{\delta_t}$. The contrast matrix can be estimated for the 8 time points using the contr.poly function.		

Appendix 6 table 1b. Output of the negative control analysis for 16–17-year-olds estimating the absolute change in the rate of children aged 16-17 starting to be looked after, per 100,000

	Negative control analysis for 16–17-year-olds	
Parameter	Estimate	Std. Err.
Fixed part		
$\boldsymbol{\beta_0}$ Intercept	299.59	13.99
$\boldsymbol{\beta_1}$ Spend per child under 5 on Sure Start children's centres and early years services	-0.05	0.04
$\boldsymbol{\beta_2}$ Employment	3.09	2.06
$\boldsymbol{\beta_3}$ Child poverty	0.26	2.92
$\boldsymbol{\delta_t}$ Year	*	
Year - Linear	37.44	16.09
Year - Quadratic	-59.82	11.36
Year - Cubic	31.54	10.29
Year - Quartic	10.35	9.93
Year - Quintic	-14.18	9.85
Year - Sextic	13.97	9.84
Year - Septic	-8.52	9.80
Parameter	Estimate	Std. Dev.
Random part: local authority level		
Intercept variance	(β_0 Intercept)	166
Random part: observation level		
Residual variance		119.8
Pseudo-R^2 (fixed effects)	0.03	
Pseudo-R^2 (total)	0.67	
AIC	15271.26	
Number of local authorities	150	
Number of observations	1200	
* Using the panelr package, orthogonal polynomial coding for trend analysis accounts for the effect of the year dummy variables $\boldsymbol{\delta_t}$. The contrast matrix can be estimated for the 8 time points using the contr.poly function.		

2. Regional-level models

Appendix 6 table 2. Output of the regional level models estimating the absolute change in the rate of children starting to be looked after, per 100,000

	Regional models			
	Age 1-4		**Age 16-17**	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part				
$\boldsymbol{\beta_0}$ Intercept	233.48	28.88	265.77	31.08
$\boldsymbol{\beta_1}$ Age-relevant prevention spend	-2.10	1.11	-10.79	2.87
$\boldsymbol{\beta_2}$ Employment	1.22	5.61	8.74	7.92
$\boldsymbol{\beta_3}$ Child poverty	5.05	2.18	2.48	2.95
$\boldsymbol{\delta_t}$ Year	*		*	
Year - Linear	-40.28	31.44	-89.00	43.32
Year - Quadratic	-13.77	9.47	-40.39	12.81
Year - Cubic	2.60	8.73	32.53	12.14
Year - Quartic	5.62	8.14	38.11	13.18
Year - Quintic	-5.89	7.85	-24.93	10.18
Year - Sextic	13.49	7.49	17.58	10.56
Year - Septic	4.86	7.24	-7.09	10.01
Parameter	Estimate	Std. Dev.		
Random part: Regional level				
Intercept variance	(β_0 Intercept)	86.05	(β_0 Intercept)	92.25
Random part: observation level				
Residual variance		21.52		29.61
Pseudo-R^2 (fixed effects)	0.01		0.08	
Pseudo-R^2 (total)	0.94		0.91	
AIC	645.38		679.11	
Number of Regions	9		9	
Number of observations	72		72	
* Using the panelr package, orthogonal polynomial coding for trend analysis accounts for the effect of the year dummy variables $\boldsymbol{\delta_t}$. The contrast matrix can be estimated for the 8 time points using the contr.poly function.				

3. Total prevention spend per child as the exposure

Appendix 6 table 4. Output of models using the broadest possible category of prevention spend, estimating the absolute change in the rate of children starting to be looked, per 100,000

