# Empirical essays on vulnerable children's care, protection and education in England

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# Abstract

Chapter 1, co-authored with Dan Anderberg, presents an empirical analysis of the relationship between Sure Start Children's Centres (SSCCs) and the rate at which children are taken into care. Sure Start is a key early intervention policy in England designed to support families with children up to the age of four. The identification strategy is based on exploiting within-Local Authority cohort variation. The results show that Sure Start provision is associated with a higher rate of entry into care for children aged 0-4, but lower rate of entry for children aged 5-9. The findings are consistent with the policy improving longer-term outcomes while identifying cases in urgent need of care.

Chapter 2 studies the impact of labour market characteristics on the prevalence of child maltreatment in England by exploring the relationship between the local unemployment rate and the number of children becoming the subject of a Child Protection Plan (CPP) in Local Authorities (LAs) in England. The impact is identified using a shift-share, or Bartik, instrument together with local fixed effects and time trends to control for any potential endogeneity of the unemployment rate. The results show that an increase of one percentage point in the local unemployment rate increases the CPP entry rate by 20 percent. The additional cases of maltreatment due to the increased unemployment rate seem to be at a lower risk than the threshold needed for taking a child into care.

Chapter 3 empirically explores what has been discussed in the literature by looking into exclusions and potential off-rolling in secondary schools in England with a greater focus on vulnerable children. The current literature shows that specific groups of children are over-represented in the population of excluded children even after controlling for other personal

characteristics. This paper confirms the existing findings and takes the analysis one step further by exploring how the exclusion probabilities for vulnerable children vary across curriculum years and whether indicators of competition faced by schools are correlated with exclusions. The main contribution of this paper to the literature is that it provides the first empirical evidence on children who disappear from the school roll. The results show that the probability of being excluded peaks at the curriculum year before GCSE exams in the general population, but not for vulnerable children. However, when it comes to potential off-rolling, the analysis shows that vulnerable children have a significantly higher probability of being removed from the school register, with the probability of a child with Special Educational Needs (SEN) disappearing from the school roll increasing significantly the year before GCSE exams.

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# Chapter 1

# Children's Social Care and Early Intervention Policy: Evidence from Sure Start

Dan Anderberg and Christina Olympiou

## 1.1 Introduction

Each year, around 30,000 children in England are taken into social care, in the majority of cases to protect them from maltreatment in the form of abuse and neglect. Looking at a specific cohort, for instance, all children born in England in 2001 and who recently turned 18, about three percent have spent some time in care, and many of them have spent a significant part of their childhood in foster or residential care. While the safeguarding of children in England is the responsibility of the Department for Education who sets out policy, legislation and statutory guidance, local safeguarding arrangements are led by Local Authorities (LAs).[1] Working together with other relevant agencies, including the National Health Service (NHS) and

[1] Local Authorities in England exist either in a "single tier" (for instance the London Boroughs) or in "two tiers" – involving an upper "county" tier and a lower "district" tier. In the two-tiered areas, the upper tier "county councils" provide services such as education and social services while the lower district tier provide services such as rubbish collection, housing and planning. For this reason, the LAs in our study are the upper tier county councils along with the single-tier LAs.

the police, they have the responsibility for coordinating and ensuring the effectiveness of work to protect and promote the welfare of children, including identifying and supporting children at risk of harm.

A key early intervention programme in England is Sure Start, which was modelled in part on the US Head Start programme and is aimed at families with children aged 0 to 4. Sure Start was initially set up in the late 1990s on a relatively small scale as Sure Start Local Programmes (SSLP) in some of the most deprived areas. However, in 2003 the government announced a long-term plan to transfer Sure Start into LA control and create a centre in every community. During the period 2004-2010 around 3,600 centres were established providing a broad range of services, including family health services, early years care, early years education, well-being programmes for children and parents and parenting skills support. Since 2010 however, funding has been reduced, and about one in seven of the centres that existed in 2010 have closed, leading to a discussion in the media and among practitioners about the impact that this may have had on the care system (see e.g. The Economist, 2018).

The relationship between policies and local organisational structures that engage with and support parents and children, on the one hand, and the care system, on the other hand, is not unambiguous. While a primary aim of early intervention is to offer support and thereby reduce the need for statutory care, LAs also face the challenge of identifying children at risk of harm. Studies consistently indicate that only a minority of children who are maltreated are identified. In the United States, the National Incidence Study has found that child protective agencies investigate maltreatment of only a minority of the children who have experienced it (Sedlak et al., 2010). In the UK, research conducted by the Children's Commissioner for England (2015) indicated that it is likely that only 1 in 8 victims of sexual abuse come to the attention of the police and children's services. In this context, schools have had long-standing legal safeguarding responsibilities, including taking appropriate action and working with services as needed. Hence a second possible impact of early intervention policy is to help identify children in need of statutory care.

The aim of the current paper is to study how the provision of family-based services through

Sure Start Children's Centres (SSCC), as a key early intervention policy, has impacted the rate of entry of children into care in England between 2007 and 2017. Over this period, the rate of entry into care has increased steadily, raising questions about the reasons behind this trend. The gradual build-up of SSCC between 2004 and 2010, along with the subsequent closures created rich geographical and temporal variation in Sure Start provision at LA level. We will relate this variation in early intervention provision to the rate of entry by age for children aged 0 to 9. In doing so, we will pay particular attention to the threshold between age 4 and 5, separating those *within* and *beyond* policy target age. First, lowering the care entry rate through an "investment effect" that reduces the incidence of abuse and neglect. Second, potentially raising the entry rate through an "identification effect". If both effects are present, SSCC provision should have differential effects on the rate of entry of children within and beyond the target age group. For children who benefited from SSCC provision when in the target age group but who are now aged 5 or above, the effect of SSCC provision should be to reduce entry into care. For children who are currently within the target age group, an identification effect would operate in the opposite direction, thus potentially increasing the rate of entry.

Our findings indeed indicate sharply different effects of SSCC provision on those within and beyond eligible age. We find that increased SSCC provision – as measured by the number of SSCC in an LA per 1,000 children aged 0 to 4 – increases the rate of entry into care for eligible children, while it is related with decreased entry into care for children aged 5-9, i.e. those who have passed eligibility. Our findings are consistent with Cattan et al. (2021) who recently explored the effect of SSCC provision on health outcomes and found that Sure Start increases hospitalisation among very young children but reduces the likelihood of hospitalisation among older children, especially adolescents aged 11-15 years old. By exploring the effect by narrow two-year age-bands, we are able to confirm that the effect of the policy on the care entry rate is discontinuous between ages 3-4 and 5-6. This strongly suggests that a direct mechanism – in addition to the investment effect – is operating in the opposite direction for eligible children, consistent with the hypothesis that the policy leads more children at risk of abuse and neglect to be identified. To corroborate this finding, we show that it holds also for a related outcome, namely the rate at which children are made the subject of child protection plans. Such plans are drawn up by LAs when there is a concern that the child is at risk of significant harm in the form of abuse and/or neglect.

The current paper contributes to a set of connected literatures, most directly to the still relatively small literature on child maltreatment and social care (Doyle & Aizer, 2018). We do this by linking children's entry into care to a key large-scale early intervention policy, Sure Start.[2] In this respect, we also contribute to the literature on the wider causal effects of early intervention policies. Further and more broadly, since child abuse and neglect (the most common reasons for a child entering care) have strong negative impact on cognitive and non-cognitive development of a child, we contribute to the rapidly growing literature on child development in early years (Currie & Almond, 2011; Conti et al., 2016).

More particularly, this is the first economic paper, to our knowledge, that looks directly into Sure Start's impact on child maltreatment. Previous Sure Start studies mainly focused on children's health, behavioural outcomes, and improved parenting indicated by improved home environments (Cattan et al., 2021; Cattan et al., 2019; Sammons et al., 2015).[3] Although there is related literature in the United States, it is mainly focused on either more intensive, small-scale programmes (Schweinhart et al., 1993; D. L. Olds, 2007; Howard & Brooks-Gunn, 2009; Avellar & Supplee, 2013), or on children's outcomes in terms of educational attainment, employability and crime (Garces et al., 2002; Carneiro & Ginja, 2014). The impact of intensive home visiting programmes is not directly comparable with that of large-scale programmes, such as Sure Start and Head Start. Small-scale programmes are usually funded at higher levels per child and are accessed by children with specific characteristics.

This study also explores the mechanisms behind the impact of family-focused, large-scale

[2]It should be noted that our analysis will not be able to say anything about the potential causal effect of being taken into care on the children's subsequent outcomes. For a recent US-focused analysis of the effect of young children being removed from the family home for abuse and neglect on their educational outcomes, see Bald et al. (2019). Their work builds on earlier seminal work by Doyle (2007) and Doyle (2008) that used random assignment to investigators to create an instrumental variables approach for studying the longer-term consequences of being placed in foster care.

[3]For evaluations of SSLP, the intervention prior to the national expansion of SSCC that was targeted to children from disadvantaged backgrounds, see Melhuish et al. (2008), Melhuish et al. (2010), Melhuish et al. (2012), and Carpenter et al. (2007).

early intervention programmes on children's social care. We do this by estimating separately the effect of Sure Start on eligible children and that on children who have passed eligible age and providing evidence that strongly suggests the existence of identification and investment effects. Finally, the study is of significant policy relevance. It provides the first empirical evidence on the ongoing discussion in the media and the early education sector in light of the continuing closures of SSCC and the constantly increasing demand for children's social care.

The paper proceeds as follows. Section 1.2 presents an overview of the literature on child abuse and neglect and family-focused interventions. Section 1.3 provides institutional background and describes the population of Children Looked After (CLA) in England. Section 1.4 discusses the history and evolution of Sure Start. Section 1.5 describes the data sources of all variables included in the estimated model and the variation in SSCC coverage observed in the data. Section 1.6 discusses the potential channels through which SSCC may affect care entry rates by age and also our empirical strategy. Section 1.7 presents our results, section 1.8 discusses the cost and benefit implications of our results and section 1.9 concludes.

## 1.2 Literature review

A recent literature in economics has started investigating potential causes and consequences of child abuse and neglect. For instance, recent work by Lindo et al. (2018) and Brown & De Cao (2020) has highlighted the effects of local labour market conditions, such as unemployment and its gender-composition, on the incidence of maltreatment.[4] More directly at family level, since the 1990s, a wider literature has documented how child maltreatment co-occurs with intimate partner violence (Appel & Holden, 1998), and also with alcohol and drug misuse (Laslett et al., 2012; Dubowitz et al., 2011). However, relatively little is known about the role of public policies in the process of reducing abuse and neglect of children. Recent work by Sandner & Thomsen (2020), exploiting the rapid expansion of universal childcare provision in Germany between 2002 and 2015, showed that policies can make a difference. More particularly, they found that maltreatment cases decline by 1.8 percent if a county increases childcare slots by

[4] For earlier contributions to this literature, see Paxson & Waldfogel (1999), Paxson & Waldfogel (2002), and Paxson & Waldfogel (2003).

one percentage point. Apart from childcare, policies aiming to alleviate poverty may also have an indirect impact on child maltreatment. Paxson & Waldfogel (2002) showed that decreases in state welfare benefits are associated with increased foster care placements, indicating that welfare programmes can contribute to improved child safety.

Other key policies are explicitly designed to directly support parents and children by providing health, parenting, and financial support, while many of them focus explicitly on young children and their families. There is some evidence that such family-focused interventions can improve outcomes. The Nurse-Family Partnership, in which specially trained nurses work with low-income, first-time, young mothers to develop their parenting capacity through home visits starting prenatally and continuing until the child's second birthday, has been shown to reduce child maltreatment, enhance cognitive development and decrease the incidence of youth crime. More particularly, according to D. L. Olds (2007), during the first two years of the child's life, nurse-visited children had fewer verified cases of child abuse and neglect than their counterparts in the control group, while two years after the programme ended, they were less likely to receive emergency room treatment and to visit a physician for injuries and ingestions.[5] Moreover, during the 15-year period after delivering their first child, women who participated in the programme had much lower probability (0.29 versus 0.54) of being identified as perpetrators of child abuse and neglect. Finally, children participants visited by nurses had fewer arrests, adjudications as persons in need of supervision, convictions and probation violations at the age of 15 years old compared to those in the control group.

In the UK, the Family Nurse Partnership (FNP) targets first-time mothers younger than 25 years old. The programme was evaluated through two major randomised control trials involving 1,645 teenage mothers. The first study looking into the first two years of children's lives did not find evidence of benefits to various primary outcomes, apart from a positive effect on early child development (Robling et al., 2016). The second evaluation focused on outcomes for the children of mothers involved in FNP up to age 6. The study showed that FNP improves children's levels

[5] The impact of the programme on verified cases of child abuse and neglect disappeared during the two-year period after the completion of the support, probably because of increased detection of child abuse and neglect in nurse-visited families and linkage of families with needed services (including child protective services) at the end of the programme (D. Olds et al., 1995).

of school readiness and increases reading scores. On the other hand, the results did not show any difference in the likelihood of treated children interacting with children's social care or attending hospital emergency departments, compared to the control group (Robling et al., 2021).

Another well known example of intensive support for pre-school children and their families is the Perry Preschool Project, which was carried out between 1962 and 1967 and combined daily half-day pre-school education with weekly 90-minute home visits. Perry Preschool Project participants in the Schweinhart et al. (1993) study outperformed their peers with similar characteristics on test scores, grades, and graduation from high school, while they had lower crime and welfare-use rates.

Howard & Brooks-Gunn (2009) reviewed the evaluation of nine home-visiting programmes and examined home visiting as a strategy for preventing child abuse and neglect. Although researchers found little evidence of direct impact on child abuse and neglect, the authors concluded that those programmes seem to strongly affect families through improved parenting practices, home environment and children's development. Additionally, enhanced parenting skills would likely be associated with improved child well-being and decreased maltreatment in the long run. Finally, Avellar & Supplee (2013) reviewed 12 early childhood home-visiting models and found evidence that most of them have favourable effects on child development. The authors also found that five programmes have an impact on some aspects of child maltreatment (e.g. family involvement with child protective services, hospital admissions, injuries, accidental poisoning, severe or very severe physical assault, and substantiated abuse or neglect).[6]

The literature discussed above indicates that the majority of intensive family-based programmes affect, directly or indirectly, various children's outcomes, including some measurements of child maltreatment. A less studied question is what role larger scale (and less intensive) interventions can play. Larger scale programmes may be used to attract and support more families (including those needing advanced help) as parents won't feel stigmatised, and their engagement with the programme will require less effort and time. One such key policy is Head Start in the

[6] Only six programmes out of the twelve included in the paper were assessed in terms of their impact on child maltreatment. Child FIRST, Early Start (New Zealand), Early Head Start, Healthy Families America, and the Nurse Family Partnership were shown to contribute to decreased child maltreatment. Healthy Steps showed no effect in one measurement in this domain.

US, a public preschool programme for disadvantaged children designed to close the gaps between the eligible children and their more advantaged peers. Head Start promotes school readiness, child development and health, and family well-being through services mainly delivered in centres. Head Start is available to all children aged 3 and 4 years old from low-income families. Garces et al. (2002) used non-experimental data on adults in the Panel Study of Income Dynamics (PSID) and showed that children who attended Head Start were more likely to complete high school than their siblings. Additionally, they found that White participants were more likely to attend college and have higher earnings than their siblings. At the same time, African-Americans were less likely to have been charged with a crime. More recently, Carneiro & Ginja (2014), using discontinuities in the probability of participation induced by programme eligibility rules, found that Head Start has a positive impact on participants' behaviour, health and mental health as adolescents. At the same time, it reduces the probability of participants being involved in criminal activities as young adults.

## 1.3 Children Looked After in England

In this section, we use publicly available data on the population of CLA in England going back to 2002, looking at trends and demographic composition in the aggregate and some variation across LAs.[7]

According to the Children Act 1989, a child is defined as "looked-after" by an LA if she or he is provided with accommodation for more than 24 hours, is subject to a care order, or is subject to a placement order.[8] Children's route through care involves decision making on various stages. These decisions are made or managed by social workers in each LA. Social workers judge when to take children into care, assess their needs and the type of placements required, and recommend when the child should leave care. The Department for Education sets out what councils must do but not how they should do it. Rather than take a national lead, the Department supports

[7] Data on the category of need and ethnicity of children entering care in 2002 was not available. Thus, analysis for these characteristics starts from 2003.

[8] A care order is an order which places a child under the care of the LA. A placement order is a court order authorising the LA to place a child for adoption with any prospective adopters it chooses.

sector-led improvement, and relies on LAs to develop practice (National Audit Office, 2014).

### 1.3.1 Entry-into-care rates

More than 30,000 children have annually been taken into care in England in recent years. At the same time, the number of children in care has been around 70,000, reflecting that the average duration of care episodes is around 2.5 years. The annual rate of entry into care, defined as the number of children entering care in a year per 10,000 children in the relevant population, has not always been as prevalent as it is now. Figure 1.1 shows the annual rate of entry into care in each year over the period 2002 - 2017. The figure shows that the entry rate has increased by about 30 percent since 2008, with the largest increase taking place between 2008 and 2010, when the entry-to-care rate jumped from around 21 children per 10,000 to 25 children. Reflecting that the time in care has not substantially changed, the figure also shows that the increase in the entry rate has been associated with a corresponding increase in the proportion of children in care.

The increase in entry-to-care rates has been the topic of an ongoing policy debate between social workers, policy analysts and the media. The 2018 Care Crisis Review identified the key factors contributing to national increases in numbers of CLA and applications for care orders, based on analysis of administrative data, review of research, surveys of families and professionals and sector consultation (C. Thomas, 2018). Some of the key factors identified are discussed next.

The period of the largest jump in entry rates (2008-2010) overlaps with the global economic recession and the following austerity policy in the UK. Recession and austerity are expected to have an impact on the demand for children's social care through putting more families under financial pressure and stress, but also due to the reduced resources available to LAs for family support and early intervention. The funding cuts have made it harder for the poorest families to cope, limited the number of LAs' programmes aimed to teach parenting skills and offer respite care and led to the closure of hundreds of SSCC for children and young people since 2010.

In 2007, the London Borough of Haringey was severely criticised (with staff members facing serious consequences) for failing to prevent the death of Peter Connelly, a toddler aged 17 months old who suffered severe abuse (more than 50 injuries) for a period of eight months. During the period of abuse, he was seen by both the LA and health professionals, but no care proceedings were initiated. The year after this case (which is also known as the "Baby P" case), care applications across England rose by 36 per cent (The Economist, 2018), potentially reflecting increased risk aversion among social workers. Finally, changes in professionals' knowledge related to the impact of neglect on children's well-being and outcomes, as well as the fact that there is not enough guidance for social workers towards working in partnership with parents, may have contributed to the increasing care entry rates.

### 1.3.2 Characteristics of children entering care

Table 1.1 shows the demographic composition of children entering care in the aggregate data. The first column shows the characteristics of children (i.e. aged 0-17) in the general population. The second column shows the prevalence of each demographic characteristic within the population of all children taken into care during the period 2002-2017. As above, the entry rate is the annual number of children entering care per 10,000 children in the relevant population. For example, the first row of the table states that on average 51.2 percent of all children in England were boys during the period studied and, correspondingly, 48.8 percent were girls. However, the proportion of boys among all children entering care was 54.4 percent, reflecting that the entry into care rate is higher for boys (25.60) than for girls (22.52).

The table shows that the entry-to-care rate has been substantially higher for infants than for any other age group: children aged $< 1$ only make 5.7 percent of the child population, but have accounted for 18.4 percent of all children entering care. The rate of entry is generally U-shaped in age, with children aged 5-9 having the lowest entry rate. The table further shows that children with Black, Mixed and Other ethnicity backgrounds are overrepresented in the population of children taken into care, whilst Asians have a relatively low rate of entry.

Figure 1.2 shows the trends in entry-to-care rates by subgroup using 2006 as base year. The top panel shows that while the entry rates for all age and gender subgroups are increasing since 2008, the entry rates of male children, children younger than 1 year old and children older than 9 years old are increasing faster. The bottom figure shows the variation in trends across groups of children with different ethnic backgrounds. While Table 1.1 showed that children with

Table 1.1: Rate of entry-to-care by demographic subgroup

| | | **Population Share** | **Share of Entry** | **Entry Rate** |
|---|---|---|---|---|
| Gender | Male | 0.512 | 0.544 | 25.60 |
| | Female | 0.488 | 0.456 | 22.52 |
| Age Group | $< 1$ | 0.057 | 0.184 | 78.15 |
| | $1 - 4$ | 0.224 | 0.189 | 20.32 |
| | $5 - 9$ | 0.274 | 0.171 | 15.00 |
| | $10 - 17$ | 0.445 | 0.456 | 24.69 |
| Ethnicity | White | 0.794 | 0.670 | 20.33 |
| | Asian | 0.096 | 0.055 | 13.94 |
| | Black | 0.047 | 0.093 | 47.68 |
| | Mixed/Other | 0.062 | 0.116 | 45.42 |

*Notes:* Annual data on all children aged 0-17 in England, pooled over the years 2002 - 2017. The "entry rate" is the average number of children entering care in a year per 10,000 children.

Black, Mixed and Other ethnic backgrounds are overrepresented in the children taken into care population compared to the general population, Figure 1.2 shows that the increase in entry rates is mainly driven by children with White ethnic background.

### 1.3.3 Category of need

Social workers record the reason for a given child entering care under one of the following categories of need: abuse or neglect, family in acute stress, family dysfunction, child's socially unacceptable behaviour, child's disability, parent's illness or disability, low income and absent parenting. Figure 1.3 shows the variation of entry rates over time across four broad categories. Abuse and neglect is the most common reason for entering care and its prevalence has been continuously increasing since 2008. In 2016/17, around 16 children in 10,000 children entered care due to abuse and neglect, while the entry rates of the rest of the categories varied from 0 to 9. Family circumstances, which includes family stress and dysfunction is the second most common category, and it has been roughly consistent over time, with only a very small increase since

2008. The increasing rates of abuse and neglect could potentially reflect improved social workers' knowledge of the impact of neglect on a child's development, as discussed in the literature (C. Thomas, 2018).

### 1.3.4 Local variation

One important feature of the sector is the variation in entry rates across LAs. Different factors including local demographic composition and labour market characteristics contribute to this variation. However, the decision to take a child into care is a local one and it is generally recognised that practice varies locally (National Audit Office, 2014), contributing to this spatial variation. Figure 1.4 shows the variation in entry rates across "cells" defined by LA and year, by age group. Entry rates of all age groups show wide variation. The figure shows that the entry rate of infants (age $< 1$) is not only substantially higher than that of other age groups, but it also shows a lot of variation. Panel A of Table 1.2 presents the variation in entry rates, within each age group, between LAs and within LAs (over time). For all age groups, there is large variation both across and within areas, with the between- and within-standard deviations being of similar size and quite large compared to the average entry rate. Panel B shows two versions of correlations between the entry rates of different age groups: the overall correlation across all cells below the diagonal and the (average) within-LA correlation above diagonal. Unsurprisingly, the overall correlation is strong and positive, reflecting permanent differences across LAs that are driving permanent variation in entry rates across all age groups. Perhaps more surprising is the substantial within-LA correlation. These within-LA correlations partly reflect the generally increasing entry rates.

Table 1.2: Variation in entry rates across local authorities and year by age group (Panel A) and correlation in entry-into-care rates across age groups (Panel B)

| Panel A: Between- and within variation | | | | |
|---|---|---|---|---|
| **Age Group** | **Entry Rate** | **St. Dev.** | **St. Dev. Between** | **St. Dev. Within** |
| $< 1$ | 78.15 | 45.07 | 31.34 | 32.48 |
| $1 - 4$ | 20.32 | 11.92 | 8.73 | 8.14 |
| $5 - 9$ | 15.00 | 9.20 | 5.89 | 7.09 |
| $10 - 17$ | 24.69 | 14.76 | 12.17 | 8.40 |
| Panel B: Overall and within-correlations | | | | |
| **Age Group** | $< 1$ | $1 - 4$ | $5 - 9$ | $10 - 17$ |
| $< 1$ | 1 | 0.319 | 0.256 | 0.252 |
| $1 - 4$ | 0.619 | 1 | 0.435 | 0.289 |
| $5 - 9$ | 0.456 | 0.625 | 1 | 0.413 |
| $10 - 17$ | 0.193 | 0.257 | 0.480 | 1 |

*Notes:* Annual data on all children aged 0-17 in England for the years 2002 - 2017. The "entry rate" is the average number of children entering care in a year per 10,000 children. Standard deviations and correlations are calculated over LA-year cells. Panel B presents overall and within-LA correlations below and above the diagonal respectively.

## 1.4 Sure Start Children's Centres

### 1.4.1 The history of Sure Start

#### Sure Start Local Programmes

Sure Start is a policy of early intervention providing support to pre-school children and their parents in England. Sure Start was launched in 1998 with the first SSLP being announced in 1999 based on high levels of local deprivation, existing good practice in early years provision, high level of teenage pregnancy and low birth weights. By November 2003, 521 SSLP were operating in England offering a range of services targeting, among others, child health and development, quality of parenting, employment and childcare (Bate & Foster, 2017).

### The SSCC expansion 2004-2010

In 2003, Sure Start was universalised and the Local Programmes were transitioned to SSCC, signalling a move from targeted intervention to a universal delivery model. In 2004, the "Choice for Parents" 10-year strategy announced the target of one children's centre in every community by 2010. This strategy was developed over three phases.

- 2004-06: Phase One - targeting 20 percent most disadvantaged areas, as defined by the Income Deprivation Affecting Children Index (IDACI).
- 2006-08: Phase Two - targeting 30 percent most disadvantaged areas, as defined by IDACI.
- 2008-10: Phase Three - one centre in every community.

By 31 July 2010, 3,633 SSCC were open in England. Children's centres opened in Phase 1 and Phase 2 offered a wide range of services similar to what was offered by SSLP and acted as a gateway to more specialised provision for young children and families. On the other hand, Phase 3 centres were more likely to operate on a part-time basis and offer a smaller range of services, while they were predominantly not located in disadvantaged areas (Smith et al., 2018).

### The SSCC reduction since 2010

In April 2011, the ring-fence on Sure Start funding was removed and an Early Intervention Grant was introduced. Consequently, Sure Start was now competing for funding with other not child-focused early intervention services including career services for young adults, substance misuse services, and young offender and crime prevention services.

In 2013, the new statutory guidance defined children's centres' core purpose as improving outcomes for young people and their families and reducing inequalities between families in *greatest need*. The new guidance was a signal for a targeted focus of SSCC on families facing difficulties and at a high risk instead of the previous aim of providing open access services to all local families.

More than 500 children's centres were closed since 2010. Apart from centres' closures, the limited funding and the changes in guidance led to other changes in provision. According to the Education Select Committee's report in December 2013, many LAs were redesigning their centres so that they operated in clusters, while an increasing number of centres started providing targeted service. The changes were partly because of reductions in funding and partly because of the new core purpose (Bate & Foster, 2017).

Although the criteria for the roll-out of SSCC were specified by the government, less is known about any systematic characteristics of areas that have reduced their SSCC provision. According to the 2018 Sutton Trust's report's findings from a survey of 124 out of 152 LAs in England, the principal reasons for major changes in children's centre provision were funding pressures, change of focus, high cost of stand-alone centres and changed national priorities (Smith et al., 2018).

### 1.4.2 The services offered in Sure Start Children's Centres

SSCC provide activities, resources and support for local families and children. When Sure Start was introduced in 1998, the programmes provided in each area were intended to be locally defined and tailored to the specific local requirements. However, all SSLP were required to offer five core services (Bate & Foster, 2017):

- outreach services and home visiting (including a visit to a new mother within tree months of giving birth),
- support for families and parents on a range of subjects (e.g. information about availability of local services such as childcare and links with Jobcentre Plus),
- good quality play, learning and childcare,
- primary and community healthcare, and
- advice on child health and development.

In 2004, when SSLP were replaced by SSCC, an increased focus on childcare resulted in centres offering ten hours of childcare per day and becoming advice hubs for parents with children under five (Goff et al., 2013). In 2007, the government committed, through the Children's Plan, to (i) additional funding to support outreach activities for the most disadvantaged families, (ii) a minimum of two outreach workers in the most disadvantaged areas, and (iii) engage fathers and offer them support in strengthening their parental skills (Bate & Foster, 2017). By 2010, each centre offered on average 28 services from a list of possible 50, ranging from a minimum of 13 to a maximum of 42 (Bate & Foster, 2017).

As part of the Evaluation of Children's Centres in England (ECCE), the Department for Education collected data from a sample of 128 Phase 1 and Phase 2 SSCC at various points in time between 2011 and 2015. The most common services provided in more than 80% of the centres in the sample were: stay and play sessions, evidence-based programmes, early learning and childcare, support of volunteers within the local community, breastfeeding support, parent forum, peers and family support, parenting classes, relationship support, adult learning activities, Bookstart Baby Bags/Treasure box (including materials such as books, rhyme sheets, and booklets with advice on reading books with children from a young age), outreach services, and benefits and tax credits advice to parents.[9] [10] Other common services include speech and language therapy, health visitor clinic, housing advice, debt advice, sports and exercise for babies and children, and antenatal classes (Goff et al., 2013).

A survey of 5,717 families registered with an SSCC between January and April 2012 revealed that from the activities provided, families most often use stay and play sessions or play and learn groups, midwife or health visitor drop-in sessions or clinics, and organised sports or exercise for babies and children. Additionally, more than a third of the families interviewed reported that they had at some point received a home visit (Maisey et al., 2013). A follow up study of the same survey showed that the largest age group of users was under one year old (27% of all users) tailing off to the age group of four plus (11%) when other early years facilities take over (Smith et al., 2014).

[9]Stay and play sessions involve parents spending time with their children in the SSCC engaging together in some activities, e.g. free play, messy play, and arts and crafts. The aim of stay and play sessions is to improve attachment and strengthen the bond between parents and children as well as contribute to children's overall development.

[10]The term "evidence-based programmes" in the Sure Start setting refers to 19 programmes identified by Allen (2011) as best quality and relevant to children's centre age group, e.g. Incredible Years, Tripe P and Family Nurse Partnerships.

The new core purpose of Sure Start, published in April 2013, appeared to have affected the structure, focus and services of SSCC. However, changes seem to have started even before the announcement of the new core purpose. When a comparison was made between the services offered in 2011/12 and 2012/13, it was observed that universal services were reduced while targeted acute social work and participation in multi-agency teamwork were increased (Goff et al., 2013). Additionally, during the same period, there was a significant increase in SSCC who supported users to gain access to services through signposting or referral rather than, or in addition to, providing services directly (Poole et al., 2015). Overall, the literature suggests that there were less compositional changes in the nature of service provision prior to 2012 compared to 2012 onwards.

## 1.5 Data

### 1.5.1 Data sources and variables

The care entry data that we will use for our main analysis uses finer age groups than is available in the published data. Through a request to the Department for Education, we have data, for the years 2007-2017, on the number of children entering care in each LA in each of five age groups $g \in G = \{g_1, ..., g_5\}$. The five age groups are defined as follows: $g_1$ is defined as age $< 1$, $g_2$ as age $1-2$, $g_3$ as age $3-4$, $g_4$ as age $5-6$ and $g_5$ as age $7-9$. This finer set of age groups has the benefit of allowing us to analyse more closely the care entry rates for children around the key Sure Start age threshold between 4 and 5. The mean and standard deviation of the care entry rate of each age group are presented in Table 1.3. [11]

We use entry rates from 2007 onwards as this allows us to relate entry rates by age group to the level of SSCC provision at the time of eligibility. In particular, for age group $g$ in LA $j$ in year $t$, we characterise the SSCC provision experienced as that available in the specific LA when the members of this age group were two years old (or as close as possible to this age). This means that for age groups $g_1$ and $g_2$ we use the contemporaneous SSCC provision, whilst for age

[11] These age groups constituted a natural refinement of the publicly available data, whilst avoiding going down to single age groups which would have resulted in several suppressed cells due to small numbers. For the same reason, the entry rates cannot be broken down by further demographic characteristics.

Table 1.3: Rate of entry into care of finer age groups

| **Age group** | **Mean** | **St. Dev.** |
|---|---|---|
| Aged $< 1$ | 88.24 | 43.46 |
| Aged $1 - 2$ | 25.04 | 13.86 |
| Aged $3 - 4$ | 19.98 | 11.63 |
| Aged $5 - 6$ | 17.29 | 10.32 |
| Aged $7 - 9$ | 16.31 | 9.34 |
| Observations | 1,617 | |

*Notes:* Annual data on all children aged 0-9 in England for years 2007-2017. The "entry rate" is the number of children entering care in a year per 10,000 children.

group $g_3$ we use the 1-year earlier provision, for age group $g_4$ we use the 3-years earlier provision, and for age group $g_5$ we use the 5-years earlier provision.[12] This data thus allows us to relate care entry rates to SSCC provision in the post-2003 policy period when SSCC were placed under direct LA control and were being rapidly expanded. Ideally we would like to accompany SSCC provision with establishment-level data on services offered in each centre and funding. However, the government does not collect data on the usage of Children Centre's nationally (House of Commons Children's & Committee, 2010), or any other establishment-level data, to the best of our knowledge. Consequently, we used the best available information, which is in line with the data used by Cattan et al. (2019) and Cattan et al. (2021).

Apart from the main variables of interest, i.e. care entry rates and SSCC provision (described below), our analysis makes use of data on LA background characteristics. Two sets of variables were used: a set of time-varying LA characteristics and a set of "baseline" LA characteristics fixed in year 2004, the beginning of the SSCC expansion period.

The time-varying variables are used to control for LA characteristics that vary significantly

[12] For age group $g_5$ we use the 2004 level of provision if the 5-year lag would have gone further back.

over time and are expected, based on the literature on abuse and neglect noted above, to be correlated with entry-to-care rates. For example, as discussed in Section 1.1 labour market characteristics, e.g. unemployment, can be strongly correlated with child maltreatment. We use LA-level time-varying data for the period 2007-2017 with measures of ethnic composition, economic activity, unemployment claimants proportion, educational qualifications, median income, and local political leadership. A data description is provided in Appendix A.1.

The baseline LA characteristics are used to control for factors that are expected to have contributed to the timing and magnitude of the SSCC expansion in each LA. The selection of those characteristics was based on sector literature on SSLP and SSCC expansion criteria (e.g. Bate & Foster, 2017) and SSCC impact studies (e.g. Cattan et al., 2021). The baseline characteristics used are: IDACI, teenage pregnancy, income inequality, school exclusions, low-birth-weight rates, and fertility. Detailed information on each baseline characteristic is provided in Appendix A.2, while more information on the selection of those variables and their relationship with SSCC provision is located in Appendix B.1.

### 1.5.2 Sure Start coverage variation over time and across Local Authorities

Figure 1.5 shows the number of SSCC in operation in England from 2004 to 2017. The figure also shows the national average "Sure Start coverage", defined as the number of SSCC per 1,000 children aged 0-4. As discussed above, the number of SSCC increased sharply after 2004, reaching more than 3,600 centres in 2010. Since 2010 the number is decreasing slowly.

Figure 1.6 shows the overall evolution of Sure Start across England. The first map shows the average SSCC coverage in each LA in England between 2004-8, as expected the average coverage over this period was low with the majority of LAs having 0-0.35 centre per 1,000 eligible children. The second map shows the period with the highest coverage, i.e. 2009-2011. The vast majority of LAs had a coverage rate close to 1 centre per 1,000 eligible children, with a few exceptions having more than 1.4 centres. The third map represents the contraction period, and it shows that the closures were concentrated in a few specific LAs and there was not a nationally widespread decrease in the number of centres.

The strong expansion between 2004 and 2010, however, was not random but reflected that the policy was initially aimed at more deprived areas. As a result, the pace and timing of expansion varied across areas of different characteristics. This feature of the expansion build-up period is highlighted in Figure 1.8. The left panel of the figure classifies the LAs by their IDACI scores in the baseline year of 2004, splitting them into quartiles and then plotting the average SSCC coverage by IDACI quartile and year. This shows how the SSCC expansion was initially faster in the more deprived LAs. For example, in 2006, the average coverage was 0.3 higher in the most deprived 25 percent of LAs than in the 25 least deprived ones. However, by 2010 the systematic gap in coverage was largely eliminated. The middle and right panels do the same exercise but instead splitting the LAs into quartiles based on their 2004 rates of teenage pregnancy and low birth weights respectively. Both panels show similar patterns as for the IDACI scores, though slightly less pronounced. The non-random expansion of SSCC provision will be an empirical challenge discussed in some detail below. Section B.1 reports the results of a regression analysis of SSCC expansion determinants.

While the build-up of SSCC provision had partly known determinants, less is known about any potential systematic patterns to the closures that have taken place since 2010. In total, 519 SSCC were closed between 2011 and 2017. Table 1.4 provides some basic information about the pattern of closures. It first notes that, effectively, half of the LAs had not closed any SSCC by 2017. Next, it shows that, among the 76 LAs that close at least one children's centre, 20 LAs accounted for only 3 percent of closures (each closing exactly one children's centre). In contrast, five LAs accounted for more than a third of all closures. The next column shows later established SSCC were more frequently closed, while the final column shows that the majority of closures occurred only after 2015. The fact that later established SSCC were more likely to close also implies an indirect link to the local level of deprivation. This is highlighted in Appendix B.2 which provides a simple "survival analysis", linking the likelihood of a given children's centre to close to local area characteristics. In general, the link between area characteristics and SSCC closures is substantially weaker than is the link to timing of SSCC build-up during the expansion period.

