Supplemental Materials

Analytic Sample

In **Supplemental Table 1**, we describe the distribution of study covariates by our analytic sample and others. Specifically, we compared the distributions of covariates between participants included in the total analytic sample (n=4438) and three other subsamples of ALSPAC: (1) participants who had at least one measure of social cognition, but were excluded based on other selection criteria (n=5239); (2) subset of the analytic sample who were exposed to sexual or physical abuse before age 10 ($n=590$); and (3) subset of the analytic sample who were exposed to caregiver physical or emotional abuse before age 10 (n=774).

Data Selection

Out of ALSPAC's 14,901 enrolled children alive at 1 year of age, there were 9677 children who had at least one measure of social cognition out of the three timepoints in which it was measured (ages 7.5, 10.5 and 14 years). With this base set of 9677 children, we then applied our exclusion criteria to identify the analytic sample. In a stepwise fashion, we first excluded children who did not have outcome measures at all three timepoints as would be needed for our life course modeling approach (5222 children remained). As the social experience of twins likely differs from singletons, we then excluded an additional 96 multiple-birth children. Lastly, as we restricted the analyses to only those children who had mothers and maternal figures as the sole reporters of their social cognition skills over the three timepoints of assessment to minimize reporter inconsistency, 688 children were additionally removed, yielding a total sample of 4,438 children.

We compared the distribution of covariates and outcome scores between the analytic sample (n=4438) and the subset of excluded participants with complete social cognition outcome data at all three time points, but who lacked consistent maternal reports (n=688). These two samples had largely similar sociodemographic characteristics and social cognition scores at all three time points; however, the excluded sample (without consistent maternal reports) were more likely to be born to mothers with slightly higher education (**Supplemental Table 2**).

Measures

ALSPAC was established to better understand how genetic and environmental features influence health and development of children (Fraser, 2013). Due to the breadth of this research question, specific scales or measures may not have been included at every time point of assessment. In **Supplemental Table 3**, we describe how each of the child maltreatment variables, described below was specially constructed including questions and time periods that were covered.

Child Maltreatment

To measure physical or sexual abuse by anyone, two items from an inventory assessing exposure to a series of life events were used. Specifically, mothers reported whether or not the child had been either "sexually abused" or "physically hurt by someone." If they answered "yes" on either of the two items, the child was coded as exposed. To measure caregiver physical or emotional abuse, both the mother and the partner provided responses to the following four items: 1) your partner was physically cruel to your children; 2) you were physically cruel to your children; 3) your partner was emotionally cruel to your children; 4) you were emotionally cruel

to your children. If either the mother or the partner answered affirmatively to any of the four questions above, the child was coded as exposed. The participants were assured that their responses were confidential and no information would be reported to child welfare agencies, as no mandatory reporting laws were in place in the UK at the time of data collection (Bell, 1994; Khan, 2018). We note that because of the questionnaire wording both measures of child maltreatment ("Caregiver physical or emotional abuse" and "Sexual or physical abuse") could double-count caregiver physical abuse. The specific time periods covered by these questions are described in **Supplemental Table 3.**

Correlations between caregiver physical and emotional abuse items are shown in **Supplemental Table 4**. Correlations between the two types of maltreatment examined in this study are shown in **Supplemental Table 5**. Of note, while the prevalence of being ever exposed to sexual abuse before age 10 was much lower in the analytic sample (0.4%) compared to the prevalence of being ever exposed to physical abuse before age 10 (13.1%), the two exposures were moderately correlated $(r_{tetrachoric} = 0.39)$.

Social Cognition

The distribution of social cognition scores across time, stratified by child sex, are shown in **Supplemental Table 6.**

Covariates

We controlled for the following covariates, measured at the time of the child's birth: *child race/ethnicity* (0=non-White; 1=White); *number of previous pregnancies* (between 0-3+); *maternal marital status* (0=never married; 1=widowed/divorced/separated; 2=married); *highest level of maternal education* (1=less than O-level, 2=O-level, 3=A-level, 4=Degree or above); *maternal age* (0=ages 15-19, 1=ages 20-35, 2=age>35); *homeownership* (0=mortgage/own home; 1=rent home; 2=other); *parent social class* (i.e. the highest social class of either parent: 1=professional; 2=managerial and technical; 3=skilled, non-manual; 4=skilled, manual; 5=semiskilled, manual; 6=unskilled manual/other); and *maternal depressive symptoms* (measured by total scores on the Edinburgh Postnatal Depression Scale; scores ranged from 0-30 with higher scores indicating higher levels of depressive symptoms) (Adkins et al., 2011; Anney et al., 2010; Baker, Taylor & The Alspac Survey Team, 1997; Chen et al., 2013; Wood, White & Royston, 2008).

