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ABSTRACT

Unveiling Shadows: The Impact of Unemployment on Child Maltreatment*

Child maltreatment is pervasive, often undetected, yet harmful. We investigate whether it is impacted by unemployment by leveraging unique administrative data including all reported cases of child abuse and neglect in the United States from 2004 to 2012. Using an industry shift-share instrument to identify county-level unemployment effects, we find a substantial rise in neglect. The likely channel is lower quality-time spent with children rather than decreased financial investments. Expenditures on children remain stable during recessions. Instead, higher local-area unemployment rate reduces parental childcare time, worsens mental health, and contributes to an increase in one-parent households.

JEL Classification: I10, D10, J12, J13, K42

Keywords: child abuse and neglect, unemployment rate, recession, Bartik, mental health

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1 Introduction

Child maltreatment is defined as any act or failure to act by a parent or caretaker that results in death, serious physical or emotional harm, sexual abuse, or exploitation, or poses an imminent risk of serious harm (U.S. Department of Health and Human Services, 2021). It is often categorized into physical, sexual, or emotional abuse, and neglect.

The long-term repercussions of being maltreated in childhood are profound, including mental health issues, substance abuse, reduced educational attainment, lower productivity and earnings, and an increased likelihood of criminal behavior (Dube et al., 2003; Springer et al., 2007; Currie and Widom, 2010; Currie and Tekin, 2012). Research shows that around 33 percent of maltreated children perform one standard deviation below the national average in cognitive functioning measures (Crozier and Barth, 2005), between a quarter and a third of them exhibit symptoms of major depression by their late 20s (Gilbert et al., 2009), and are 14 percent less likely to be employed in middle age (Currie and Widom, 2010). Beyond the immediate and lifelong costs borne by the victims, child maltreatment imposes a significant economic burden on society at large (Peterson, Florence and Klevens, 2018). In 2021, the United States reported 588,229 cases of child maltreatment, translating to a rate of 8.1 victims per 1,000 children (U.S. Department of Health and Human Services, 2021). However, these figures likely represent only a fraction of the actual incidence, as the majority of child maltreatment occurs within the home, perpetrated by caregivers, and often remains undetected. Despite the widespread nature of this issue and its significant societal implications, the economic research on child maltreatment has been relatively limited.

Economic hardship is often depicted as a strong predictor of child abuse and neglect. Yet, there remains a significant paucity of causal empirical research in this area coupled with a lack of clear understanding of the mechanisms at play.[1] We fill this gap by examining the impact of unemployment on child maltreatment in the United States from 2004 to 2012, a period that includes the Great Recession. Our analysis utilizes a restricted-access dataset from the National Child Abuse and Neglect Data System (NCANDS), comprising individual records of every reported

[1] For a comprehensive review of studies addressing the economic drivers and consequences of child abuse and neglect, refer to Berger and Waldfogel (2011) and Slack, Berger and Noyes (2017). Literature examining the correlation between macro-economic conditions and maltreatment presents mixed results (Paxson and Waldfogel, 1999, 2002; Bitler and Zavodny, 2004; Seiglie, 2004; Stephens-Davidowitz, 2013; Frioux et al., 2014; Raissian, 2015; Raissian and Bullinger, 2017; Schneider, Waldfogel and Brooks-Gunn, 2017).

case of child abuse and neglect received by Child Protective Services across nearly all U.S. counties. Our focus is exclusively on substantiated cases of child maltreatment. These are instances where investigations conducted by Child Protective Agencies have yielded supportive evidence confirming abuse or neglect. To identify the impact of county-level unemployment, we use an industry shift-share or Bartik instrument which we create by interacting initial county industry shares and national industry unemployment rates (Bartik, 1991; Blanchard and Katz, 1992).[2]

In reduced form analysis, we find that a one percentage point increase in local unemployment rate leads to a 5.9 percent increase in overall abuse, which is mainly driven by a 13.6 percent increase in *neglect*. With a median prevalence of 536 cases of neglect per year per county, this would be equivalent to an additional 73 cases per year.

Given that our Bartik instrument is a combination of all sectors, it is important to understand what variation it uses. The instrument is invalid if the industry composition or associated unobserved variables directly influence our outcomes of interest (Baum-Snow and Ferreira, 2015). Following Goldsmith-Pinkham, Sorkin and Swift (2020), we conduct various tests to affirm our instrument's validity. Our findings indicate that the manufacturing sector predominantly contributes to the variation in the Bartik instrument. However, we show that the impact of unemployment on neglect is not exclusively attributed to this sector but is similar across various industries.

Underreporting is a notable concern in studies like ours. Firstly, our data offer an improvement over previous studies that depend on self-reported retrospective accounts of childhood abuse or neglect, or harsh parenting measures (Berger et al., 2016; Schneider, Waldfogel and Brooks-Gunn, 2017). Secondly, we demonstrate that the effect of unemployment captures an effect on the actual incidence of neglect and not reporting behaviour. This is established in three ways: unchanged results after accounting for employment shifts in high-reporting sectors; exclusion of reports from friends, neighbors, or other relatives, who, in the event of their unemployment, may be more prone to observe and report child maltreatment due to increased proximity to the child; and no significant impact of unemployment on unsubstantiated reports, which are less likely to represent true maltreatment cases.