Table 1.4: Patterns of SSCC closures over the period 2011 to 2017

| **Proportion** | | **Concentration** | | **Phase** | | **Sub-period** | |
|---|---|---|---|---|---|---|---|
| Proportion closed | Local Authorities | Local Authorities | Share of closures | Phase created | Proportion closed | Year of closure | Share of closures |
| 0 | 75 | 20 | 3.4% | 1 | 9.8% | 2011-13 | 10.6% |
| $0-0.5$ | 65 | 51 | 61.7% | 2 | 17.0% | 2014-15 | 27.1% |
| $0.5-1$ | 11 | 5 | 34.9% | 3 | 24.2% | 2016-17 | 62.3% |
| | 151 | 76 | 100% | | | | 100% |

*Notes:* The table describes SSCC closure patterns between 2011 and 2017. Over this period there were 519 SSCC closures out of the 3,615 that existed in 2010.

## 1.6 Conceptual framework and empirical strategy

The aim of Sure Start was "giving children the best possible start in life" through family support, improved childcare, health and early education (Department for Children, Schools and Families, 2008). As such, SSCC provision can be viewed as a facility for investment in young children's development, heath and well-being, as well as a vehicle for supporting parents' employment, parenting behaviour and mental health. Thus, benefits from SSCC provision can be expected to have long-term returns not only in terms of children's health and educational attainment, but also in terms of encouraging improved family outcomes.

These potential long term benefits have indeed so far been the focus of evaluations of Sure Start. While findings have been positive, as a general characterisation, the effects have also been found to be relatively modest. The National Evaluation of Sure Start (NESS) team reported that families in SSLP areas showed less negative parenting – inducing less chaotic home environments and creating a more stimulating home learning environment with less harsh disciplining – along with some improved child outcomes – lowering BMIs, improved social behaviour, and higher rates of immunisation and fewer accidental injuries (Melhuish et al., 2008; Melhuish et al., 2010; Melhuish et al., 2012). Additionally, the Department for Education evaluated the impact of children's centres in improving family and child outcomes for a broader sample of user families than earlier NESS evaluations (Sammons et al., 2015). The findings were in line with previous studies, predicting improved home-learning environment, reduced parental distress and improved social child behaviour. More recent evidence by Cattan et al. (2021), exploiting the full expansion of SSLP and SSCC found that the availability of children's centres had led to lower rates of hospitalisation for respiratory illness and infections among children (once children have passed eligibility).

### 1.6.1 Hypothesised effects

The first channel through which SSCC provision may have affected the incidence of statutory care would thus be through a longer-term positive investment effect, reducing dysfunctional family behaviour including abuse and neglect. Such improvements would not only occur contemporaneously but would reduce entry to care over time, including beyond the target age of SSCC. However, while the investment effect of SSCC provision would reduce the need for entry into care, such provision could also lead to the identification of children in need of statutory care. Such an identification effect would increase the rate of entry within the target age group. One version of this effect would be towards earlier identification. Such a timing of identification effect could contribute to reducing entry among the children beyond the SSCC target age. This section discusses the various mechanisms that are hypothesised to contribute to the investment and identification effects.

SSCC provide a broad range of activities, combining childcare with parenting and family services. The provision of learning activities and childcare services in a local setting is expected to improve the labour market opportunities for parents and contribute to childhood education and child development. As described by Sandner & Thomsen (2020), when childcare placements become available, families usually switch either from home care (where usually the mother is the main caregiver) or from informal care (e.g. where childcare is provided by other relatives or partners of parents) to formal childcare. If informal care is substituted with childcare, there is a high probability of improved quality of care. At the same time, the time spent with potentially abusive carers is decreased (for example, Lindo et al. (2018) found that increased time with informal male caregivers due to increased mother employment led to higher child maltreatment rates). If childcare substitutes home care, then the mother has the opportunity to work, resulting in higher family income and reduced stress, to recover from childcare duties, and to interact with nursery staff to obtain advice and guidance. Additionally, female employment may increase the bargaining power of mothers, which is translated into more significant investments in children (Lundberg et al., 1997; Duflo, 2003).

SSCC are not solely childcare centres, and childcare provision would be available even without the existence of those centres. However, SSCC may increase the impact of childcare through two main channels. Firstly, providing childcare or advice on childcare availability at a pram-pushing distance makes it easier for new mothers to find the services they need. Secondly, combining those services with employment, debt and benefits advice allows parents to find a job, a childcare place and receive financial support as easily and quickly as possible.

SSCC provide services that target parents and families directly and thus can substantially impact parental behaviour (e.g. home visiting, stay and play sessions, parenting skills training and healthcare and child development advice). Such services can improve parenting skills, enhance the attachment between children and their parents and educate parents on how their behaviour can affect children's well-being and development. The literature on home visiting programmes has shown that similar programmes are associated with lower child maltreatment and improved parenting skills (D. L. Olds, 2007; Howard & Brooks-Gunn, 2009; Avellar & Supplee, 2013).

All of the above contribute to an investment effect where families and parents have reduced risk of child maltreatment, and their challenges are minimised before escalating into needing statutory support. SSCC services, however, can also increase the identification of families already needing statutory support. More particularly, the provision of the services described above (e.g. home visiting, parenting classes, support services for adults, healthcare clinics) bring staff at SSCC in direct contact and communication with parents and allow them to understand their parenting techniques and observe signals of child maltreatment. In a relevant study, Fitzpatrick et al. (2020) showed that time spent in US schools and the resulting contact with education professionals leads to increases in the number of reports of child maltreatment. Their results indicated that the additional cases reported wouldn't be identified by someone else in contact

Table 1.5: Predicted effects of SSCC provision on care entry rates by age group

| **Channel** | **Currently Eligible (0-4)** | **Past Eligible (5+)** |
|---|---|---|
| Investment | - | - |
| Identification | + | -/0 |
| **Total** | +/- | - |

with the child. Thus, they concluded that teachers are playing a key role in the early detection and reporting of child maltreatment. The services offered in a SSCC provide staff with similar, if not richer, information with that available to school teachers and thus an identification effect would be very likely in this paper's setting.

One crucial difference between schools and SSCC is that SSCC created a key communication channel between parents and professional when children are too young to attend early education or school. This can be extremely important as SSCC may help social services identify children in need of statutory support at a very young age who wouldn't be identified otherwise or who would be identified years later when children would have already experienced long-term maltreatment. Consequently, SSCC can contribute to decreasing the duration of abuse and the long- and short-term impact of child maltreatment.[13]

Table 1.5 summarises the hypothesised effects. Two key features should be noted. First, the threshold age between 4 and 5 provides key information on the underlying mechanisms: if there was no identification effect – only an investment effect – then we would expect SSCC provision to reduce entry into care among all age groups and, furthermore, there should be no discontinuity in the effect of SSCC provision at the end of the SSCC target age, that is the effect of SSCC provision should be similar for children aged closely up to 4 as for children just beyond that age. If a positive investment effect is present, then the impact of SSCC provision should be associated with lower entry into care among children aged 5 and above.

For a child to be removed from their family, there needs to be strong evidence that they are

[13]Statutory support does not necessarily mean that the child will be taken into care, there are lower levels of support available, e.g. a child in need plan or a child protection plan.

experiencing serious harm and their well-being is at serious risk. Therefore, data on children entering care refer to cases of danger to the child and are synonymous with incidence. On the other hand, an unknown rate of unreported cases remains, and thus, it is always possible to increase identification. Suppose a positive relationship between entry rates and SSCC coverage is found. In that case, it is expected that it will refer to a higher detection as SSCC cannot, to the best of our knowledge, contribute to an increase in child maltreatment itself. On the other hand, if Sure Start coverage negatively affects care entry rates, we expect this to be related to a decrease in child maltreatment through an investment effect, as there is no clear channel through which cases that would have been detected prior to Sure Start will now be missed.

### 1.6.2 Empirical model and identification

To identify the effects of SSCC provision on care entry rates we exploit the variation introduced by the expansion of SSCC provision over time, which generated differences in coverage across LAs and, critically, across cohorts within LAs. The outcomes of interest that we observe in our data are the entry rates of children of different age groups. In particular, we will model the entry-to-care rate in age group $g$, area $j$ and year $t$, denoted $y_{gjt}$ as follows

$$\log(y_{gjt}) = \beta^g \widehat{cc}_{gjt} + \eta_g I_g + \delta_j I_j + \nu_t I_t + \omega_g I_g t + \mu_j I_j t + \rho Z_{jt} + \varepsilon_{gjt}. \quad (1.1)$$

In this specification, $\widehat{cc}_{gjt}$, defined for children in age group $g$ in year $t$ and in area $j$, measures the level of SSCC coverage that was available to children in that area at the time when this cohort were of central SSCC target age. As noted above, for age groups $g_1$ (age $< 1$) and $g_2$ (age $1-2$) $\widehat{cc}_{gjt}$ is measured with the contemporaneous level of SSCC coverage while for age groups $g_3$ through to $g_5$ coverage $\widehat{cc}_{gjt}$ is measured one, three and five years earlier respectively for area $j$. Note that the model allows the effect of SSCC coverage to have age-group-specific effects on care entry rates, $\beta^g$. These age-group-specific effects are the key parameters of interest.

The estimating equation (1.1) further includes age-group fixed-effects $\eta_g$. The age-group specific effects model the fact that entry rates differ substantially with age, for instance being markedly higher among infants (age group $g_1$) than among the older age groups. The use of the outcome entry rates in log form also reflects the fact that the average entry rates are different across age groups as it allows us to interpret the various estimated effects as proportional effects.

The model further includes LA fixed-effects $\delta_j$, and year fixed-effects $\nu_t$. The area fixed-effects $\delta_j$ control for permanent unobserved differences across areas while the year fixed-effects $\nu_t$ control for a common national trend. As noted above, the national trends were fairly similar across age groups. Nevertheless, in order to allow for age-group-specific national trends, we include interactions between the age group dummies and time. The associated estimated parameters $\omega_g$ thus measure any additional age-group-specific (linear) national trends. The area fixed effects, $\delta_j$, while controlling for any permanent unobserved differences across areas, will not account for any local time-varying characteristics that could influence both the local development of SSCC provision and the care entry rates. To tackle this threat to identification we adopt two complementary strategies. First, we include additional LA-specific linear time trends $\mu_j$. Second, we include a set of time-varying LA characteristics $Z_{jt}$. These include e.g. labour market conditions, ethnicity and educational demographic composition and political leadership. In specification tests, we also make use of a set of baseline characteristics, denoted $Z_j^b$, that were found above to be related to the timing of SSCC expansion. We replace first the area-specific linear trends with $Z_j^b$ interacted with time, and second we replace the LA fixed effects directly with $Z_j^b$.

Our identification strategy is in line with the methodology of Cattan et al. (2019) and Cattan et al. (2021), the most recent papers examining the impact of SSCC and particularly focusing on hospitalisations, obesity and mothers' mental health. Cattan et al. (2021) used a dataset reporting the location and opening date of all Sure Start centres to study the period from when SSLP, the predecessor of SSCC, were firstly created up to the end of the SSCC expansion period, i.e. from 1999-2010. On the other hand, our paper investigates the post-2003 policy period when SSCC were placed under direct LA control up to 2017, seven years after the beginning of SSCC contraction. The methodology of estimating the causal impact of SSCC and the definition of SSCC coverage is consistent between Cattan et al. (2019), Cattan et al. (2021) and this study. All three papers focus on the SSCC offer and availability to local families rather than the impact

Table 1.6: Illustration of variation in current/post SSCC exposure generated by variation in the timing of SSCC build-up across local authorities

| | **Local Authority A** | | | **Local Authority B** | |
|---|---|---|---|---|---|
| Sub-period | SSCC | Cohorts | | SSCC | Cohorts |
| $Period = 0$ ("02-05") | No | $CE(c_0) = 0$ | | No | $CE(c_0) = 0$ |
| $Period = 1$ ("05-07") | Yes | $PE(c_0) = 0$<br>$CE(c_1) = 1$ | <br>$\Leftrightarrow$ | No | $PE(c_0) = 0$<br>$CE(c_1) = 0$ |
| $Period = 2$ ("07-09") | Yes | $PE(c_1) = 1$<br>$CE(c_2) = 1$ | $\Leftrightarrow$ | Yes | $PE(c_1) = 0$<br>$CE(c_2) = 1$ |
| $Period = 3$ ("09-11") | Yes | $PE(c_2) = 1$<br>$CE(c_3) = 1$ | | Yes | $PE(c_2) = 1$<br>$CE(c_3) = 1$ |

of specific services, as older evaluations have tried.

A stylised illustration of our identification strategy is provided in Table 1.6. The figure contrasts two hypothetical LAs, $A$ and $B$. Children born "early" (say 2002-2005) in either area had no current SSCC provision ($CE(c_0) = 0$) available whilst of eligible age. Correspondingly, when we observe the entry rates from these children a few years later (around 2005-2007) when they are beyond SSCC target age we know that they had no access to SSCC services when they were of eligible age ($PE(c_0) = 0$ in both areas). Suppose then that area $A$ creates SSCC capacity at this time, but area $B$ does not yet do so. The current young children in area $A$ thus enjoyed SSCC availability while the corresponding children in area $B$ did not ($CE(c_1) = 1$ in area $A$ but $CE(c_1) = 0$ in area $B$). A further few years later we observe this cohort being of post-target age, with only the children in area $A$ having earlier enjoyed SSCC availability. As area $B$ now expands SSCC provision, we get a first cohort in this area benefiting from SSCC provision when young.

The figure thus illustrates how the build-up of SSCC coverage created cohort variation in SSCC availability both for children of current eligible age and for children beyond eligible age. Moreover, as the timing of SSCC expansion was different across LAs, the cohort variation was not synchronized across areas, facilitating the identification of SSCC effects from common trends. Finally, note that at key phases, children of the same age from different areas would have enjoyed different levels of current or past SSCC provision. However, such variation would confound differences in SSCC provision with area differences. In the stylized example, area $A$ could for instance be expected to be characterised by a higher level of deprivation than area $B$. Hence it is key that specification (1.1) identifies the effect of SSCC provision from within-LA cohort variation and not from contemporaneous differences in SSCC provision across LAs.

## 1.7 Results

### 1.7.1 Main regression results

Table 1.7 presents our basic estimates of equation (1.1). The estimations model the care entry rates for the five age groups in $G$, for 147 LAs, and for 11 years. Hence the maximum number of observations is 8,085. As our main interest is in the estimated effects of SSCC provision, we only present the estimates of the $\beta^g$ terms: further estimated coefficients on time-varying and baseline LA characteristics from selected specifications are presented in Appendix B.3.

Specification (1) in Table 1.7 starts by constraining the estimated effect of SSCC provision on care entry rates to be uniform across all age-groups. The estimated common effect is positive but fairly modest in size (an additional centre per 1,000 eligible children would increase the care entry rate of all children aged 0-9 by around six percent) and statistically significant only at the five percent level. Specification (2) is the first estimated specification with age-group specific effects. This specification shows that the initially estimated common effect masks effects that vary substantially across age groups. For each of the youngest three age groups $g_1$ - $g_3$, the estimated effects of SSCC are strongly positive and statistically significant. In contrast, for the two higher age groups, $g_4$ and $g_5$, the estimated effects are negative but smaller in absolute terms and not statistically significant above the ten percent level.

These finding of a differential effects of SSCC provision on children who are still within the target age (0-4) and on children beyond this age (5-9) is thus consistent with the predictions from section 1.6. In particular, the estimated positive effects for age groups $g_1$ - $g_3$ indicate the presence of an identification effect. In contrast, the estimated entry-reducing effects of SSCC

Table 1.7: Effect of SSCC provision on care entry rates: main results

| | (1) | (2) | (3) |
|---|---|---|---|
| Any age group | 0.0584* | | |
| | (0.0283) | | |
| Aged $< 1$ | | 0.252*** | 0.259*** |
| | | (0.0560) | (0.0575) |
| Aged $1 - 2$ | | 0.198*** | 0.204*** |
| | | (0.0574) | (0.0592) |
| Aged $3 - 4$ | | 0.148** | 0.157** |
| | | (0.0471) | (0.0484) |
| Aged $5 - 6$ | | -0.0618 | -0.0578 |
| | | (0.0457) | (0.0466) |
| Aged $7 - 9$ | | -0.111+ | -0.105+ |
| | | (0.0561) | (0.0541) |
| Observations | 8,085 | 8,085 | 7,930 |
| Year effects | Y | Y | Y |
| Age group effects | Y | Y | Y |
| Age group trends | Y | Y | Y |
| LA effects | Y | Y | Y |
| LA trends | Y | Y | Y |
| Time-Varying LA | N | N | Y |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The table presents estimated $\beta^g$ coefficients from estimating equation (1.1) on data on log entry rates into care among five age groups across 147 Local Authorities in England between 2007 and 2017. The time-varying LA characteristics are described in Appendix A. Standard errors are clustered at the LA level and observations are weighted by the LA population of children in the corresponding age group.

provision for age-groups $g_4$ and $g_5$ is consistent with a lasting investment effect of past eligibility and access to SSCC services leading to a lower current need for statutory care. Specification (2) did not include any time-varying LA characteristics, $Z_{jt}$. Such characteristics are added in specification (3) and the estimated coefficients for these variables are presented in column (1) of Table B3 in Appendix B.3. Inspection of those estimated coefficients reveals that no single variable in $Z_{jt}$ is statistically significant, suggesting that the already included area-level trends control well for local time-varying factors. Correspondingly, the estimated age-group-specific effects of SSCC provision on care entry rates are barely affected by the inclusion of the time-varying LA characteristics.

Our results show a large impact of SSCC provision on care entry rates. More particularly, specification (3) shows that one additional SSCC per 1,000 children aged 0-4 will increase the number of children aged $< 1$ entering care by 25.9 percent. As shown in Table 1.3, an average LA has an entry rate of 88 per 10,000 children aged $< 1$. Consequently, our findings translate into an increase of around 23 children aged under one year old per 10,000 residing in an average LA in England. Similarly, we find a 20.4 percent increase of the care entry rate for children aged 1-2, and 15.7 percent increase of the care entry rate for children aged 3-4. In an average LA, the above effects would lead to around five more children aged 1-2 per 10,000 entering care and three more children aged 3-4 per 10,000. All of the above findings are statically significant at the 0.1 percent level. We find no statistically significant impact on children aged 5-6. The entry rate for children aged 7-9 seems to be decreasing with SSCC coverage but the coefficient is statistically significant at only 10 percent level. We find that one additional SSCC per 1,000 eligible children would decrease the rate of entry of those children when aged 7-9 by 10.5 percent, which equates to a decrease of two children per 10,000 in a LA with the average care entry rates. Our findings are consistent with recent results by Cattan et al. (2021) who found that SSCC provision increases hospitalisations among very young children (due to increased support on using health services and more exposure to infectious illnesses) but reduces them during childhood and adolescence (when children have developed stronger immune systems).

### 1.7.2 Alternative specifications

Table 1.8 presents a sequence of alternative specifications to test for the robustness of the results. The first column in Table 1.8 reiterates our preferred specification (3) from Table 1.7 for purposes of comparison. Specification (2) in Table 1.8 removes the area-specific linear time-trends and replaces them with baseline characteristics interacted with time $Z_j^b t$, while leaving in the time-varying LA characteristics. Specification (3) further replaces the area-fixed effects with the time-invariant baseline LA characteristics $Z_j^b$. In either case, the estimated $\beta^g$-effects are strikingly robust. The estimated coefficients on $Z_j^b t$ and $Z_j^b$ from these two specifications are presented in Table B3 in Appendix B.3. These show that, once we no longer include the

Table 1.8: Effect of SSCC provision on care entry rates: sensitivity analysis

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Aged $< 1$ | 0.259*** | 0.217*** | 0.229*** | 0.549*** | 0.204*** | 0.358*** | 0.282*** | | |
| | (0.0575) | (0.0592) | (0.0607) | (0.0919) | (0.0534) | (0.0843) | (0.0625) | | |
| Aged $1-2$ | 0.204*** | 0.162** | 0.174** | 0.491*** | 0.164** | 0.232** | 0.223*** | | 0.210** |
| | (0.0592) | (0.0617) | (0.0638) | (0.0882) | (0.0557) | (0.0813) | (0.0628) | | (0.0676) |
| Aged $3-4$ | 0.157** | 0.120* | 0.133* | 0.480*** | 0.137** | 0.213** | 0.163** | 0.135 | |
| | (0.0484) | (0.0495) | (0.0564) | (0.0821) | (0.0475) | (0.0725) | (0.0529) | (0.0826) | |
| Aged $5-6$ | -0.0578 | -0.0848+ | -0.0533 | 0.366*** | -0.0693 | -0.144+ | -0.115+ | -0.0764 | -0.0775 |
| | (0.0466) | (0.0498) | (0.0612) | (0.0844) | (0.0469) | (0.0814) | (0.0613) | (0.0792) | (0.0647) |
| Aged $7-9$ | -0.105+ | -0.105* | -0.0477 | 0.403*** | -0.116* | 0.00856 | -0.155* | | |
| | (0.0541) | (0.0526) | (0.0632) | (0.0899) | (0.0500) | (0.0911) | (0.0774) | | |
| Observations | 7,930 | 7,930 | 7,930 | 8,085 | 7,930 | 4,330 | 7,930 | 3,172 | 3,172 |
| Year effects | Y | Y | Y | Y | Y | Y | N | Y | Y |
| Age gr. effects | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Age gr. trends | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| LA effects | Y | Y | N | N | Y | Y | Y | Y | Y |
| LA trends | Y | N | N | N | Y | Y | Y | Y | Y |
| Time-varying | Y | Y | Y | N | Y | Y | Y | Y | Y |
| Baseline LA | N | N | Y | N | N | N | N | N | N |
| Baseline×time | N | Y | Y | N | Y | N | N | N | N |
| Baseline×age | N | N | N | N | Y | N | N | N | N |
| Cohort effects | N | N | N | N | N | N | Y | N | N |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The table presents estimated $\beta^g$ coefficients from estimating equation (1.1) on data on log entry rates into care among five age groups across 147 Local Authorities in England between 2007 and 2017. The time-varying and baseline LA characteristics are described in Appendix A. Standard errors are clustered at the LA level and observations are weighted by the population of children.

area-specific linear time trends, the measured economic activity rates in particular is negatively associated with the care entry rates, as would be consistent with the literature indicating that higher rates of economic activity are associated with lower rates of child maltreatment. When we further replace the LA fixed effects with the baseline characteristics $Z_j^b$ we find that high levels of deprivation and teenage pregnancies are associated with higher entry rates.

Specification (4) in contrast confirms that controlling for permanent differences across LAs – either via fixed-effects or via baseline characteristics – is critical. This specification removes both the LA fixed effects and the use of baseline characteristics. Doing so implies that the $\beta^g$ coefficients are now estimated using cross-LA variation in SSCC provision. In this case we should expect the estimated coefficients to be strongly biased upwards as the SSCC provision would typically have been higher in more deprived areas where the care entry cares would also have been substantially higher. Indeed, when the "effect" of SSCC provision is estimated using such cross-area variation, the estimated coefficients increase substantially and all turn (implausible) positive, thus indicating a strong upward bias.

As we will show below, there is some evidence of age-entry profiles varying with area-baseline characteristics. In order to account for this, specification (5) includes interactions between LA baseline characteristics and age group. However, doing so does not substantially affect the estimated parameters of interest.

Specification (6) reduces the sample period to 2007 - 2012, thus using measures of coverage mainly from the SSCC expansion period. In particular, the specification avoids using the sample years when some SSCC were closed and, more generally, funding was being reduced. Doing so generally increases the estimated SSCC effects in absolute terms, but of course also makes the estimates less precise.

Specification (7) controls for cohort effects rather than for year fixed effects.[14] In this case we find that the estimated values of $\beta^{g_1}$ - $\beta^{g_3}$ are largely unaffected, but the estimated entry-reducing effects on children aged five and above increases.

Specification (8) takes a closer look at the entry rates for children in the age groups just below and above the threshold, delineating those currently in the Sure Start target age group and those beyond it. In other words, the specification only includes age groups $g_3$ and $g_4$, and hence only estimates $\beta^{g_3}$ and $\beta^{g_4}$. These two groups are naturally close in age and can be expected to be similar in other respects, except age group $g_3$ are within SSCC target age while $g_4$ are instead just of schooling age. Estimating equation ( 1.1) using only these two groups does not change the estimated coefficients in any noticeable way (both in terms of magnitude and sign), but $\beta^{g_3}$ is no longer statistically significant at 1 percent significance level (the p-value of the coefficient is now 0.105). We consider the decrease in precision of $\beta^{g_3}$ as expected. Firstly, the sample is largely decreased and secondly, children aged $3-4$ years old are less affected by SSCC than younger children. Additionally, the group of children aged $5-6$ is the only group that doesn't seem to be significantly affected by the local SSCC coverage in any specification. Consequently, comparing only these two age groups is expected to result in less precise and less powerful

[14]Cohorts are defined as year minus age. But, of course, our age groups are banded. Hence we define the cohort of age group $g_1$ in year $t$ as $t$, the cohort of age group $g_2$ as $t-1$, the cohort of age group $g_3$ as $t-3$, and the cohort of age group $g_4$ as $t-5$, and finally the cohort of age group $g_5$ as $t-7$. The specification further controls for general trends using year and year-squared.

estimated coefficients of SSCC coverage. For comparison, specification (9) does a corresponding estimation using only age groups $g_2$ and $g_4$, and the results are largely unaffected.[15]

### 1.7.3 Further robustness checks

#### Age-group pairwise comparisons

The final two columns of Table 1.8 introduced the idea of comparing age groups pairwise. The approach of making pairwise age-group comparisons can be taken further. Differencing the estimating equation (1.1) between any two age groups $g$ and $g'$, where $g < g'$, and decomposing the difference $\beta^g \widehat{cc}_{gjt} - \beta^{g'} \widehat{cc}_{g'jt}$, into a difference in coverage and a difference in impact of coverage, we obtain that

$$\begin{aligned} \Delta \log y_{jt}^{g,g'} &= \beta^g \left( \widehat{cc}_{gjt} - \widehat{cc}_{g'jt} \right) + \left( \beta^g - \beta^{g'} \right) \widehat{cc}_{g'jt} \\ &\quad + \left( \eta_g - \eta_{g'} \right) + \left( \omega_g - \omega_{g'} \right) t + \varepsilon_{gjt} - \varepsilon_{g'jt} \end{aligned} \tag{1.2}$$

This shows that the parameters of main interest can be recovered from estimations that make pairwise use of the various age groups. In particular, regressing the log difference in the entry rates on the *difference* in SSCC coverage experienced by the two groups as well as on the *level* experienced by group $g'$ provides estimates of $\beta^g$ and of $\Delta\beta^{g,g'} \equiv \beta^g - \beta^{g'}$. It consequently also provides an estimate of $\beta^{g'}$ as $\beta^{g'} \equiv \beta^g - \Delta\beta^{g,g'}$. The constant in the regression (1.2) estimates the difference in group averages as represented by the difference in the age-group fixed effects $\eta_g - \eta_{g'}$ in the original estimating equation. Furthermore, the estimated coefficient on time $t$ captures the (linear) difference in the age-group trends.

An advantage of estimating in age-group differenced form is that it does not rely on the original estimating equation (1.1) being correct with respect to the linear specification of LA-specific trends and time-varying characteristics. For instance, these could take non-linear forms; as long as they are additive and can plausibly be assumed to be the same for the two age groups

[15] We expect the identification effect to be stronger for younger children, as it is very common for mothers to contact their local SSCC during pregnancy or soon after the birth of their first child. Consequently, we expect fewer families to contact a centre when their child is older than $2-3$ years old.

Table 1.9: Effect of SSCC provision on care entry rates: pairwise regressions

| | $(g_1, g_2)$ | $(g_1, g_3)$ | $(g_1, g_4)$ | $(g_1, g_5)$ | $(g_2, g_3)$ | $(g_2, g_4)$ | $(g_2, g_5)$ | $(g_3, g_4)$ | $(g_3, g_5)$ | $(g_4, g_5)$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $\beta^{g_1}$ | (.) | 0.0842 | 0.230*** | 0.246*** | | | | | | |
| | | (0.0763) | (0.0643) | (0.0475) | | | | | | |
| $\beta^{g_2}$ | (.) | | | | 0.0738 | 0.206** | 0.207*** | | | |
| | | | | | (0.0739) | (0.0656) | (0.0491) | | | |
| $\beta^{g_3}$ | | 0.00509 | | | 0.0533 | | | 0.155* | 0.154*** | |
| | | (0.0711) | | | (0.0689) | | | (0.0753) | (0.0462) | |
| $\beta^{g_4}$ | | | -0.123 | | | -0.0740 | | -0.0392 | | -0.0218 |
| | | | (0.0638) | | | (0.0651) | | (0.0800) | | (0.0589) |
| $\beta^{g_5}$ | | | | -0.274*** | | | -0.152*** | | -0.0922 | -0.0436 |
| | | | | (0.0570) | | | (0.0587) | | (0.0589) | (0.0701) |
| $\Delta\beta$ | 0.0547 | 0.0791+ | 0.353*** | 0.520*** | 0.0204 | 0.280*** | 0.359*** | 0.194*** | 0.246*** | 0.0218 |
| | (0.0359) | (0.0429) | (0.0596) | (0.0702) | (0.0415) | (0.0608) | (0.0722) | (0.0567) | (0.0699) | (0.0668) |
| Obs. | 1,617 | | | | | | | | | |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* Each column corresponds to a regression of the form (2) for a pair of age groups. $g_1$ = age $< 1$, $g_2$ = age $1-2$, $g_3$ = age $3-4$, $g_4$ = age $5-6$, $g_5$ = age $7-9$. For the pair $(g,g')$ with $g < g'$, the directly estimated coefficients are $\beta^g$ and $\Delta\beta = \beta^g - \beta^{g'}$. $\beta^{g'}$ is recovered as the difference between the estimated coefficients, $\beta^{g'} = \beta^g - \Delta\beta$.

that are being compared, these effects are removed by the differencing.

Note that (1.2) can be estimated for any pair of age groups. Since we have five age groups in $G$, we can form ten age-group pairs. The upshot of this is that we obtain (up to) four estimates of each $\beta^g$-term. The one exception is the comparison between $g_1$ and $g_2$ as, for both these age groups we measure SSCC coverage with the contemporaneous coverage. This implies that $\widehat{cc}_{g_1jt} - \widehat{cc}_{g_2jt}$ has no variation and we can only estimate the difference $\Delta\beta^{g_1,g_2}$ – we cannot separate out estimates of $\beta^{g_1}$ and $\beta^{g_2}$ from this age-group pair.

Table 1.9 shows the results from all pairwise regressions. The general findings is that every point estimate of the effect of SSCC provision on the entry rates of children *within* the Sure Start target age, that is every estimate of $\beta^{g_1}$, $\beta^{g_2}$ and $\beta^{g_3}$, is positive. In contrast, every point estimate of the effect of SSCC provision on the entry rates of children *beyond* the target age, that is every estimate of $\beta^{g_4}$ and $\beta^{g_5}$, is negative. Comparing the estimates for $\beta^{g_1}$, $\beta^{g_2}$ and $\beta^{g_3}$ the general pattern is that the estimates tend to decrease with age, both in terms of range and average.

The estimated positive coefficient on $\beta^{g_3}$ in the $(g_3, g_4)$-pairwise regression suggests that recent expansions of SSCC provision would be associated with increases in the *relative* rate of entry into care for age group $g_3$ who are still within the target age group compared to the "just-beyond-target-age" group $g_4$. This is illustrated in Figure 1.9. Defining $\Delta \log y_{jt}^{g,g'} \equiv \log(y_{gjt}) - \log(y_{g'jt})$ as the log difference in entry rates between age groups $g$ and $g'$, the top left panel plots the distribution of $\Delta \log y_{jt}^{g_3,g_4}$. The distribution is centered around 0.15, indicating that the entry rate is, on average, about 15 percent higher among children aged 3 - 4 compared to children aged 5 - 6.

Next we define $\Delta \widehat{cc}_{jt}^{g,g'} \equiv \widehat{cc}_{gjt} - \widehat{cc}_{g'jt}$. Note in particular that $\Delta \widehat{cc}_{jt}^{g_3,g_4}$ will be positive if the SSCC coverage for children now aged 3 - 4 was higher than that for children now aged 5 - 6, that is, if there was a recent expansion of SSCC provision. The right panel of figure 1.9 plots the average of $\Delta \log y_{jt}^{g_3,g_4}$ by quartile of $\Delta \widehat{cc}_{jt}^{g_3,g_4}$. The figure confirms that recent increases in SSCC provision are associated with higher relative entry into care for children aged $3-4$ compared to children aged $5-6$.

The lower two panels correspondingly compare age group $g_2$ (aged 1 - 2) to age group 4. In this case, the left panel shows that the distribution of $\Delta \log y_{jt}^{g_2,g_4}$ is somewhat further to the right, reflecting that the average rate of entry into care of children aged 1 - 2 is on average about 45 percent higher than the corresponding rate for those aged 5 - 6. Hence age groups $g_2$ and $g_4$ are, naturally, not as similar as are $g_3$ and $g_4$. Nevertheless, the same pattern emerges. When we characterise the change in coverage $\Delta \widehat{cc}_{jt}^{g_2,g_4} \equiv \widehat{cc}_{g_2jt} - \widehat{cc}_{g_4jt}$ for each $(j,t)$-cell we find that cells associated with recent increases in SSCC provision are also associated with an increase in the relative entry of children aged 1 - 2 compared with children aged 5 - 6.

#### Relative entry rates by baseline LA characteristics

The main concern with the above analysis is the possibility that some local time-varying factors could influence both the local SSCC provision and care entry rates. We tackled this issue by including a set of time-varying LA characteristics and by allowing for LA-specific linear time trends. Moreover, as our results have shown, for any unobserved time-varying factors to threaten the validity of our results, they would have to have differentially affected the entry rates of children within and beyond Sure Start target age.

Nevertheless, a further robustness test can be done by relating the relative age-group entry rates directly to baseline LA-characteristics. From Figure 1.8 we know that, in line with the stated Sure Start rollout principles, between 2004 and 2010, LAs that were "disadvantaged" – as measured by higher baseline values of the IDACI deprivation score, the baseline rate of teenage pregnancy, and the baseline rate of low birth weight – had higher levels of SSCC coverage.

This allows us to test the robustness of our finding that SSCC provision was associated with higher relative rates of entry into care for children within target age. Specifically, the finding would imply that disadvantaged areas should be observed to have had higher relative rates of entry *for age groups within the SSCC target age* in *among cohorts who were within eligible age during the Sure Start expansion period.* This prediction can be tested using a simple difference-in-difference approach. The attractiveness of such a test is that it relies only on observable *baseline* characteristics of LAs, making it unaffected by temporary local shocks that could have affected both SSCC provision and entry rates.

In order to implement such a test we proceed as follows. We start by creating a standardised index of disadvantage, denoted, $\zeta_j^b$, which is a linear combination of the baseline (2004) IDACI, teenage pregnancy and low birth weight rate. The index is created – using a simple regression – as the linear combination of these three factors that best predicts SSCC coverage over the period 2004 to 2010. [16] Next we split our sample period for the entry analysis into (i) an "early" subperiod 2007-2012 that includes most entry observations associated with SSCC eligibility up to 2010, and (ii) a "late" subperiod 2013-2017 that includes most entry observations associated with post-2010 SSCC eligibility.[17] We then estimate the following regression, relating the log difference in entry rates between two age groups $g$ and $g'$, with $g < g'$, to the disadvantage index $\zeta_j^b$, the index interacted with a dummy for "early" subperiod, and a set of year fixed effects where the latter allow us to control for any general national trend in relative entry rates.

$$\Delta \log y_{jt}^{g,g'} = \gamma_0 \zeta_j^b + \gamma_1 \zeta_j^b I_{2007 \leq t \leq 2012} + \eta_t I_t + \epsilon_{jt}^{g,g'}. \tag{1.3}$$

[16] Specifically, we regress local SSCC coverage, $cc_{jt}$, over the period 2004-2010 on the standardised baseline (2004) IDACI, teenage pregnancy and low birth weight rate and generate predicted values – which per construction are time-invariant. Our index $\zeta_j^b$, which loads positively particularly on the IDACI score and the teenage pregnancy rate, is obtained by standardizing the predicted values.

[17] Note that, as we will be using pairs of age groups, the age groups would have had different timing of SSCC eligibility. This leads to some inevitable misclassification, e.g. for infants, $g_1$, observed and contemporaneously eligible in 2011-12, and for oldest children, $g_5$, in 2013-14 who were mainly SSCC eligible pre-2010.