LARs Variable Selection and Structural Modeling

We achieved a single dataset for analysis by implementing LARs on the covariance structure among all variables, estimated by averaging the covariance structure across all multiply imputed datasets. This allowed us to avoid potential problems arising from different model selections across multiply imputed datasets (Wood et al., 2008).

We then evaluated the relative importance of these maltreatment variables using a twostage structured lifecourse modeling approach (SLCMA) originally developed by Mishra (Mishra et al., 2009) for analyzing repeated, binary exposure data across the lifecourse. Relative to a more traditional regression model, the main advantage of the SLCMA is that it provides a structured and unbiased way to compare multiple competing theoretical models simultaneously and identify the most parsimonious explanation for the observed outcome variation.

In the first stage, we followed the approach of Smith (Smith et al., 2015) and entered the set of maltreatment variables described previously into a Least Angle Regression (LARs)

procedure (Efron et al., 2004) in order to identify, separately for each type of maltreatment, the single theoretical model (or potentially more than one theoretical models working in combination) that explained the most variability in child social cognitive difficulties. We used a covariance test (Lockhart et al., 2014) and examined elbow plots (**Supplemental Figure 1**) to determine whether the selected models were supported by the ALSPAC data. Compared to other variable selection procedures, including stepwise regression, the SLCMA has been shown to not over-inflate effect size estimates (Efron et al., 2004) or bias hypothesis tests (Lockhart et al., 2014). Compared to other methods for the structured approach, LARs has been shown to have greater statistical power and not bias subsequent stages of analysis (Smith et al., 2015). To adjust for potential confounding, we regressed each encoded variable on the covariates and implemented LARs on the regression residuals (Smith et al., 2016).

In the second stage, the theoretical models determined by a covariance test p-value threshold of 0.05 in the first stage (which appeared before the elbow; see **Supplemental Figure 1**) was carried forward to a single multiple regression framework, where measures of effect would have been estimated for all selected hypotheses. The goal of this second stage was to determine the contribution of a selected theoretical model after adjustment for covariates as well as other selected theoretical models, in instances where more than one theoretical model was chosen in the first stage.

Multiple Imputation

As noted above, there were 4,438 children with complete outcome data at all three time points who met our inclusion criteria. However, a small proportion of these 4,438 children had missing exposure or covariate data; rates of missingness for exposure or covariate data ranged per variable from 4.3% (n=279 for maternal birth age) to 19.1% (n=1244 for presence versus absence of maternal psychopathology at 6 years).

To reduce potential bias and minimize loss of power due to attrition, we performed multiple imputation, separately for each exposure, using logistic regression in 20 datasets with 25 iterations each among all children with complete outcome data. In addition to imputing exposures, we also imputed covariates as described here. Of note, variables were included in the imputation models following the guidance of van Buuren and colleagues (van Buuren, Boshuizen & Knook, 1999; van Buuren & Groothuis-Oudshoorn, 2011) as well as prior research with imputation in the ALSPAC dataset (Evans et al., 2012; Ramchandani et al., 2008). The following variables were allowed to enter the imputation models: all covariates and exposures to the specific type of maltreatment from ages 0-8. Variables uncorrelated with the missing variable $(r<0.10)$ were excluded from the imputation model (van Buuren et al., 1999; van Buuren & Groothuis-Oudshoorn, 2011). Imputation was performed with chained equations (Azur et al., 2011) with the *mice* package in R (van Buuren & Groothuis-Oudshoorn, 2011). To reduce noise in estimation of effect estimates, we did not impute the outcome (White, Royston & Wood, 2011). For each maltreatment, we assessed the convergence of the imputation model and the distribution of imputed data as compared to the observed data.

Results

7.

Study results after winsorizing social cognition scores are shown in **Supplemental Table**

Exploring the Possibility that Social Cognition Predicts Child Maltreatment

A primary hypothesis tested in this paper was that childhood maltreatment predicts future social cognitive skills. However, children with poor social cognitive skills may also be more likely than their peers to be exposed to child maltreatment. To explore this possibility, we performed a secondary analysis to examine the association between social cognition and child maltreatment. The first assessment of social cognition was available at age 7.5 years, which preceded the last two assessments of child maltreatment that we included in the analysis: sexual or physical abuse by anyone at 8 years and caregiver physical or emotional abuse at 9 years. We therefore fitted logistic regression models to test whether being abused later on (at 8 or 9 years) was predicted by levels of social cognition at 7.5 years. All baseline covariates included in our original analysis were also adjusted for here. Specifically, we assessed the associations between social cognition measured at age 7.5 years and odds of being exposed to each type of maltreatment separately in sex-stratified analyses (i.e., a total of four logistic regression models were fitted). We did not differentiate between incident cases of exposure to maltreatment at 8 or 9 years and cases with prior history of exposure, to preserve statistical power and keep the model parsimonious.