[2]These types of instruments have been widely used in the literature since pioneer studies of local labour market dynamics by Bartik (1991) and Blanchard and Katz (1992), including related research that investigates the effect of economic conditions on domestic violence (e.g., Aizer, 2010; Anderberg et al., 2016; Lindo, Schaller and Hansen, 2018). A growing body of work discusses the validity and interpretation of these instruments (e.g., Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2022; Adao, Kolesár and Morales, 2019).

We explore various mechanisms by which unemployment might escalate child neglect, traditionally defined as a caregiver's failure to provide essentials like food, clothing, shelter, medical care, or supervision, thereby endangering the child's health, safety, and wellbeing.

Firstly, we empirically investigate an income channel. Neglect may arise from reduced family income or an increase in the prices of children's goods. By using individual-level data from the Consumer Expenditure Survey, we construct per-child expenditure measures for the period 2004-2012 (Schneider, Hastings and LaBriola, 2018). Controlling for state and year fixed effects, as well as, for individual and family characteristics, we find that our predicted unemployment does not alter the spending on education, childcare nor consumption goods. Results are similar when expenditure items are adjusted by income. Utilizing the American Community Survey which has a much larger coverage, we investigate whether unemployment reduces family income which it does. Despite the decrease in disposable income spending on children is not affected, indicating the lack of a direct pecuniary mechanism.

Secondly, we explore a time allocation channel. Changes in parental time allocation due to the recession can affect childcare. We use the American Heritage Time Use Study and we construct two aggregate measures of parental time allocation to children's activities which are time for basic care or management, and for educational or recreational activities (as in Amuedo-Dorantes and Sevilla (2014)). The total time spent in such activities corresponds to a measure of total care. We find that higher unemployment reduces the total time allocated to children. When unpacking the aggregate measures into specific activities, suggestive evidence shows that parents invest less in reading or talking to the child which could lead to educational or emotional neglect. Heterogeneous exercises show that most of the unemployment effect is concentrated among the 0-4 years old. Very young children are at higher risk of neglect and may be more vulnerable to insufficient parental time investment. This is particularly alarming given the importance of the early years in shaping long-term outcomes (Almond, Currie and Duque, 2018).

Finally, we test three indirect channels. Mental health issues, substance abuse or family instability stemming from financial stress can impair parental capacity to provide adequate care and supervision, either through incapacitation or directly via budget constraints. We construct individual-level outcomes on parental alcohol consumption and mental health using the Selected Metropolitan/Micropolitan Area Risk Trends Behavioral Risk Factor Surveillance System (BRFSS)

City and County Database which is a county-level representative version of the BRFSS which exists to derive more localized measures of health. These data allow to study the impact of our county-level Bartik on health and substance abuse controlling for county and year fixed effects. The results indicate a negligible and marginally statistically significant decrease in heavy drinking. Simultaneously, they show a substantial rise in parents reporting being in mental distress during an economic downturn which could explain the increase in neglect.

As a proxy for family instability, we derive three outcomes which are married, living apart, and being widowed or single from the American Community Survey. We find that the chances of being a married couple go down in a recession, and the ones of being apart increase. Taken together these findings show that the rise of one-parent households can be considered a potential channel.

Overall, child neglect seems to arise during economic downturns because of parental inability to adequately care as indicated by parental poorer mental health and lower time investments. Reductions in income do not seem to alter expenditure on children but may operate via exacerbating mental stress or the allocation of time which could be lower in single-earner families. Extensive related research shows how poor parental mental health hampers the development of children, particularly their emotional and behavioural developments (e.g., Dinarte Diaz et al., 2023).[3]

Our paper contributes to three strands of literature. Firstly, it advances our understanding of the causal impact of the business cycle on child's health and well-being. A vast literature has focused on the impact of unemployment on birth outcomes (Dehejia and Lleras-Muney, 2004), with recent works showing babies' health to be pro-cyclical (De Cao, McCormick and Nicodemo, 2022; Dettling and Kearney, 2023). Children's mental health also seems to get worse in economic busts (Golberstein, Gonzales and Meara, 2019).[4] Surprisingly, little attention has been paid to child maltreatment which is a critical measure of child well-being. Lindo, Schaller and Hansen (2018) investigate the impact of gender-specific employment on child abuse and neglect in California using predicted gender-specific employment rates in the spirit of a Bartik instrument. The authors find both abuse and neglect to drop when male employment increases, but to rise when female employment increases. They provide evidence that time spent with children is the main channel for the results on child abuse, given that

[3]Most parenting interventions aim at changing the parent-child interactions eliminating negative actions such as corporal punishment, rather than increasing financial or time investments (e.g., Campbell and Ramey, 1994; Heckman et al., 2017; Olds et al., 2019; Baker-Henningham, Bowers and Francis, 2023). For a discussion on parental investments and early childhood development see Attanasio, Cattan and Meghir (2022).

[4]Parallel research on foreclosure reaches similar conclusions (Lindo, 2011; Carlson, 2015; Currie and Tekin, 2012).

fathers are more likely to be the perpetrators. Their gender-specific opposite employment effects on neglect are harder to explain. Contrarily to child abuse, child neglect is a multifaceted type of maltreatment that hardly depends on the (in)actions of the mother or father alone. Lindo, Schaller and Hansen (2018) also consider overall unemployment (male plus female) showing that it does not change child maltreatment. We first replicate this result only for California confirming Lindo, Schaller and Hansen (2018)'s finding. Nevertheless, when using data for nearly all U.S. counties, we find a sizable and meaningful impact of the recession on neglect.[5] Contrarily to child abuse, child neglect is a multifaceted type of maltreatment that hardly depends on the (in)actions of one parent alone. Collating different survey data, we empirically test new mechanisms which are family income, expenditure on children, family structure and self-reported parental alcohol consumption and mental health.