As we have five age groups in $G$ we can, as before, form ten age group pairs and estimate (1.3) for each pair separately. The results from doing so are presented in Table 1.10. The ten estimated $\gamma_0$ values are presented below the diagonal while the corresponding ten $\gamma_1$ values are presented above the diagonal. Note that a positive value on $\gamma_0$ would indicate that relatively disadvantaged areas have a higher relative care entry rate for the younger age group $g$ compared to older age group $g'$. In fact, most estimated $\gamma_0$ values are negative – and often statistically significantly – hence indicating that the more disadvantaged areas tend to have a slightly different entry age-profiles tilted more towards relatively older children than the less disadvantaged areas.[18]

Our main parameter of interest, however, is $\gamma_1$, and in particular for $(g, g')$-pairs that involve one age group within Sure Start target age ($g_1 - g_3$) and one beyond target age ($g_4 - g_5$). There are six such age group pairs and the associated estimated values of $\gamma_1$ are highlighted by the box in the top right corner of the table. Consistent with our main results, the coefficients on each of these six interaction terms are positive and in a number of cases statistically significant (in contrast to the remaining four estimated $\gamma_1$ values). Consider for instance age groups $g_3$ and $g_4$. The negative estimated value for $\gamma_0$ for this pair indicates that, in the "later" period 2013 to 2017, areas that were disadvantaged according to their 2004 baseline characteristics ($\zeta_j^b > 0$) had a higher entry rate for children aged 5-6 relative to children aged 3-4 than the corresponding relative entry rate among "'non-disadvantaged" areas ($\zeta_j^b \leq 0$). The positive and numerically larger value for $\gamma_1$ for the same age-group pair indicate that, the opposite was true during the early period 2007-2012: during this subperiod the disadvantaged areas had a higher entry rate for children aged 3-4 relative to children aged 5-6 than the corresponding relative entry rate among "'non-disadvantaged" areas.

Similarly, when comparing age groups $g_2$ and $g_4$, the table shows that in the later subperiod, the areas that were disadvantaged at baseline had a substantially higher rate of entry of children aged 5-6 relative to children aged 1-2 than the non-disadvantaged areas. In contrast, in the early subperiod the disadvantaged and non-disadvantaged areas had similar relative entry rates for the two age groups.

[18] This relationship between the age-profiles of care entry rates and local disadvantage motivated specification (5) in Table 1.8 that allowed for an interaction between LA baseline characteristics and age group

Table 1.10: The relationship between relative age group entry rates and baseline disadvantage over time

| | $g_1$ $(< 1)$ | $g_2$ $(1-2)$ | $g_3$ $(3-4)$ | $g_4$ $(5-6)$ | $g_5$ $(7-9)$ |
|---|---|---|---|---|---|
| $g_1$ | - | -0.0251 | -0.0281 | 0.0328 | 0.0174 |
| $(< 1)$ | | (0.0188) | (0.0223) | (0.0284) | (0.0258) |
| $g_2$ | 0.0279* | - | -0.00317 | 0.0574* | 0.0420 |
| $(1-2)$ | (0.0138) | | (0.0215) | (0.0289) | (0.0263) |
| $g_3$ | -0.0186 | -0.0460** | - | 0.0619* | 0.0457+ |
| $(3-4)$ | (0.0162) | (0.0156) | | (0.0293) | (0.0266) |
| $g_4$ | -0.0543** | -0.0815*** | -0.0357+ | - | -0.0171 |
| $(5-6)$ | (0.0205) | (0.0208) | (0.0210) | | (0.0282) |
| $g_5$ | -0.0793*** | -0.107*** | -0.0608** | -0.0251 | - |
| $(7-9)$ | (0.0187) | (0.0190) | (0.0190) | (0.0202) | |
| Obs. | | | 1,617 | | |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* A "disadvantage index", denoted $\zeta_j^b$, was created by regressing the level of SSCC coverage, $cc_{jt}$, in area $j$ in year $t$ for years 2004-2010 on the baseline (2004) IDACI score, teenage pregnancy rate, and rate of low birth weight. The (time-invariant) index, $\zeta_j^b$, was generated as the standardized predicted values from this regression. The sample period 2007-2017 for the observed care entry rates was split into two subperiods, 2007-2012 and 2013-2017. For each age-group pair $(g, g')$, with $g < g'$, the log difference in entry rates, $\Delta \log y_{jt}^{g;g'}$, was regressed on the disadvantage index, $\zeta_j^b$, the index interacted with a sub-period 1 dummy $\zeta_j^b \times I_{2007 \leq t \leq 2012}$, along with a full set of year dummies. The terms *below* the diagonal are the estimated coefficients on $\zeta_j^b$ in each pairwise regression. The terms *above* the diagonal are the estimated coefficients on the interaction term $\zeta_j^b \times I_{2007 \leq t \leq 2012}$.

The results are thus consistent with the age-composition of children entering care changing over time differently in the disadvantaged and non-disadvantaged areas, and in particular with entry being relatively high for age groups within the SSCC target age in disadvantaged areas in the early subperiod. This is thus consistent with earlier entry rates being high in SSCC target age groups in LAs that, due to their baseline characteristics, developed SSCC capacity earlier.

**Placebo test**

In our final robustness check will verify that our estimated effects of SSCC provision indeed reflect the timing of the policy roll-out by performing a placebo test – specifically, we will show that a fictive policy roll-out occurring two years earlier had no estimated effects. To make this analysis as transparent as possible we will represent (substantial) SSCC provision as an event that occurred in different LAs at different points in time. We define a binary version of our main coverage variable that categorises an LA as having SSCC "in-place" when its coverage rate is at least 0.4 SSCC per 1,000 eligible children. Using this definition, all 147 LAs in our sample achieved SSCC in-place status between 2005 and 2008: five LAs in 2005, 49 in 2006, 25 in 2007 and 68 in 2008.[19] Using the above definition the average coverage rate in sample LA-year cells classified as SSCC "not in-place" and "in-place" is then 0.25 and 1.01, respectively.

Table 1.11 presents two regressions. Column (1) is a re-estimation of our preferred specification (3) from Table 1.7 where we simply replace the actual coverage rate $\widehat{cc}_{gjt}$ with its binary representation. Note that this means that we apply the same lag structure as in our main regressions to characterise whether SSCC coverage was in-place in area $j$ at the time when the members of age group $g$ were of policy target age (see Section 1.5).

Given that the regression in column (1) is simply a re-estimation of our preferred specification with the key regressor put into binary form we naturally obtain similar results: the estimated effects are positive for the three within-target age groups and negative (but not statistically significant) for the two beyond-target age groups. The estimated coefficients are generally smaller in magnitude, but this is expected for two reasons. First, the coefficients in Table 1.7 are for a unit increase (e.g. 0 to 1) in the coverage rate; in contrast, the difference in the coverage rate between cells with the dummy "on" and "off" is, as noted above, only about 0.75. Second, the binary representation of coverage introduces measurement error on the right hand side.

In column (2) we estimate the effect of a counterfactual policy roll-out occurring two years earlier than the actual one. Specifically, we shift our binary SSCC in-place indicator by two years such that if LA $j$ passed the 0.4 coverage threshold in, say, 2007, then in our shifted version this event occurred in 2005. We then re-estimate the model using this shifted version of our key policy indicator and we find no effect for any age group. Indeed, for the key within-target age groups, we reassuringly obtain fairly precisely estimated zero effects. This very precise effect of the timing of the policy provides strong evidence that the estimated policy effects in our main regressions are not driven by other time-varying local factors.

[19] From 2014 onwards, due to closures, a small set of LAs switched back. In these cases our dummy variable is correspondingly switched off.

Table 1.11: Effect of SSCC provision on care entry rates - event study: main analysis and placebo experiment

| | (1) | (2) |
|---|---|---|
| Aged $< 1$ | 0.095* | -0.019 |
| | (0.0424) | (0.0337) |
| Aged $1-2$ | 0.070+ | -0.040 |
| | (0.0418) | (0.0392) |
| Aged $3-4$ | 0.103* | -0.006 |
| | (0.0459) | (0.0362) |
| Aged $5-6$ | -0.052 | -0.058 |
| | (0.0416) | (0.0412) |
| Aged $7-9$ | -0.043 | 0.041 |
| | (0.0379) | (0.0369) |
| Observations | 7,930 | 7,930 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The table shows the estimated effect of SSCC coverage on the CLA entry rate by age group, i.e. the $\beta^g$ coefficients from estimating equation (1) using the binary SSCC "in-place" variable ($I_{\widehat{cc}_{gjt} \geq 0.4}$) instead of the original $\widehat{cc}_{gjt}$ coverage variable. Specification (i) shows the main results and specification (ii) presents the results of counterfactually shifting the "in-place" variable by two years. Standard errors are clustered at the LA level and observations are weighted by the LA population of children in the corresponding age group.

### 1.7.4 Counterfactual entry-intro-care rates

The above findings strongly suggest that SSCC provision has led to higher rates of entry into care among children within the target age range $0-4$ but also to a reduction in the rate of entry for children age $5-9$. To gauge the potential impact of the SSCC on the rates of entry of the various age groups over time, we can use a counterfactual simulation. Specifically, we can compare the model-predicted care entry rate in age group $g$ and year $t$ under the actual level of SSCC provision to that predicted under the counterfactual scenario in which no SSCC services were provided. The result of this exercise is shown in Figure 1.10.

Each panel plots first the actual empirical care entry rate, followed by the model-predicted rate, and finally the care entry rate predicted for the counterfactual scenario without SSCC provision. Looking first at the older age groups, $g_4$ and $g_5$, the model predicts that provision of SSCC services reduced the entry into care among these children, aged $5-9$. The gap in the prediction is essentially zero for the first few sample years – this reflects that the level of SSCC provision experienced by children in these age groups at the time when they were of eligible age was very low. From about 2010 onwards, the predictions diverge as the children in these age groups would have benefited from more substantial levels of SSCC provision when younger.

In contrast, the model predicts that SSCC provision raised the entry rates for children in age groups $g_1$ through to $g_3$: that is, under the counterfactual, the predicted entry rates are lower. The gaps in the predictions that appear already at the beginning of the sample period reflect that children aged $0-4$ in 2007 were already benefiting from some positive levels of SSCC provision. Over time the gap between the factual and counterfactual predictions increase as the level of SSCC provision increases.

### 1.7.5 Further evidence

#### Child Protection Plans

If a child is considered to be at risk of harm from abuse or neglect, the LA in question will, as an initial step, make them the subject of a Child Protection Plan (CPP).[20] A CPP will detail, for instance, what needs to be done to reduce the concern, how the child is to be kept safe, and a time-frame for this to happen. CPPs are reviewed every three to six months and if there is no improvement, care proceedings will be initiated. Hence a CPP directly indicates that a concern about potential abuse and neglect has been identified.[21]

As a robustness check, we will consider the relationship between SSCC provision and the rate at which children are issued CPPs. As a CPP is an intermediate step for many children who are eventually taken into care, we expect this relationship to be similar to that estimated for SSCC provision and care entry rates. A positive effect of SSCC provision on CPPs for children

[20] CPPs are used in England. In Northern Ireland, Scotland and Wales, children at risk of harm are placed on a child protection register. A CPP in England is the closest equivalent to a record of abuse and neglect by Child Protective Services within the US system, as used by Brown & De Cao (2020) and Lindo et al. (2018).

[21] More detailed information about the procedures related to child protection in England and the characteristics of children subject to CPPs is provided in Chapter 2.

Table 1.12: Effect of SSCC provision on Child Protection Plan entry rates

| Panel A: CPP Descriptive Statistics | | | | |
|---|---|---|---|---|
| **Age Group** | **Average CPP Entry Rate** | **Average Annual Rate of Growth** | **CPP-CLA Entry Rate Corr. (gross)** | **CPP-CLA Entry Rate Corr. (net)** |
| $< 1$ | 113.29 | 0.054 | 0.698 | 0.393 |
| $1 - 4$ | 52.70 | 0.052 | 0.644 | 0.352 |
| $5 - 9$ | 43.33 | 0.060 | 0.596 | 0.307 |

| Panel B: Effect of SSCC Provision of CPP Entry Rate | | | | |
|---|---|---|---|---|
| **Age Group** | **(i)** | **(ii)** | **(iii)** | **(iv)** |
| $< 1$ | 0.142** | | 0.153** | 0.142** |
| | (0.0476) | | (0.0477) | (0.0459) |
| $1 - 4$ | 0.153*** | 0.164*** | 0.161*** | 0.159*** |
| | (0.0350) | (0.0363) | (0.0364) | (0.0341) |
| $5 - 9$ | 0.022 | 0.049 | 0.050 | 0.035 |
| | (0.0403) | (0.0433) | (0.0404) | (0.0381) |
| Observations | 4,384 | 2,924 | 4,402 | 4,851 |
| Year 2010 included | N | N | Y | Y |
| Missing LAs included | Y | Y | N | Y |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* Panel A presents descriptive statistics on the distribution of CPP entries across Local Authority for the years 2007 to 2017. The maximum number of observations, per age group, in Panel A is 4,851. Panel B of the table presents estimated effect of SSCC coverage on the CPP entry rate by age group, the $\beta^g$ coefficients from estimating equation (1) using the log CPP entry rate as outcome variable. Due to a change in reporting, the CPP data is incomplete and is missing across all three age groups for 13 LAs in 2010 (Brent, Derbyshire, Durham, East Sussex, Gloucestershire, Hackney, Havering, Kent, Lancashire, Leicestershire, Liverpool, North Yorkshire and Redbridge). All specifications include year-, LA- and age-group fixed-effects, along with age-group and LA-specific trends. Specifications (i) and (ii) exclude 2010 altogether. Specification (iii) includes 2010, but excludes all observations relating to the aforementioned 13 LAs. Specification (iv) includes all available observations. Standard errors are clustered at the LA level.

aged 0 - 4, in particular, would support the hypothesis of a positive identification effect.

Data on the number of children being made subject of CPPs is only available in the coarser age groups $< 1$, $1-4$, and $5-9$. In addition, the process by which data was collected was revised in 2010 and for this year, 13 LAs having missing data for all three age groups.[22] We will hence pay attention to this potential data quality issue. To make the analysis directly comparable to the care entry rates, we measure the CPP entry rates as the number of children, per 10,000, who we made the subject of a CPP in the relevant year, LA and age group.

The upper panel of Table 1.12 summarises some core descriptive statistics on the CPP data. Column (i) shows the average CPP entry rate by age group. These entry rates are directly

[22] CPP data by age group was initially published for the years 2007 to 2009. Data for subsequent years was obtained through a request to the Department for Education.

comparable to the care entry rates by age group in Table 1.1. For infants, the CPP entry rate is about 50 percent higher than the rate of entry into care. For children aged $1-4$ and $5-9$, the "CPP entry rates" are close to three times as large as the care entry rates. The CPP rates have grown substantially over time. Column (ii) shows the average annual growth rates in the CPP rate by age group: a 5-6 percent annual rate of growth in each CPP rate is substantially higher than the age-group-specific rates of growth of care entry rates shown in Figure 1.2. Column (iii) shows the overall correlation between the CPP entry rate and the care entry rate by age group. These correlations are naturally very high as they reflect both permanent differences between LAs as well as increasing trends in both CPP entry rates and care entry rates. Column (iv) nets out the common trends and permanent LA differences in each entry rate before estimating the correlation.[23] The strong remaining correlation confirms that in periods when, in a given LA and age group, more children are made the subject of CPPs more children are also being taken into care.

The lower panel of Table 1.12 presents the main results of estimating an equation similar to equation 1.1, but with the log CPP entry rate rather than the care entry rate as the dependent variable. All specifications include year-, LA- and age-group fixed effects, and also age-group and LA-specific linear trends. Due to the issue with data reporting in 2010, specifications (i) and (ii) leave this year out. Specification (iii) includes 2010 but maintains a balanced panel by excluding all observations for the 13 LAs with missing information in 2010. Finally, specification (iv) includes all available data. Specification (i) shows that the estimated effect of SSCC coverage is positive and statistically significant for children aged up to four. In contrast, for children aged $5-9$ the estimated effect is very small and not statistically significant. These results are in line with the estimated impact of SSCC coverage on care entry rates presented in Table 1.7, both in terms of patterns and magnitudes. Specification (ii) shows that the estimated effects for the two central age groups are largely unaffected by leaving infants out. Specifications (iii) and (iv) show that the results are robust to 2010 being included.

[23] Specifically, each entry rate is regressed, by age group, on year and LA dummies and the residuals are obtained. These residuals contain the variation in the respective entry rate that is not accounted for by common trends and permanent LA differences. The column then reports the correlations between the CPP- and the CLA-residuals.

Table 1.13: Effect of SSCC provision on the incidence of Serious Case Reviews

| Panel A: SCR Descriptive Statistics | | | |
|---|---|---|---|
| **Age Distribution** | | **Count Distribution** | |
| **Age Group** | **Proportion** | **No. of SCRs** | **Frequency** |
| Aged $< 1$ | 0.451 | 0 | 0.768 |
| Aged $1-4$ | 0.246 | 1 | 0.172 |
| Aged $5-9$ | 0.107 | 2 | 0.049 |
| Aged $\geq 10$ | 0.265 | 3-4 | 0.012 |

| Panel B: Effect of SSCC Provision on SCR Count | | |
|---|---|---|
| | **(i)** | **(ii)** |
| SSCC | -0.265+ | -0.332+ |
| Coverage | (0.148) | (0.193) |
| Pop. Age $1-4$ | 0.339 | 0.307 |
| (10,000) | (0.321) | (0.250) |
| Observations | 1,617 | 1,617 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* Panel A presents descriptive statistics on 815 Serious Case Reviews (SCRs) between 2007-2017 with known year and place of incident. Panel B presents estimated coefficients from regressions of the counts of SCRs involving children aged 0-4 on SSCC coverage (defined as the number of SSCCs per 1,000 children aged 0-4 and lagged one year) in the previous year for a sample of 147 Local Authorities in England between 2007 and 2017. Each regression controls for the number of children aged 0-4, and further includes LA- and year fixed-effects. Specification (i) reports OLS-estimated coefficients while specification (ii) reports the marginal effects from a negative binomial regression. Robust standard errors in parenthesis.

Overall, the CPP results align with our care-entry results and the hypothesis of a positive identification effect. To support this conclusion, we present one final piece of indicative evidence drawing on data on Serious Case Reviews (SCR). SCR are conducted when a child dies or is seriously injured due to suspected abuse and neglect. A positive identification effect should make SSCC provision associated with a lower incidence of SCRs.

### Serious Case Reviews

SCRs were established under the Children Act (2004), and they aim to establish learning for agencies and professionals to improve the way that they work together to safeguard children. SCR are commissioned by Local Safeguarding Children Boards (LSCBs). From the national case review repository created by the National Society for the Prevention of Cruelty to Children

(NSPCC), we identified 815 SCR covering the period 2007-2017.[24]

Panel A of Table 1.13 provides descriptive statistics on the reviewed cases. The first column notes that a clear majority of the SCR referred to children of pre-school age 0-4. This trend is in sharp contrast to the much lower prevalence of SCR involving children aged 5-9.[25] A total of 510 cases (63 percent of all cases reviewed) involved the death of a child. The second column shows the distribution of the count of SCR involving children aged 0-4 across all LA-year cells. At least one such review occurred in close to a quarter of all cells, while two or more SCR occurred in just over six percent of cells.

Inspection of the data shows that the proportion of SCRs involving pre-school children reduced over the sample period and mainly over the first five years. This trend would be consistent with a positive identification effect of SSCC expansion. In Panel B, we report the coefficients from regressing the count of SCR (for children aged 0-4) on SSCC coverage, controlling for the size of the age 0-4 population, as well as for LA- and year fixed-effects. Specification (i) is based on a simple linear regression, whilst specification (ii) reports the marginal effects from a poisson regression. Given the nature of the outcome variable and the demanding specification, the precision of the estimated effect of SSCC provision is naturally fairly low. Nevertheless, compared to the mean of the SCR count (0.41), the point estimates, each significant at the 8 percent level, suggest a substantial effect of SSCC provision in terms of reducing the likelihood of a review into the death, or serious harm, of a child aged 0-4. Taken at face value, this suggests that the SSCC may, over the past 15 years, have saved the lives of potentially several hundred pre-school children in England.

[24] There were only a limited number of reviews for 2004-2006. Hence, we focus on the same sample period as in our main analysis above, i.e. 2007-2017. Overall, the count and age distribution of SCR is well in line with child mortality data. In the last five years, there has been an average of 62 child deaths by assault (or undetermined intent) per year in the UK, with children under the age of one being the most likely age group (NSPCC, 2020).

[25] Note that the unit of observation in Panel A is a case review. Since a case review may involve more than one child, the proportions in the first column do not add to unity and are also not additive across age groups.

## 1.8 Costs and benefits discussion

Our results have significant policy implications. They show that universal, low-intensity interventions can substantially impact child maltreatment and the demand for children's social care services, both through identification and investment effects. Child maltreatment can severely affect children's lives and their outcomes as adults, while it can have major cost implications for public services and society in general. Conti et al. (2017) undertook a preliminary analysis of lifetime costs of child abuse and neglect and estimated that the average lifetime cost of non-fatal child maltreatment by a primary caregiver is £89,390 (with a 95% certainty that the costs fall between £44,896 and £145,508). The analysis included short- and long-term health-related costs, criminal justice system costs, child social care costs, special education costs, and productivity losses due to reduced employment.

A small literature has already looked into quantifying the costs and benefits associated with SSCC. Gaheer & Paull (2016) have used data collected from 24 centres to explore the value for money of centres. They estimated that the average cost per user hour was £30, ranging from £6 for childcare to £55 for finance and work support. The authors compared the costs with estimated benefits that can occur via the impact of Sure Start services on education, smoking, crime, mental and physical health, and employment. Their results showed that family and parent support services (both specialist and general) after the child is aged one can offer the greatest increase in home learning environment for each pound spent. The costs and benefits of each service were compared, with most services having a positive net benefit. Parent and family services had the highest benefit-to-cost ratio, driven by lower costs than child-based services. On the other hand, when the authors calculated the value for money for the government, most service groups had negative net benefits.

Cattan et al. (2021) considered the costs of having access to Sure Start, rather than the costs of using specific services, and the corresponding benefits of reducing hospitalisations for injuries and infections. They computed the cost of Sure Start per eligible child by dividing the overall government spending on Sure Start by the number of eligible children averaged over the years 2000-14, which amounts to £416. They also calculated that the estimated costs of Sure Start for one cohort of children is £1,055 million. We consider this estimate to be the most relevant to our study as we are exploring the impact of being exposed to a local centre rather than using the centre. The cost-benefit analysis reported by Cattan et al. (2021) estimated that the impact of Sure Start on hospitalisations offsets around 31% of the cost of Sure Start provision. Cattan et al. (2021) focused on the financial impacts that come from the effects on hospitalisations, which is the outcome explored by the paper. Similarly, the following discussion focuses on the financial impacts of the effect of Sure Start on the number of children entering care, the prevalence of child maltreatment and the SCR.

The economic benefits of Sure Start based on the findings of this study are not straightforward to calculate. Increasing the number of children entering care usually implies an increase in costs. However, there are also significant benefits to a child being removed from an abusive home or a child being identified earlier. UK literature has shown that younger children have a higher probability of being provided with a permanent placement (with fewer disruptions and returns to social care) and a higher probability of being adopted. More particularly, the national statistics published by the Department for Education show that the vast majority of children adopted are pre-school children consistently over the years. For example, according to the Department for Education (2017b), during the period 2013-2017, 76-80 percent of children adopted were younger than five years old, while this age group consisted only 18-24 percent of CLA at the end of each year. Mc Grath-Lone et al. (2017) found that about one-third of children leaving care re-enter within five years, with those older at exit having a higher risk of re-entry. Neil et al. (2019) used longitudinal administrative data from one LA in England, and they found a higher probability of staying in the care of this LA for an extended period (defined as more than two years) for children entering care older than three years old.[26] Finally, an obvious consideration of the impact of entering care is that although it can be traumatic and challenging for a child to be removed from their home, it will also protect them from an abusive environment, decreasing the duration of the period the child is exposed to maltreatment as well as preventing the death of a child. Consequently, entering care can significantly impact the outcomes of children as adults,

[26] Neil et al. (2019) used data from only one LA, and thus their results should not be generalised without additional supporting evidence.

and it may offset some of the consequences and costs of child maltreatment to society and the government.

Apart from our main results on the impact of SSCC on the number of children entering care, our analysis also suggests an effect of SSCC provision in reducing the likelihood of a review into the death or serious harm of a child aged 0-4. Taking our results at face value, we estimate that there are 0.33 less SCR in an LA during one year when the SSCC coverage rate is one rather than zero. Taking into account that 66 percent of SCRs in our data involved the death of a child, and that an LA has on average a SSCC coverage rate of 0.97 per 1,000 children aged 0-4, we end up with an estimated number of 340 averted deaths over the period of study, which gives us an average of 31 prevented deaths per year. This number combined with the value of life (which, according to P. Thomas (2018) is now estimated at £8.6 million), gives us a total of £267 million saved due to deaths prevented on average for every year of SSCC.[27] We calculated that the expenditure of LAs on SSCC is ranging from around £940 million to £1,000 million per year (on average, in 2017 prices).[28]

In summary, considering only the decrease in SCR related to the death of a child, our results suggest that SSCC can offset around 27-28 percent of the total costs. This calculation does not include all the other benefits discussed above, e.g. the impact of shorter period of abuse and earlier removal from the abusive home, the impact of decreased number of total SCs, and the benefits related to the key targets of SSCC, e.g. child education, child health and family-level outcomes.

Overall, to comprehensively discuss the costs and benefits of the impact of SSCCs related the outcome studied by this paper, we need to have a better understanding of the outcomes

[27] Traditionally the value of human life in the UK it was calculated based on the Value of Prevented Fatality (VPF) which is estimated at around £1.83 million. However, this method has been criticised about the small and outdated sample used (it is based on a 1997 opinion survey of 167 people), as well as other methodological issues (P. Thomas, 2020). Consequently, we used a new estimate provided by P. Thomas (2018) which is closer to the estimates used by other countries, e.g. in the US various governmental departments use estimates varying from $7.4 million to $9.6 million.

[28] Cattan et al. (2021) estimate the cost of providing an additional children's centre per 1,000 children to a representative cohort at £1,055 million in 2018-19 prices. We calculated our own estimate at £940 million per year based on the total expenditure of LAs on SSCC during the period 2011-2017, as published by the Department for Education (the costs are adjusted for inflation and the estimate refers to the average cost per year). Since our estimate does not include information for the period 2007-2010 due to gaps in the data, and the estimate of Cattan et al. (2021) refers to an earlier period than the one we study (1999-2010), we use the two estimates as the lower and upper bounds of a range of plausible values of the cost.

of children entering care (compared to the counterfactual of having similar experiences but remain in the family home). Such research is not available in the UK context, and it remains scarce without a clear consensus in the international context. For a complete understanding of the outcomes of CLA, the impact of different routes and experiences into care should also be analysed, e.g. long and short periods of care, different exit routes and entering care at different ages. Consequently, our results highlight a key research gap with significant policy implications, while they also show that Sure Start can have a promising impact in preventing maltreatment and SCR in general, contributing significantly to the overall benefits of the programme.

## 1.9 Conclusions

A small but growing literature in economics looks at child maltreatment and at consequences of foster care. Given the number of children who die each year due to abuse and neglect, more research into interventions to improve child safety and well-being is needed. This paper looks at the impact of the expansion of a key early intervention policy in England, Sure Start, on the rate of children's entry into social care.

Sure Start has, for about two decades, been a flagship policy aimed at pre-school children and their parents in England. During the period 2004-2010, over 3,600 children's centres were established, providing a wide range of services including child healthcare, childcare, good quality play, parenting support and advice on child health and development. Since 2011, more than 500 centres have however been closed.

The theoretical impact of SSCC on care entry rates is ambiguous. Early intervention, through supporting families, reduce current and future need for care (an "investment effect"). At the same time, SSCC provision may lead to identifying further cases where care is needed (an "identification effect").

Exploiting the variation in timing of the build-up of SSCC provision across LAs, we estimate the impact of SSCC provision on the care entry rate by age group. In particular, we look for a potential discontinuity in the effect of the policy between children who are "within" and "beyond" eligible age, respectively, arguing that any "identification effect" would apply in the former but not among the latter. Our findings suggest that the SSCC impact differs substantially and discontinuously across age groups. The estimated effects of SSCC provision on the care entry rate are strongly positive and statistically significant for the within-eligible age groups but negative (and not always statistically significant) for the beyond-eligible age groups. The results are thus consistent with both effects operating.

Of course, taking more children into care cannot be a priori taken to be a positive outcome. To this end, we provided further evidence based on the incidence of so-called SCR conducted when a child dies due to abuse and neglect. We present some tentative results suggesting that the SSCC expansion reduced the frequency of such local reviews, specifically in relation to pre-school children.

## 1.10 Figures for Chapter 1

Figure 1.1: Number of children entering care and in care by year

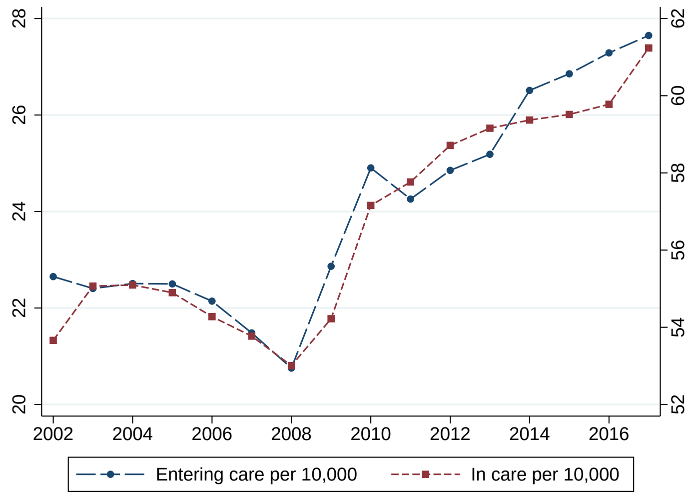


Figure 1.2: Trends in care entry rate by demographic subgroup (index 2006 = 100)

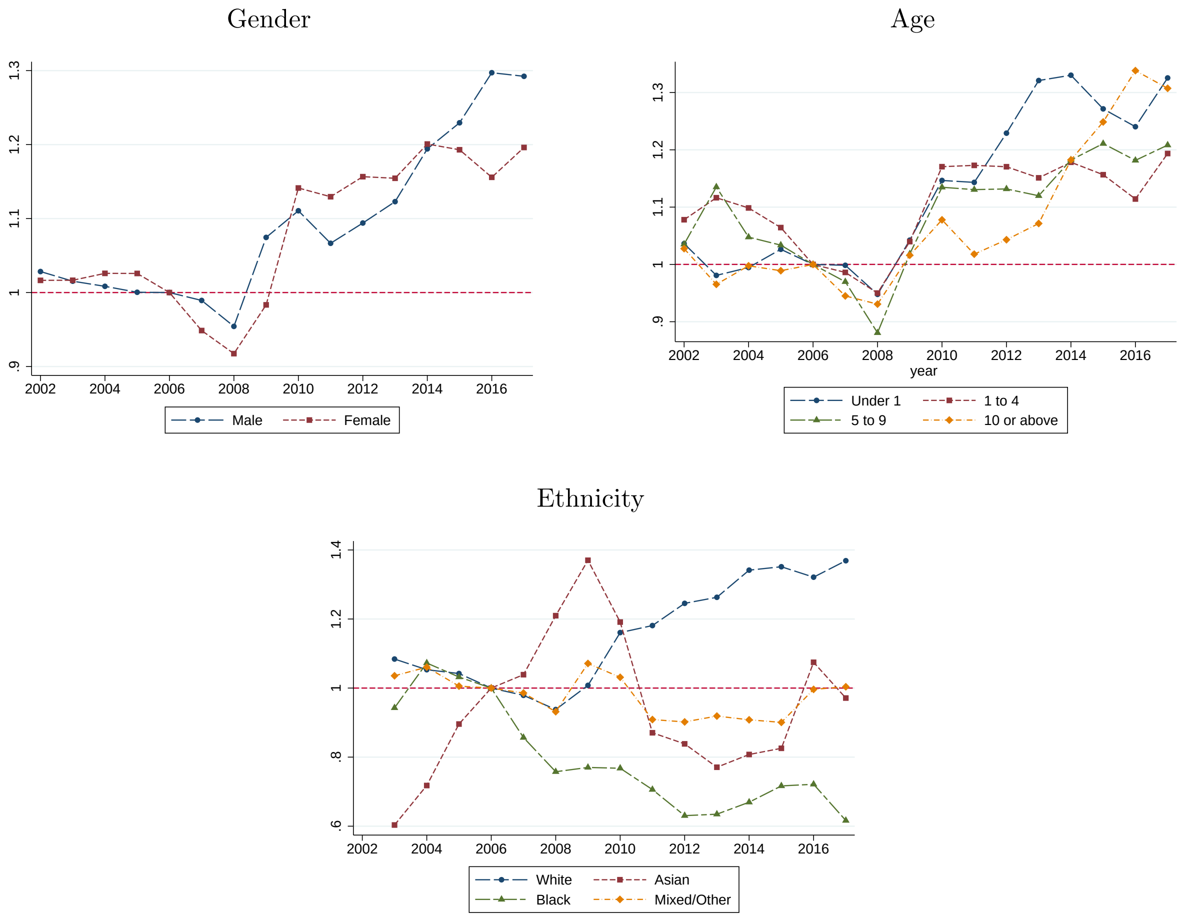



Figure 1.3: Care entry rate by reason for care

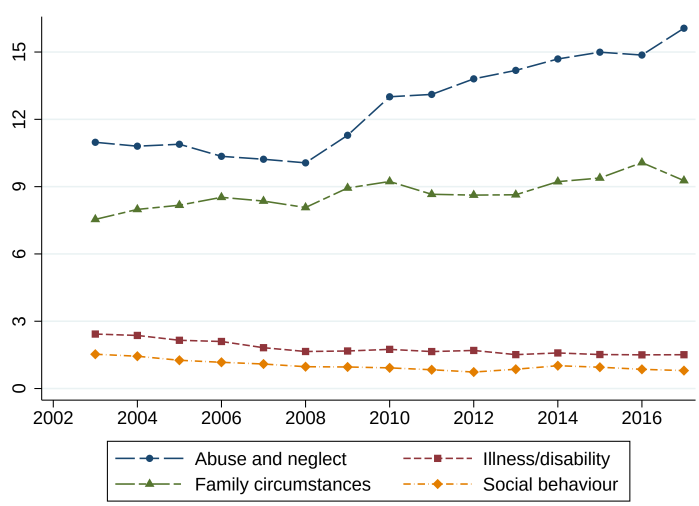


Figure 1.4: Variation in care entry rates across cells defined by Local Authority and year

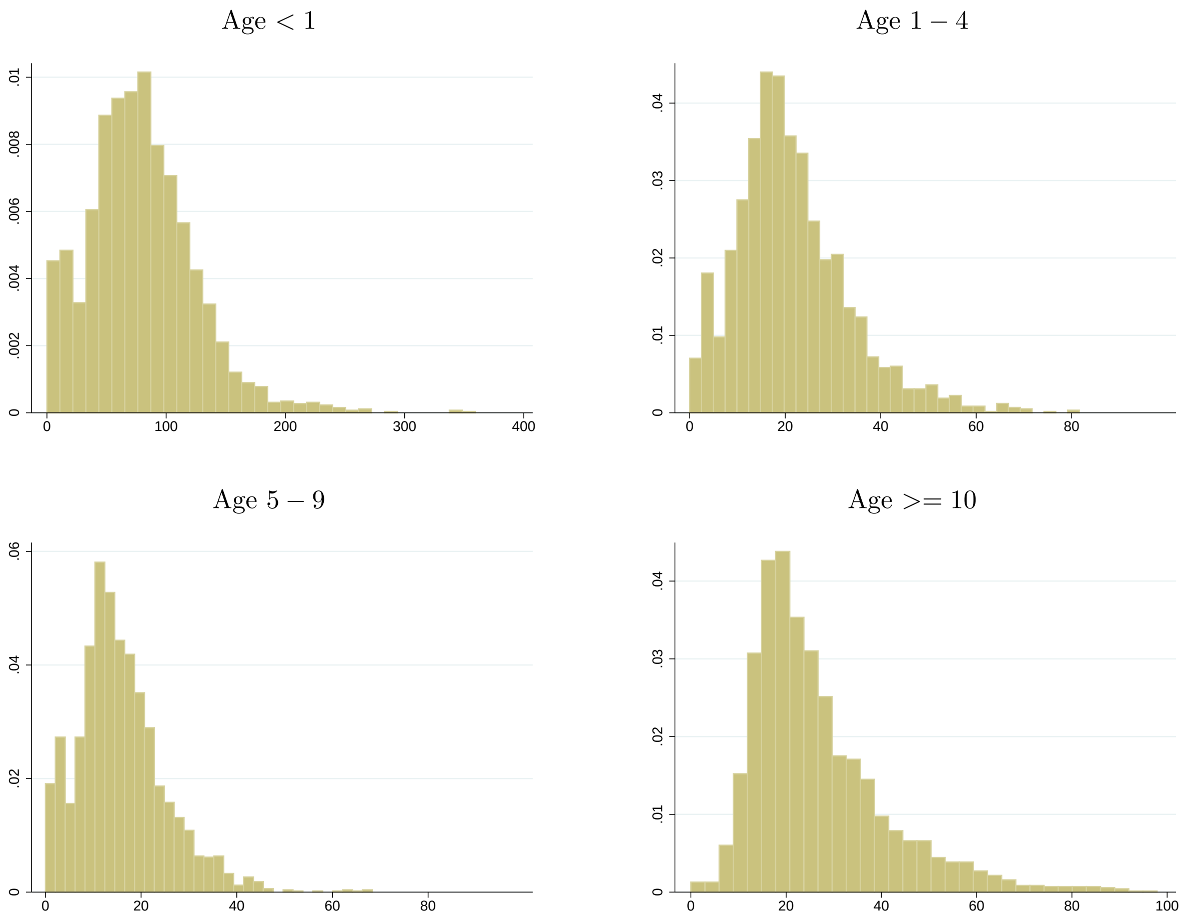



Figure 1.5: Number of SSCCs in operation in England by year, and number of SSCCs per 1,000 children aged 0-4