	Models with total prevention spend as the exposure			
	Age 1-4		**Age 16-17**	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part				
$\boldsymbol{\beta_0}$ Intercept	233.96	8.87	299.59	13.99
$\boldsymbol{\beta_1}$ **Total prevention spend per child**	0.00	0.05	-0.28	0.08
$\boldsymbol{\beta_2}$ Employment	-0.41	1.26	3.06	2.05
$\boldsymbol{\beta_3}$ Child poverty	2.89	1.79	1.01	2.92
$\boldsymbol{\delta_t}$ Year	*		*	
Year - Linear	-14.04	9.93	24.33	16.18
Year - Quadratic	-8.11	6.94	-61.20	11.31
Year - Cubic	4.67	6.28	31.61	10.24
Year - Quartic	-1.20	6.14	15.48	10.00
Year - Quintic	4.13	6.01	-16.35	9.79
Year - Sextic	12.15	6.02	16.12	9.80
Year - Septic	7.53	5.99	-9.68	9.75
Parameter	Estimate	Std. Dev.		
Random part: local authority level				
Intercept variance	(β_0 Intercept)	105.5	(β_0 Intercept)	166.1
Random part: observation level				
Residual variance		73.2		119.2
Pseudo-R^2 (fixed effects)	0		0.03	
Pseudo-R^2 (total)	0.68		0.67	
AIC	14109.16		15259.76	
Number of local authorities	150		150	
Number of observations	1200		1200	
* Using the panelr package, orthogonal polynomial coding for trend analysis accounts for the effect of the year dummy variables $\boldsymbol{\delta_t}$. The contrast matrix can be estimated for the 8 time points using the contr.poly function.				

4. Poisson models

Note: for Poisson model output, coefficients for prevention spend reflect a £100 per child increase in age-relevant prevention spend per child.

Appendix 6 table 3. Output of the Poisson models estimating the relative change in the rate of children starting to be looked after, logged

	Poisson models			
	Age 1-4		**Age 16-17**	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part				
$\boldsymbol{\beta_0}$ Intercept	-6.16	0.04	-5.64	0.05
$\boldsymbol{\beta_1}$ Age-relevant prevention spend	0.00	0.00	-0.04	0.01
$\boldsymbol{\beta_2}$ Employment	-0.00	0.00	0.01	0.00
$\boldsymbol{\beta_3}$ Child poverty	0.01	0.00	0.02	0.00
$\boldsymbol{\delta_t}$ Year	*		*	
Year - Linear	-0.07	0.02	0.52	0.03
Year - Quadratic	-0.04	0.02	-0.15	0.02
Year - Cubic	-0.00	0.01	0.04	0.02
Year - Quartic	-0.01	0.01	0.09	0.01
Year - Quintic	-0.01	0.01	0.02	0.01
Year - Sextic	0.05	0.01	0.02	0.01
Year - Septic	0.02	0.01	-0.07	0.01
Parameter	Estimate	Std. Dev.	Estimate	Std. Dev.
Random part: LA level				
Intercept variance	(β_0 Intercept)	0.45	(β_0 Intercept)	0.58
Pseudo-R^2 (fixed effects)	0		0.01	
Pseudo-R^2 (total)	0.03		0.06	
AIC	9867.38		10360.62	
Number of local authorities	150		150	
Number of observations	1200		1200	
* Using the panelr package, orthogonal polynomial coding for trend analysis accounts for the effect of the year dummy variables $\boldsymbol{\delta_t}$. The contrast matrix can be estimated for the 8 time points using the contr.poly function.				

5. Excluding outlier local authorities

1–4-year-olds

We removed local authorities whose change in prevention spend per child under 5 and change in rate of 1–4-year-olds starting to be looked after between two timepoints, 2011 and 2018, exceeded three times the interquartile range.

Prevention spend outliers: Southwark; The Medway Towns

CLA rate outliers: North-East Lincolnshire; Sunderland

Appendix 6 table 5a. Output of the model for 1–4-year-olds after excluding possible outlier local authorities, estimating the absolute change in the rate of children aged 1-4 starting to be looked after, per 100,000

	Model for 1–4-year-olds, excluding outliers	
Parameter	Estimate	Std. Err.
Fixed part		
$\boldsymbol{\beta_0}$ Intercept	230.18	8.68
$\boldsymbol{\beta_1}$ Prevention spend per child under 5	-0.04	0.27
$\boldsymbol{\beta_2}$ Employment	-0.10	1.25
$\boldsymbol{\beta_3}$ Child poverty	2.72	1.77
$\boldsymbol{\delta_t}$ Year	*	
Year - Linear	-20.37	9.56
Year - Quadratic	-6.28	6.83
Year - Cubic	3.62	6.20
Year - Quartic	-1.59	6.00
Year - Quintic	4.39	5.93
Year - Sextic	12.81	5.91
Year - Septic	7.04	5.89
Parameter	Estimate	Std. Dev.
Random part: local authority level		
Intercept variance	(β_0 Intercept)	101.9
Random part: observation level		
Residual variance		71.06
Pseudo-R^2 (fixed effects)	0	
Pseudo-R^2 (total)	0.67	
AIC	13658.41	
Number of local authorities	146	
Number of observations	1168	
* Using the panelr package, orthogonal polynomial coding for trend analysis accounts for the effect of the year dummy variables $\boldsymbol{\delta_t}$. The contrast matrix can be estimated for the 8 time points using the contr.poly function.		