Secondly, our work speaks to the booming literature on the impact of social safety net programs on child maltreatment prevention or reduction (e.g., Berger et al., 2016; Carr and Packham, 2021; Schneider, Bullinger and Raissian, 2021; Kovski et al., 2022; Bullinger and Boy, 2023; Bullinger, Packham and Raissian, 2023; Rittenhouse, 2023). For example, Bullinger, Packham and Raissian (2023) find that providing cash transfers to families in infancy reduces referrals to the child protective agencies later in life, as well as, the risk of physical abuse and mortality. Similarly to us, their results are not explained by a direct income effect, but by improving family stability and by increasing parental and/or relative childcare.

Lastly, our finding on neglect is policy relevant. Existing prevention programs have shown some success in reducing sexual and physical abuse, but not yet neglect (Bullinger et al., 2020). Nevertheless, neglect is the most frequent form of child maltreatment counting roughly 76 percent of all the cases of maltreatment in 2021 alone (U.S. Department of Health and Human Services, 2021). It is also the deadliest, being registered in 80 percent of fatal cases (Welch and Bonner, 2013; Bullinger et al., 2020). Given the latest estimates of the economic burden of child maltreatment spanning from 428 billion dollars for annual substantiated incident cases to two trillion dollars for investigated cases, disregarding the potential impact of future recessions on neglect would be damaging (Peterson, Florence and Klevens, 2018).

[5] This is similar to Oikawa et al. (2022) who investigate the impact of the recession on maltreatment in Japan. This paper is relevant as it sheds light on a different country, but lacks to provide evidence on any mechanism.

The paper is structured as follows. In Section 2, we present our empirical strategy and data. In Section 3, we outline the main results and several robustness checks. In Section 4, we explore the mechanisms for our results, and we conclude in Section 5.

2 Identification Strategy and Data

2.1 Identification Strategy

We wish to understand the effect of the unemployment rate on the incidence of child abuse and neglect. However, changes in the unemployment rate depend both on changes in labour demand and labour supply. In particular, any unobservable worker characteristic within a county might be correlated with both the unemployment rate and the incidence of child maltreatment in that county. To deal with this concern, we construct an exogenous variable that is more likely to isolate demand-driven changes in the unemployment rate, and is often referred to as shift-share or Bartik-instrument (Bartik, 1991; Blanchard and Katz, 1992).

Our Bartik is a predicted county-level unemployment rate constructed by taking the weighted average of the national-level unemployment rates across industries, where the weights or shares are the fraction of the employed working-age population in each industry and county the year before the start of the sample period as follows:

$$Bartik_{cst} = \Sigma_k N_{tk} w_{csk}. \tag{1}$$

Here, N_{tk} is the national-level unemployment rate, in each industry, k, in each time period, t. The weights or shares, w_{csk}, are the fractions of employed working-age individuals in each industry, k, in county c, state s, in the year 2003. Then, $Bartik_{cst}$ captures variation in unemployment that is driven by changes in the country's economy, but varies across counties because of historical differences in the distribution of nationwide industry employment by location. The identifying assumption is that counties that house industries with high unemployment rates do not experience other shocks that affect their number of children abused or neglected. We discuss threats to this identifying assumption in Subsections 3.2, 3.4, and 3.5 by following recent literature on the econometrics of the shift-share instrument (Goldsmith-Pinkham, Sorkin and Swift, 2020).

Our main reduced form equation is then:

$$Y_{cst} = \gamma + \delta Bartik_{cst} + X'_{cst}\phi + \psi_{st} + \eta_c + \epsilon_{cst} \tag{2}$$

where Y_{cst} is the natural logarithm of the number of abuses per year, for the type of maltreatment of interest, and $Bartik_{cst}$ is the Bartik instrument estimated as in Equation (1).[6] X'_{cst} include the natural logarithm of the child population, and the fractions of the population that are Black, Hispanic, and other race/ethnicity (non-White). County fixed effects, η_c, are included to control for any unobserved fixed differences between counties, while ψ_{st} captures state-year fixed effects which are needed to control for differences in the measurement of maltreatment (across states and over time within states).[7] We weight observations by the child population in the county-year, and we cluster standard errors at the state level. The coefficient of interest is δ which indicates the percentage change in the number of abuses in a county as a result of an increase in the unemployment rate by one percentage point. In Section (3.5), we demonstrate the robustness of our results to a variety of changes to our main specification.

2.2 Data and Summary Statistics

Child Maltreatment Data All fifty states and the District of Columbia have a Child Protective Services (CPS) agency, which is responsible for investigating reports of child maltreatment (Appendix B reports details about CPS and the process of reporting). We use a dataset which contains every reported incident of child abuse and neglect made to the CPS in nearly every state in the U.S. for the years 2004-12. This dataset comes from the National Child Abuse and Neglect Data System (NCANDS), produced by the National Data Archive on Child Abuse and Neglect (NDACAN). Our restricted-access version of the data with information on all counties of the report is part of a unique

[6] We also provide instrumental variable estimates in Subsection 3.4.