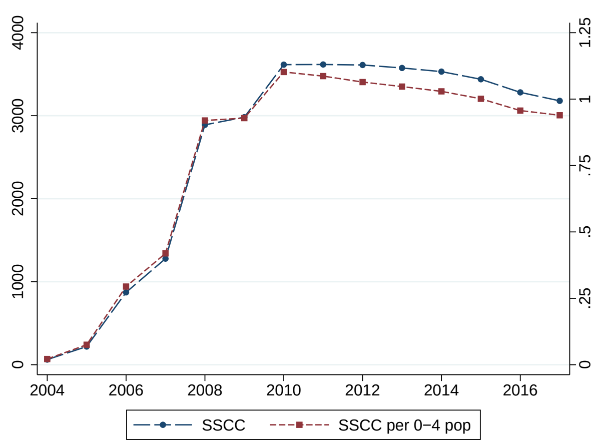


Figure 1.6: Evolution of Sure Start coverage variation

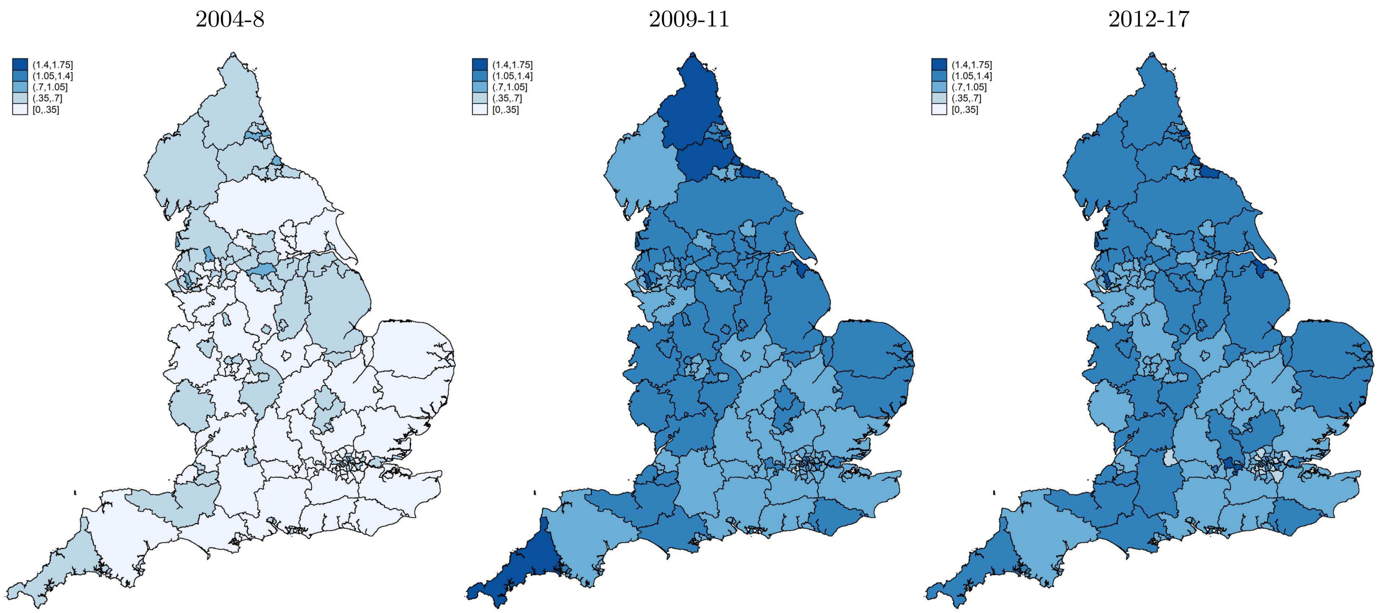



Figure 1.7: Number of LAs switching to a coverage equal or higher than 0.4 SSCC per 1,000 eligible children per year

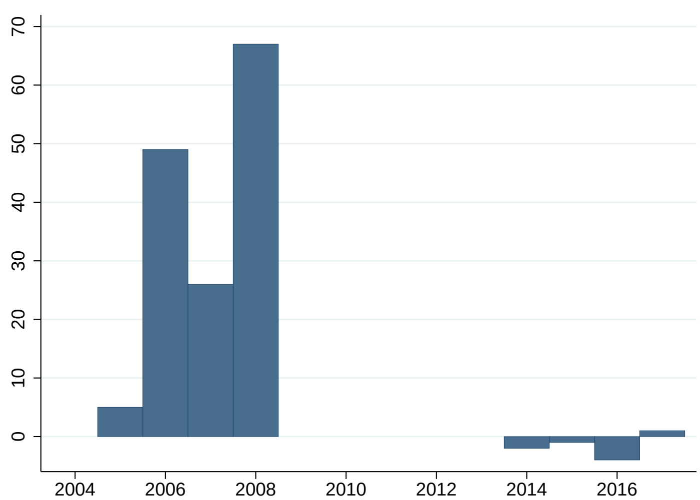


Figure 1.8: SSCC coverage: different expansion paths by local characteristics

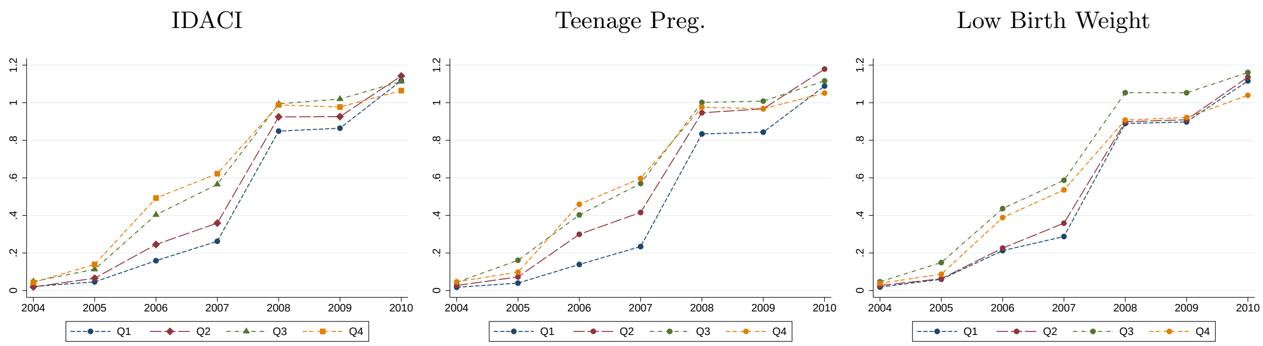



Figure 1.9: Relating relative entry rates to SSCC expansion

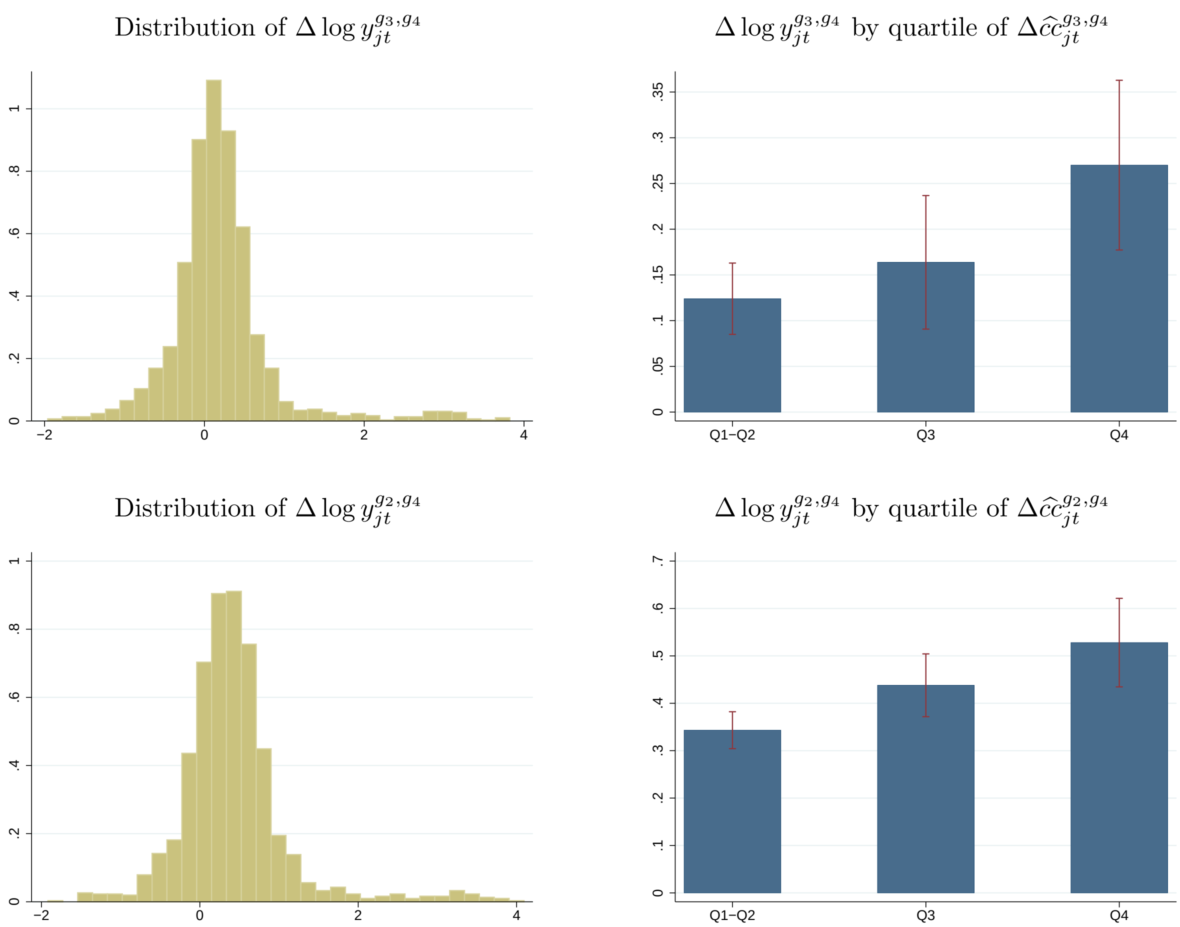
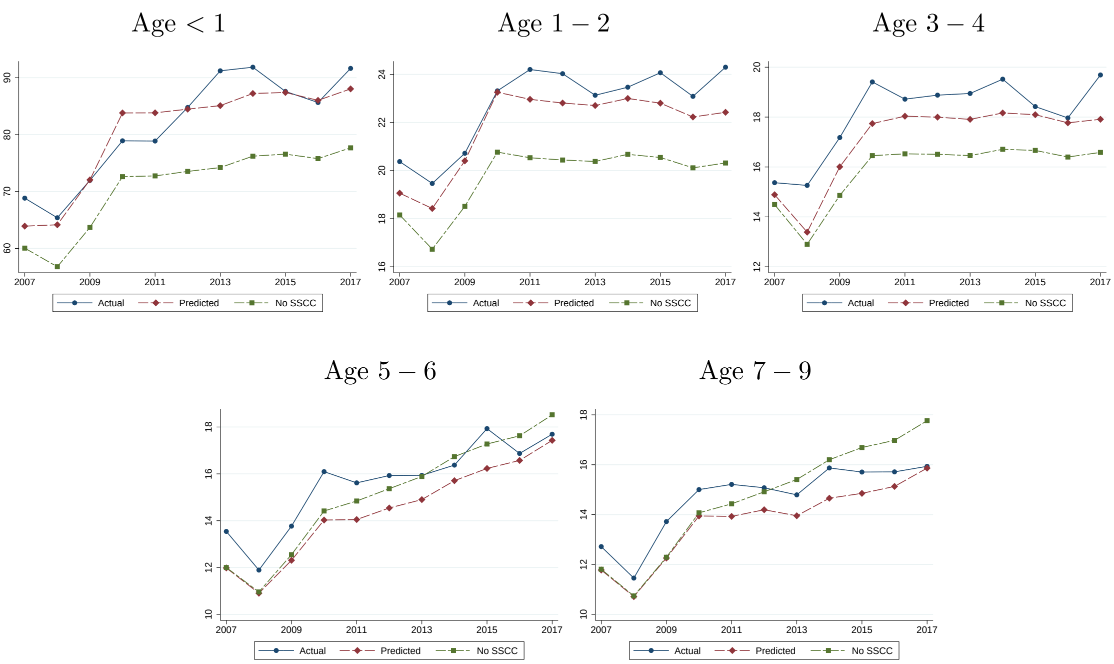


Figure 1.10: Factual and counterfactual entry rates



# Chapter 2

# The impact of unemployment on child maltreatment

Christina Olympiou

## 2.1 Introduction

Nearly 300 million children younger than four years old regularly suffer physical punishment or psychological violence at the hands of parents and caregivers all over the world.[1] In the UK, the Crime Survey for England and Wales (CSEW) estimated that one in five adults aged 18 to 74 years old had experienced at least one form of child abuse before the age of 16 years. In other words, 8.5 million adults currently living in England and Wales have suffered or are still suffering the consequences of child maltreatment.[2] Additionally, the last seven years have seen an increasing trend in recorded offences of cruelty and neglect of children under 16 by a parent or carer in England, Wales and Northern Ireland (Bentley et al., 2018).

The experience of child maltreatment can sometimes define the adult life, opportunities and lifelong happiness of the person who suffered the abuse, especially if she or he cannot access the appropriate support.[3] The consequences may include impaired physical or mental health,

[1] https://www.who.int/news-room/fact-sheets/detail/child-maltreatment

[2] https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/bulletins/childabuseinenglandandwales/january2020

[3] According to the World Health Organisation, child maltreatment is the abuse and neglect that occurs to

such as depression and behavioural problems (Fletcher, 2009), as well as disruptions in brain, nervous system and immune system development due to extreme long-term stress. The severe health issues may lead to inequalities in education and later on in employment opportunities (Zielinski, 2009). Apart from the directly affected child and family, the whole society is also significantly impacted through economic and social costs, e.g. costs of hospitalisation, mental health treatment, child welfare, and the multi-generation impact of the cycle of violence which takes place when a child who has been abused is more likely to abuse others as an adult. A recent study estimated the average lifetime cost of child maltreatment by a primary caregiver at around £90,000, with social care costs, health care costs and the costs related to the difficulty of the victims to be employed as adults being the largest contributors (Conti et al., 2017).

A key challenge with child abuse is that it is usually hidden from view. Adults in contact with the victim may not identify the signs, while children may not tell anyone what is happening in their family for many reasons including being ashamed, scared, or threatened, while sometimes they even consider abusive behaviour normal. The hidden nature of child abuse leads to imperfect data related to this issue. Service data only show reported cases, while, surveys asking parents or guardians are expected to under-report abuse as respondents may have incentives to conceal what is actually happening in their household. Finally, there are no current time-varying surveys that measure self-reported children's experience of abuse because of the challenge in asking children such sensitive questions.[4].

Taking into account the limitations of surveys discussed above and the difficulty to find local data on any information related to self-reported children's experiences, the most complete and consistent over time information is the number of children reported to children's services. Local safeguarding arrangements are led by Local Authorities (LAs) along with the police and other relevant agencies, including the National Health Service (NHS). LAs have the responsibility to coordinate the different agencies to identify and support children at risk of harm. Once a child

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children under the age of 18, including physical, emotional, and sexual abuse, as well as neglect, negligence and any form of exploitation. Child maltreatment results in actual or potential harm to the child's health, survival, development or dignity and it usually takes place in the context of a relationship of responsibility, trust or power.

[4]There are some studies that have surveyed children directly, but they are usually one-off studies and do not report estimates at a local level, e.g. see Radford et al. (2011)

is identified as being at continued risk of significant harm, a Child Protection Plan (CPP) is developed by the children's services team of the LA. Consequently, the number of children who are the subject of a CPP is a key indicator of identified child abuse in each area over time.

Recent literature in economics has started studying factors affecting child maltreatment. Brown & De Cao (2020) recently studied the effect of unemployment on child maltreatment at the county level in the United States by using administrative data on incidents of child maltreatment reported to the Child Protective Services. They found a large positive effect of unemployment on child maltreatment, with neglect driving the impact of overall abuse. They estimated that a one percent increase in the local unemployment rate causes a 20 percent increase in neglect. Their identification strategy was based on industry shift-share instruments, also known as Bartik instruments, defined by combining county industry shares at baseline with time-varying national unemployment rate by industry. They also found evidence indicating that unemployment affects abuse, and more specifically neglect, through a direct income channel.

Another recent paper examining the impact of local labour market characteristics and child maltreatment is a study by Lindo et al. (2018). This paper studied the effect of different labour market conditions on child maltreatment, using county-level data from California, with a greater focus on the impact of gender-specific labour market characteristics. Their identification strategy used Bartik predicted employment and employment growth as the variables of interest instead of actual employment levels. They showed modest evidence of the impact of overall employment on child maltreatment, but they found interesting results on gender-specific effects. More particularly, they estimated that child maltreatment decreases with male employment and increases with female employment. The results are consistent with household-time-use models, where a child's probability of being maltreated is affected by the caregivers' propensity for maltreatment and their time spent in the household.

Recent economic literature looking explicitly at the impact of labour market conditions and child maltreatment in the UK is extremely scarce. In a study looking at a related issue and using a methodology closely related with this paper, Anderberg et al. (2016) found that an increased risk of male unemployment lowers the incidence of intimate partner violence. In contrast, an increased risk of female unemployment increases the domestic abuse rate. This paper showed the potential effect of economic incentives and bargaining power within the family. The above result is not directly related to child abuse but gives valuable insights into the relationship between within-household abuse and gender-specific parental unemployment in England and Wales.

Earlier economic literature has also shown some evidence of association of various local economic conditions with child maltreatment prevalence (see Bitler & Zavodny, 2004; Seiglie, 2004; Paxson & Waldfogel, 1999; Paxson & Waldfogel, 2002; and Paxson & Waldfogel, 2003), without though explicitly controlling for potential endogeneity of local labour market characteristics. In summary, although the link between economic conditions and child maltreatment is well established and has been discussed for a long time, the economic literature is scarce. Recent contributions show very interesting evidence of the impact of unemployment and employment rates on abuse within the family, as well as differential effects of gender-specific labour market characteristics. A significant gap in the literature is the study of the relationship in question (labour market characteristics and child maltreatment) in the UK setting.

This paper builds on the work of Brown & De Cao (2020) by applying their identification strategy to data from England to explore the relationship between local unemployment and child maltreatment in a country with different experience of recession and austerity than the US and most importantly, different welfare state and maternal support. Consequently, the aim of this paper is to present the first, to my knowledge, economic evidence of the impact of local unemployment rate on child maltreatment in England, and contribute to the literature on gender- and age-specific effects recently studied by Lindo et al. (2018). The paper also contrasts the estimated impact of unemployment on CPP rates with a similar analysis for Children Looked After (CLA) to provide an insight on the type and level of need of the added cases of child maltreatment due to local increases in unemployment.

The identification strategy is based on a shift-share instrument defined as the sum of the products of each LA's industry share at baseline with the corresponding time-varying industry-specific unemployment rate. The estimated results show that an increase of one percentage point in the local unemployment rate increases CPP entry rate by 20 percent. The additional CPPs seem to be at a lower risk than the threshold of taking a child into care. Additional analysis shows a preliminary negative impact of the gender gap in unemployment on child maltreatment, indicating that female unemployment decreases maltreatment.

The rest of the paper is organised as follows. Section 2.2 describes the institutional setting of child protection in England and presents trends and key characteristics of children becoming the subject of a CPP during the period of study. Section 2.3 presents the literature on mechanisms and considers how the welfare state in England may affect those. Section 2.4 describes the empirical strategy used to identify the relationship in question, while section 2.5 provides information on the data used and key summary statistics. Section 2.6 presents the main results and section 2.7 explores additional empirical results and discusses their potential interpretation. Finally, section 2.8 concludes.

## 2.2 Child protection in England

This section describes the procedures related to child protection in England and defines the main indicator of child abuse used in this paper, the CPPs. Additionally, it presents the trends of CPPs over time and the key characteristics of children becoming the subject of a CPP in England during the period 2007 to 2017. The information used in this section is mainly based on data included in the annual statistics published by the Department for Education "Characteristics of children in need", unless otherwise stated.

### 2.2.1 Institutional background

#### Overview of children's social care and child protection in England

Child protection and social care consists of different groups of children and levels of support. This section will provide a brief overview of child protection and children's social care in England.

Although not exhaustive, the most common services available to vulnerable children in England are: (i) universal services, (ii) Common Assessment Frameworks (CAFs), (iii) Need Plans, (iv) CPPs, and as a last resort (v) LA care, when the child enters the care of the LA and she or he is removed from the care of their birth family (in most cases). Universal services are available to all children, while CAFs are early-intervention plans aiming to identify any unmet needs of a child. On the other hand, Children in Needs Plans (CINPs), children subject to CPPs and children entering the care of a LA have higher needs and risks.

Children in CINPs, CPPs and looked-after children are all considered Children in Need (CIN). A child will be considered in need if (i) they are unlikely to achieve or maintain or to have the opportunity to achieve or maintain a reasonable standard of health or development without provision of services from the LA, (ii) their health or development is likely to be significantly impaired, or further impaired, without the provision of services from the LA, or (iii) they have a disability. As will be discussed in the rest of the section, children who become the subject of a CPP are considered to be at a high risk of significant harm. These children are supported, through the CPP, while remaining in the care of their family. In contrast, the parental responsibility for looked-after children is transferred from their birth parents to the LA. Children in CINPs are children receiving support who are neither in CPPs or looked-after by the LA. Depending on the circumstances, a child may go through multiple levels of support, while if there is a need for urgent intervention they might skip stages and become directly in care or the subject of a CPP. Many children will stay "in need" and never need additional support.

Referrals to children's social care are usually made by professionals in contact with the child (e.g. school teachers) or by the police. According to the Department for Education (2017a), during the school year 2016/2017, 27.5 percent of referrals were from the police, followed by schools with 17.7 percent, and health services with 14.4 percent. Not all children referred to children's social care are being defined as CIN. In fact, a large proportion of referrals do not end up in the provision of statutory support. For example, during 2016/17, 10 percent of referrals resulted in no action, while 30 percent of referrals were assessed, and it was decided that no further action was needed.

The different groups of children are not mutually exclusive, as it is common for children to return to social care under the same or different categories. More particularly, almost two-thirds of children who were looked-after in 2017/2018 had spent some time on a needs plan in the previous five years (62 percent), while 39 percent of those children had spent some time on a CPP before (Department for Education, 2019).

### Child Protection Plans

If a child is taken into police protection, is the subject of an emergency protection order or there are reasonable grounds to suspect that a child is suffering or is likely to suffer significant harm (physical abuse, sexual abuse, emotional abuse or neglect), a Section 47 enquiry is initiated. If the child is judged to be at continued risk of significant harm, a Section 47 enquiry results in a child protection conference. Based on the information discussed at the child protection conference, the LA decides whether a CPP is needed or not.

A CPP is a plan detailing the ways in which a child is to be kept safe, and it is created by the LA. It includes guidelines on how the child's health, development and welfare will be promoted and how professionals can support the child and their family if this is in the child's best interest. For example, a CPP may ask the parents to take weekly parenting classes, the social workers to visit the family home to offer practical or emotional support, the child's teachers to provide after-school support, or the housing officers to solve issues related to the child's house that may affect their health.

CPPs are reviewed at further review conferences which take place every three to six months. If the social workers decide that the child is no longer suffering or at risk of suffering harm, then the child is no longer the subject of a CPP. On the other hand, if the concerns for the child are getting greater and the social workers judge that a CPP is not enough to keep the child safe, then they may start care proceedings, i.e. they may apply to the court for the child's parental responsibility to be transferred to the LA. According to national statistics provided by the Department for Education (2019), around 70% of children cease to be the subject of a CPP in less than one year, while the vast majority of remaining children have their CPP monitored for a maximum of two years. Families may remain the subject of a CPP for a longer time, if social workers considered that they are still at risk, to be supported and to monitor their progress.

### 2.2.2 Children becoming the subject of a Child Protection Plan

More than 60,000 children become the subject of a CPP every year. In other words, more than 50 children out of every 10,000 in England are identified by Local Authorities as suffering or being at risk of suffering significant harm as a result of neglect, emotional abuse, physical abuse or sexual abuse. The number of children in this group has seen a significant increase during the last 10 to 15 years. This paper is examining the period from 2007 to 2017, during which there has been an increase in demand for all services related to children's social care, especially during the period of the economic recession in the UK.

It is well known in the literature and the policy sector that children's social care is affected by economic recession and austerity due to various reasons. For example, families are under financial pressure and stress, parents may not be able to afford childcare any more, parental unemployment is increasing, potentially abusive adults spend more time in the house, and resource constraints may result in necessities being not available to children. Austerity also results in LAs having reduced resources available for early intervention support to families, such as parenting skills programmes and children's centres.

Figure 2.1 shows the number and rate of children becoming the subject of a CPP over time. The CPP entry rate is defined as the number of children becoming the subject of a CPP during a year per 10,000 children in England. The CPP entry rate almost doubled during the period examined as it has grown from 30 to 55 children per 10,000 children in England. The largest jump of the CPP entry rate occurred during the period 2008-2012, i.e. the period of economic recession and austerity in the UK when the rate was increased by more than 40%.

The prevalence of CPPs varies significantly across different age groups. Figure 2.2 shows the national CPP entry rate of different age groups over time. The CPP rate of children younger than one-year-old is consistently much higher than that of any other age group, with around 140 per 10,000 babies becoming the subject of a CPP during 2017. The oldest age group, i.e. children aged 10 to 17, has the lowest CPP rate, with 40 out of 10,000 children starting a CPP in 2017. The CPP entry rates of all age groups have increased over the period studied, with children aged 10 to 17 seeing the largest percentage increase, as the CPP entry rate more than doubled, increasing from 17 to 41 from 2007 to 2017.

### 2.2.3 Category of abuse

When a CPP is commenced the social workers assess the information and identify the type of abuse that the child is suffering or is at risk of suffering. The main types of abuse are: neglect, physical abuse, sexual abuse, emotional abuse, and multiple abuse.

Figure 2.3 shows the number of CPPs per 10,000 children in England by category of abuse overt ime for the period 2007-2017.[5] Neglect has always been by far the most common category of child abuse. In 2007, neglect was around two times higher than emotional abuse, which is the second more common category, and three times higher than physical abuse. Emotional abuse and neglect are increasing over the period of study. Neglect entry rate jumped from 13 to 26 children per 10,000 population during the period 2007-2017, and emotional abuse increased from 7 seven to just above 19. On the other hand, physical, sexual and multiple abuse remained relatively stable over time.

A key issue with the reporting of the above categories is the consistency of categorisation across areas, people and over time, as social workers' knowledge on signs and consequences of neglect and emotional abuse is being improved over time (C. Thomas, 2018). The definitions of the different types of abuse may not be identically perceived by different people within an area, people in different areas, or people over time. A typical example of potential inconsistency is the difference between neglect and emotional abuse. While the signs of physical and sexual abuse are more easily separated from those of other types of maltreatment, neglect and emotional abuse are more difficult to identify and even more difficult to distinguish from each other. Emotional abuse and neglect may just reflect similar cases reported under different categories over time and by different people. Figure 2.4 shows the national ratio of neglect to emotional abuse over time. The fact that the ratio decreases over time indicates a potential tendency to report cases previously categorised as neglect under the category of emotional abuse. These potential inconsistencies cannot really be proved, and they may exist across all different categories of

[5] The tables reporting the category of abuse are at a CPP-level instead of child-level, i.e. if a child had more than one plan during a year, each plan is reported in those tables.

abuse (e.g. physical neglect is closely related to physical abuse, sexual abuse to physical abuse etc.).

## 2.3 Theoretical considerations of potential mechanisms and motivation

This paper aims to quantify the impact of unemployment on child maltreatment. This section presents the literature providing evidence related to the mechanisms that can drive a relationship between labour market conditions and child abuse and neglect. The UK welfare state is also discussed and compared to the US support system to understand potential differences in the mechanisms driving the relationship between the two settings.

### 2.3.1 Literature on potential mechanisms

The literature has identified several mechanisms through which a change in employment status of a parent can affect the probability of a child being maltreated. The most commonly reported and explored mechanisms include changes in income, time spent with parents or carers, and parental mental health difficulties and substance abuse.

A change in the employment status of a parent has a direct impact on the family income and on the expenditure on basic goods, which are essential for the health and well-being of a child. Low family income can result in failure to provide medicines, healthcare (depending on the healthcare system of each country), food, clothes, a clean, warm and safe home, and safe transportation. The inability to provide these necessities can lead to physical and medical neglect, while it can also be related to other types of neglect, such as educational neglect. Brown & De Cao (2020) studied the impact of unemployment on the expenditure on goods and services that are related to neglect to explore whether their findings could be driven by an income effect. They found that increases in unemployment cause a statistically significant decline in household expenditure on food and beverages, energy and transportation services. On the other hand, they did not find any evidence that the expenditure on housing, utility and healthcare services are affected by unemployment.

Economic hardship and insufficient resources may cause or contribute to other types of maltreatment (e.g. emotional neglect and abuse) through indirect channels such as parental stress, overburden, depression and other mental health issues, and substance abuse (Slack et al., 2017; Ruhm, 2000; Ruhm, 2003). McLoyd (1990) studied the effect of economic hardship on children and showed that economic loss negatively affects supportive, consistent and involved parenting. At the same time, it makes parents more vulnerable to other challenges or adverse life events, mostly due to psychological distress. The above mechanisms may also contribute to increased parental substance abuse. However, evidence by Brown & De Cao (2020) and Ruhm & Black (2002) showed that unemployment might decrease such behaviours due to low income. Disadvantaged families, single-parent families and divorced parents are expected to be more vulnerable to depression, stress, substance abuse and limited resources. Thus, those families might be affected more by a change in their employment status than families facing fewer challenges at the time of such an event. Finally, being employed involves having a routine daily schedule, increased social network, and thus limited isolation. The above may contribute to improved parenting capacity and enhanced support for both parents and children.

Unemployment may also increase parents' time spent with children. The literature has shown that the sign and magnitude of such mechanism may vary between fathers and mothers (or female and male caregivers). More specifically, Lindo et al. (2018) explored the impact of gender-specific labour market conditions on child maltreatment. Their conceptual framework was based on two key factors of a child maltreatment production function: (i) the propensity of each parent to maltreat, and (ii) the share of child's time spent with each parent. Their results showed that improvements in employment opportunities for men result in decreases in child abuse and neglect rates. On the other hand, when labour market conditions for women are improved, child maltreatment increases. They showed that holding the first factor fixed (and considering that fathers have, on average, higher propensity to maltreat than mothers), shifts in time use from high-risk caregivers to low-risk caregivers can explain the differential effect found.

Page et al. (2019) looked into the impact of local labour market opportunities and child health. Their results showed that women's increased employment opportunities are consistently associated with worse child health, while the opposite effect is present for men. The authors explored empirically different mechanisms and concluded that their results are consistent with the notion that mothers provide larger time investments, on average, and fathers higher monetary support. The authors also mentioned that another potential driver of gender-specific effects could be that fathers experience greater increases in stress than mothers following a job loss. Finally, the bargaining power of the employed adult in the household could also be a mechanism of the differential impact of changes in labour market conditions. Literature has shown that resources provided to women translate into larger investments in children than those provided to men (Lundberg et al., 1997; Duflo, 2003).

In summary, the literature has provided evidence for a direct income effect and other indirect effects, including time spent with each parent, parental stress, and parental mental health issues. Evidence exploring gender-specific drivers suggests a positive effect of additional maternal time on children's well-being, but the opposite effect for fathers (or male caregivers). The differential effects may be due to the two parents' different propensities to maltreat, time involvement, and monetary support.

### 2.3.2 Welfare state in England

Recent literature on the effect of labour market conditions on child maltreatment and related mechanisms utilises mainly data from the US. This section gives a brief overview of some key characteristics of England's welfare state and family support system to explore whether differential effects of unemployment could be observed in the two countries.[6]

Both UK and US governments provide allowance to support people becoming unemployed (e.g. the unemployment insurance benefits in the US and the Job Seekers Allowance and Universal Credit in the UK). Additional benefits can also be claimed under specific circumstances and family characteristics, especially for low-income households and disabled or vulnerable people. Both welfare states provide unemployment benefits under specific conditions. For example, some of the key conditions to receive such benefits are sufficiently high earning histories and earlier

[6]This paper focuses on England, but welfare state and family support are similar across different countries in the UK.

contributions to national insurance. Additionally, both welfare states aim for the unemployment allowances to be short-term support, i.e. until people find a new job unless they are eligible for long-term benefits. However, the two welfare states differ in various other aspects.

One of the key differences between the systems in the two countries, and the most relevant to the topic of this paper, is the different approaches to family-focused support. For example, in the UK, there is a child benefit of around £100 a month, which is available to everyone (with lower earnings than £50,000 a year) responsible for a child younger than 16 years old, and it is supposed to help with the everyday expenditure of the child. Similar child benefits did not exist in the US during the study period.[7] Additionally, the UK government has been offering universal childcare support over the last ten years. In 2010, the Department for Education announced 15 hours of free childcare per week for all children aged 3-4 years old. In 2013, free childcare became also applicable to younger children aged two years old from disadvantaged families. Since 2017, free childcare has been extended to 30 hours per week (during term time) for all children aged 3-4 years old. The eligibility criteria include mostly parents being employed with earnings less than £100,000 per year. The US has similar programmes for supporting families by covering parts of children's expenditure (e.g. childcare subsidies, Temporary Assistance for Needy Families, Head Start and Early Head Start). However, most of the programmes seem to be focused on low-income or disadvantaged families (rather than being universal or available to the majority of families). Secondly, there is a large variety of how and if different programmes are implemented in each state.

A related topic to childcare and child support is maternity leave and pay. In the UK, there is statutory maternity leave of 52 weeks. Mothers can choose the length of their maternity leave, with the first two weeks after the baby is born being obligatory. Out of the 52 weeks, 39 weeks are paid (for employed mothers) through the Statutory Maternity Pay (SMP). The government provides maternal allowance for those who have recently stopped working and those who are employed but not able to receive SMP. On the other hand, in the US, the Family and Medical Leave Act requires the US employers (with 50 or more employees) to allow mothers to take up

[7] The US launched a temporary monthly child benefit of around £200 in July 2021.

to 12 weeks of maternal leave, while there is no national statutory maternity pay, with a few states passing their own family leave laws.

In summary, the UK has a more family-focused welfare state, more supportive laws for parents (especially new mothers) and more widely available free childcare. Similar programmes and schemes do exist in the US, but they are usually focused on specific populations, and there is a high variation in the adaptation of those policies across states. The above discussion shows that the UK and US settings differ significantly in some ways that may affect the impact of unemployment on children's well-being and the related mechanisms. Firstly, the impact of unemployment on babies under one year old may be less pronounced if the SMP and statutory maternity leave provide enough support to new mothers. Additionally, free childcare could lead to a smaller indirect effect of redistributing parental time when one of the two parents or caregivers becomes unemployed. However, since free childcare requires the parents to be working and it was not full-time during the time period studied in this paper, parental time spent with children may still be an important potential mechanism in the setting of this paper. Finally, although welfare support can decrease the family income shock resulting from unemployment, those benefits wouldn't provide everything that can be provided when parents receive labour market income. Families relying on benefits and support will still struggle both in terms of resources and other indirect channels, such as stress and mental health difficulties.[8]

## 2.4 Identification strategy

This section presents the methods used to produce evidence on the relationship between child maltreatment of children younger than nine years old and local unemployment in England during the period 2007-2017. The identification strategy used to control for potential endogeneity of unemployment and the estimated equations are presented and discussed.

[8]The above discussion is not exhaustive, there are other schemes, benefits and cash transfers or tax credits that are applied to parents and are relevant to both countries. This section mostly focuses on giving some examples of the family-related aspects of welfare state in England that could affect the mechanisms underlying the impact of unemployment on child maltreatment.

### 2.4.1 Main analysis

This paper explores the relationship between the local unemployment rate and child maltreatment as indicated by the number of children becoming the subject of a CPP during the period 2007-2017. The main empirical complication of this research question is that changes in the unemployment rate may reflect changes in either labour demand or labour supply. Thus, there is the possibility that any relationship found between the unemployment rate and CPP rate is mainly driven by unobserved characteristics of the economically active population of the LA. Consequently, a simple OLS specification would produce a potentially biased estimated coefficient of the unemployment rate on child maltreatment. To overcome this issue, I use (i) LA fixed effects to control for time-invariant unobserved characteristics, (ii) LA-specific time trends to control for time-varying unobserved LA characteristics, and (iii) a Bartik instrument (Bartik, 1991; Blanchard et al., 1992) to isolate the demand-side of the unemployment rate and thus correct any remaining endogeneity, following the identification strategy of Brown & De Cao (2020).