Among youth exposed to caregiver physical or emotional abuse at 9 years (n=158), there were 65 children whose parents had reported incident maltreatment, meaning children who had experienced new instances of caregiver physical or emotional abuse. Among youth exposed to physical or sexual abuse (by anyone) at 8 years (n=137), there were 59 were incident cases.

As shown in **Supplemental Table 8**, we found that poorer earlier social cognition skills were generally associated with lower levels of exposure to maltreatment. Specifically, the odds of being exposed to maltreatment were lower by 6-11% for each one-point increase on the social cognition scale (or worsening of social cognition scores). For example, for female participants, each one-point increase in social cognition at age 7.5 years was associated with a 9% decrease in the odds for being exposed to sexual or physical abuse by anyone at 8 years (*OR*=0.91, *p*=0.012). Similarly, each one-point increase in social cognition at age 7.5 was linked to a 11% decrease in the odds of being exposed to caregiver physical or emotional abuse at 9 years (*OR*=0.89, *p*=0.0001).

However, for boys, social cognition scores were only associated with sexual or physical abuse. Taken together, these findings do not suggest the possibility that children with poor social cognitive skills are at a substantially higher risk than their peers to be exposed to child maltreatment.

Supplemental Table 1. Comparisons of baseline sociodemographic characteristics in the total analytic sample versus among three subsamples of ALSPAC participants

We compared the distributions of baseline characteristics between participants included in the total analytic sample (n=4438) and three other subsamples of ALSPAC: (1) participants who had at least one measure of social cognition, but were excluded based on other selection criteria (n=5239); (2) subset of the analytic sample who was exposed to sexual or physical abuse before age 10 $(n=590)$; and (3) subset of the analytic sample who was exposed to caregiver physical or emotional abuse before age 10 (n=774). Notably, the original eligible sample (N=9677) consisted of all children that had at least one measure of social cognition. We restricted these analyses to singleton births with complete outcome data who had mothers and maternal figures as the sole reporters of their social cognition skills over the three timepoints of assessment.

p-values were determined from chi-squared tests, assessing whether the distributions of categorical covariates were different across samples. Values corresponding to education level are presented in rank order from lowest education level (less than O or Ordinary level) to Degree.

Supplemental Table 2. Distributions of covariates and social cognition scores in the analytic sample versus the sample of participants who were excluded due to having non-maternal reports

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We compared the distributions of baseline characteristics between participants included in the total analytic sample (n=4438) and a subset of excluded participants who had complete outcome data at all three time points but non-maternal reports $(n=688)$.

p-values were determined from chi-squared tests and t-tests assessing the differences between the distributions of baseline covariates and social cognition skills in the two samples.

Supplemental Table 3. Summary of the two maltreatment measures and the time periods covered by

Supplemental Table 4. Tetrachoric correlations between caregiver physical and

Tetrachoric correlation coefficients are presented in each cell to show the pairwise correlation between caregiver physical and emotional abuse at each time point. Notably, the two measures, when measured at the same tie point (see the diagonal), were strongly correlated (*rho* > 0.7).

Note. These results were generated using non-imputed datasets.

Note. At each time period of measurement, there was a significant difference (p<0.001) between boys' and girls' scores

Supplemental Table 7. Results of the SLCMA for each measure of maltreatment on social cognition that were winsorized at the 90% percentile to address data skewness

Physical or emotional abuse

Stage 1 cell entries are r² values and p-values. Stage 2 cell entries are betas, standard errors, and pvalues derived from multiple linear regression (one regression for each type of maltreatment) and social cognition measurement). Models were only reported at Stage 2 when the covariance test pvalue was below the threshold of 0.1 .

Supplemental Figure 1. Example elbow plot illustrating LARs variable selection procedure ental Figure 1. Example elbow
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LARs begins by first identifying the single variable with the strongest association to the outcome; it then identifies the combination of two variables with the strongest association, followed by three variables, and so on, until all variables are included. LARs therefore achieves parsimony by identifying the smallest combination of encoded variables that explain the most amount of outcome variation. In addition to a covariance test, which is calculated at each stage of the LARs procedure and tests the null hypothesis that adding the next encoded variable does not improve r^2 , results can also be summarized in an "elbow plot," showing the increase in overall model r^2 as additional predictors are added to the model. The point where this plot levels off indicates the point of diminishing marginal improvement to the model goodness-of-fit from adding additional predictors, suggesting that the predictors included in the model at this point represent an optimal balance of parsimony and thoroughness. In this example, both accumulation and sensitive period 1 were selected in the best fitting models. SP =Sensitive Period.

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