[7] Differences in measurement arise from several sources. First, the exact definitions of child abuse and neglect can vary slightly across states and over time within states (Child Welfare Information Gateway, 2014). For example, Washington state does not recognize emotional abuse. Second, some states include specific exceptions in their definitions of child abuse and neglect. For example, in thirty-one states and D.C., an exception is made for parents who choose not to seek medical care for their children due to religious beliefs. Third, states differ in who is mandated to report child abuse. Fourth, states have different systems to determine whether a referral should be classified as substantiated. Given these state-specific differences in child maltreatment measurement, we cannot perform the analysis focusing on commuting zones as often done in recent labour economic papers that use shift-share designs (e.g., David, Dorn and Hanson, 2013; Acemoglu and Restrepo, 2020). Some commuting zones cut across different states which would imply combining different forms of abuse or neglect together.

pilot secure micro-data program.[8] We focus on reports of neglect, physical, sexual and emotional abuse. For each child maltreatment report, we observe the gender, age and ethnic group of the perpetrator and victim, the report date, the type of maltreatment alleged, the county of the report and the outcome of the investigation.

For each county and year, we create a count of the total number of incidents of each type of maltreatment. If multiple children are maltreated within a single report, we count an incident for each of the children. We consider only incidents where that specific type of maltreatment is found to be substantiated by the CPS. We take the natural logarithm of those counts, after first adding 0.001 to all county-years, since some county-years have zero reports of some types of maltreatment.[9] Our analysis focuses on a final sample of 2,803 counties from forty-six states (Appendix C reports further details on how we constructed the working dataset).[10]

Unemployment Data We focus on the annual unemployment rate at the county level, using data from the Local Area Unemployment Statistics (LAUS) produced by the Bureau of Labour Statistics (BLS).[11] This county-level unemployment rate is partially model-based, as the number of unemployed new entrants and re-entrants is estimated by combining state-level data on labour force entry with county-level demographic information.[12] This introduces a measurement error which is also addressed by the Bartik.

To calculate the weights for the instrument (w_{csj}), we use county-level data from the Quarterly Census of Employment and Wages (QCEW) in 2003.[13]

We measure the national-level unemployment rates by industry using the Current Population Survey, where the industry of an unemployed person is the industry of their last job.[14] We consider the 2-digit industry classification provided by the North American Industry Classification System

[8]These data were accessible through contractual arrangements with NDACAN, and are solely available through the Cornell Restricted Access Data Center at CRADC@Cornell.edu.

[9]This varies by the type of maltreatment, but, for example, 10 percent of county-years have no incidents of physical abuse and 8 percent of county-years have no incidents of neglect.

[10]In each year, a small number of states do not submit information to NCANDS, which is a voluntary reporting system. We exclude Alaska, South Dakota, Illinois, North Dakota and Oregon from the analysis because their reports are not available for several counties or years, or because their geographical boundaries are not counties.

[11]Data can be downloaded from: `https://www.bls.gov/lau/`.

[12]See `http://www.bls.gov/lau/laumthd.htm` for further details.

[13]Data can be downloaded from: `https://www.bls.gov/cew/`. We first sum the annual average number employed across all ownership sectors (government and private), for each industry at a county level in 2003. This tells us the total number employed in each industry in 2003. We then sum these totals across all industries, and then divide the total employed in each industry by that sum to give the fraction of employed individuals in each industry.

[14]Data was sent to us by the BLS.

(NAICS), which consists of 20 industries.[15]

Extra Data We measure the child population, and the fraction of the population that are Black, Hispanic and Other Race using the Population and Housing Unit Estimates (PHUE), produced by the Census Bureau.

Summary Statistics In Table I, we present unweighted means, standard deviations, 25th, 50th and 75th percentiles for the main variables we use in the regression analysis. Neglect is considerably more common than the other three types of maltreatment. The mean number of incidents of neglect is four times greater than that of physical abuse, the next most frequent type of maltreatment. The variance in the number of incidents of all types of maltreatment per year is large, but particularly so for emotional abuse. Figure A1 in Appendix A shows a sharp increase in the unemployment rate between 2007 and 2009, following the onset of the Great Recession. The median county in our sample experienced an increase in the unemployment rate of 4.5 percentage points between 2007 and 2009. Both the size of the unemployment shock and the change in abuse rates vary considerably across counties within states as can be seen in Figures A2 and A3.

3 Results

3.1 Main Estimates

We initially test how well our Bartik instrument explains the raw county-level unemployment rate. The Bartik relevance is tested in two ways. First, in Figure A4 we show the correlation between the raw unemployment rate and our instrument using pooled data from the period 2004-2012. The figure indicates a strong positive relationship between the two measures of unemployment. Second, in Table II, we present the first stage results.[16] The coefficient on the Bartik instrument suggests that a one percentage point increase in the predicted unemployment rate leads to a 0.63 percentage

[15] We consider the following twenty industry categories: agriculture, forestry and fishing; mining; utilities; construction; manufacturing; wholesale trade; retail trade; transportation and warehousing; information; finance and insurance; real estate, rental and leasing; professional, scientific, and technical services; management of companies/enterprises; administrative, support, waste management and remediation services; educational services; health care and social assistance; entertainment and recreation services; accommodation and food services; other services; public administration.

[16] The first stage equation is: $Unemp_{cst} = \sigma + \theta Bartik_{cst} + X'_{cst}\kappa + \nu_{st} + \rho_c + \mu_{cst}$.

point increase in the actual unemployment rate. The instrument is highly relevant, the Kleibergen-Paap F-statistic on the first stage is 34.9. The identifying assumption is that counties that house industries with high unemployment rate do not experience other shocks affecting their number of children abused or neglected. We discuss threat to validity of the identifying assumption later in Subsection 3.2 and provide further robustness checks in Subsections 3.4-3.5.