A Bartik-like instrument is any variable that combines local industry shares at baseline with a national time-varying indicator of the economic condition in question. The Bartik instrument used here aims to predict local unemployment rates, and thus it is defined as the weighted average of the national unemployment rate across all industries. The role of the Bartik instrument is to isolate the demand-side change of the unemployment rate. The local industry shares measure differential exposure to common shocks, and the identification is based on the exogeneity of the shares (Goldsmith-Pinkham et al., 2020). The formal definition of the instrument used is shown below:

$$\widehat{Unempl}_{jt} = \sum\nolimits_{i} \phi_{ji} Unempl_{it} \tag{2.1}$$

$Unempl_{it}$ is the national unemployment rate in the UK in industry $i$ at time $t$, and $\phi_{ji}$ is the fraction of employed population at LA $j$ in 2006 who were working in industry $i$. The weights are fixed at baseline to avoid potential simultaneity, while the national unemployment rate varies over time to capture national shocks.

$$\log\left(cpp_{gjt}\right) = \beta Unempl_{gjt} + \eta_g I_g + \delta_j I_j + \nu_t I_t + \omega_g I_g t + \mu_j I_j t + \rho Z_{jt} + \varepsilon_{gjt} \qquad (2.2)$$

Specification 2.2 is the main equation of this paper, as it estimates the relationship of CPP rates with unemployment, controlling for all observed and unobserved local characteristics and national shocks. The dependent variable is the logarithm of the CPP rate in age group $g$, area $j$ and year $t$. As discussed in section 2.5, the CPP rate is defined as the number of children aged $g$ in area $j$ becoming the subject of a CPP during the year $t$ per corresponding 10,000 child population. The estimating equation also includes age-group fixed effects ($\eta_g$) and age-group-specific linear trends ($\omega_g I_g t$) to model the fact that CPP entry rates differ significantly across different age groups and may also have different trends over time. LA fixed-effects ($\delta_j$) and year fixed-effects ($\nu_t$) are also included in the model. The area fixed-effects control for permanent unobserved differences across areas, while the year fixed-effects control for a common national trend. To control for potential changes in local characteristics that may affect both local labour markets and prevalence and identification of child maltreatment, the model includes LA-specific linear trends ($\mu_j I_j t$), as well as time-varying local characteristics ($\rho Z_{jt}$). $\rho Z_{jt}$ consists of variables capturing LAs' ethnicity composition, educational qualifications, and median income. Since our model includes area fixed effects, area-specific trends, and year fixed effects, a standard approach since Ruhm (2000) to control for spurious trends in the aggregate and omitted fixed and time-varying local characteristics, it estimates how CPP rates in an area deviate from trend when unemployment deviates from trend, over and above changes occurring across all areas (Lindo et al., 2018).

$$Unempl_{jt} = \gamma \widehat{Unempl}_{jt} + \eta_g I_g + \delta_j I_j + \nu_t I_t + \omega_g I_g t + \mu_j I_j t + \rho Z_{jt} + \varepsilon_{gjt} \qquad (2.3)$$

The local unemployment rate is identified through a Two-Stage Least Squares (TSLS) regression with a Bartik instrument to control for potential endogeneity. The first-stage regression is shown in equation 2.3, where everything is identical with equation 2.2 apart from the dependent variable being local unemployment rate in area $j$ and year $t$ and main variable of interest being the Bartik instrument. Estimated coefficient $\gamma$ is the key estimate here as it indicates the power of the instrument and if it can be used in a TSLS regression.

### 2.4.2 Gender gap analysis

As an additional analysis, this paper also looks into any potential impact of gender gap in the local unemployment rate on child maltreatment. To explore this research question, I use a Bartik-like instrument of the gender gap. Firstly, I construct the Bartik instrument for each gender and then calculate the predicted gap. Our methodology in this section is in line with the Bartik instruments used by Anderberg et al. (2016) in exploring the impact of unemployment gender gap on domestic violence. The definition of gender-specific Bartik instrument is shown below:

$$\widehat{Unempl}_{sjt} = \sum\nolimits_i \phi_{sji} Unempl_{sit} \tag{2.4}$$

In specification 2.4 the industry shares refer to the fraction of the working population of the gender $s$ in area $j$ who are employed in industry $i$, while the national unemployment rate refers to the unemployment rate of people of gender $s$ whom their last job was in industry $i$. Consequently, the above Bartik definition provides one predicted unemployment rate for women and one for men for each area and year in our sample. The predicted gender gap is simply the difference between the two Bartik instruments, as shown in equation 2.5.

$$\widehat{Unempl.Gap}_{jt} = \widehat{Unemp.Fem.}_{jt} - \widehat{Unempl.Male}_{jt} \tag{2.5}$$

The estimating equation for this part of analysis is the same as equation 2.2 with the unemployment variable being replaced by the unemployment gender gap, which is identified through a TSLS regression using predicted unemployment gap, as defined by equations 2.4 and 2.5, as instrument.

## 2.5 Data and summary statistics

This section describes the data used to produce the results of this paper. The data sources and the key summary statistics of the data used are presented and discussed.

### 2.5.1 Children becoming the subject of a Child Protection Plan

One of the key variables used in this paper is the CPP entry rate. For the purposes of this paper, the CPP rate is defined as the number of children becoming the subject of a CPP per 10,000 child population in each LA in England for each year during the period 2007-2017. The original source of data on this group of children is the CIN census maintained by the Department for Education. Summary statistics from this data source on the number and characteristics of CIN and children subject to a CPP are published annually through the national statistics "Characteristics of children in need".

Apart from the general CPP entry rate, it is interesting to explore how the rate varies across different age groups and how children of different age groups are affected by their parents' or caregivers' employment status. Labour market characteristics can have differential effects on children of different ages, e.g. babies spend more time in the household and thus more time with parents or guardians. On the other hand, older children may have more needs in terms of expenditure (e.g. related to education and activities) and psychological support. Thus, they may also be affected by changes in the employment status of the adults in the households.

This study combines data from two main sources: (i) the annual national statistics, and (ii) tables provided by the Department for Education through a Freedom of Information request.[9] The Freedom of Information request asked for a panel dataset of the number of all children who became the subject of a CPP during each year between 2007 and 2017 in 147 LAs in England by age group.[10] As abuse and neglect are more common among younger children, as shown in

[9]Published data include the number of children becoming the subject of a CPP by age group until 2009. From 2010 to 2012, the national statistics include age-segregated data, but the same table is also divided by gender. This additional segregation led to many concealed numbers due to confidentiality. From 2013 onwards, the national statistics do not include data divided by age at all. Thus, published data are used for the period 2007-2009, while for 2010 onwards, the data were provided by the Department for Education through a Freedom of Information request.

[10]The analysis includes 147 Local Authorities in England, i.e. all Local Authorities in England apart from:

Figure 2.2, and also due to data gaps in the number of CPPs for children older than 9 years old, the analysis is focused on children aged 0-9 years old. The age groups studied are: (i) younger than 1 year old, (ii) 1 to 4 years old, and (iii) 5 to 9 years old. Figure 2.5 shows the distribution of CPP entry rates across all LAs and years in our sample. As expected, the youngest age group has the highest CPP entry rates ranging from 0 to 300, with a few LAs having rates even higher than that. The other two age group also have quite large variation across areas and over time, as the majority of cells varies from 0 to 100.

For the CPP entry rate to be calculated, the number of children becoming the subject of a CPP in each age-LA-year cell was divided by the population of children in the same cell. The population data was extracted by Nomis, a service provided by the Office for National Statistics, and it is based on annual mid-year population estimates produced by the Office for National Statistics (ONS).

### 2.5.2 Unemployment rate

#### Actual local unemployment rate

The local unemployment rate is the number of unemployed people in an area as a percentage of the labour force in the same area. The Nomis website provides estimates of the local unemployment rate in all LAs in England for the period studied based on data from the Annual Population Survey (APS). Data on unemployment is available for different age groups (e.g. those aged 25-49, 16-64) and gender.

Nomis also provides the official unemployment figures for LAs, which are model-based and are only available for the total unemployed population. This indicator improves on the APS estimates by using the claimant count, which is an administrative count with no sampling error and strongly correlated with unemployment, to produce a more precise estimate for local areas with a small number of representatives in the APS. Model-based unemployment used in this paper refers to the unemployment rate for everyone aged 16 years old and above. The main

City of London, Rutland, and Isles of Scilly. These Local Authorities are not included in the sample due to small populations and missing data. Additionally, Bedford Borough and Central Bedfordshire are combined and studied together as Bedfordshire. Similarly, Cheshire East and Cheshire West and Chester are combined into Cheshire.

analysis uses the model-based unemployment rate to increase precision, but additional analysis on gender-specific unemployment refers to APS estimates.

Figure 2.6 shows the average unemployment rate in our sample over time. It presents both the model-based unemployment rate and the unemployment rate estimate for those aged 16 plus from the APS. The two indicators are almost identical on average, as expected as the model-based estimates mainly improve the accuracy of estimates in LAs with small samples. Thus, the model-based estimates are not expected to vary from the APS significantly in magnitude. The unemployment rate was increased during the recession period in England, and it peaked in 2012, with the rate increasing from under 6% in 2008 to almost 9% in 2012, i.e. a 50% increase. From 2012 until the end of the period being examined, the unemployment rate was decreasing, with the average being around 5% in 2017. Figure 2.7 shows the average unemployment rate by gender. Both unemployment rates increased between 2008 and 2012 and decreased afterwards, with the male unemployment having larger changes during both the increasing and decreasing period.

Unemployment varies significantly across LAs, and it is strongly correlated with demographic characteristics, geography and location of each area. Figure 2.8 presents the distribution of model-based unemployment across all LA-year cells in our sample.

#### Bartik instrument

As described in Section 2.4 the Bartik instrument is constructed by combining two main variables: (i) the annual national unemployment rate by industry for the period of interest, and (ii) the local industry composition at baseline.

The national unemployment rate by industry is defined as the number of unemployed people whose last job was in the specific industry as a percentage of the labour force in this specific industry during the year (i.e. the unemployed plus those employed in the industry). The data for this variable were obtained from the dataset "Unemployment by previous industrial sector" published by the ONS. The estimates are originally sourced from the Labour Force Survey (LFS). Gender-specific unemployment rates were also reported in this dataset. Figure 2.9 shows the national unemployment rate by industry over time. Overall, unemployment in all sectors increased during the recession and went back to lower levels than in 2007 by 2017. Construction seems to be the sector that was most immediately affected by the recession, as the relevant unemployment rate almost tripled from 2008 to 2010, but the period of decrease also started earlier than in other industries. Manufacturing has a similar pattern with construction but at lower levels of unemployment. The public sector (including public administration, education and health) is the sector with the lowest unemployment in any given year and the sector with the smallest and slowest increase. The unemployment rate in the rest of the industries increased during the recession, remained high until 2014 and then decreased until 2017.

Industry composition is defined as the percentage of employed people in an LA who are working in each specific industry. For example, if the industry composition of the public sector in LA X is 0.30, it means that 30% of the population of employed adults are working in this sector. To construct these variables, I used data on the total and industry-specific employment in each LA in England in 2006 (for both the total and gender-specific populations). 2006 is used as the baseline year as it is the year before the beginning of the period of interest. The data used for this variable were retrieved from Nomis, and the original source is the APS. Figure 2.10 shows the average contribution of each industry in 2006. The public sector's contribution is the highest as it is just below 30%, while agriculture is the lowest with a contribution of around 2%. Figure 2.11 contrasts the average industry composition of males and females employed during the study period. The proportion of women working in agriculture, construction and manufacturing is extremely small, while the vast majority of women work in the public sector, banking and finance or hotels and restaurants sector. On the other hand, male employment seems to be more spread out in the different industries. One consequence of the above characteristic of gender-specific industry composition is that the Bartik instrument might better predict the male unemployment rate. This is because the population of unemployed men consists of a much higher population working in industries with large changes in unemployment rates (namely, manufacturing and construction). Table C2 in Appendix C shows the average industry composition over all areas in our dataset in 2006 and contrasts the average industry shares of women with those of men.

### 2.5.3 Local Authority characteristics

Apart from the main variables of interest, i.e. CPP entry rate and unemployment-related variables, the analysis makes use of data on LA background characteristics. The time-varying variables are used to control for LA characteristics that vary significantly over time and are expected, based on the literature, to be correlated with abuse and neglect (i.e. ethnic composition, educational qualifications, and median income). A data description of those variables is provided in Appendix C.

Table C1 in Appendix C presents the summary statistics of all the variables discussed in this section.

## 2.6 Results

### 2.6.1 Pooled regressions

This paper explores the impact of the local unemployment rate on child maltreatment, as measured by the CPP entry rate. As a natural first step, I start by pooling all age groups together, i.e. looking at the impact of unemployment on the CPP entry rate of all children aged 0-9 years old. Table 2.1 presents the estimates of the OLS and TSLS regressions. Column (1) presents the OLS results of estimating equation 2.2 with the actual unemployment rate. As discussed in section 2.4, an OLS regression of CPP entry rate on the local unemployment rate is expected to produce biased estimates. Column (2) and (3) present the results of estimating equation 2.3 for all children aged 0-9, i.e. the first-stage estimates. Column (2) presents the results when using the natural logarithm of the unemployment rate, while column (3) uses levels. The first-stage results show that when the Bartik instrument increases by 1, the actual unemployment rate increases by around 40%. The results of the TSLS regression show an estimated impact of unemployment on CPP entry rates of around 18.4%, which is statistically significant at only 10% significance level.

While the results seem inconclusive, there is a critical limitation of the analysis presented so far; the pooled regressions do not exploit the full variation available in the data. For example,

Table 2.1: Effect of unemployment rate on CPP entry rates: Pooled analysis

| | (1) Log(CPP) | (2) Log(Unempl. Rate) | (3) Unempl. Rate | (4) Log(CPP) |
|---|---|---|---|---|
| Unempl. Rate | -0.006 | | | 0.184+ |
| | (0.0091) | | | (0.103) |
| Pred. Unempl. Rate | | 0.393*** | 2.138* | |
| | | (0.112) | (0.889) | |
| High qualif. | -0.003 | -0.005* | -0.016 | -0.001 |
| | (0.0046) | (0.0023) | (0.0213) | (0.0060) |
| Medium qualif. | -0.007 | -0.0005 | -0.003 | -0.006 |
| | (0.0045) | (0.0024) | (0.0173) | (0.0048) |
| Median income (1,000) | -0.011 | -0.007 | -0.001 | -0.009 |
| | (0.0097) | (0.0046) | (0.0309) | (0.0108) |
| White ethn. | 0.006 | 0.002 | 0.008 | 0.005 |
| | (0.0068) | (0.0040) | (0.0285) | (0.0081) |
| Black ethn. | 0.001 | 0.014* | 0.0940+ | -0.0156 |
| | (0.0110) | (0.0060) | (0.0531) | (0.0191) |
| Asian ethn. | -0.004 | 0.007 | 0.099** | -0.021 |
| | (0.0114) | (0.0047) | (0.0328) | (0.0157) |
| Year effects | Y | Y | Y | Y |
| LA effects | Y | Y | Y | Y |
| LA trends | Y | Y | Y | Y |
| Observations | 1579 | 1603 | 1603 | 1579 |
| Adjusted $R^2$ | 0.791 | 0.909 | 0.908 | 0.663 |

Standard errors in parentheses

$+ \ p < 0.10$, $^{*} \ p < 0.05$, $^{**} \ p < 0.01$, $^{***} \ p < 0.001$

*Notes:* The table presents estimated *beta* coefficients from estimating equation (2) pooled together for all children aged 0-9 years old. Column (1) shows the OLS results, columns (2) and (3) show the estimated First-Stage equation, and column (4) shows the 2SLS results. The sample includes 147 Local Authorities (LAs) in England and refers to the period 2007-2017. The time-varying LA characteristics (educational qualifications, median income and ethnic composition) are described in Appendix A. Standard errors are clustered at the LA level, and observations are weighted by the population of children aged 0-9 in the corresponding LA.

some areas will have more families with younger children (e.g., LAs with many young professionals) who may experience different trends in unemployment than families with school-aged children. Another example of hidden variation is the different trends in CPP entry rates across age groups. As Figure 2.2 shows, while all age groups have an increasing trend in CPPs, the CPP entry rate of children younger than one-year-old increased more and quicker than that of older children within our sample (the CPP entry rates for those aged ¡1 increased by 75% during 2007-2017, while for those aged 1-4 years the entry rate grew by 50%). Finally, there are potentially differential effects of unemployment on children of different ages. For example, preschool children might be affected more by increasing unemployment (either positively or negatively) as they spend more time at home and they are more vulnerable than school-aged children (differential impact across different age groups is discussed in more detail in section 2.6.2). In summary, the pooled regressions average varying trends, potentially mask differential effects and treat all LAs with similar populations of children aged 0-9 equally. Consequently, provided that there are data on CPP entry rates by different age groups, pooling all age groups together does not maximise efficiency and probably contributes to lower precision of estimates.

Based on the considerations discussed above, the rest of the paper presents analysis utilising data with age group breakdown and estimates equation 2.2 as shown in Section 2.4.

### 2.6.2 Main results

I start by estimating a simple linear regression. Table 2.2 presents OLS estimates under different specifications. Column (1) shows a simple regression with only year, LA and age group effects, as well as age group trends,while the second specification adds time-varying LA characteristics and the final column shows the most complete specification with added LA linear trends. The estimated impact is generally very small, while it decreases (both in magnitude and significance) as more variables are added, with the final estimate showing no impact of unemployment rate on CPP entry rates.

As discussed in Section 2.4, the OLS estimates are expected to be biased and thus an Instrumental Variable approach needs to be applied. The instrument used is a shift-share, or Bartik, instrument which predicts local unemployment based on local industry shares at baseline and national time-varying unemployment rate by industry. Figure 2.12 shows the correlation between actual local unemployment rate and predicted unemployment rate, while Figure 2.13 shows the average actual and predicted unemployment rates across all 147 LAs over time. The scatter plot shows a positive relationship between the instrument and the endogenous variable, while the average of Bartik instrument follows the same trend as the average of the unemployment rate, as expected.[11]

Column (1) of Table 2.3 presents the first-stage estimates, i.e. the estimated relationship

[11] The Pearson correlation coefficient of the two variables is 0.52. The average Bartik instrument is always lower than the average unemployment rate due to the Annual Population Survey having gaps in the industry of last job of unemployed people.

Table 2.2: Effect of unemployment rate on CPP entry rates: OLS estimates

| | (1) Log(CPP) | (2) Log(CPP) | (3) Log(CPP) |
|---|---|---|---|
| Unempl. Rate | 0.014* | 0.011+ | -0.004 |
| | (0.0067) | (0.0063) | (0.0066) |
| High qualif. | | -0.016*** | -0.005 |
| | | (0.0034) | (0.0032) |
| Medium qualif. | | -0.019*** | -0.008** |
| | | (0.0037) | (0.0030) |
| Median income (1,000) | | -0.009 | -0.009 |
| | | (0.0064) | (0.0065) |
| White ethn. | | 0.014* | 0.007 |
| | | (0.0057) | (0.0049) |
| Black ethn. | | 0.003 | 0.0006 |
| | | (0.0101) | (0.0081) |
| Asian ethn. | | 0.001 | -0.005 |
| | | (0.0082) | (0.0077) |
| Year effects | Y | Y | Y |
| Age group effects | Y | Y | Y |
| Age group trends | Y | Y | Y |
| LA effects | Y | Y | Y |
| LA trends | N | N | Y |
| Observations | 4783 | 4741 | 4741 |
| Adjusted $R^2$ | 0.742 | 0.748 | 0.802 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The table presents estimated *beta* coefficients from estimating equation (2) on data on log CPP rate among three age groups across 147 Local Authorities in England between 2007 and 2017. The time-varying LA characteristics are described in Appendix A. Standard errors are clustered at the LA and age group level, and observations are weighted by the population of children in the corresponding LA and age group.

between the endogenous variable, the local unemployment rate, and the Bartik instrument. The coefficient of the instrument is highly significant, while the estimated regression has a high R-squared of 0.92. The estimated coefficient show that one percentage increase in predicted unemployment rate is correlated with an increased unemployment rate of 2.1 percentage points. To formally test whether the Bartik instrument is weak, I used the method of Olea & Pflueger (2013), as their test allows for homoskedasticity. The effective F-statistic is equal to 19 and the TSLS critical values (at a 5% confidence level) are 15.06 and 23.11 for $\tau$ equal to 20% and 10% respectively. The critical values show the threshold of bias each researcher is willing to tolerate. In this case, as the effective F-statistic is between the two critical value, the null hypothesis that the bias in the estimator is greater than 20% of the worst-case bias can be rejected. On the other hand, this is not true when setting the threshold at the 10% level.

Table 2.3: Effect of unemployment rate on CPP entry rates: TSLS results

| | (1)<br>Unemployment Rate | (2)<br>Log(CPP) | 3<br>Log(CPP) |
|---|---|---|---|
| Pred. Unempl. Rate | 2.101*** | 0.484*** | |
| | (0.529) | (0.124) | |
| Unempl. Rate | | | 0.202** |
| | | | (0.0701) |
| Year effects | Y | Y | Y |
| Age group effects | Y | Y | Y |
| Age group trends | Y | Y | Y |
| LA time-varying characteristics | Y | Y | Y |
| LA effects | Y | Y | Y |
| LA trends | Y | Y | Y |
| Montiel-Pflueger test - Effective F-stat. | 18.99 | 18.99 | 18.99 |
| Observations | 4,741 | 4,741 | 4,741 |
| Adjusted $R^2$ | 0.920 | 0.790 | 0.816 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The table presents estimated *beta* coefficients from estimating equations (2.3) and (2.2). Column (1) shows the First-Stage estimates, column (2) shows the estimates from the reduced-form regression, and column (3) shows the TSLS results. The time-varying LA characteristics are described in Appendix C. Standard errors are clustered at the LA and age group level, and observations are weighted by the population of children.

Columns (2) and (3) of Table 2.3 present the main results of this paper, i.e. the IV estimates of the local unemployment rate on the logarithm of CPP rate. The results show a quite large and significant impact of unemployment on child maltreatment. More particularly, it is estimated than one percentage point increase in the local unemployment rate increases CPP entry rate by 20 percent. To understand what the estimated impact means in levels, if the impact is universal across all age groups, then this result will translate into an increase in the number of children starting a CPP of around 25 children younger than one year old per 10,000 corresponding population, 11 children aged 1-4 years old, and nine children aged 5-9 years old.[12] Applying the above numbers to the 2017 child population in England, this would mean more than 7,500 additional children starting a CPP during one year, plus any potential increases in children older than nine years old.

[12] CPP average rates by age are reported in Table C1 in Appendix C.

The results of this paper are broadly in line with the results of Brown & De Cao (2020) who predicted a 10 percent increase in overall abuse and 20 percent increase in cases of neglect specifically. Our results refer to the overall abuse, but as shown in Figure 2.3, the vast majority of CPPs in England are related to either neglect or emotional abuse.[13] Additionally, the data used in this paper refer to the number of children becoming the subject of a CPP, while related literature refers to number of cases, and thus the magnitude may not be directly comparable.

Table 2.4 stratifies the main results to explore any indications of underlying mechanisms and whether these differ from the literature. Panel A shows the impact of unemployment on child maltreatment stratified by the child's age. The estimated coefficients show that the main result is driven by children aged 1-4 years old, while the precision decreases for teenagers. Surprisingly, infants younger than one year old seem not to be affected by an increase in unemployment rates. A potential mechanism that needs empirical exploration is that babies are protected from income and time effects probably due to welfare support and statutory maternal pay and leave, which, as described in section 2.3.2 can have a duration of up to 36 weeks after birth. Panel B shows the impact of unemployment by different levels of deprivation. The first group refers to LAs with the lowest levels of deprivation. In this setting, deprivation is defined as the percentage of LSOAs in each LA in the top percentile of the Income Deprivation Index Affecting Children (IDACI) distribution. IDACI is defined as the proportion of all children aged 0 to 15 living in low-income families. The results show that although all groups have a positive coefficient, the most deprived LAs have a much more precise coefficient, which is statistically significant (although the coefficient is lower than other groups). As discussed in section 2.3, low-income families or families facing other challenges are more vulnerable to adverse life events and shocks, such as unemployment and loss of income, even if there are benefits in place.

[13] Looking into the the impact of unemployment on specific types of abuse would be really useful to shed light on what drives our results and will also make them directly comparable with the work of Brown & De Cao (2020). Unfortunately, current data do not report type of abuse by age, and additionally, as explained in Section 2.2.3, the data on type of abuse may include significant bias.

Table 2.4: Effect of unemployment rate on CPP entry rates: effect by age and deprivation

| Panel A: Impact of unemployment by age group | |
|---|---|
| | **Log(CPP)** |
| $< 1$ | -0.041 |
| | (0.0904) |
| $1 - 4$ | 0.257* |
| | (0.1211) |
| $5 - 9$ | 0.207+ |
| | (0.1107) |
| **Panel B: Impact of unemployment by deprivation** | |
| Low IDACI rank | 0.231 |
| | (0.1414) |
| Medium IDACI rank | 0.200 |
| | (0.2072) |
| High IDACI rank | 0.099** |
| | (0.0338) |

*Notes:* This table stratifies the main analysis presented in Table 2.3 by two key population characteristics: (i) children's age group, and (ii) Income Deprivation Affecting Children Index (IDACI).

### 2.6.3 Robustness checks

Table 2.5 shows different specifications of the main model and serves as a robustness check. The first column repeats the main results for comparison. Column (2) shows the estimated impact of the claimants proportion, i.e. the claimant count as the proportion of the economically active population, on the CPP rate. The claimant count measures the number of people claiming benefits principally for the reason of being unemployed, and thus it includes out of work Universal Credit claimants, as well as Jobseeker's Allowance claimants. As discussed in 2.5, our main specification uses unemployment rates from APS, which corrects the sampling error for small areas by using the claimant count. This additional specification uses the claimant count for all LAs in England. The proportion of people claiming unemployment-related benefits is always lower than unemployment rate, but they follow a very similar trend (see Figure 2.6). Clancy & Stam (2010) studying the trends in the two indicators (claimant count and unemployment) from the late 1990s until 2010 found that women aged 25-49 have contributed the most to the gap (i.e. more women are unemployed than those claiming benefits) along with young men aged 18-24. Column (2) shows that using the claimants proportion instead of unemployment rate gives a similar coefficient with an effective F-statistic of 37.15, which allows to reject the null of weak instrument. Based on the discussion above, there are differences between the local unemployment and claimant counts that could explain the slightly stronger first-stage regression of the claimant proportion. For example, people who have the option not to claim benefits (e.g. they have other sources of income or their partner does) won't be affected as much by a labour market shock as people who once become unemployed will need to claim benefits. Overall, the two estimates are consistent with each other, and taken together or individually provide evidence for a strong impact of unemployment on child maltreatment.

Column (3) presents the results of estimating the main model with the observations being weighted by the total child population of the LA instead of the population corresponding to the specific age group, and column (4) presents what happens when you drop from the sample the LAs with the highest and lowest population (5%). The coefficient of interest in all these different specifications is always statistically significant at least at the five percent significance level, positive and it ranges between 14.5 percent and 30.8 percent.

Table 2.5: Effect of unemployment rate on CPP entry rates: robustness checks

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Log(CPP) | Log(CPP) | Log(CPP) | Log(CPP) | Log(CPP) | Log(CPP) | Log(CPP) | Log(CPP) | Log(CPP) |
| Unempl. Rate | 0.202** | 0.308** | 0.145* | 0.178* | 0.201*** | -0.123 | 0.149+ | 0.106+ | 0.023+ |
| | (0.0701) | (0.0948) | (0.0642) | (0.0694) | (0.0475) | (0.235) | (0.0810) | (0.0560) | (0.0132) |
| Year effects | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Age group effects | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Age group trends | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| LA time-varying characteristics | Y | Y | Y | Y | Y | N | Y | Y | Y |
| LA effects | Y | Y | Y | Y | N | N | Y | Y | Y |
| LA trends | Y | Y | Y | Y | N | N | Y | Y | Y |
| Effective F-statistic | 18.99 | 37.15 | 22.72 | 20.23 | 25.18 | 1 | 8.75 | 25.26 | |
| Hansen Overid test p-value | | | | | | | | | 0.00 |
| Observations | 4,741 | 4,741 | 4,741 | 4,300 | 4,741 | 4,783 | 4,741 | 4,741 | 4,741 |
| Adjusted $R^2$ | 0.721 | 0.790 | 0.805 | 0.735 | 0.484 | -0.119 | 0.757 | 0.779 | 0.801 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The table presents estimated *beta* coefficients from alternative specifications of equation (2.2). Column (1) presents the main results for comparison, column (2) uses the claimants proportion (of economically active population) as an alternative indicator of unemployment, column (3) weights observations by the total child population instead of age-specific, column (4) drops population outliers (5% highest and lowest), column (5) drops LA trends and effects, column (6) does not control for LA time-varying characteristics, trends and fixed effects, in column (7) Bartik weights are replaced by 2004 industry shares, in column (8) Bartik weights are constructed by using a more disaggregated list of industries than in the main analysis, and column (9) uses the initial industry shares as instruments following Goldsmith-Pinkham, Sorkin and Swift (2018). The time-varying LA characteristics are described in Appendix C. Standard errors are clustered at the LA and age group level, and observations are weighted by the population of children in the corresponding age group.

Column (5) and column (6) show what happens when LA effects, linear trends and time-varying characteristics are excluded from the model. When time-varying characteristics are still included (column (5)), the coefficient remains the same, but when both linear trends and time-varying characteristics are dropped together with fixed effects, the impact of unemployment rate disappears. This is expected because while the Bartik instrument controls for the endogeneity of the unemployment rate in terms of the labour market drivers; demographic characteristics are also expected to affect both CPP entry rates and unemployment rates, thus excluding them adds bias to the estimates.

Columns (7), (8) and (9) use alternative Bartik instruments. Column (7) replaces Bartik weights from 2006 with weights from 2004 to limit the possibility of the exogeneity assumption being violated. The coefficient of interest is now significant at 10 percent significance level, as the first stage is not as powerful as before, but it is still consistent in magnitude and sign with the main and alternative specifications. The Bartik instrument in specification (8) was constructed by using a more disaggregated definition of the different sectors. More particularly, the number of industries in the main specification is 8, while in this specification is 13.[14] The estimate is lower but consistent with the rest of the specifications and significant at the 10 percent significance level.[15]

Specification (9) shows the results of using the industry shares as instruments instead of the Bartik unemployment rate. The coefficient is much smaller than in the rest of the specifications but still significant at the 10 percent significance level. This estimation is based on the tests proposed by Goldsmith-Pinkham et al. (2020) to evaluate the validity of using a Bartik variable as an instrument when expecting the identification coming from the exogeneity of the industry shares. Column (9) also reports the results of the overidentification test, which rejects the null hypothesis that all industry shares are valid. However, the test is more demanding than what is needed in this setting. In fact, the identification assumption in the setting of this

[14] In this new specification wholesale and retail are treated separately from accommodation and food services, financial intermediation and real estate activities are also separated. Similarly, utilities - electricity, gas and water supply- were previously combined with agriculture, forestry and fishing. Finally, public administration, education and health and social work are also now included as individual industry shares rather than combined.

[15] There are two reasons why this estimation is not used as our main specification, as a longer list of industries can produce a better approximation of unemployment. Firstly, the data available for 2006 - the baseline year-were provided only for the academic year, instead of financial year 2005/6, and thus the baseline overlaps with the first year of the time period we studied, and secondly some of the industry shares were based on small samples, especially for small LAs and sectors.

paper is that in LAs with high shares of industries experiencing high unemployment rates, there should not be other shocks happening at the same that could affect child maltreatment directly. Consequently, in what follows, I decompose the Bartik variable to understand which industries are more important and further investigate the instrument's validity.

Goldsmith-Pinkham et al. (2020) showed that the Bartik instrument is numerically equivalent to using industry shares as instruments for a particular weight matrix in GMM. Based on this finding, they proposed decomposing the Bartik instrument into a weighted combination of just-identified estimates based on each instrument. These weights are called Rotemberg weights, and they show the sensitivity-to-misspecification elasticities of each industry. Table 2.6 shows the Rotemberg weights for each industry in the sample. Construction and financial services are by far the industries of major importance. In other words, the main source of potential bias would be unobserved shocks affecting these sectors (and thus the LAs with high related industry composition) and child maltreatment.

Table 2.6: Rotemberg weights

| Panel A: Rotemberg weights | |
|---|---|
| **Industry** | **Weights** |
| Construction | 0.59 |
| Financial and insurance services,real estate activities and professional, scientific and technical activities | 0.38 |
| Manufacturing | 0.09 |
| Wholesale, retail and accommodation | 0.07 |
| Agriculture, forestry fishing, mining and utilities | 0.05 |
| Transport, storage, information and communication | 0.04 |
| Arts, entertainment, recreation and household activities | 0.04 |
| Public administration, defence, educational, health and social work | -0.25 |

*Notes:* The table presents the Rotemberg weights for the industries used in the construction of the Bartik instrument. The Rotemberg weights were constructed in line with the methodology outlined in Goldsmith-Pinkham, Sorkin and Swift (2018).

Table 2.7 shows the just-identified IV estimates using each of the key industries, i.e. construction and financial services. The coefficients are fairly consistent with each other and the Bartik IV estimates, although lower in magnitude. These results are reassuring as the two industries are quite different in terms of individuals working and areas in which they are more prevalent.

As a final robustness check, I summarise the estimates of the different just-identified models in a figure proposed by Goldsmith-Pinkham et al. (2020) and applied in a similar setting by Brown & De Cao (2020). Figure 2.14 shows the F-statistic of each first-stage on the x-axis and the $\beta$ coefficient for each industry on the y axis. The dashed line presents the $\beta$ coefficient estimated by the main Bartik IV. The circles indicate positive Rotemberg weights, while the diamond represents a negative weight. Finally, the size of each diamond and circle indicates the magnitude of the absolute value of the Rotemberg weight. Overall, the estimated coefficients are close to the initial estimate, especially those with an F-statistic higher than 10, ranging from 0.09 - 0.19. On the other hand, there is one negative coefficient which also reflect a negative Rotemberg weight. The F-statistic and the absolute value of the negative Rotemberg weight is lower than the share of the industries with positive weights. However, it is not negligible. The fact that six out of eight industries behave well, including the two key industries, is positive and reassuring. However, further exploration would be valuable to understand whether the negative Rotemberg weight could affect the final estimates, e.g. exploring a larger number of industries may allow for decomposing the coefficient and understanding the underlying mechanisms.

## 2.7 Additional results

### 2.7.1 Gender gap analysis

Table 2.8 presents estimates of the relationship between the gender gap in the unemployment rate and the CPP entry rate, following the identification strategy discussed in section 2.4. Column (1) shows the OLS results of regressing the logarithm of CPP entry rate on the local unemployment gender gap, column (2) presents the results of the first-stage regression, column (3) reports the final TSLS estimates and column (4) shows the results of the TSLS regression when using an alternative indicator for local unemployment rate, the proportion of claimants.

The OLS regression shows no impact of unemployment gender gap on CPP entry rates. When using the Bartik variable as instrument, the regression estimates a negative impact of unemployment gap on CPP entry rates, which is only significant at 10 percent significance level.

Table 2.7: Just-identified TSLS estimates

| | **Log(CPP)- Construction** | **Log(CPP)- Financial services** |
|---|---|---|
| Unempl. Rate | 0.134** | 0.093* |
| | (0.052) | (0.042) |
| High Qualif. | -0.003 | -0.003 |
| | (0.0037) | (0.0034) |
| Medium Qualif. | -0.008* | -0.008** |
| | (0.0031) | (0.0030) |
| Median Income | -0.008 | -0.009 |
| | (0.0070) | (0.0067) |
| White ethn. | 0.005 | 0.006 |
| | (0.0053) | (0.0050) |
| Black ethn. | -0.012 | -0.008 |
| | (0.0110) | (0.0102) |
| Asian ethn. | -0.017 | -0.013 |
| | (0.009) | (0.0084) |
| Year effects | Y | Y |
| Age group effects | Y | Y |
| Age group trends | Y | Y |
| LA effects | Y | Y |
| LA trends | Y | Y |
| Observations | 4,741 | 4,741 |
| $R^2$ | 0.78 | 0.80 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The table presents estimates of the impact of local unemployment rate on CPP entry rates when using specific industries as instruments. The regressions presented here use the industries with the highest Rotemberg weights. The Rotemberg weights were constructed in line with the methodology outlined in Goldsmith-Pinkham, Sorkin and Swift (2018). The regressions include three age groups in 147 LAs in England over the period 2007-2017. The regressions are clustered at the LA and age-group level and the observations are weighted by the child population in the corresponding group.