16-17-year-olds

We removed local authorities whose change in prevention spend per child over 12 and change in rate of 16-17-year-olds starting to be looked after between two timepoints, 2011 and 2018, exceeded three times the interquartile range.

Prevention spend outliers: Barnsley; St Helens; Tower Hamlets

CLA rate outliers: Camden; Hammersmith and Fulham

Appendix 6 table 5b. Output of the model for 16–17-year-olds after excluding possible outlier local authorities, estimating the absolute change in the rate of children aged 16-17 starting to be looked after, per 100,000

	Model for 16–17-year-olds, excluding outliers	
Parameter	Estimate	Std. Err.
Fixed part		
$\boldsymbol{\beta_0}$ Intercept	293.85	13.71
$\boldsymbol{\beta_1}$ Prevention spend per child over 12	-2.27	0.69
$\boldsymbol{\beta_2}$ Employment	2.42	2.03
$\boldsymbol{\beta_3}$ Child poverty	-0.18	2.82
$\boldsymbol{\delta_t}$ Year	*	
Year - Linear	30.86	16.10
Year - Quadratic	-57.60	11.06
Year - Cubic	28.76	9.98
Year - Quartic	14.74	9.77
Year - Quintic	-14.84	9.51
Year - Sextic	14.13	9.54
Year - Septic	-5.80	9.50
Parameter	Estimate	Std. Dev.
Random part: local authority level		
Intercept variance	(β_0 Intercept)	160
Random part: observation level		
Residual variance		114.3
Pseudo-R^2 (fixed effects)	0.03	
Pseudo-R^2 (total)	0.67	
AIC	14648.97	
Number of local authorities	145	
Number of observations	1160	
* Using the panelr package, orthogonal polynomial coding for trend analysis accounts for the effect of the year dummy variables $\boldsymbol{\delta_t}$. The contrast matrix can be estimated for the 8 time points using the contr.poly function.		

6. Excluding London local authorities

Appendix 6 table 6. Output of models after excluding London local authorities, estimating the absolute change in the rate of children starting to be looked, per 100,000

	Models excluding London local authorities			
	Age 1-4		**Age 16-17**	
Parameter	Estimate	Std. Err.	Estimate	Std. Err.
Fixed part				
β_0 Intercept	260.25	9.74	242.01	9.45
β_1 Total prevention spend per child	-0.10	0.31	-2.24	0.66
β_2 Employment	0.84	1.69	-0.81	2.17
β_3 Child poverty	1.55	2.16	-1.29	2.76
δ_t Year	*		*	
Year - Linear	-9.88	11.93	40.74	15.57
Year - Quadratic	-5.88	8.98	-37.12	11.50
Year - Cubic	5.11	7.67	25.22	9.84
Year - Quartic	-1.33	7.47	18.85	9.64
Year - Quintic	3.29	7.26	-7.55	9.27
Year - Sextic	11.80	7.25	7.48	9.30
Year - Septic	9.57	7.23	-4.44	9.26
Parameter	Estimate	Std. Dev.		
Random part: local authority level				
Intercept variance	(β_0 Intercept)	102.1	(β_0 Intercept)	166.1
Random part: observation level				
Residual variance		78.41		119.2
Pseudo-R^2 (fixed effects)	0		0.04	
Pseudo-R^2 (total)	0.63		0.5	
AIC	11192.74		11590.67	
Number of local authorities	118		118	
Number of observations	944		944	
*** Using the panelr package, orthogonal polynomial coding for trend analysis accounts for the effect of the year dummy variables δ_t. The contrast matrix can be estimated for the 8 time points using the contr.poly function.**				