We now present the OLS estimates between raw unemployment and child maltreatment in Table A1 in the Appendix using OLS. All estimated coefficients are positive, except for the association between unemployment and emotional abuse. None of them is statistically significant, apart marginally for physical abuse.[17]

We then report the reduced form estimates by regressing the number of maltreatment cases on our predicted unemployment rate following our baseline specification. Instrumental variable estimates are discussed in Subsection 3.4, but throughout the paper we present reduced form estimates as in Lindo, Schaller and Hansen (2018). Table III reports the results. In column (1), we estimate the effect of unemployment on overall abuse. The measure of overall abuse combines any incident of neglect, physical, sexual or emotional abuse. In columns (2) to (5), we separate out the four different types of maltreatment. The results in column (1) show that a one percentage point increase in the estimated unemployment rate leads to an 6 percent increase in overall abuse, and to a highly significant 14 percent increase in neglect in column (3).[18]

To benchmark our findings, we restrict our analysis to California as in Lindo, Schaller and Hansen (2018). The Appendix Table A2 reports these results which confirm the lack of significant effect between the overall predicted unemployment rate and maltreatment found by the authors. Nevertheless, focusing on the U.S. as a whole, we identify a clear rise in overall maltreatment driven by neglect. This is consistent with the findings reported by Oikawa et al. (2022) for Japan. In terms of magnitude, our estimates are similar to the impact of gender-specific employment rates reported by Lindo, Schaller and Hansen (2018). They find that male predicted employment rate decreases overall abuse and neglect by respectively 7-11 percent and 5-9 percent, while female predicted employment rate increases total abuse by 9-18 percent and neglect by 7-10 percent. Oikawa et al.

[17] Lindo, Schaller and Hansen (2018)'s OLS estimate of the overall unemployment rate on overall abuse is also statistically insignificant.

[18] Results are robust if we exclude the top one percent counties with the highest predicted unemployment rate (available upon request).

(2022) instead report a 80 percent increase in neglect when the local unemployment rate increases by 50 percent. In our case a 50 percent increase in the U.S. unemployment rate compared to its average is roughly an extra 4.3 percentage points which would result in a 55 percent increase in neglect, two-thirds of the Japanese effect.

In the remainder of the paper, we concentrate on analyzing the impact on neglect.

3.2 The Role of the Manufacturing Sector

The identifying assumption is that counties that house industries with high unemployment rates do not experience other shocks affecting their number of children abused or neglected. Given that the Bartik instrument is a combination of all sectors, it is important to understand what variation the instrument uses (Goldsmith-Pinkham, Sorkin and Swift, 2020).

In Figure A5 we plot the industry-specific Bartik instrument and we can see that the manufacturing sector has the highest predicted unemployment rate of any sector. To more formally test whether the manufacturing sector indeed has the greatest weight in our instrument we follow Goldsmith-Pinkham, Sorkin and Swift (2020). Goldsmith-Pinkham, Sorkin and Swift (2020) discuss how the Bartik instrument is equivalent to using the initial industry shares (multiplied with time fixed effects when multiple periods are used as in our case) as instruments in a weighted GMM estimation. They decompose the Bartik instrument into a weighted combination of just-identified estimates, each using a single share as an instrument. The weights are called Rotemberg weights.[19] We follow their approach and calculate these weights using our main specification for overall abuse and neglect. In Table A3 in Appendix A we report the Rotemberg weights only for industries with a weight above 3 percent. Manufacturing has the highest weight, about 73 percent, followed by Professional, Scientific, and Technical Services (11 percent), Construction (10 percent), Public Administration (6.4 percent), and Finance and Insurance (4.4 percent). This raises the concern that our estimates might be confounded by other changes affecting the manufacturing sector in particular.

[19] Borusyak, Hull and Jaravel (2022) instead offer a different interpretation of the Bartik where the identification assumption comes from the shocks - in our case, the national unemployment rate N_{tj} in each industry (see also Adao, Kolesár and Morales (2019) who develop the inference for Borusyak, Hull and Jaravel (2022)'s set-up). Goldsmith-Pinkham, Sorkin and Swift (2020) consider a setting with a large sample of locations, but a fixed number of time periods and industries, while Borusyak, Hull and Jaravel (2022)'s approach relies on the use of several industries. Therefore, our Bartik design follows Goldsmith-Pinkham, Sorkin and Swift (2020)'s reasoning, and is similar to recent applications based on a small number of shares (Card, 2001; Kovak, 2013; Acemoglu and Restrepo, 2020).

To address this issue, in Table IV we report reduced-form regressions based on our baseline specification where the Bartik is decomposed in a predicted unemployment rate only for the manufacturing sector and a predicted unemployment rate for all other industries (as in Acemoglu and Restrepo, 2020). We never reject the null hypothesis that the coefficients for the manufacturing and non-manufacturing Bartik variables are equivalent. This reinforces the credibility of our main findings, indicating that the observed effects of unemployment on child maltreatment are not exclusively influenced by the manufacturing sector but are rather consistent across various sectors.

3.3 An Effect on Actual Incidence or Reporting?

In this section we provide evidence that our results capture an effect of unemployment on the actual incidence of overall abuse and neglect and not on the reporting of maltreatment.