The low significance of the third column is expected to be strongly related to the first-stage estimates reported in column (2). The fact that the coefficient of the predicted gender gap is significant at only 5 percent level shows a clearly positive relationship between the actual gender gap and the predicted gender gap but not strong enough to secure a non-biased TSLS estimate. Additionally, the effective F-statistic does not allow us to reject the null of weak instruments. There are two main potential reasons for the low power of the first-stage estimation. Firstly, the unemployment rate data used for the main analysis are the model-based estimates that include adjustments for the small sampled areas. Those estimates are not available by gender. Secondly, as shown in Figure 2.11, women's participation is concentrated in specific sectors, which were less affected by recession and austerity (e.g. the public sector) and thus female unemployment

Table 2.8: Effect of unemployment gender gap on CPP entry rates

| | (1) Log(CPP) - OLS | (2) Unempl. Gap | (3) Log(CPP) - TSLS | (4) Log(CPP) - TSLS |
|---|---|---|---|---|
| Unempl. Gap | -0.001 | | -0.096+ | -0.06* |
| | (0.0021) | | (0.0583) | (0.0294) |
| Pred. Unempl. Gap | | 1.421* | | |
| | | (0.581) | | |
| High qualif. | -0.005 | 0.052 | 0.001 | -0.004 |
| | (0.0032) | (0.0320) | (0.0053) | (0.0031) |
| Medium qualif. | -0.008** | -0.039 | -0.0116** | -0.007* |
| | (0.0030) | (0.0280) | (0.0043) | 0.0029 |
| Median income (1,000) | -0.009 | 0.002 | -0.008 | -0.009 |
| | (0.0065) | (0.0573) | (0.0081) | (0.0063) |
| White ethn. | 0.007 | -0.141** | -0.007 | 0.008+ |
| | (0.0049) | (0.0469) | (0.0107) | (0.0047) |
| Black ethn. | 0.000 | -0.169+ | -0.0214 | -0.001 |
| | (0.0081) | (0.0938) | (0.0180) | (0.0075) |
| Asian ethn. | -0.005 | -0.087 | -0.017 | -0.001 |
| | (0.0077) | (0.0548) | (0.0137) | (0.0070) |
| Effective F-stat. | | 6.21 | 6.21 | 281 |
| Year effects | Y | Y | Y | Y |
| Age group effects | Y | Y | Y | Y |
| Age group trends | Y | Y | Y | Y |
| LA effects | Y | Y | Y | Y |
| LA trends | Y | Y | Y | Y |
| Observations | 4,741 | 4,809 | 4,741 | 4,741 |
| Adjusted $R^2$ | 0.802 | 0.359 | 0.689 | 0.8147 |

Standard errors in parentheses

$+\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

*Notes:* The table presents estimated *beta* coefficients from equations (2.1) and (2.2) with unemployment gender gap as the endogenous variable. Column (1) shows the OLS results, column (2) shows the estimated First-Stage equation, column (3) shows the 2SLS results, and column (4) shows the 2SLS results when using the proportion of economically active adults who claim unemployment-related benefits, as and alternative indicator of unemployment. The model explores the impact of unemployment gap on child maltreatment for three age groups across 147 Local Authorities in England between 2007 and 2017. The time-varying LA characteristics are described in Appendix C.

rate is much more difficult to predict than the general or male one.

To overcome the first challenge discussed above, I replaced the local unemployment rates with the proportion of economically active population who claims unemployment-related benefits. As discussed in section 2.6.3, claimant count is based on administrative records and it is not affected by sample bias. On the other hand, the local unemployment rate is a survey-based estimate. Given that in this part of the analysis the data are gender-specific, we expect a small sample in many LA-year cells. The variable used was constructed using data from the claimant count records (available at Nomis website) on the count of claimants in each LA for the period 2007-2017, and data from the APS on the economically active population aged 16-64 in each LA for the same period (also available at Nomis). The results are presented in column (4) of Table 2.8 and they show a negative impact of 6 percent of unemployment gap on child maltreatment. The coefficient is now significant at the 5 percent level. The effective F-statistic allows us to reject the null of weak instruments, providing confidence for the validity of this specification.

As discussed in section 2.3, there are several potential mechanisms that could lead to a significant impact of unemployment on child maltreatment. The results of the gender gap analysis suggest that an increase in unemployment rate affecting women can cause a decrease in child maltreatment. Consequently, this section indicates a mechanism in line with the household-time-use models and consistent with the findings of Lindo et al. (2018), who showed that maltreatment decreases with male employment and increases with female employment. Whether this mechanism comes from additional risks entailed in children spending more time with male carers or other mechanisms (e.g. male carers may provide more monetary support and be the primary source of income of the households) remains unknown. Future research using additional information on the effect of unemployment on different types of maltreatment in England could explore further the gender-specific mechanisms, as well as more information on the socio-economic characteristics of families affected. Finally, the results of this section should be treated as exploratory as the analysis does not control for levels of unemployment, due to not being able to instrument for both the level and gap simultaneously, and thus it focuses on gender gap.

### 2.7.2 Unemployment and children entering care

This section explores the impact of unemployment on the demand for the most advanced level of statutory support, i.e. LA care, and compares the results with the findings on the impact of CPP to explore potential insights of underlying mechanisms.

As section 2.2.1 discusses children in CPPs attend review conferences where the social workers decide whether the child continues to be at risk of harm. The CPPs are a temporary form of support, and they usually last less than one year. At the review conferences, the social workers might decide to continue the CPP, cease the CPP due to progress being made or, in cases of no progress or even deterioration of the family circumstances, the LA might decide to apply to court for the child to be taken into care. Consequently, children entering care may be children with higher needs who have survived more severe harm than children in CPPs. They can also be children who have been in CPPs for a year or so, and the issues escalated (or did not improve) resulting in ending up in care. Although there are statistics showing that children who have been in CPPs might end up in care years later, there is no information on the number of children entering care immediately after the cessation of the CPP.

Table 2.9 shows the estimates of the impact of unemployment rate on the number of children entering care during the year. The first-stage results of this analysis are identical to the ones reported in Table 2.3. Although the magnitude of the coefficient of interest is not very different from what has been estimated for the CPP entry rate, the coefficient is statistically significant only at the 10 percent significance level, with the confidence interval ranging from -0.02 to 0.29. Consequently, these additional results show that although areas with higher unemployment have higher CLA entry rates, causation cannot be proved. In other words, it cannot be argued that additional unemployment will lead to an increase in the number of children entering care, at least during the same year. Since many children at risk pass through other stages of support (like CPPs and CINPs) before entering care, the table also presents results on the impact of lagged unemployment on the rates of children entering care. These specifications are used to explore whether children becoming the subject of a CPP due to an unemployment shock today will end up in care in a year (column (2)) or in a couple of years (column (3)) later. The results do not show a more substantial impact of unemployment on the number of children entering care a year or two years later.

Looked-after children are children who are assessed to be at such a high risk that they need to be taken away from their family or at least the parental responsibility needs to be shared between the LA and the family. Consequently, the results of this section, taken together with the main analysis results, indicate that additional unemployment leads to a significant increase in the number of children becoming the subject of a CPP but not those entering care. In other words, the number of children suffering abuse or neglect or being at risk of abuse or neglect increases with unemployment. However, the additional cases seem to be handled within the family. For example, the additional CPPs may be for families that can be helped and overcome the significant risk through financial, housing, or parenting methods support. This analysis provides a first indicative exploration of the level of need of the children maltreated due to increases in unemployment and indicates that potentially these children are at a lower level of need than the threshold of entering care.

Table 2.9: Effect of unemployment rate on CLA entry rates: TSLS results

| | (1) Log(CLA) | (2) Log(CLA) | (3) Log(CLA) |
|---|---|---|---|
| Unempl. Rate | 0.153+ | | |
| | (0.0913) | | |
| Unempl. Rate (t-1) | | 0.138+ | |
| | | (0.0799) | |
| Unempl. Rate (t-2) | | | 0.104 |
| | | | (0.091) |
| Year effects | Y | Y | Y |
| Age group effects | Y | Y | Y |
| Age group trends | Y | Y | Y |
| LA effects | Y | Y | Y |
| LA trends | Y | Y | Y |
| Observations | 4,809 | 4,374 | 3,942 |
| Adjusted $R^2$ | 0.733 | 0.775 | 0.796 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The table presents estimated *beta* coefficients from estimating equations (2.2) but with the dependent variable being the logarithm of CLA entry rate. CLA entry rate is defined as the number of children entering care during the year per 10,000 relevant child population in the area. The time-varying LA characteristics are described in Appendix C. Standard errors are clustered at the LA and age-group level, and observations are weighted by the population of children. The related First-Stage regression is identical to the one presented in Table 2.3.

## 2.8 Conclusion

Although it is estimated that more than 8.5 million adults living in England and Wales have been abused as children and more than 60,000 children are becoming the subject of a CPP every year in England, the literature on factors affecting child maltreatment in England is extremely scarce. This paper aims to fill this gap by producing the first empirical evidence of the impact of local unemployment on child maltreatment, as indicated by CPP entry rates. This paper builds on the work of Brown & De Cao (2020) by following their identification strategy and applying it to England's setting. Furthermore, this paper explores the possibility of different impact of unemployment on children of different age groups, the variation of impact by gender of the unemployed adult in the household and it also contrasts the main results with additional analysis on the impact of unemployment on entry into care.

It has been well established that a linear relationship between child maltreatment indicators and the local unemployment rate can be biased due to potential endogeneity of the unemployment rate. To overcome this issue, a shift-share instrument is used, defined as the weighted sum of industry unemployment rates, with weights being the industry shares of each LA in England in 2006. The period of study is from 2007 to 2017, including the period of great recession, and the sample includes 147 LAs in England. This paper focuses on the impact of unemployment on children younger than 10 years old.

The results show that an one percentage increase in local unemployment rate causes a 20 percent increase in CPP entry rates of LAs in England. The estimates seemed to be driven mostly by children aged 1-4 years old living in deprived areas. The children becoming the subject of a CPP rate due to the increase in unemployment in their area seem to be at a lower level of risk than children entering care. Finally, I report some indicative results on the impact of unemployment gender gap showing a potential negative relationship of female unemployment being higher than male unemployment on child maltreatment.

The results of this paper have significant policy implications, as they show that supporting parental employability during periods of recession, as the one we are currently experiencing, may have crucial current and long-term effect. Helping parents to remain or become employed not only helps their families to survive but also decreases the probability of abuse and neglect of thousands of children, improving their opportunities as adults and decreasing future costs to the society.

## 2.9 Figures for Chapter 2

Figure 2.1: CPP entry rate over time

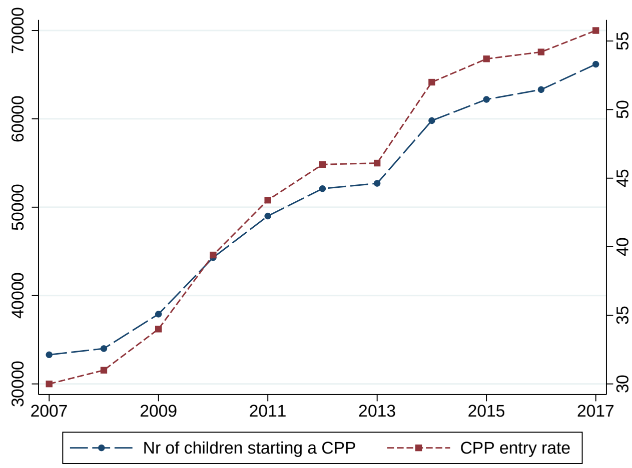



Figure 2.2: CPP entry rates by age over time

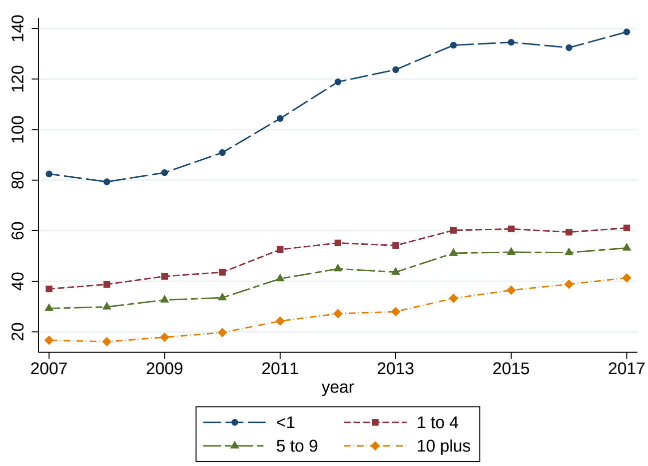


Figure 2.3: CPP entry rate by relevant category of abuse

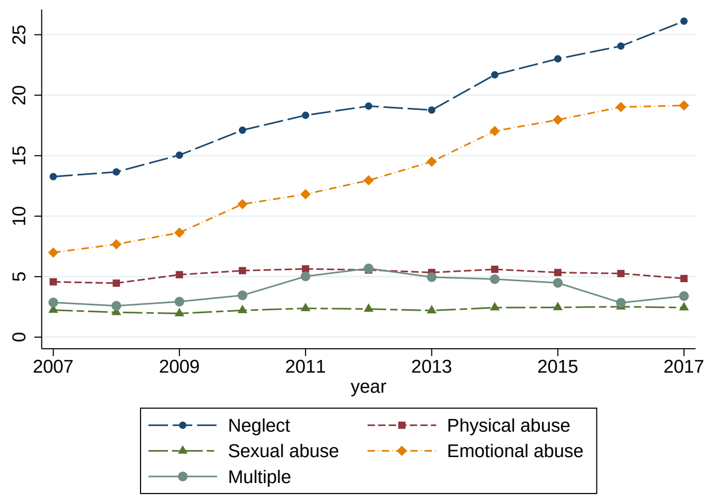



Figure 2.4: Neglect entry rate to emotional abuse entry rate over time

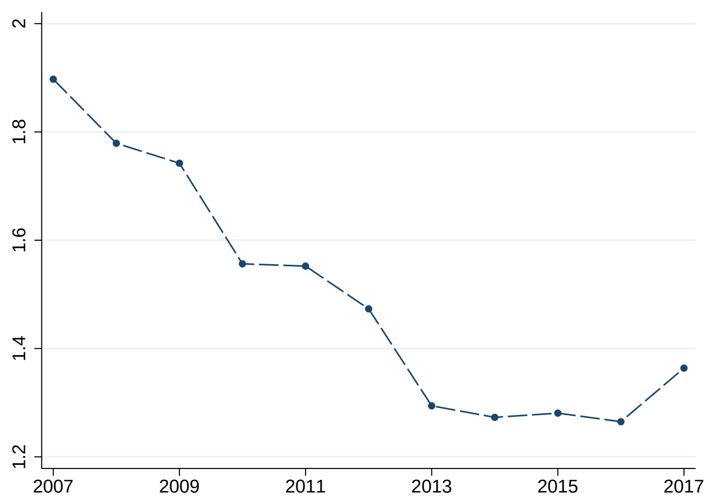
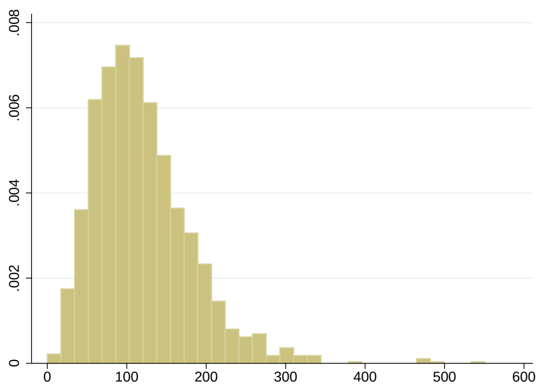
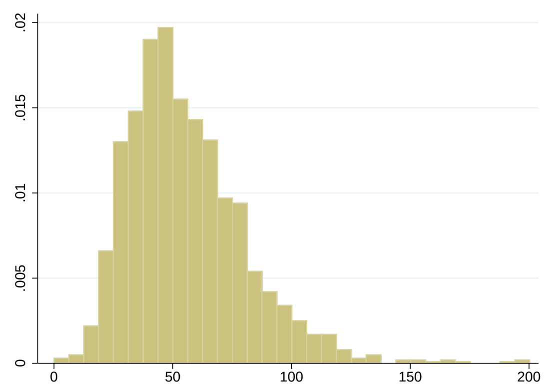


Figure 2.5: Distribution of CPP entry rates by age group

(i) children younger than 1 year old




(ii) children aged 1-4




(iii) children aged 5-9

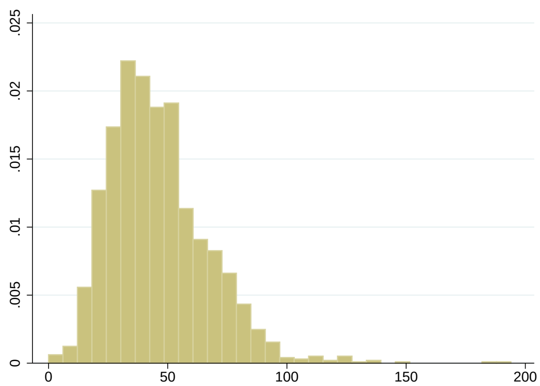



Figure 2.6: Average unemployment rate over time

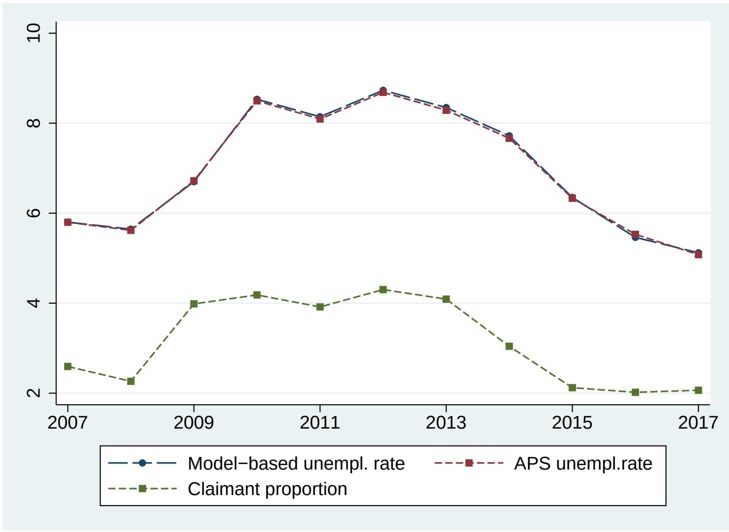


Figure 2.7: Average gender employment rate over time

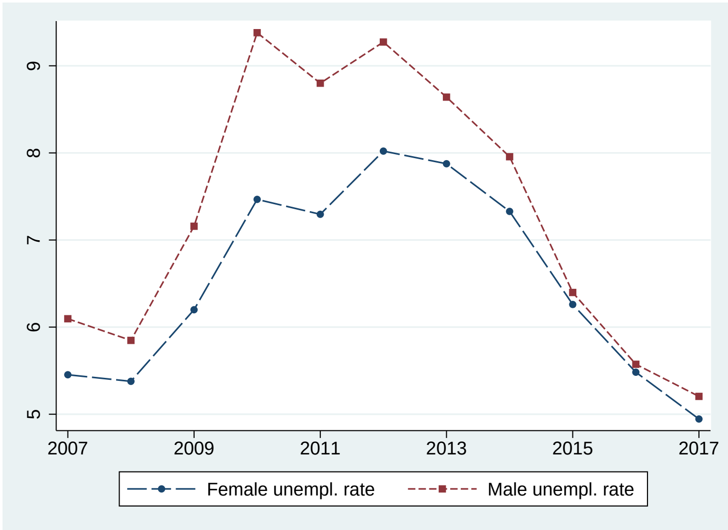



Figure 2.8: Distribution of model-based estimates of unemployment

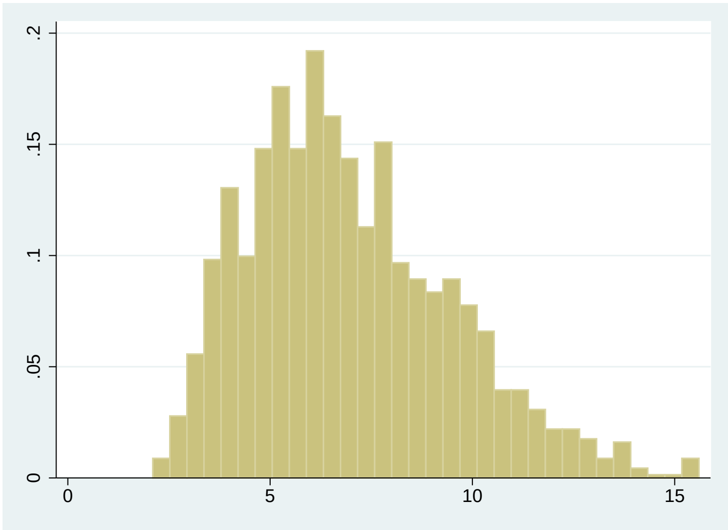


Figure 2.9: National unemployment rate by industry

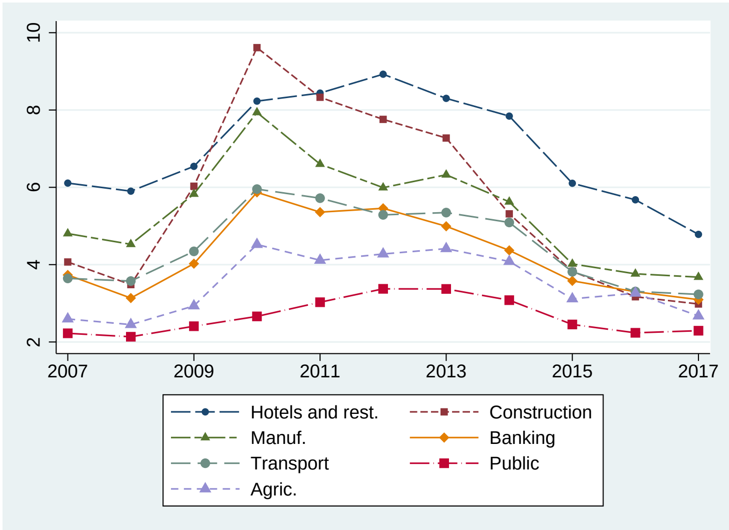



Figure 2.10: National industry composition

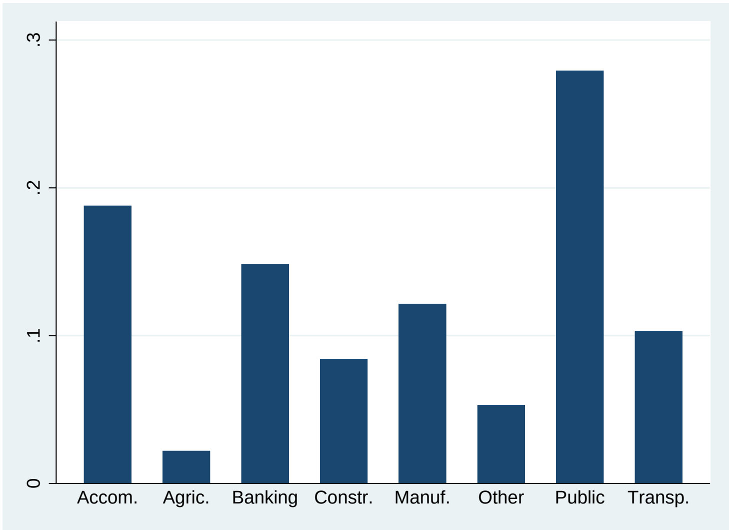
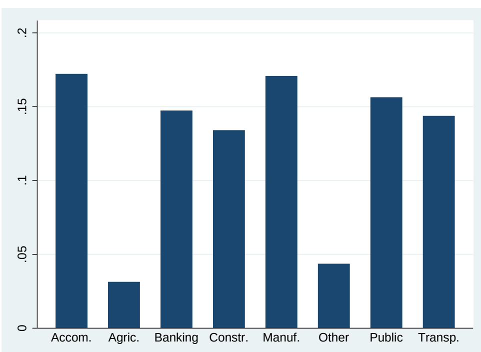


Figure 2.11: National industry composition by gender

(i) Male industry composition




(ii) Female industry composition

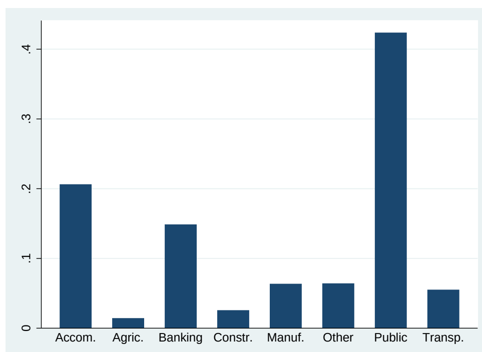


Figure 2.12: Correlation between unemployment rate and predicted unemployment rate

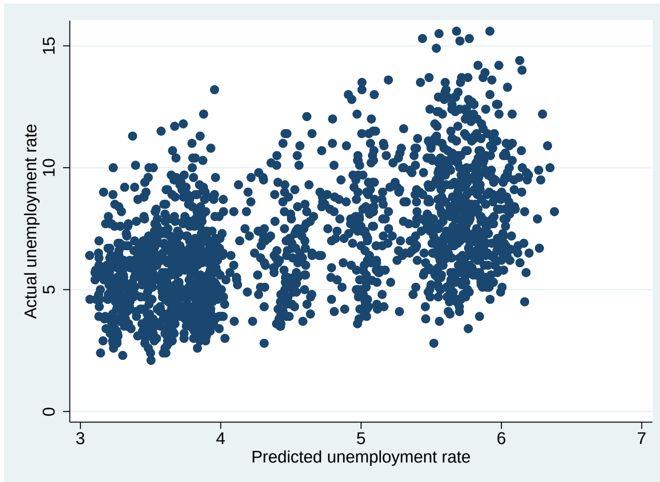



Figure 2.13: Average actual and predicted unemployment rate

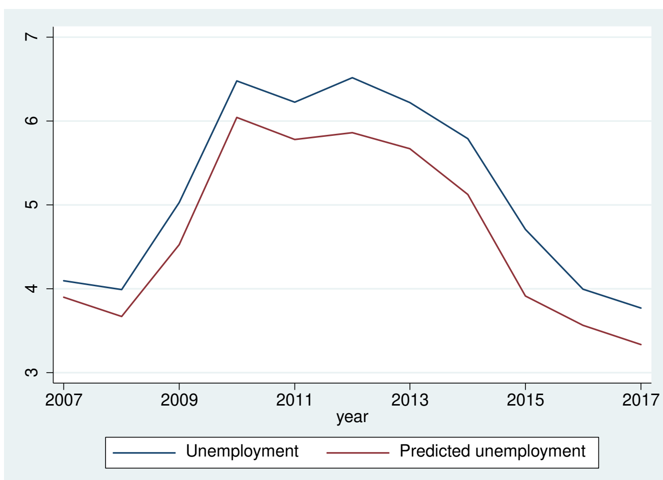
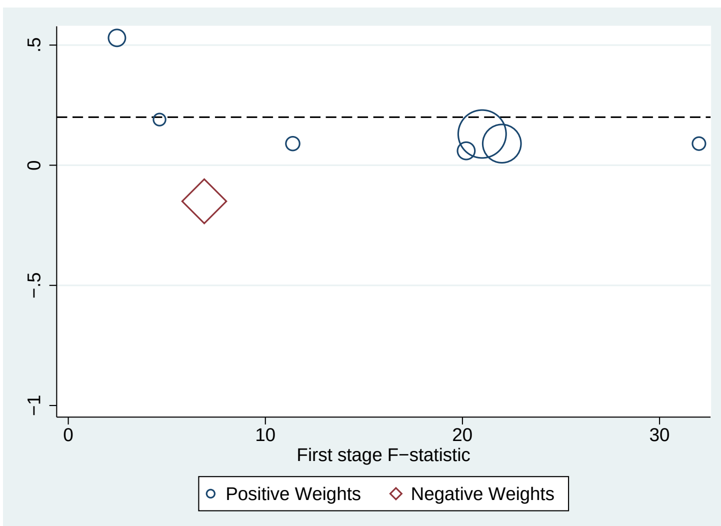


Figure 2.14: Rotemberg weights and just-identified *beta* estimates



# Chapter 3

# Who is being excluded from education? An empirical exploration of formal and informal school exclusions in England.

Christina Olympiou

## 3.1 Introduction

The UK has a school exclusion rate that is ten times higher than any other country in Europe. Over the last ten years, there have been more than 400,000 fixed period exclusions every year in England's schools, while the permanent exclusions have increased by more than 70 per cent since 2013 (Department for Education, 2021). Apart from official exclusions, there is also increasing concern in the sector about informal exclusions, also known as "off-rolling", where school leaders convince parents to remove their children from the provider's roll for the school's benefit rather than the child's benefit.

Researchers have recently studied and discussed the potential consequences of school exclusions (either through formal procedures or not). Exclusions can cause or exacerbate feelings of rejection and isolation and thus potentially affect children's mental and physical health (Tillson & Oxley, 2020). Preventing children from accessing education may also discourage them from improving their performance and thus their opportunities as adults in the labour market. Only seven percent of children who were permanently excluded and 18 percent of children who received multiple fixed-period exclusions went on to achieve good grades in English and mathematics GCSEs in 2016/17 (Timpson, 2019). An additional consequence of exclusions is that children, who are very often vulnerable and face difficulties at the time of exclusion, are spending less time in the safe school environment and more time exposed to the risks of, among others, gangs and child exploitation, e.g. being recruited into county lines drug running. Consequently, school exclusions are associated with current and future costs to children themselves and society.

The impact of excluding children from education depends on the child's characteristics, personality and family environment. If a child has the support and the personal traits needed, they may overcome an exclusion more easily than a child with certain vulnerabilities. In other words, excluding vulnerable children may make them more vulnerable. On the other hand, a vulnerable child may be more disruptive due to behavioural and societal difficulties. A 2018 report published by the House of Commons showed that an increasing number of children were being unnecessarily excluded from school, while it highlighted that children with vulnerabilities were the most likely to be excluded (House of Commons Education Committee, 2018). Additionally, the Institute for Public Policy Research (2017) showed that children of specific ethnic backgrounds are disproportionately represented in Alternative Provision (AP) schools. Finally, a recent survey undertaken by Ofsted uncovered that over 300 schools in England have high levels of off-rolling, where pupils disappear from the school register just before GCSEs (Ofsted, 2019a), indicating a potential strategy of schools to improve their overall performance.

This paper empirically explores what has been discussed in the literature by looking into exclusions and potential off-rolling in secondary schools in England with a greater focus on vulnerable children. The current literature shows that specific groups of children are over-represented in the population of excluded children even after controlling for other personal characteristics (Timpson, 2019). This paper confirms the existing findings and takes the analysis one step further by using a panel dataset to explore how the exclusion probabilities for vulnerable children vary across curriculum years and whether indicators of competition faced by schools are correlated with exclusions. The main contribution of this paper to the literature is that it provides the first empirical evidence on children who disappear from the school roll. While the current literature on off-rolling is primarily qualitative and descriptive, this paper studies whether children with certain vulnerabilities have a higher probability of disappearing from the school roll after controlling for individual, area and school characteristics. In addition, this paper shows whether the indicator of of-rolling varies significantly over curriculum years and whether competition faced by schools is correlated with the likelihood of being removed from a school's register. Additional analysis on children who change schools, the timing of change and their destination is also provided to explore any patterns indicating children being forced to change schools strategically.

The results show that vulnerable children and children from specific ethnic (especially Black pupils and pupils with Mixed ethnic backgrounds) and socio-economic backgrounds have a higher probability of being excluded, even after controlling for other characteristics of children, schools and local areas. The probability of being excluded peaks at the curriculum year before GCSE exams with a small but significant difference from previous and next academic years. There is no clear pattern showing an increased likelihood of exclusion as approaching Year 11 and GCSE exams for vulnerable children, while the competition indicator was also not found to be significant. Regarding potential of-rolling, I find that specific groups of children, including those with Special Educational Needs (SEN), children who have been looked after, and pupils eligible for Free School Meals (FSM), have a significantly higher probability of being removed from the school register. Interestingly, the probability of a child with SEN disappearing from the school roll increases significantly the year before GCSE exams, while this is not true for pupils without SEN. A similar pattern is observed for pupils changing schools. Finally, while overall competition does not seem to be correlated with a higher probability of students being removed from the school roll in general, we do find a small but significant impact for academies.

The results described above are preliminary and suggestive, aiming to shed light on persistent trends to direct future research. The above results show correlations and insightful trends. Still, they do not show a causal impact of characteristics of children on being excluded or clear evidence of strategic exclusion (either formal or informal) by schools. Additionally, actual off-rolling cannot be identified by the data. As an indication for off-rolling, the analysis presented here uses a variable showing whether a pupil who has been included in the national school census data in 2012 in curriculum year 8 is present in subsequent years' data up to Year 11 in 2015. However, there are other reasons for children not being included in census data, e.g. data gaps, migration, and moving to independent schools. The fact that those children seem to be of specific characteristics and the increasing trends just before GCSE exams indicates an interesting pattern in line with what the literature is suggesting, providing further motivation for future research.

The next section provides information on the institutional setting, the educational system and the related literature. Section 3.3 describes the data used in this analysis. Section 3.4 presents key summary statistics and shows the characteristics of students in the sample. Section 3.5 presents and discusses the empirical strategy and the results of preliminary econometric analysis, and Section 3.6 discusses the limitations and methodological considerations that should be taken into account when interpreting the results of this study. Finally, Section 3.7 concludes.

## 3.2 Institutional setting and related literature

### 3.2.1 Formal exclusions in England

In England, only the headteacher of a school can exclude a pupil. A pupil may be excluded for one or more fixed periods (up to a maximum of 45 school days in a single academic year) or permanently. According to the Department for Education's statutory guidance, a headteacher can exclude a pupil only on disciplinary grounds. It is unlawful to exclude a child for any other reasons, such as the child's additional needs that the school feels unable to meet or the child's academic attainment or ability (Department for Education, 2021). The reasons for exclusion reported by the Department for Education in their annual statistics include persistent disruptive behaviour, physical assault (against pupils or adults), verbal abuse (against pupils or adults), drug and alcohol-related incidents, bullying, sexual misconduct, racist abuse, damage, and theft (Department for Education, 2021). Figure 3.2 shows the prevalence of each reason in fixed-period and permanent exclusions during the academic year 2014/15, as a share of the total exclusions during the year. Persistent disruptive behaviour is the most common reason for both types of exclusions, followed by physical assault, verbal abuse, and others. Verbal abuse is more prevalent among fixed-period exclusions rather than permanent exclusions. At the same time, drugs and alcohol are more common among permanent exclusions.[1]

A fixed-period exclusion occurs when a child is temporarily removed from a school for a specified number of days, and she or he is expected to be back. The school is required to set and mark excluded children's work during the first five school days of the exclusion period. If a child is excluded for a more extended period, then alternative full-time education should be arranged from the sixth school day (or the first day for looked after children) until the end of the fixed-period exclusion. Governing bodies and proprietors of maintained schools and academies are responsible for arranging alternative education. This duty is held by the Local Authority (LA) in other schools. During the academic year 2015/16, there were around 340,000 fixed-period exclusions. This number is equivalent to a rate of four percent of all pupil enrolments. During the same period, there were around 6,700 permanent exclusions, i.e. a rate of 0.08 per cent.[2] Primary school pupils experience a much lower number of exclusions, with the rate being between one and 1.40 precent over the last 15 years (Department for Education, 2021). Figure 3.1 shows the fixed-period and permanent exclusion rates of all state-funded secondary schools in England, as this paper focuses on secondary education.

Permanent exclusion occurs when a pupil is no longer allowed to attend the school, and their name is removed from the school roll. If a child is permanently excluded, it is the LA's responsibility to find them an alternative school. According to the Department for Education's statutory guidance, permanent exclusions should only be used as a last resort. More particularly, permanent exclusions should occur in response to a serious breach or persistent breaches of the

[1] All the data discussed in this section is from the annual statistical release published by the Department for Education named "Permanent and fixed-period exclusions in England".

[2] A pupil may receive more than one fixed-period exclusions and the rate includes students with repeat exclusions

school's behaviour policy and when allowing the pupil to remain in school would seriously harm the education or welfare of the pupil or others in the school. Consequently, permanent exclusions are much more uncommon than fixed-period exclusions, as shown in Figure 3.1.

In July 2018, a report published by the House of Commons showed that an increasing number of children were being excluded from school, while it highlighted that vulnerable children were the most likely to be excluded (House of Commons Education Committee, 2018). Additionally, the House of Commons highlighted that the number of children in AP is higher than those permanently excluded. This additional number of students comprises pupils who remain on the roll of their mainstream school but attend AP full- or part-time, and pupils whose parents have been encouraged to voluntarily take their child out of school.

In May 2019, the "Timpson Review of School Exclusion" was published. Prior to that, the Prime Minister announced in 2017 that an external review would be commissioned to examine school exclusions. Timpson (2019) showed, among many other insightful results, that 78 percent of permanent exclusions were issued to pupils who either had SEN, were classified as in need or were eligible for Free School Meals (FSM), with children having all three vulnerabilities receiving 11 percent of all permanent exclusions in 2016/17. Additionally, boys with social, emotional and mental health difficulties were almost five times more likely to be permanently excluded than children without SEN. Finally, the report concluded that ethnic minority children are more likely to be excluded. The results showed that even after accounting for other factors, including children's characteristics, Black Caribbean and Mixed White pupils were 1.7 and 1.6 times more likely to be permanently excluded than White British pupils.Finally, Timpson (2019) identified potential drivers of the current practice of some schools using exclusions excessively, as well as certain schools excluding more children with specific characteristics and vulnerabilities. Among other potential factors, the report identified differences in leadership (including different exclusion thresholds and different LA guidance) and differences in schools' capacity to support additional needs and manage poor behaviour.