This is done in three ways as reported in Table V. First, an unemployment shock may result in a reallocation of labour to high-reporting sectors, such as schools, social services, health care, police, clergy and childcare, which could increase reporting rates for a given level of actual maltreatment Lindo, Schaller and Hansen (as in 2018). We use the American Community Survey data to compute the fraction of the working age (18-64) population who are employed in each sector.[20] In columns (1) and (2), we control for the fraction of the working-age population employed in these six high-reporting sectors. We find that the coefficient on the unemployment rate barely changes in either the regression for overall abuse or neglect, and the estimated coefficients on the high-reporting sectors are all statistically insignificant except one.

Second, unemployed individuals often spend more time at home, potentially increasing their chances of observing maltreatment among children of neighbors, friends, or extended family, even if the actual level of maltreatment remains constant. The NCANDS dataset contains a variable that records the identity of the reporter for each report. We therefore create a new dependent variable which excludes incidents reported by a friend, neighbor or other relative (those three groups account for 10.7 percent of all reports in our working sample). We only count reports made by groups of reporters who are not affected by this concern: professionals, parents and the alleged victim or

[20] To reflect the sampling design of the ACS, we sum the individual person weights to create the total (weighted) number employed in each sector, and divide this by the total (weighted) number of working age individuals. Since the geographic identifier in the ACS is the PUMA, we aggregate the data at county level by using the 2010 county to 2000 PUMA cross-walk.

perpetrator.[21] By definition, professionals only interact with the maltreated children through their job, and parents are sufficiently close to their own children that they have an opportunity to observe maltreatment whether they are employed or unemployed. In columns (3) and (4), we rerun the baseline regressions using this dependent variable. We restrict the sample to state-years where the reporter's identity is non-missing for more than 80 percent of substantiated reports. Again, we find that the coefficient on the unemployment rate barely changes in size or statistical significance in either regression.

Third, we have so far only considered substantiated reports, which comprise 19 percent of all reports. If unemployment affects reporting, then we should estimate a very similar effect on unsubstantiated reports.[22] If unemployment affects the actual incidence of maltreatment, then we should only see an effect on substantiated reports. In columns (5) and (6), we run the baseline regressions but now include only unsubstantiated reports in the dependent variable. There is no significant effect of unemployment on unsubstantiated reports of either overall abuse or neglect, and the point estimates are approximately one third of the size of the estimates for substantiated reports. In columns (7) and (8) we consider all reports (substantiated and unsubstantiated). As in Lindo, Schaller and Hansen (2018), we find our estimates to be qualitatively similar to our main results, even if the effects of the unemployment rate are smaller and only statistically significant for neglect.

3.4 Instrumental Variable Estimates

We also assess the recession's impact through an instrumental variable (IV) approach, detailed in Table A4.[23] Here, we showcase the second-stage results, where the unemployment rate is instrumented using our Bartik instrument. The Kleibergen-Paap F-statistics are about 35 confirming the

[21]Professionals are those employed in the following professions: social services, medical, mental health, legal, law enforcement, criminal justice, education; as well as child day care providers and substitute care providers.

[22]Stephens-Davidowitz (2013) focuses on physical abuse using Google search data and finds that the Great Recession led to a decrease in the reporting of abuse, but an increase in the rate of child mortality due to neglect. He notes that national economic shocks like recessions can decrease government spending on child protection across the country and so lower reporting of both substantiated and unsubstantiated maltreatment. Unfortunately, NCANDS did not share with us data on deaths due to neglect to allow us to replicate Stephens-Davidowitz (2013)'s analysis. We also could not find a county-level dataset of CPS budgets covering our sample period to explore if unemployment rate leads to cuts in CPS staff and resources. However, even if it does our main IV estimates can be thought of as a lower bound for the true effect.

[23]The second stage equation is: $Y_{cst} = \gamma^* + \beta \widehat{Unemp}_{cst} + X'_{cst}\phi^* + \psi^*_{st} + \eta^*_c + \epsilon^*_{cst}$.

relevance of our instrument.[24] A one percentage point increase in the unemployment rate leads to a significant 10, and 20 percent increase in respectively overall abuse (column (1)), and neglect (column (2)). In the county with the median prevalence of neglect, which has 536 cases per year, a one percentage point increase in the unemployment rate leads to an increase in neglect by 110 cases per year. These results resemble the reduced form estimates even if larger in magnitude.

In columns (3) and (4), we instead use industry shares times year fixed effects as instruments as suggested by Goldsmith-Pinkham, Sorkin and Swift (2020).[25] The effect of unemployment on overall abuse is positive, but is smaller in size and not significant. The effect on neglect is robust, still statistically significant, at the 10 percent level, and the point estimate is 0.06. In columns (3)-(4), we also report the over-identification tests for the validity of the source of variation coming from each industry. The tests reject the null hypothesis that all industry shares are valid. However, the identification assumption in these models is that each initial industry share is exogenous, a much stronger assumption than in our baseline specification which requires that counties where industries have a high unemployment rate are not experiencing other shocks which can affect child maltreatment. Based on the fact that the Bartik estimator combines many instruments, Goldsmith-Pinkham, Sorkin and Swift (2020) offer a way to investigate the failure of the overidentification. The idea is to explore whether the just-identified IV estimates associated with each industry share instrument (particularly the ones with high Rotemberg weight) are similar to the IV estimate obtained with the Bartik instrument. We follow this approach and find that the point estimates among the high-powered and the high-weight industries are clustered closely to 0.20 which is the effect of unemployment on neglect identified with the overall Bartik instrument.[26] We can then be less concerned by the rejection of the overidentification test.

[24]The first stage estimates are reported in Table II.

[25]To be able to estimate this model, the standard errors need to be clustered at the county level instead of state level as the number of clusters needs to exceed the number of exogenous regressors and excluded instruments.

[26]In Figure A6 we adopt the visual diagnostic offered by Goldsmith-Pinkham, Sorkin and Swift (2020) in order to see how disperse the just-identified IV estimates ($\hat{\beta}_k$) are around the overall Bartik instrument (β). The x-axis is the first-stage F-statistic and the y-axis is the $\hat{\beta}_k$ associated with each instrument. The outcome is neglect. The figure only includes instruments with a first-stage above five. The horizontal line corresponds to the Bartik instrument. Every individual point of β_k is scaled by his respective Rotemberg weight, and presents a different shape depending on the sign of the Rotemberg weight. The Rotemberg weights can also be negative, but in our case the industries with negative weights are only a small fraction of the overall weight (the total share of overall $\hat{\beta}$ with negative weights is 0.051, versus 0.949 with positive weights) (see Section 4 of Goldsmith-Pinkham, Sorkin and Swift, 2020, for further details).

3.5 Robustness Checks

In Table A5, we estimate our main specification by replacing the weights in our Bartik with the fraction of the employed working-age population in each industry in the county in 1995 instead of 2003. Using industry shares observed in 1995, about ten years before the start of our sample period, further mitigates concerns about the potential correlation between our predicted unemployment rates and contemporaneous confounders of child maltreatment outcomes. The results resembles our main ones reported in Table III even if the effects are slightly smaller in magnitude.

We make several other changes to the specification, and present the results in Table A6. In columns (1) and (2), we control for linear county trends. In columns (3) and (4), we drop the state-year fixed effects. In columns (5) and (6), we weight observations using the child population in the county at the start of the sample period, in 2003. In columns (7) and (8), we weight observations by the total population of all ages in the county-year. Finally, in columns (9) and (10), we cluster standard errors at the county level. The results are still very similar to those in Table III.

We check the robustness of the results to five alternative choices for the dependent variable in Table A7. In columns (1) and (2), we use the natural logarithm of the rate of maltreatment per 100,000 children, and accordingly no longer control for the natural logarithm of the child population on the right hand side. In columns (3) to (8), we use three alternative methods of dealing with the county-year cells with zero cases of maltreatment. In columns (3) and (4), we take the inverse hyperbolic sine transformation of the rate of maltreatment per 100,000 children. In columns (5) and (6), we add 0.01 to the number of incidents before taking the natural logarithm, and in columns (7) and (8), we add 0.0001. Finally, in columns (9) and (10), we count the number of children who are victims of maltreatment in each county-year, rather than the number of incidents. The results are again robust.

Finally, we show in Table A8 that our results are not driven by outlier counties, by dropping the counties with a child population of more than one million at the start of the sample period, in 2003 (columns (1)-(2)), and by dropping the smallest 10 percent of counties in terms of their child population at the start of the sample period, in 2003 (columns (3)-(4)).

4 Conceptual Framework and Empirical Mechanisms

In this section we describe the conceptual framework that helps us to understand the mechanisms through which unemployment can lead to child neglect.

Child neglect can take different forms. It can be physical neglect which is the failure to provide proper food, clothing, shelter, and hygiene; medical neglect when a caregiver fails to provide necessary medical care or treatments for a child's health conditions; educational neglect which pertains to not ensuring a child's access to proper education; supervisory neglect which occurs when a caregiver does not adequately supervise a child, leading to situations where the child is at risk of harm; emotional neglect which is the failure to meet a child's emotional needs for love, affection, attention, and support; or finally environmental neglect which relates to inadequate housing, exposure to hazardous materials (Radford, 2019).[27]

Economic hardship or income shocks may impact any type of child neglect via introducing financial constraints or impacting parental emotional availability or ability to care (DePanfilis, 2006; Hornor, 2014).

Different channels exist: a direct pecuniary or income mechanism and indirect non-pecuniary mechanisms. As in Paxson and Waldfogel (2002), we can think of a simple model of expenditure on 'children's goods' which includes goods, services and the time parents spend with children. Parents maximize their welfare given prices and endowments of time and money. Children's welfare and the set of goods and services they consume depend on prices, parental endowments and preferences. In this simple framework, child neglect happens when there is a decrease in income or an increase in the prices of children's goods.[28]

This model however ignores other important indirect mechanisms that can lead to neglect. Parental poor mental health or substance abuse have been found to be correlated with child neglect (Slack et al., 2011). Individuals may increase alcohol consumption or drug use to cope with stress after being made unemployed (Eliason and Storrie, 2009). Stress and depression also seem to

[27] Unfortunately, the existing NCANDS data do not allow to distinguish between the various categories of neglect which has been highlighted as a crucial limitation (Bullinger et al., 2020). Only for a few states and few years we observe medical neglect which is about 2 percent of the total child maltreatment cases. Using this subsample we test whether unemployment influences medical neglect but while we find an increase it is not statistically significant (results are available upon request).

[28] Since for 86.8 percent of substantiated incidents at least one of the perpetrators is a parent, we refer to parents when discussing the mechanisms.

increase with economic recessions (Ruhm, 2000, 2003; Hauksdóttir et al., 2013), particularly for disadvantaged or single-parent families (Paxson and Waldfogel, 1999; Currie, Duque and Garfinkel, 2015). Both higher substance abuse or worse mental health can limit a parent's ability to care for their children. Alternatively, they may have a pecuniary effect on neglect if they drain resources that could otherwise be used to materially satisfy the needs of the child.