An additional potential driver that has been extensively discussed in the sector and has also been identified by Timpson (2019) is that the current performance and funding systems do not provide incentives or reward schools for addressing the needs of all children. Consequently, schools try to boost their performance through their children's educational achievement. Schools are being selected by parents mainly based on two criteria: (i) the Performance Tables published by the Department for Education, and (ii) their rating according to the Office for Standards in Education, Children's Services and Skills (Ofsted). The Performance Tables present the average educational performance of students in each school, with a focus on children at Key Stage 2 (KS2) for primary schools (the year of national tests) and Key Stage 4 (KS4) for secondary schools (the year of GCSE exams). Ofsted inspects and regulates the education and care providers for children and young people. Ofsted inspects schools and publishes a rating for each school in England. This rating takes into account different factors, including the students' average educational performance - which is one of the most important indicators according to stakeholders in the sector, attitudes, leadership and management. Consequently, both the Performance Tables and Ofsted rating are affected vastly by students' performance and not by the schools' ability to support students' needs. Thus, schools may focus on their students' educational performance rather than anything else to be able to attract high-performing future students and ensure a good Ofsted rating.

Suppose the above mechanism does exist in reality. In that case, we expect more exclusions for children with lower attainment and characteristics that are related to poorer educational outcomes, e.g. having SEN, being looked after, or coming from deprived areas. On the other hand, as will be discussed more extensively in Section 3.6, these characteristics can also be related to disruptive behaviour, contributing to the probability of being lawfully excluded. An additional indicator of potential strategic use of exclusions by schools is the increased use of exclusions the year just before the GCSE exams, either for all students or for those with characteristics related to lower educational attainment. Finally, related to the above mechanism is also the competition faced by each school.

### 3.2.2 The phenomenon of off-rolling

Exclusions might not be used directly as a performance measure for schools, but they are considered part of the risk assessment process, where Ofsted decides when schools should be inspected. Additionally, formal exclusions require schools to provide a formal support process and find a new school for the child excluded. Over the last couple of years, there has been an ongoing discussion within the sector of whether leaders in some schools put pressure on students and their parents to convince them to leave their schools without a formal exclusion. This process is referred to as off-rolling. According to Ofsted, off-rolling is informally defined as the practice of removing a learner from the provider's roll without a formal, permanent exclusion or by encouraging a parent to remove their child, when the removal is primarily in the interests of the provider rather than in the best interests of the learner (Ofsted, 2019a).

The FTE Education Datalab found that out of the 553,000 students who finished their secondary education in 2017, around 22,000 pupils left mainstream state schools at some point between Year 7 and Year 11 and were not recorded in state education ever again. This number peaked in Year 10, i.e. the year just before the GCSE exams. Similar to exclusions, the FTE Education Datalab found that the group of children leaving mainstream education (either to move to AP or entirely) is a group of vulnerable children compared to their peers. Children eligible to FSM, those with SEN, and children with low attainment at primary school were overrepresented in the group of children who have left mainstream education.[3]

Out of those 22,000 pupils who have left mainstream education, around 15,400 students were not recorded as having taken GCSEs or equivalent qualifications, or if they did, their results did not count towards any establishment. The FTE Education Datalab estimated that around 50 to 60 percent of those students may have moved to one of the other home nations or emigrated to another country. However, they are particularly concerned about the remaining 6,200 - 7,000 pupils who seem to have stayed in the country but not taken GCSE exams or equivalent qualifications. The analysis also stated that it is impossible to identify off-rolling directly from the data alone. The authors also discussed the potential incentives of schools to use off-rolling to boost their educational performance, based on the finding that off-rolling peaks in year 10, which could be linked with the fact that school league tables measure those who remain on the

[3]The analysis was undertaken by Philip Nye and Dave Thomson and was presented in June 2018 through a series of posts called "Who's Left 2018". The series can be found here: https://ffteducationdatalab.org.uk/tag/whos-left-2018/.

school roll in January of year 11. The strategic use of off-rolling cannot be proved just from the summary statistics provided. However, the fact that children with lower prior attainment are consistently more likely to leave education in this way reinforces the concerns.[4]

Ofsted (2019b) published the results of a large survey of education professionals and other stakeholders exploring the issue of off-rolling. The survey results showed that the problem of off-rolling is known by the sector and confirmed its existence. One in four teachers in England said they have witnessed pupils being illegitimately removed from schools, often to boost average performance. Some teachers mentioned that parents with a low understanding of the educational system or who are not well educated themselves were more at risk of being approached and pressured to agree to move or home-school their child. Half of the more than 1,000 teachers surveyed said that the real reason for most off-rolling was achieving or maintaining a high position on league tables. Twenty percent of the sample mentioned that off-rolling might also be used to avoid having to formally exclude pupils. Around 15 percent of respondents said that schools would be motivated to use this strategy to gain a high Ofsted grade.

The research by Ofsted (2019b) also revealed that education professionals believe that academies, schools with low Ofsted grades and struggling schools in disadvantaged areas are most likely to use off-rolling. Finally, those professionals with experience of off-rolling agree that it usually occurs before GCSEs, i.e. in years 9, 10 and before January of year 11.[5]

## 3.3 Data

This paper utilises data from the National Pupil Database (NPD), a rich dataset provided by the Department for Education. It includes a wide range of information about students and schools in England, including personal characteristics, demographics, exams' performance, and exclusions. The NPD is also merged with the Children Looked After (CLA) census, which

[4]Students who have left mainstream education and their GCSEs have been later recorded are students who moved to independent providers or their provision was organised by the LA.

[5]In May 2019, Ofsted published an updated guidance on the education inspection framework. The updated framework stated that one of the key aspects of inspection - leadership and management - will now include ensuring that all learners complete their programmes of study and that leaders provide the support for staff to make this possible and do not allow gaming or off-rolling (Ofsted, 2019a).

includes information on all children who have been in care during the period of study. This paper studies one specific cohort of children, the cohort of all children in state-funded education in England who gave KS2 exams in 2010, and follows them from the first year of secondary school (i.e. curriculum year 7 and school year 2010/11) until the end of curriculum year 11 (2014/15), i.e. the year of GCSE exams.

One of the key variables used in the empirical analysis is a dummy variable taking the value of one if a child has been excluded at least once during each school year. The variable refers to both permanent and fixed-period exclusions. Potential off-rolling is measured by a dummy variable taking the value of one when a pupil is present in the census data, i.e. in the school's register, during the current year but not in next year's data, indicating that the child has left the country, moved to independent education, stopped education or started being home-educated. A similar variable has been constructed for children who have changed schools by looking into children registered at the same school every year. If pupils change schools over time, the dataset allows us to observe between which school years the change took place, whether they moved within their LA, and what type of school the students moved to.

All statistics and regression results discussed in the rest of this paper refer to the same cohort. However, analysis on off-rolling uses data referring to the period 2012-2015, i.e. curriculum years 8-11, due to gaps in census data that wouldn't allow to accurately identify the number of children disappearing from the schools' register between 2011 and 2012. Additionally, since off-rolling and change of school refer to next year's data, the time period studied ends in 2014. Finally, the analysis uses data on the characteristics of children and schools. These variables are defined and summarised in Appendix D.

## 3.4 Summary statistics

This section provides summary statistics on the cohort analysed, i.e. all children in state-funded education in England who gave KS2 exams in 2010. It summarises their characteristics and outcomes from 2010/11, when they were in curriculum year 7, to 2014/15, the end of year 11.

### 3.4.1 Formal exclusions in secondary schools in England

Figure 3.3 shows the rate of fixed-period and permanent exclusions by curriculum year in the sample. The exclusion rate is defined as the number of exclusions divided by the number of students enrolled in secondary schools in England each year. The fixed-period exclusion rate cannot be interpreted as the percentage of children being excluded due to children often being excluded more than once during a school period. On the other hand, the permanent exclusion rate is almost identical to the percentage of children being permanently excluded every year. As expected, the rate of fixed-time exclusions is much higher than that of permanent exclusions. The fixed-period exclusion rate varies from 0.06-0.11 in the period of study, while around 0.6-2 percent of students were permanently excluded per year over the same period. The graph shows an increasing trend from year 7 to year 10, and then a small drop in year 11. This trend aligns with the Ofsted research showing that many students disappear from school registers the year before CGSE exams, i.e. in year 10.

Figure 3.4 shows the reasons for exclusions over time. The prevalence of different reasons is relatively stable over time. For both exclusions, the main reasons are persistent disruptive behaviour, physical assault, verbal abuse and others. Permanent exclusions have a relatively higher rate of drug and alcohol-related issues and a lower rate of verbal abuse. Table 3.1 also shows the prevalence of each reason for fixed-period and permanent exclusions that took place between 2011 and 2015 for the cohort analysed.

### 3.4.2 Characteristics of excluded children and children missing from school roll

As described in the literature and discussed in the media, some populations of children are over-represented among formally excluded children and potentially informally excluded students. Table 3.2 presents the share of pupils with each demographic and vulnerability characteristic among four different populations: (i) the general population of all pupils in the cohort analysed while attending secondary education in England over the period 2011 -2015, (ii) the population of children with at least one fixed-period exclusion over the same period from the same sample,

Table 3.1: Reasons for fixed and permanent exclusions

| | **Fixed Exclusions** | **Permanent Exclusions** |
|---|---|---|
| Bullying | 1.57 | 0.96 |
| Damage or theft | 4.32 | 3.36 |
| Drug or alcohol | 3.17 | 8.37 |
| Persistent disruptive behaviour | 23.78 | 31.18 |
| Physical assault | 21.68 | 23.85 |
| Racist abuse | 1.32 | 0.31 |
| Sexual misconduct | 1.00 | 1.70 |
| Verbal abuse | 25.06 | 14.10 |
| Other | 18.09 | 16.17 |
| Observations | 537,297 | 8,993 |

*Notes:* The table presents the share of excluded children by the reason for exclusion. The sample includes all children in curriculum year 7 in 2011 in state schools in England, which are followed until the end of curriculum year 11 in 2015.

(iii) the population of children being permanently excluded over the same period from the same sample, and (iv) the population of children who disappeared from the school roll at some point between year 8 and 11 over the same period in the same sample.

There are important differences among the different populations. Firstly, boys are highly over-represented in the population of excluded children. More particularly, 71 percent of pupils with one or more fixed exclusions and 75 percent of permanently excluded pupils are male students. Additionally, the share of Black children and children with Mixed ethnicity is higher than in the general population by 3-4 percentage points for Black pupils and 1-2 percentage points for children from Mixed ethnic backgrounds. On the other hand, the population of children missing from the school register is more similar to the general population in gender and ethnicity.

Extremely pronounced are the differences in the shares of vulnerable children, particularly children from low-income households or deprived areas, children with SEN and CLA. Only 16 percent of students are eligible for FSM in the general population, while the average IDACI score is 22 percent. In contrast, 36 percent of children with fixed-period exclusions and 44 percent of permanently excluded children were eligible for FSM, while the average IDACI score was also higher by around eight percentage points. Children who have been looked after at any time since 2010 consist of 5-6 percent of the excluded population, while their share is only 1 percent in the general population. Children with SEN are the most over-represented in the excluded population. The percentage of children with SEN is more than double in the population of children with at least one fixed exclusion and more than triple in the permanently excluded population. Among those children, the most common difficulties are social, emotional, and mental health within the excluded population (59% and 71%). Learning difficulties are relevant to almost the rest of the excluded children with SEN. On the other hand, in the general population, the majority of children have learning difficulties.

The characteristics of children missing from school roll follow a similar pattern with those formally excluded, but the differences with the general population are smaller than those of excluded pupils. The smaller differences could be related to the fact that a large sample of those missing from school roll may have moved to another country or to independent education, and thus they might not have any vulnerabilities. CLA seems to be the only group of vulnerable children that is similarly overrepresented between excluded children and children missing from the school register. Additionally, Figure 3.5 shows an interesting difference between the type of needs of students with SEN in the general population and among those who have disappeared from the school register. While in the former, just 25 percent of students with SEN face social, emotional and mental health challenges, this is over 50 percent in the latter population. Finally, in terms of educational outcomes, all excluded and missing from roll pupils have on average lower performance than the general population. Although the differences are small, permanently excluded children have the lowest average performance.

## 3.5 Empirical strategy and results

The descriptive analysis showed an over-representation of vulnerable children, children living in low-income families or deprived areas and children of specific ethnic backgrounds among

Table 3.2: Excluded children characteristics

| | General | Fixed Excl. | Perm. Excl. | Miss. from roll |
|---|---|---|---|---|
| Female | 0.50 | 0.29 | 0.25 | 0.46 |
| Male | 0.50 | 0.71 | 0.75 | 0.54 |
| White Ethn. | 0.81 | 0.79 | 0.79 | 0.75 |
| Asian Ethn. | 0.09 | 0.06 | 0.05 | 0.08 |
| Black Ethn. | 0.05 | 0.08 | 0.09 | 0.08 |
| Mixed and Other Ethn. | 0.05 | 0.07 | 0.08 | 0.09 |
| English lang. | 0.88 | 0.89 | 0.91 | 0.80 |
| FSM elig. | 0.16 | 0.36 | 0.44 | 0.31 |
| IDACI score | 0.22 | 0.29 | 0.31 | 0.27 |
| Children Looked After | 0.01 | 0.05 | 0.06 | 0.06 |
| KS2 maths level achieved | 4.11 | 3.70 | 3.68 | 3.72 |
| KS2 English level achieved | 4.07 | 3.55 | 3.48 | 3.63 |
| Special Educ. Needs | 0.21 | 0.51 | 0.65 | 0.43 |
| - Autism Spectrum Dis. (ASD) | 0.10 | 0.04 | 0.02 | 0.08 |
| - Behav., Social, emotional and MH | 0.22 | 0.58 | 0.71 | 0.52 |
| - Impairment | 0.07 | 0.02 | 0.01 | 0.03 |
| - Learn. Diff. | 0.46 | 0.28 | 0.20 | 0.28 |
| - Speech, Lang. and Comm. Needs | 0.09 | 0.04 | 0.02 | 0.05 |
| - Other | 0.06 | 0.04 | 0.04 | 0.05 |
| Observations | 2,545,000 | 124,000 | 3,850 | 19,511 |

*Notes:* The table presents the characteristics of one cohort of secondary school pupils in England, those in curriculum year 7 in 2011. The first column refers to the general population, the second column refers to all children with at least one fixed exclusion, the third to all children being permanently excluded, and the fourth refers to children who disappeared from the school roll sometime between curriculum year 8 and year 11. Each line shows the percentage of the population with each characteristic. The IDACI score shows the average proportion of children under the age of 16 that live in low-income households in the areas of the children in the sample. FSM eligibility shows the percentage of children eligible for Free School Meals. The CLA indicator shows the percentage of children who have been looked after at any time within the time frame studied in this paper, i.e. if a child has been looked after and left care prior to 2010, his or her CLA indicator will be 0 in this paper. The categories of need for children with Special Educational Need (SEN) show the percentage of children with the specific need out of the total number of children with SEN, i.e. they do not refer to the whole population in each column.

the population excluded children. Additionally, the trends over curriculum years showed some indications of higher exclusion rates just before KS4 exams. This paper studies empirically what has been discussed in the literature by using a panel dataset to explore how the exclusion probabilities for vulnerable children vary across curriculum years and whether indicators of competition faced by schools are correlated with exclusions after controlling for pupils' personal and school characteristics. Additionally, indicators of potential informal exclusions are being discussed and explored empirically for the first time in the literature.

$Excl_{ijst}$ is a dummy variable showing whether student $i$, leaving in area $j$ and attending school $s$, has been excluded (either permanently or for a fixed period) during school year $t$. I estimate a Probit regression of $Excl_{ijst}$ on children and school characteristics. More particularly, the regression controls for pupils' demographic, socio-economic and other characteristics, children's prior educational outcomes (at KS2), school characteristics, schools' lagged performance (average performance of their students at KS4), and LA and year effects. The children's previous performance is used as an indicator of children's ability. The schools' lagged KS4 results are included to control for any unobserved characteristics of the quality of the school. The detailed list and summary statistics of all the variables included in the Probit regression are shown in Table D1 and the variables are defined in Appendix D.

Table 3.3 presents the marginal effects from estimating Probit regressions as described above. Column (1) shows the impact of all children's characteristics on the probability of school exclusion. The impact of Black and Mixed ethnic background is present even after controlling for the child's educational performance, family economic conditions and vulnerabilities (SEN and CLA). The above ethnic backgrounds increase the probability of being excluded by 1.8 percent over and above the impact of other factors. Similarly, being eligible for FSM increases the probability by 2.8 percent. The IDACI score has a large positive impact, while KS2 performance have a small negative impact, as expected. Being a child with SEN or a CLA increases the probability of exclusion by 3-4 and 4-6 percent, respectively, ceteris paribus. In terms of curriculum years, there is no evidence of a significant difference between year 7 and year 10. However, there is a small drop in the probability of being excluded once children enter the year of KS4 exams. The regression also includes an indicator of competition faced by schools. The main indicator used in this analysis is the lagged average KS4 performance (as measured by the percentage of students achieving 5 A*-C in their GCSEs, including English and mathematics) of the secondary schools in a radius of three miles from each school. The results do not show an impact of competitors' performance on the pupils' probability to be excluded.

Column (2) shows the same results for the number of children who have disappeared from the school register between curriculumn years 8 and 11. Although the coefficients are small, as the average probability of disappearing from the school roll, some interesting patterns are identified. Ethnicity is not correlated with this indicator, in contrast with exclusions. On the other hand, similar to the previous results and in line with what has been proposed by the literature, vulnerable children (including children with SEN and CLA) have a higher probability of being missing from the school register than their peers. More particularly, the coefficient for CLA ranges from 1-2 percent, while children with SEN have an increased probability ranging from 0.5 to 1 percent. While there is not a clear pattern of statistically significant differences in the probability of being absent from school roll over different curriculum years, the probability for children with SEN, keeping all other factors equal, peaks the year before the GCSE exams [6]. Another interesting finding is that competition seems to have a small but statistically significant effect on academies, which is in line with the literature suggesting that academies are more likely to use strategic methods to improve their outcomes. Although we know that there are other reasons for missing from school roll, such as data gaps, moving to another country in the UK or moving to independent education, the pattern of higher probability of SEN in the particular curriculum year is a potential indicator of an increased probability of off-rolling in that specific year. As an additional result, column (3) presents the same analysis for the probability of pupils changing schools. The marginal effects produced by estimating the Probit regression of changing schools are in line with the results for children missing from the school roll.

Overall, the results confirm the literature that vulnerable children and children from specific ethnic (especially Black pupils and pupils with a Mixed ethnic background) and socio-economic backgrounds have a higher probability of being excluded, after controlling for other characteristics of children, schools and local areas. The probability of being excluded peaks the curriculum year before GCSE exams with a small, but significant, difference from previous and next academic years. There is no clear pattern showing an increased likelihood of exclusion as approaching Year 11 and GCSE exams for vulnerable children, while the competition indicator was also not found to be significant. On the other hand, when looking into indicators that maybe correlated with off-rolling, the results show an increased probability of children with SEN to either change school or disappear completely from the school roll the year before GCSE examinations.

[6] The difference between the coefficient of year 10 and year 11 is statistically significant with a p-value equal to 0.

Table 3.3: Probit regressions of the probability of being excluded or missing from a school's register

| | (1) Prob(excluded) | (2) Prob(Potential off-rolling) | (3) Prob(Change of school) |
|---|---|---|---|
| Mixed ethn. | 0.017*** | 0.001 | 0.001 |
| | (0.0022) | (0.0010) | (0.0025) |
| Black ethn. | 0.018*** | -0.001+ | -0.005* |
| | (0.0022) | (0.001) | (0.0023) |
| Asian ethn. | -0.005* | -.005*** | -0.015*** |
| | (0.0025) | (0.0010) | (0.0025) |
| Free School Meals | 0.028*** | 0.006*** | 0.019*** |
| | 0.0006 | (0.0003) | (0.0007) |
| Year 8 | 0.020*** | | |
| | (0.0013) | | |
| Year 9 | 0.028*** | -0.002*** | 0.016** |
| | (0.0017) | (0.0003) | (0.0057) |
| Year 10 | 0.036*** | 0.001 | 0.025*** |
| | (0.0019) | (0.0005 | (0.0051) |
| Year 11 | 0.026*** | | |
| | (0.0020) | | |
| SEN - Year 7 | 0.037*** | | |
| | (0.0011) | | |
| SEN - Year 8 | 0.041*** | 0.005*** | 0.011*** |
| | (0.0009) | (0.0004) | (0.0016) |
| SEN - Year 9 | 0.038*** | 0.005*** | 0.017*** |
| | (0.0011) | (0.0004) | (0.0013) |
| SEN - Year 10 | 0.0036*** | 0.011*** | 0.034*** |
| | (0.0010) | (0.0005) | (0.0020) |
| SEN - Year 11 | 0.024*** | | |
| | (0.0012) | | |
| CLA - Year 7 | 0.056*** | | |
| | (0.0030) | | |
| CLA - Year 8 | 0.056** | 0.014*** | 0.056*** |
| | (0.0028) | (0.0011) | (0.0030) |
| CLA - Year 9 | 0.052*** | 0.013*** | 0.054*** |
| | (0.0022) | (0.0009) | (0.0028) |
| CLA - Year 10 | 0.051*** | 0.016*** | 0.060*** |
| | (0.0021) | (0.0008) | (0.0031) |
| CLA - Year 11 | 0.044*** | | |
| | (0.0026) | | |
| Comp. - Academy | 0.008+ | 0.003* | 0.018* |
| | (0.0050) | (0.0014) | (0.0091) |
| Comp. - Community | 0.004 | -0.001 | 0.026* |
| | (0.004) | (0.0012) | (0.0125) |
| Comp. - Other | -0.019 | 0.004 | -0.008 |
| | (0.1047) | (0.0611) | (0.0540) |

*Notes:* The table presents marginal effects from probit regressions of the probability of a student being excluded (1), missing from school roll (2) or change school (3). Standard errors are clustered at the LA level.

## 3.6 Limitations and methodological considerations

This analysis does not aim to estimate a causal relationship between specific characteristics of children and the probability to be excluded. Firstly, although we do control for a long list of individual and school characteristics, there is always potential endogeneity, especially when looking into educational outcomes. Many other unobserved factors, such as family environment or parental characteristics, can directly affect both the observed characteristics of children and the probability to be excluded. For example, the relationship between exclusions and specific ethnic backgrounds could also be driven by other socio-economic characteristics. Similarly, being a CLA can affect other aspects of children's lives, personality and character that could directly impact their behaviour and attainment at school.

Regarding children who disappear from the school roll or change schools, there could be child or family characteristics that impact the probability of leaving the country, moving to independent education, becoming home educated, or changing school. In addition to this limitation, it should be taken into consideration that the indicator of children missing from the school roll should be treated as a signal but not as a direct measure of off-rolling. Similarly, children change schools usually for many reasons, e.g. moving to another area within the country or, the child or parents are not happy with the school.

In summary, the results of this study are not meant to be interpreted as showing a causal relationship between a characteristic and the probability to be formally or informally excluded. The study aims to explore potential indicators that could shed some light on whether off-rolling and strategic exclusions could be happening and the population of children that could be affected the most. Moreover, the indicative results of this study motivate future research to explore this crucial policy issue.

## 3.7 Conclusion

School exclusions in England have recently been discussed extensively in the media. Research has indicated an increasing rate of exclusions, vulnerable children being overrepresented in the population of excluded children, and exclusion rates varying significantly across different ethnic backgrounds. Additionally, Ofsted research has identified a potential strategic use of exclusions by schools to boost their performance. This paper empirically explores what has been discussed in the literature. The results show that vulnerable children and children from specific ethnic and socio-economic backgrounds have a higher probability of being excluded, even after controlling for other characteristics of children, schools and local areas. The probability of being excluded peaks at the curriculum year before GCSE exams with a small but significant difference from previous and next academic years. There is no clear pattern showing an increased likelihood of exclusion as approaching Year 11 and GCSE exams for vulnerable children. This analysis does not find any direct evidence of the average performance of schools' competitors having an impact on the exclusion probability.

This study also explores indicators of potential off-rolling. The results are consistent with what the literature suggests, as specific groups of children have a significantly higher probability of being removed from the school register (those with SEN, children who have been looked after, and pupils eligible for FSM). Additional findings show that the probability of a child with SEN disappearing from school roll increases significantly the year before GCSE exams, while this is not true for pupils without SEN. A similar pattern is observed for pupils changing schools. Finally, while overall competition does not seem to be correlated with a higher probability of students being removed from the school roll in general, there is a small but significant impact when the analysis is specific to academies.

Concluding, the results from this study do not prove any causation between characteristics of children and the probability to be excluded from school, either formally or informally. This study is mainly exploratory and aims to direct future research. Further research on more accurate measures of off-rolling could potentially explore and identify better the magnitude of the problem and the mechanisms behind it.

## 3.8 Figures for Chapter 3

Figure 3.1: Exclusion rates over time

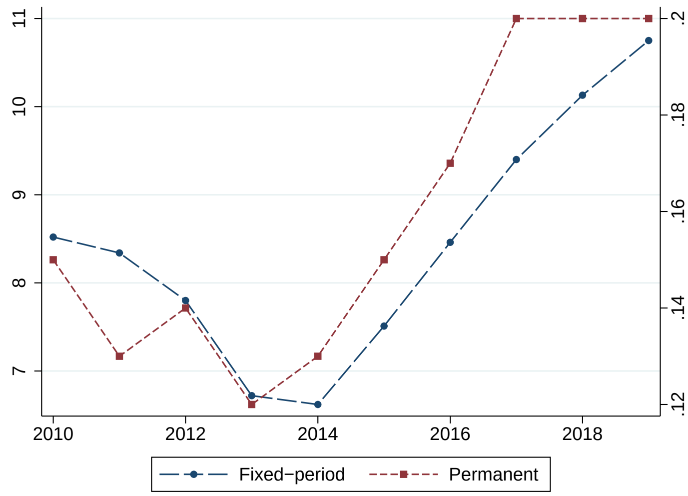
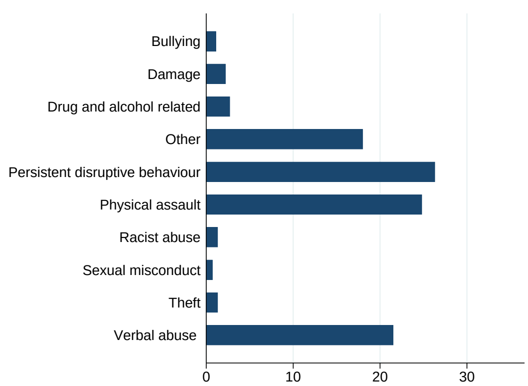



Figure 3.2: Reasons of exclusions in 2014/15

(i) Fixed-period exclusions




(ii) Permanent exclusions

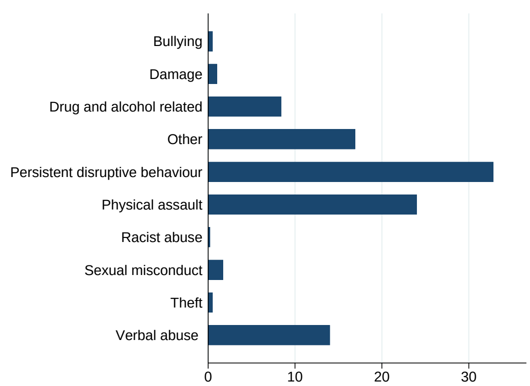


Figure 3.3: Exclusion rate by curriculum year in the sample

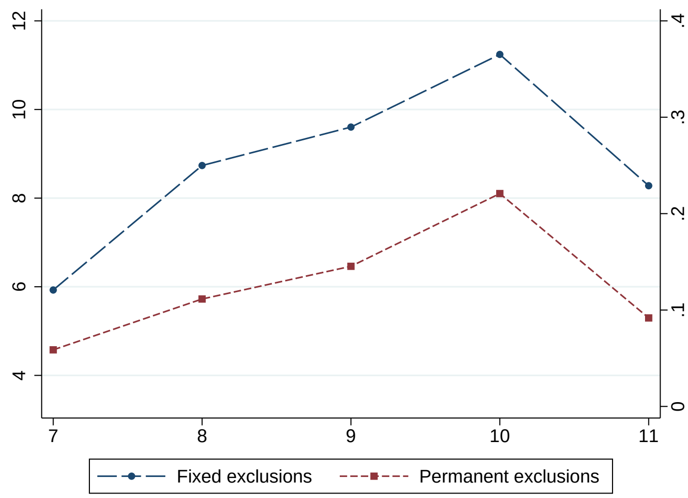



Figure 3.4: Reasons of exclusions over time in the sample

(i) Fixed-period exclusions

(ii) Permanent exclusions

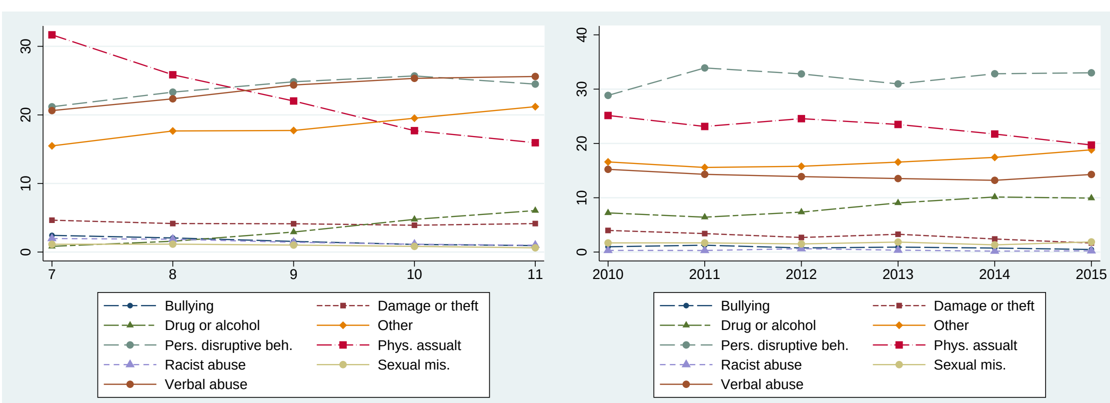
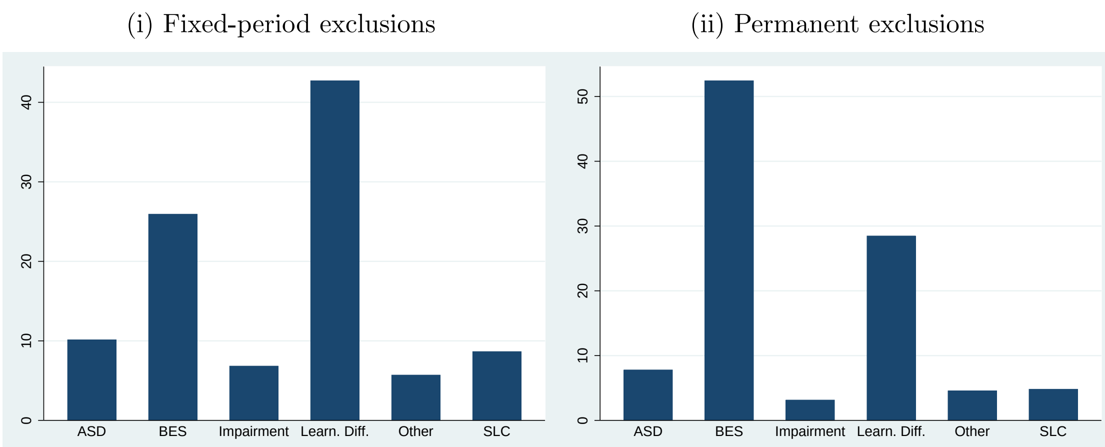


Figure 3.5: SEN in the general population and the population of pupils missing from school register



# Appendix A

# Chapter 1: Local Authorities' characteristics

This section presents detailed information on all control variables used in the analysis. The sample consists of 147 LAs in England over the period 2007-2017, while baseline characteristics refer to 2004 unless otherwise specified.[1]

## A.1 Time-varying characteristics

- **Ethnicity**: Ethnicity is measured as the proportion of the adult population with each of the following ethnic backgrounds: White, Black, Asian and Mixed and Other. The data is provided by the Office for National Statistics (ONS) through the Nomis website and their original source is the Annual Population Survey (APS).
- **Economic activity rate**: Economic activity rate shows the percentage of people (older than 15 years old) who are economically active. As above, the data was provided by ONS through the Nomis platform, while their original source is APS.
- **Claimants proportion**: Claimants proportions is defined as the proportion of the pop-

[1] City of London, Rutland and Isles of Scilly are not included in our sample due to very small numbers and missing data in many cases. Bedford Borough and Central Bedfordshire are merged together, and Cheshire East and Cheshire West and Chester are also merged together.

ulation claiming benefits principally for the reason of being unemployed out of all people aged 16-64 years old. The data was provided by ONS through the Nomis platform and it was collected for the last month of each financial year (March).

- **Education qualifications**: Our indicators show the proportion of the population aged 16-64 owning a qualification within the following broad categories: university/college degree or above, GCE/GCSE or equivalent, any qualification of a lower level than the ones stated above. The data was collected through the Nomis platform (provided by the ONS), and their original source is the APS.

- **Income**: Our analysis uses the median annual gross income of full-time workers. The original data source is the Annual Survey of Hours and Earnings (ASHE), and the data was accessed through the Nomis platform. The data was adjusted for inflation.

- **Political control**: The political party controlling each LA at each point in time is included in our analysis with the main categories being: the Conservative Party, the Labour Party, Liberal Democrats, and no overall control. The Elections Centre provides data on the annual political composition of all local councils.

## A.2 Baseline characteristics

- **Income Deprivation Affecting Children Index (IDACI)**: IDACI measures the proportion of all children aged 0 to 15 living in low income families. Our variable represents the percentage of Lower Super Outputs Areas (LSOA) in each LA that are in the top percentile of the IDACI distribution. IDACI is provided by the Ministry of Housing, Communities and Local Government (MHCLG) as part of the Index of Multiple Deprivation.

- **Low-birth-weight rate**: The Low-birth-weight rate is defined as the proportion of low-birth-weight babies ($< 2,500$g) of 37 weeks or more gestation ("full-term") out of all full-term live births. The data is is published by the NHS England and the ONS.[2]

[2] No data has been found for 2004, so data from the 2005 calendar year were used instead.

- **Teenage pregnancy**: Teenage pregnancy is measured as the number of pregnancies of girls younger than 18 years old during each financial year per 1,000 population of girls aged 15 to 17. Teenage conception data is provided by the ONS through the quarterly publication "Quarterly conceptions to women aged under 18".

- **Gross fertility rate** : The gross fertility rate is the number of live births per 1,000 women aged 15-44. Annual data on fertility are included in the ONS Birth Summary Tables.

- **Income Inequality**: We define income inequality as the ratio of the 80th percentile over the 20th percentile of the weekly income distribution in each LA. Income data was collected through the Nomis platform, while the original source is the ASHE.

- **Exclusions**: Our analysis controls for school exclusions by using the ratio of the total number of fixed period exclusions and the number of all pupils in each LA. Data on schools exclusions are provided annually by the Department for Education through the publication "Permanent and fixed period exclusions in England ".

The data on care entry rates are provided on an annual financial year basis (i.e. April to March next year). Consequently, our priority was to collect data on the above variables based on financial years. Where this was not possible we used the period overlapping the most with each financial year.

Table A1 presents the descriptive statistics of LA characteristics described in this section over LA-year cells (baseline characteristics' statistics are analysed only over LAs and not over time).

Table A1: Descriptive statistics of Local Authority characteristics.

| Panel A: Baseline Characteristics | | |
|---|---|---|
| **Variable** | **Mean** | **St. Dev.** |
| IDACI (2004) | 12.66 | 14.10 |
| Low birth weight (2004) | 3.12 | 1.14 |
| Teenage pregnancies (2004) | 45.10 | 14.31 |
| Gross fertility rate (2004) | 57.61 | 6.12 |
| Inequality (2004) | 2.28 | 0.24 |
| Exclusions (2004) | 4.59 | 1.73 |
| Observations | 147 | |

| Panel B: Time Variant Characteristics | | |
|---|---|---|
| **Variable** | **Mean** | **St. Dev.** |
| White | 85.78 | 15.14 |
| Black | 3.48 | 5.02 |
| Asian | 5.98 | 8.06 |
| Mixed-Other | 4.68 | 4.70 |
| Ec. Activity Rate | 63.51 | 3.84 |
| Claimant Prop. | 3.00 | 1.51 |
| Prop. High Qual. | 24.66 | 9.86 |
| Prop. Medium Qual. | 52.72 | 8.97 |
| Prop. Low Qual. | 22.71 | 6.82 |
| Median Income | 29,999 | 4,481 |
| Cons. control | 0.436 | 0.496 |
| Lib. Dem. control | 0.032 | 0.177 |
| Labour control | 0.320 | 0.467 |
| No overall control | 0.210 | 0.407 |
| Observations | 1,617 | |

*Notes:* See text for variable definitions.

# Appendix B

# Chapter 1: Additional analysis

## B.1 SSCC coverage: modelling the expansion period

This section presents a background econometric analysis on the SSCC coverage during the period of SSCC expansion, i.e. from 2004 to 2010, aiming to understand systematic differences in SSCC coverage across areas with different characteristics.

We developed a model predicting the SSCC coverage in each LA at the end of each year based on LA baseline characteristics in 2004 and time-varying political composition variables. Those characteristics were selected based on the SSLP and SSCC focus and aims. For example, the 2017 House of Commons Briefing Paper on Sure Start stated that the first 60 Sure Start districts were chosen based on high levels of deprivation and existing good practice in early years provision (Bate & Foster, 2017). Cattan et al. (2019) mention that SSLP targeted disadvantaged areas with high levels of teenage pregnancy and low birth weight. Phase 1 SSCC targeted 20 percent most disadvantaged areas and Phase 2 SSCC focused on 30 percent most disadvantaged areas. Phase 3 SSCC were focused on covering areas with lower provision, and thus they are expected to have been built on reverse criteria. The final list of SSCC predictors is presented in Appendix A.2, apart from the time-varying political composition variables described in Appendix A.1.

Our model is presented in Equations (B1) and (B2).

$$\log\left(cc_{jt}\right) = \beta Z_j^b + \gamma Z_j^b t + \rho Z_{jt} + \eta_t + \varepsilon_{jt} \tag{B1}$$

whereby

$$\frac{\partial \log\left(cc_{jt}\right)}{\partial Z_j^b} = \frac{\partial cc_{jt}/\partial Z_j^b}{cc_{jt}} = \beta + \gamma t \tag{B2}$$

The dependent variable $cc_{jt}$ denotes the number of children's centres per 1,000 children aged 0-4. $Z_j^b$ includes all the area characteristics at baseline. Time is defined as $t = 0$ for 2004, $t = 1$ for 2005, etc., and thus $Z_j^b t$ includes interaction terms of baseline area characteristics with time. Finally, the model includes time-varying political control variables defined as $Z_{jt}$ .

Our analysis uses baseline variables to capture how the decision of expansion was formed based on the information available in the beginning of the intervention. Our methodology is consistent with the methodology used by Cattan et al. (2019). Additionally, those LA characteristics show very little variation over time within LAs. Interaction terms between baseline characteristics and time are used to explore the hypothesis that SSCC predictors defined mainly the provision in the first two phases of the expansion period, with Phase 3 targeting areas with lower provision.

Table B1 shows the results of the above analysis. The results are consistent with what is described in the literature. Areas with high deprivation, teenage pregnancy rates, and low-birth-weight rates in 2004 had higher SSCC coverage, but, as expected, the impact was decreasing over time. The results also show that LAs controlled by the Conservative and Liberal Democrats parties had significantly lower SSCC coverage during the period 2004-2010.

Cattan et al. (2019) in their study of the impact of SSCC on children's health outcomes present results in line with our findings. Their dataset is at a Lower Super Output Area level and thus the magnitude of the coefficients is not directly comparable, but the direction of impact has the same interpretation. The paper shows that being in the 20-30 percent most deprived LSOAs is correlated with higher SSCC coverage. Low birth weight and teenage conception are also positively correlated with SSCC coverage, but their impact is much smaller and not always significant. Finally, LSOAs in LAs aligned with the national government (Labour during the whole expansion phase) tended to open centres earlier and to have higher coverage.

Table B1: SSCC prediction analysis

| | (1) | (2) | (3) |
|---|---|---|---|
| IDACI Index (2004) | 0.0164*** | 0.0219*** | 0.0209*** |
| | (0.00407) | (0.00427) | (0.00429) |
| Teenage Preg. Rate (2004) | 0.0216*** | 0.0184*** | 0.0156*** |
| | (0.00397) | (0.00440) | (0.00443) |
| LBW rate (2004) | -0.0136 | 0.0926* | 0.0732 |
| | (0.0427) | (0.0459) | (0.0459) |
| IDACI-04 $\times$ time | -0.00275* | -0.00353** | -0.00373** |
| | (0.00110) | (0.00116) | (0.00115) |
| TPR-04 $\times$ time | -0.00309** | -0.00262* | -0.00264* |
| | (0.00108) | (0.00119) | (0.00119) |
| LBW-04 $\times$ time | -0.00108 | -0.0161 | -0.0145 |
| | (0.0115) | (0.0123) | (0.0122) |
| Gr. Fertility Rate (2004) | | -0.0475*** | -0.0442*** |
| | | (0.00756) | (0.00766) |
| Inequality (2004) | | -0.299 | -0.139 |
| | | (0.227) | (0.231) |
| School Exclusion Rate (2004) | | 0.0153 | 0.0141 |
| | | (0.0261) | (0.0262) |
| GFR-04 $\times$ time | | 0.00695*** | 0.00621** |
| | | (0.00205) | (0.00204) |
| Inequality-04 $\times$ time | | 0.0687 | 0.0492 |
| | | (0.0622) | (0.0623) |
| SER-04. $\times$ time | | 0.00232 | 0.00199 |
| | | (0.00706) | (0.00707) |
| Cons. Control | | | -0.265*** |
| | | | (0.0679) |
| Lib Dem control | | | -0.220* |
| | | | (0.0986) |
| No Overall Control | | | -0.0626 |
| | | | (0.0610) |
| Constant | -5.082*** | -1.974* | -2.226** |
| | (0.170) | (0.780) | (0.786) |
| Year Fixed Effects | Y | Y | Y |
| Observations | 1,029 | 1,029 | 1,026 |
| Adjusted $R^2$ | 0.830 | 0.838 | 0.840 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The unit of observation is an LA-year cell. The dependent variable is the SSCC coverage rate, defined as the number of operating SSCC per 1,000 children aged 0-4. The years included are 2004-2010. For variable definitions, see Appendix A.

## B.2 SSCC closures: survival analysis

As discussed in Section 1.5.2, SSCC closures were concentrated in specific areas (five LAs accounted for more than a third of all closures that took place during the period 2011-2017). Consequently, the link between area characteristics and SSCC closures is expected to be substantially weaker than the link with the timing of SSCC expansion. Additionally, Table 1.4 shows that Phase 3 centres had higher probability of closure than the rest of the centres. Consequently, closures might be more prominent in less deprived areas.

In this section, we use survival analysis to predict the probability of a closure for each children's centre. The estimation equation is shown below:

$$cens_{it} = \beta Z_i^b + \gamma Z_{jt} + \eta_t + \varepsilon_{jt} \tag{B3}$$

The dependent variable is a binary variable which follows this logic: If centre $i$ 's survival time is censored (i.e. if it is opened until the 31st March 2017, the last day we are examining), the binary dependent variable is equal to 0 for all of $i$'s time spells; if centre $i$'s survival time is not censored (i.e. it has been closed), the binary dependent variable is equal to 0 for all but the last of $i$'s spell. The rest of the variables follow the logic of SSCC expansion analysis, with the difference that the baseline year in this part of analysis is 2010.

Table B2 shows the results of the survival analysis. As expected, there is a very weak relationship between LA characteristics and the probability of closure. Nevertheless, the predictors of SSCC expansion seem to have the opposite effect on closures (e.g. deprivation is positively correlated with expansion and negatively correlated with closures), as expected, but the magnitude of the impact is very small.

Table B2: SSCC survival analysis

| | (1) | (2) | (3) |
|---|---|---|---|
| IDACI Index (2010) | -0.0000841 | -0.0000955 | -0.000162+ |
| | (0.0000858) | (0.0000862) | (0.0000916) |
| Teenage Preg. Rate (2010) | 0.0000962 | 0.000206+ | 0.000142 |
| | (0.000102) | (0.000106) | (0.000118) |
| LBW rate (2010) | -0.00783*** | -0.00845*** | -0.00886*** |
| | (0.00161) | (0.00179) | (0.00184) |
| Gr. Fertility Rate (2010) | | 0.0000897 | 0.0000441 |
| | | (0.000132) | (0.000131) |
| School Exclusion Rate (2010) | | -0.00281*** | -0.00268*** |
| | | (0.000780) | (0.000781) |
| Lib Dem control | | | -0.0126 |
| | | | (0.00839) |
| Labour control | | | 0.00526+ |
| | | | (0.00308) |
| No Overall Control | | | -0.00363 |
| | | | (0.00276) |
| Constant | 0.0234*** | 0.0280** | 0.0348*** |
| | (0.00566) | (0.00922) | (0.00946) |
| Year | Y | Y | Y |
| Observations | 24,126 | 24,126 | 23,693 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The unit of observation is an open SSCC in a given year. The dependent variable is an indicator for the SSCC closing over the following 12 month period. For variable definitions, see Appendix A. Baseline variables are measured in 2010. Political control variables are time-varying.

## B.3 Additional estimated coefficients

Table B3 presents further estimated coefficients from specifications (1) - (3) in Table 1.8.

Table B3: Alternative specifications: further estimated coefficients

| | (1) | (2) | (3) |
|---|---|---|---|
| Black | -0.00935 | -0.0168* | -0.00599 |
| | (0.00855) | (0.00823) | (0.00547) |
| Asian | 0.00175 | -0.00371 | -0.00219 |
| | (0.00677) | (0.00696) | (0.00313) |
| Mixed-Other | -0.0129+ | -0.0165* | 0.00206 |
| | (0.00709) | (0.00816) | (0.00634) |
| Ec.Act. Rate. 16+ | -0.00708 | -0.0221*** | -0.0159** |
| | (0.00532) | (0.00522) | (0.00500) |
| Claimant Prop. | 0.00325 | 0.0237 | 0.0179 |
| | (0.0307) | (0.0272) | (0.0195) |
| High Qualified | 0.00361 | -0.00438 | 0.00272 |
| | (0.00512) | (0.00515) | (0.00435) |
| Medium Qualified | -0.0000678 | -0.00617 | 0.00872+ |
| | (0.00441) | (0.00544) | (0.00452) |
| Income | -0.00000933 | 0.000000844 | -0.0000135* |
| | (0.0000112) | (0.0000110) | (0.00000621) |
| Cons. Control | -0.00810 | 0.0211 | 0.0294 |
| | (0.0590) | (0.0425) | (0.0419) |
| Lib. Dem. Control | -0.0361 | 0.0766 | 0.0501 |
| | (0.0729) | (0.0505) | (0.0706) |
| No Overall Control | 0.00319 | 0.0754* | 0.0798* |
| | (0.0461) | (0.0360) | (0.0376) |
| IDACI (2004) $\times$ time | | -0.000286 | -0.000502 |
| | | (0.000359) | (0.000366) |
| Teenage Preg. Rate (2004) $\times$ time | | 0.000172 | 0.000192 |
| | | (0.000390) | (0.000393) |
| Gr. Fertility Rate (2004) $\times$ time | | -0.00113 | -0.00112 |
| | | (0.000691) | (0.000691) |
| Low Birth Weight (2004) $\times$ time | | -0.000713 | -0.00180 |
| | | (0.00276) | (0.00281) |
| Exclusions (2004) $\times$ time | | -0.00389 | -0.00384 |
| | | (0.00241) | (0.00241) |
| Inequality (2004) $\times$ time | | -0.0397+ | -0.0422+ |
| | | (0.0230) | (0.0240) |
| IDACI (2004) | | | 0.00729* |
| | | | (0.00287) |
| Teenage Preg. Rate (2004) | | | 0.0138*** |
| | | | (0.00287) |
| Gr. Fertility Rate (2004) | | | 0.000614 |
| | | | (0.00560) |
| Low Birth Weight (2004) | | | 0.0406 |
| | | | (0.0249) |
| Exclusions (2004) | | | 0.0164 |
| | | | (0.0166) |
| Inequality (2004) | | | 0.0829 |
| | | | (0.142) |
| Observations | 7,930 | 7,930 | 7,930 |

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* The specifications in the current table correspond to specifications (1)-(3) in Table 1.8.

# Appendix C

# Chapter 2: Additional information and summary statistics

- **Ethnicity**: Ethnicity is measured as the proportion of the adult population with each of the following ethnic backgrounds: White, Black, Asian and Mixed and Other. The data is provided by the Office for National Statistics (ONS) through the Nomis website and the original source is the Annual Population Survey (APS).
- **Education qualifications**: These indicators show the proportion of the population aged 16-64 with a qualification within the following broad categories: university/college degree or above, GCE/GCSE or equivalent, any qualification of a lower level than the ones stated above. The data was collected through the Nomis platform (ONS), and the original source is the APS.
- **Income**: The analysis uses the median annual gross income of full-time workers. The original data source is the Annual Survey of Hours and Earnings (ASHE), and the data was accessed through the Nomis platform. The data is adjusted for inflation.
- **Child population**: This indicator refers to the population of children and young people aged 0-17 living in each Local Authority. The data was extracted by the Nomis website and it is based on annual mid-year population estimates produced by the ONS.

Table C1: Summary statistics of main and additional variables

| Panel A: Main Variables | | |
|---|---|---|
| **Variable** | **Mean** | **St. Dev.** |
| CPP entry rate younger than 1 | 120.1 | 62.1 |
| CPP entry rate 1-4 | 55.9 | 24.9 |
| CPP entry rate 5-9 | 46.1 | 20.8 |
| Unemployment rate | 7 | 2.5 |
| Predicted unemployment rate | 4.6 | 1.0 |
| Panel B: Additional Local Authority characteristics | | |
| **Variable** | **Mean** | **St. Dev.** |
| White ethn. | 85.9 | 15.0 |
| Black ethn. | 3.4 | 5 |
| Asian ethn. | 5.8 | 7.9 |
| Mixed or other ethn. | 4.8 | 5.0 |
| Median income | 29,927 | 4,917 |
| High qualification | 24.5 | 11.0 |
| Medium qualification | 52.7 | 9.7 |
| Low qualification | 22.8 | 6.9 |
| Observations | 1,617 | |

*Notes:* The table shows the average across 147 Local Authorities and all years in the period 2007-2017. CPP entry rates show the average number of children starting a CPP during each year during the period of study per 10,000 child population of the relevant age. All other variables, apart from median income, are percentages. Median income is adjusted for inflation.

Table C2: Average industry compositions

| | General | Male | Female |
|---|---|---|---|
| Hotels and restaurants | 0.19 | 0.17 | 0.21 |
| | (0.027) | (0.029) | (0.039) |
| Agriculture, fishing and energy | 0.02 | 0.03 | 0.01 |
| | (0.096) | (0.015) | (0.008) |
| Banking, finance and insurance | 0.15 | 0.15 | 0.15 |
| | (0.056) | (0.064) | (0.049) |
| Construction | 0.08 | 0.13 | 0.02 |
| | (0.019) | (0.033) | (0.011) |
| Manufacturing | 0.12 | 0.17 | 0.06 |
| | (0.050) | (0.072) | (0.028) |
| Public admin., education and health | 0.28 | 0.16 | 0.42 |
| | (0.036) | (0.034) | (0.050) |
| Transportation and communication | 0.10 | 0.14 | 0.05 |
| | (0.030) | (0.040) | (0.026) |
| Other | 0.05 | 0.04 | 0.06 |
| | (0.016) | (0.016) | (0.020) |
| Observations | | 147 | |

*Notes:* The table presents the share of the relevant population that worked in each industry in 2006. The shares should sum up to 1. When the total of each column does not sum up to 1 exactly is because of rounding. The parentheses show the standard deviation of each industry share. The relevant population is 147 Local Authorities.

# Appendix D

# Chapter 3: Additional information and summary statistics

- **KS2 level achieved**: This variables shows the average level achieved by students in the sample. Students in Key Stage 2 are expected to perform at level 4.
- **IDACI**: The Income Deprivation Affecting Children Index (IDACI) is defined as the proportion of children under the age of 16 that live in low income households in a local area.
- **CLA**: A Child Looked After in this paper is defined as any child that has spent time in care at some point during the period 2010 - 2015. If a child has entered and left care before 2010, then their care experience won't be visible in this data.
- **Schools' characteristics**: All schools' characteristics (apart from performance and competitors' related variables described below) show the average share of students with each characteristic in all schools in England. For example, around 15 percent of pupils are eligible for Free School Meals (FSM) in an average school in the sample.
- **Schools' KS4 performance**: The proportion of schools' children who have achieved 5 A*-C in their GCSE exams (i.e. the exams taking place at the end of Key Stage 4, usually at year 11), including English and mathematics.
- **Competitors' KS4 performance**: The lagged average KS4 performance (as defined above) of all secondary schools in a 3 miles radius of the school of the child observed.

Table D1: Summary statistics of all variables

| Panel A: Students' educational outcomes | | |
|---|---|---|
| **Variable** | **Mean** | **St. Dev.** |
| Fixed exclusions rate | 0.085 | 0.536 |
| Permanent exclusions rate | 0.001 | 0.037 |
| Excluded pupils | 0.045 | 0.207 |
| Pupils who disappeared from school roll | 0.009 | 0.095 |
| Pupils who changed school | 0.067 | 0.250 |
| Pupils who changed school within their LA | 0.047 | 0.211 |
| KS2 maths level achieved | 4.090 | 0.877 |
| KS2 English level achieved | 4.049 | 0.928 |
| Panel B: Students' characteristics | | |
| **Variable** | **Mean** | **St. Dev.** |
| Female | 0.488 | 0.500 |
| White ethn. | 0.812 | 0.391 |
| Asian ethn. | 0.088 | 0.284 |
| Black ethn. | 0.046 | 0.211 |
| Mixed ethn. | 0.041 | 0.198 |
| Other ethn. | 0.012 | 0.110 |
| Free School Meals | 0.166 | 0.372 |
| IDACI score | 0.220 | 0.173 |
| Special Educational Needs | 0.223 | 0.416 |
| Child Looked After since 2010 | 0.012 | 0.109 |
| Panel C: Schools' characteristics | | |
| **Variable** | **Mean** | **St. Dev.** |
| % FSM elig. | 14.80 | 11.61 |
| % SEN without statement | 16.85 | 9.788 |
| % SEN with statement | 3.627 | 12.65 |
| % English lang. | 86.61 | 18.94 |
| KS4 perf. (lagged) | 58.67 | 17.51 |
| Competitors' KS4 | 48.33 | 15.04 |
| Nr. competitors | 6.354 | 5.247 |
| Observations | 2,825,000 | |

*Notes:* The table shows the average children's and schools' characteristics in the sample. The sample includes all children in England who gave KS2 exams in 2010 and are included in the National Pupil Database. The sample is followed through their secondary school years and up to the KS4 exams (curriculum year 11). Children's characteristics, apart from IDACI score and KS4 level, are all dummy variables and thus they show the proportion of the sample with each characteristic. The number of observations refers to the number of pupils times the years in the panel dataset. The number of pupils per school year varies between 535,000 - 553,000.

# References

Allen, G. (2011). *Early Intervention: The next steps, an independent report to Her Majesty's Government by Graham Allen MP*. The Stationery Office. Retrieved from https://www.gov.uk/government/publications/early-intervention-the-next-steps--2

Anderberg, D., Rainer, H., Wadsworth, J., & Wilson, T. (2016). Unemployment and domestic violence: Theory and evidence. *The Economic Journal*, *126*(597), 1947–1979. Retrieved from http://sticerd.lse.ac.uk/seminarpapers/wpa05022014p.pdf

Appel, A. E., & Holden, G. W. (1998). The co-occurrence of spouse and physical child abuse: A review and appraisal. *Journal of Family Psychology*, *12*(4), 578-599. Retrieved from https://psycnet.apa.org/doiLanding?doi=10.1037%2F0893-3200.12.4.578

Avellar, S. A., & Supplee, L. H. (2013). Effectiveness of home visiting in improving child health and reducing child maltreatment. *Pediatrics*, *132*(Supplement). Retrieved from http://pediatrics.aappublications.org/cgi/doi/10.1542/peds.2013-1021G

Bald, A., Chyn, E., Hastings, J. S., & Machelett, M. (2019). *The causal impact of removing children from abusive and neglectful homes.* Retrieved from https://www.nber.org/papers/w25419

Bartik, T. J. (1991). Boon or boondoggle? The debate over state and local economic development policies. Retrieved from https://research.upjohn.org/cgi/viewcontent.cgi?referer=https://scholar.google.com/&httpsredir=1&article=1095&context=up_bookchapters

Bate, A., & Foster, D. (2017). *Sure Start (England).* Retrieved from https://commonslibrary.parliament.uk/research-briefings/cbp-7257/

Bentley, H., Burrows, A., Clarke, L., Gillgan, A., Glen, J., Hafizi, M., ... Walker, J. (2018). *How safe are our children?* NSPCC. Retrieved from https://learning.nspcc.org.uk/media/1067/how-safe-are-our-children-2018.pdf

Bitler, M. P., & Zavodny, M. (2004). Child maltreatment, abortion availability, and economic conditions. *Review of Economics of the Household*, *2*(2), 119–141. Retrieved from https://link.springer.com/article/10.1023/B:REHO.0000031610.36468.0e

Blanchard, O. J., Katz, L. F., Hall, R. E., & Eichengreen, B. (1992). Regional evolutions. *Brookings papers on economic activity*, *1992*(1), 1–75.

Brown, D., & De Cao, E. (2020). *Child maltreatment, unemployment, and safety nets.* Retrieved from https://dx.doi.org/10.2139/ssrn.3543987

Carneiro, P., & Ginja, R. (2014). Long-term impacts of compensatory preschool on health and behavior: Evidence from Head Start. *American Economic Journal: Economic Policy*, *6*(4), 135-73. Retrieved from http://www.aeaweb.org/articles?id=10.1257/pol.6.4.135

Carpenter, J., Brown, S., & Griffin, M. (2007). Prevention in integrated children's services: the impact of Sure Start on referrals to social services and child protection registrations. *Child Abuse Review*, *16*(1), 17–31. Retrieved from http://doi.wiley.com/10.1002/car.969

Cattan, S., Conti, G., Farquharson, C., & Ginja, R. (2019). The health effects of Sure Start. Retrieved from https://www.nuffieldfoundation.org/project/the-health-effects-of-early-interventions-evidence-from-sure-start

Cattan, S., Conti, G., Farquharson, C., Ginja, R., & Pecher, M. (2021). The health impacts of Sure Start. Retrieved from https://ifs.org.uk/uploads/BN332-The-health-impacts-of-sure-start-1.pdf

Children's Commissioner for England. (2015). *Protecting children from harm.* Retrieved from https://www.childrenscommissioner.gov.uk/wp-content/uploads/2017/06/Protecting-children-from-harm-full-report.pdf

Clancy, G., & Stam, P. (2010). Explaining the difference between unemployment and the claimant count. *Economic & Labour Market Review*, *4*(7), 21–27. Retrieved from https://link.springer.com/article/10.1057/elmr.2010.93

Conti, G., Heckman, J. J., & Pinto, R. (2016). The effects of two influential early childhood interventions on health and healthy behaviour. *The Economic Journal*, *126*(596). Retrieved from https://academic.oup.com/ej/article/126/596/F28-F65/5077840

Conti, G., Morris, S., Melnychuk, M., & Pizzo, E. (2017). *The economic cost of child maltreatment in the uk.* NSPCC. Retrieved from https://learning.nspcc.org.uk/research-resources/2017/economic-cost-child-maltreatment

Currie, J., & Almond, D. (2011). Human capital development before age five. In *Handbook of Labor Economics* (Vol. 4, pp. 1315–1486). Elsevier. Retrieved from https://linkinghub.elsevier.com/retrieve/pii/S0169721811024130

Department for Children, Schools and Families. (2008). *The Sure Start journey.* Retrieved from https://dera.ioe.ac.uk/8110/7/FINAL%20The%20Sure%20Start%20Journey_Redacted.pdf

Department for Education. (2017a). *Characteristics of children in need: 2016 to 2017 England.* Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/656395/SFR61-2017_Main_text.pdf

Department for Education. (2017b). *Children looked after in England (including adoption), year ending 31 march 2017.* Retrieved from https://www.gov.uk/government/statistics/children-looked-after-in-england-including-adoption-2016-to-2017

Department for Education. (2019). *Children in need of help and protection.* Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/809108/CIN_review_final_analysis_publication.pdf

Department for Education. (2021). Permanent exclusions and suspensions in England. Retrieved from https://explore-education-statistics.service.gov.uk/find-statistics/permanent-and-fixed-period-exclusions-in-england

Doyle, J. J. (2007). Child protection and child outcomes: Measuring the effects of foster care. *American Economic Review*, *97*(5), 1583-1610. Retrieved from https://www.jstor.org/stable/i30034572

Doyle, J. J. (2008). Child protection and adult crime: Using investigator assignment to estimate causal effects of foster care. *Journal of Political Economy*, *116*(4), 746-770. Retrieved from https://www.jstor.org/stable/10.1086/589908

Doyle, J. J., & Aizer, A. (2018). Economics of child protection: Maltreatment, foster care, and intimate partner violence. *Annual Review of Economics*, *10*(1), 87–108. Retrieved from https://www.annualreviews.org/doi/10.1146/annurev-economics-080217-053237

Dubowitz, H., Kim, J., Black, M. M., Weisbart, C., Semiantin, J., & Magder, L. S. (2011). Identifying children at high risk for a child maltreatment report. *Child Abuse and Neglect*, *35*(2), 96-104. Retrieved from https://www.sciencedirect.com/science/article/pii/S0145213411000135?via%3Dihub

Duflo, E. (2003). Grandmothers and granddaughters: old-age pensions and intrahousehold allocation in south africa. *The World Bank Economic Review*, *17*(1), 1–25. Retrieved from https://academic.oup.com/wber/article-abstract/17/1/1/1676291

Fitzpatrick, M. D., Benson, C., & Bondurant, S. R. (2020). *Beyond reading, writing, and arithmetic: The role of teachers and schools in reporting child maltreatment* (Tech. Rep.). National Bureau of Economic Research. Retrieved from https://www.nber.org/papers/w27033

Fletcher, J. M. (2009). Childhood mistreatment and adolescent and young adult depression. *Social Science & Medicine*, *68*(5), 799–806. Retrieved from https://www.sciencedirect.com/science/article/abs/pii/S0277953608006527

Gaheer, S., & Paull, G. (2016). The value for money of children's centre services. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/535811/ECCE_Strand_5_Value_for_Money_Analysis_Research_Brief.pdf

Garces, E., Thomas, D., & Currie, J. (2002). Longer-term effects of Head Start. *American Economic Review*, *92*(4), 999-1012. Retrieved from http://www.aeaweb.org/articles?id=10.1257/00028280260344560

Goff, J., Hall, J., Sylva, K., Smith, T., Smith, G., Eisenstadt, N., … Chu, K. (2013). Delivery of family services by children's centres. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/224096/DFE-RR297.pdf

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586–2624. Retrieved from 10.1257/aer.20181047

House of Commons Education Committee. (2018, July). Forgotten children: alternative provision and the scandal of ever increasing exclusions. (HC 342). Retrieved from https://publications.parliament.uk/pa/cm201719/cmselect/cmeduc/342/342.pdf

House of Commons Children's, S., & Committee, F. (2010). *Sure Start Children's Centres.* Retrieved from https://publications.parliament.uk/pa/cm200910/cmselect/cmchilsch/130/130i.pdf

Howard, K. S., & Brooks-Gunn, J. (2009). The role of home - visiting programs in preventing child abuse and neglect. *The Future of Children*, *19*(2), 119–146. Retrieved from http://muse.jhu.edu/content/crossref/journals/future_of_children/v019/19.2.howard.html

Institute for Public Policy Research. (2017). Making the difference: Breaking the link between school exclusion and social exclusion. Retrieved from https://www.ippr.org/files/2017-10/making-the-difference-report-october-2017.pdf

Laslett, A. M., Room, R., Dietze, P., & Ferris, J. (2012). Alcohol's involvement in recurrent child abuse and neglect cases. *Addiction*, *107*(10), 1786-1793. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1360-0443.2012.03917.x

Lindo, J. M., Schaller, J., & Hansen, B. (2018). Caution! Men not at work: Gender-specific labor market conditions and child maltreatment. *Journal of Public Economics*, *163*, 77–98. Retrieved from https://doi.org/10.1016/j.jpubeco.2018.04.007

Lundberg, S. J., Pollak, R. A., & Wales, T. J. (1997). Do husbands and wives pool their resources? Evidence from the United Kingdom child benefit. *Journal of Human resources*, 463–480. Retrieved from https://www.jstor.org/stable/146179?seq=1#metadata_info_tab_contents]

Maisey, R., Speight, S., & Haywood, S. (2013). Baseline survey of families using children's centres in the most disadvantaged areas. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/191007/DFE-RR260.pdf

Mc Grath-Lone, L., Dearden, L., Harron, K., Nasim, B., & Gilbert, R. (2017). Factors associated with re-entry to out-of-home care among children in England. *Child Abuse & Neglect*, *63*, 73-83. Retrieved from https://www.sciencedirect.com/science/article/pii/S0145213416302708 doi: https://doi.org/10.1016/j.chiabu.2016.11.012

McLoyd, V. C. (1990). The impact of economic hardship on Black families and children: Psychological distress, parenting, and socioemotional development. *Child development*, *61*(2), 311–346. Retrieved from https://doi.org/10.1111/j.1467-8624.1990.tb02781.x

Melhuish, E., Belksy, J., & Leyland, A. (2010). The impact of Sure Start Local Programmes on five years olds and their families. Retrieved from https://assets

.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/182026/DFE-RR067.pdf

Melhuish, E., Belksy, J., & Leyland, A. (2012). The impact of Sure Start Local Programmes on seven year olds and their families. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/495329/The_impact_of_Sure_Start_local_programmes_on_7-year-olds_and_their_families.pdf

Melhuish, E., Belsky, J., Leyland, A. H., Barnes, J., & the National Evaluation of Sure Start Research Team. (2008). Effects of fully-established Sure Start Local Programmes on 3-year-old children and their families living in England: a quasi-experimental observational study. *The Lancet*, *372*(9650), 1641–1647. Retrieved from https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(08)61687-6/fulltext

National Audit Office. (2014). Department for Education - Children in care. Retrieved from https://www.nao.org.uk/report/children-in-care/

Neil, E., Gitsels, L., & Thoburn, J. (2019). Children in care: Where do children entering care at different ages end up? an analysis of local authority administrative data. *Children and Youth Services Review*, *106*, 104472. Retrieved from https://doi.org/10.1016/j.childyouth.2019.104472

NSPCC. (2020). *Statistics briefing: child deaths due to abuse or neglect.* Retrieved from https://learning.nspcc.org.uk/

Ofsted. (2019a, May). The education inspection framework. (190015). Retrieved from https://www.gov.uk/government/publications/education-inspection-framework/education-inspection-framework

Ofsted. (2019b). Off-rolling: exploring the issue. Retrieved from https://www.gov.uk/government/publications/off-rolling-exploring-the-issue

Olds, D., Henderson, C. R., Kitzman, H., & Cole, R. (1995). Effects of prenatal and infancy nurse home visitation on surveillance of child maltreatment. *Pediatrics*, *95*(3), 365–372. Retrieved from https://publications.aap.org/pediatrics/article-abstract/95/3/365/59736/Effects-of-Prenatal-and-Infancy-Nurse-Home

Olds, D. L. (2007). Preventing crime with prenatal and infancy support of parents: The nurse-family partnership. *Victims and Oenders*, *2*(2), 205-225. Retrieved from https://www.tandfonline.com/action/showCitFormats?doi=10.1080%2F15564880701263569

Olea, J. L. M., & Pflueger, C. (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics*, *31*(3), 358–369. Retrieved from https://doi.org/10.1080/00401706.2013.806694

Page, M., Schaller, J., & Simon, D. (2019). The effects of aggregate and gender-specific labor demand shocks on child health. *Journal of Human Resources*, *54*(1), 37–78. Retrieved from http://jhr.uwpress.org/content/54/1/37.short

Paxson, C., & Waldfogel, J. (1999). Parental resources and child abuse and neglect. *The American Economic Review*, *89*(2), 239–244. Retrieved from http://www.jstor.org/stable/117113

Paxson, C., & Waldfogel, J. (2002). Work, welfare, and child maltreatment. *Journal of Labor Economics*, *20*(3), 435-474. Retrieved from https://doi.org/10.1086/339609

Paxson, C., & Waldfogel, J. (2003). Welfare reforms, family resources, and child maltreatment. *Journal of Policy Analysis and Management*, *22*(1), 85–113. Retrieved from http://www.jstor.org/stable/3325847

Poole, E., Fry, A., & Tanner, E. (2015). Children's centres evaluation in England follow-up survey of centre leaders. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/433850/RR373_Evaluation_of_children_s_centres_in_England_survey_of_leaders.pdf

Radford, L., Corral, S., Bradley, C., Fisher, H., Bassett, C., Howat, N., & Collishaw, S. (2011). Child abuse and neglect in the UK today. Retrieved from https://www.researchgate.net/profile/Lorraine_Radford/publication/230558737_Child_Abuse_and_Neglect_in_the_UK_Today/links/0fcfd501700b021c5a000000.pdf

Robling, M., Bekkers, M.-J., Bell, K., Butler, C. C., Cannings-John, R., Channon, S., ... others (2016). Effectiveness of a nurse-led intensive home-visitation programme for first-time teenage mothers (Building Blocks): a pragmatic randomised controlled trial. *The Lancet*, *387*(10014), 146–155. Retrieved from https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(15)00392-X/fulltext

Robling, M., Lugg-Widger, F., Cannings-John, R., Sanders, J., Angel, L., Channon, S., ... Slater, T. (2021). The Family Nurse Partnership to reduce maltreatment and improve child health and development in young children: the BB:2–6 routine data-linkage follow-up to earlier RCT. *Public Health Research*, *9*(2). Retrieved from https://doi.org/10.3310/phr09020

Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly Journal of Economics*, *115*(2), 617–650. Retrieved from https://doi.org/10.1162/003355300554872

Ruhm, C. J. (2003). Good times make you sick. *Journal of Health Economics*, *22*(4), 637–658. Retrieved from https://doi.org/10.1016/S0167-6296(03)00041-9

Ruhm, C. J., & Black, W. E. (2002). Does drinking really decrease in bad times? *Journal of Health Economics*, *21*(4), 659–678. Retrieved from https://doi.org/10.1016/S0167-6296(02)00033-4

Sammons, P., Hall, J., Smees, R., & Goff, J. (2015). The impact of children's centres: studying the effects of children's centres in promoting better outcomes for young children and their families. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/485346/DFE-RR495_Evaluation_of_children_s_centres_in_England__the_impact_of_children_s_centres.pdf

Sandner, M., & Thomsen, S. L. (2020). *Preventing child maltreatment: Beneficial side effects of public childcare provision* (Hannover Economic Papers (HEP) No. 669). Hannover. Retrieved from http://hdl.handle.net/10419/216969

Schweinhart, L. J., et al. (1993). *Significant benefits: The High/Scope Perry Preschool Study through age 27.* ERIC. Retrieved from https://eric.ed.gov/?id=ed366433

Sedlak, A. J., Mettenburg, J., Basena, M., Petta, I., McPherson, K., Greene, A., & Li, S. (2010). Fourth National Incidence Study of Child Abuse and Neglect (NIS-4): Report to Congress. Retrieved from https://www.acf.hhs.gov/opre/resource/fourth-national-incidence-study-of-child-abuse-and-neglect-nis-4-report-to

Seiglie, C. (2004). Understanding child outcomes: An application to child abuse and neglect. *Review of Economics of the Household*, *2*(2), 143–160. Retrieved from https://link.springer.com/article/10.1023/B:REHO.0000031611.38185.d3

Slack, K. S., Berger, L. M., & Noyes, J. L. (2017). Introduction to the special issue on the economic causes and consequences of child maltreatment. *Children and Youth Services Review*, *72*, 1-4. Retrieved from https://psycnet.apa.org/doi/10.1016/j.childyouth.2016.11.013

Smith, G., Field, K., Smith, T., Noble, S., Smith, T., & Plunkett, E. (2014). The extent to which centres 'reach' eligible families, their neighbourhood characteristics and levels of use. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/318227/RR358_-_FINALrevisedReachReport07042014.pdf

Smith, G., Sylva, K., Smith, T., Sammons, P., & Omonigho, A. (2018). Stop Start - Survival, decline or closure? Children's Centres in England. Retrieved from https://www.suttontrust.com/our-research/sure-start-childrens-centres-england/

The Economist. (2018). The troubling surge in English children being taken from their parents. Retrieved from https://www.economist.com/britain/2018/03/22/the-troubling-surge-in-english-children-being-taken-from-their-parents

Thomas, C. (2018). The Care Crisis Review: Factors contributing to national increases in numbers of looked after children and applications for care orders. Retrieved from https://www.frg.org.uk/involving-families/reforming-law-and-practice/care-crisis-review

Thomas, P. (2018). *Calculating the value of human life: safety decisions that can be trusted* (Tech. Rep.). PolicyBristol. Retrieved from https://www.bristol.ac.uk/media-library/sites/policybristol/PolicyBristol-Report-April-2018-value-human-life.pdf

Thomas, P. (2020). Minimum sample size for the survey measurement of a wealth-dependent parameter with the UK VPF as exemplar. *Measurement*, *150*, 107044. Retrieved from https://www.sciencedirect.com/science/article/pii/S0263224119309108

Tillson, J., & Oxley, L. (2020). Children's moral rights and UK school exclusions. *Theory and Research in Education*, *18*(1), 40-58. Retrieved from https://journals.sagepub.com/doi/full/10.1177/1477878520912509

Timpson, E. (2019, May). *Timpson review of school exclusion.* Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/807862/Timpson_review.pdf (Presented to Parliament by the Secretary of State for Education by Command of Her Majesty)

Zielinski, D. S. (2009). Child maltreatment and adult socioeconomic well-being. *Child Abuse & Neglect*, *33*(10), 666–678. Retrieved from https://doi.org/10.1016/j.chiabu.2009.09.001