Child maltreatment can occur in families of various compositions, including two-parent households, extended families, and single-parent households. Children in single-parent families however may be at higher risk of neglect because they have access to fewer financial resources or parental time. They may experience increased stress related to financial strain or time management and be unable to provide adequate care.

In what follows, we test the direct financial investment channel by exploring whether unemployment causes a decrease in family income and in expenditure on children's goods and services. We then study how the recession has impacted the time spent with children in various activities. We investigate whether alcohol consumption has increased, as well as, mental health issues. Finally, we focus on marital status as an extra potential mechanism for our findings. It is important to bear in mind that with the data at hand we cannot disentangle the effects of changes in economic conditions that work via changes in parental behaviors or directly via budget constraints (Paxson and Waldfogel, 2002).

4.1 Parental Expenditure on Children

In this section we empirically test whether the inadequate parental financial investments on children is a potential mechanism for the effect on neglect. Correlations have been found between child neglect and food shortages, difficulty with paying for clothing, housing, utilities, or other important bills (e.g. Courtney et al., 2005; Yang, 2015; Kim, Gundersen and Windsor, 2023).

We use individual data from the Consumer Expenditure Survey (CEX) for the period 2004-2012.[29] The CEX collects information on the income, expenditures and characteristics of a nationally representative sample of households in the United States. We use data from the interview

[29] We follow Schneider, Hastings and LaBriola (2018) and utilize their dataset built from CEX and available here: `https://ophastings.com`. For further details please see here: `https://www.bls.gov/cex/pumd-getting-started-guide.htm`. We convert all expenditure items to be in real terms, adjusted to 2014 dollars with CPI-U-RS.

surveys, which are collected quarterly for each household for 12 consecutive months. The data are organized into a household-quarter structure.[30] We restrict the sample to households with children with the oldest parent between 25-65 years of age. We focus on four different types of parental expenditure: schooling, lessons, childcare, and consumption goods (as in Schneider, Hastings and LaBriola, 2018). Schooling includes all costs related to school supplies, tuitions and accommodation. Lessons are expenditure for recreational lessons. Childcare expenditures are costs for nurseries, babysitters, nannies or daycare centers. Consumption goods instead are expenses for clothing and furniture (toys, books, games, electronic equipment, travel, and sporting goods). We also consider these four outcomes adjusted by household income.[31]

We estimate the following regression model that examines the effect of state-level predicted unemployment on parental financial investments on children:

$$Expenditure_{ist} = \tau + \pi Bartik_{st} + X'_{ist}\iota + \varpi_s + \zeta_t + \xi_{st} \tag{3}$$

$Expenditure_{ist}$ corresponds to the natural logarithm of real expenditure item per child for individual i living in state s and surveyed in year t. We create a state-level Bartik instrument, $\Sigma_j w_{sj} N_{tj}$, which is identical to the original Bartik instrument but with state-level weights, w_{sj}.[32] The vector X'_{ist} includes the following individual controls: household size, age of the oldest parent and age-squared, race of each parent, and work hours of each parent. We control for state and year fixed effects (ϖ_s and ζ_t). Regressions are weighted using CEX sampling weights to get representative calendar year estimates.[33]

We present the results in Table VI. For each expenditure item we estimate two regressions without (columns (1), (3), (5) and (7)) and with individual controls (columns (2), (4), (6) and (8)). We find that a one percentage point increase in the estimated unemployment rate causes a 3.7 percent decrease in expenditure on schooling per capita (column (1)), a 24 percent decrease in expenditure for recreational lessons (column (3)), a large 50 percent drop in childcare spending

[30] A household could be present between one and four times in the working dataset. For additional details see Schneider, Hastings and LaBriola (2018).

[31] In particular, we create measures of quarterly spending as a portion of quarterly income.

[32] The validity of the Bartik instrument in state-level regressions relies on the assumption that no individual state dominates national-level production in an industry, since otherwise state-level unobservable worker characteristics may be related to the national-level unemployment rate in that industry.

[33] We restrict the sample to the four hundred state-years that are included in the baseline regressions.

(column (5)), and finally a 5.4 percent reduction in expenditure on clothes, furniture and equipment (column (7)). Nevertheless, none of these estimates are statically different from zero. Including individual controls shifts these estimates to positive values, yet they remain statistically insignificant. Further analysis in Table A9 explores real expenditure items per child, adjusted for household income. The patterns are similar, except for schooling expenses, which increase by 26-29 percent following a one percent rise in the unemployment rate.

Overall, this analysis suggests that a direct financial channel is unlikely to explain the estimated increase in child neglect during economic downturns. While expenses like medical care or food consumption might decrease with rising unemployment, our current data does not allow us to determine the specific amounts spent on each family member, including children.[34]

4.2 Parental Time Investment

Unemployment increases the amount of time parents can theoretically spend with their children. Simultaneously, demands of job searching and stress can detract from the quantity of care and supervision provided.

To investigate how the recession impacts parental time investment on children we use the American Heritage Time Use Study (ATHUS). The study is a harmonized data set for American time use surveys, it is cross-sectional and representative at national level. It collects single-time diary from a selected adult in the household. We extract ATHUS data from IPUMS for the period 2004-2012. We exclude low-quality diary and we restrict the sample to households with children age 0 to 18.

We construct outcome variables that represent minutes spent by the mother or father in different activities with the children which in a day sums up to approximately 77 minutes on average. In particular, we follow Amuedo-Dorantes and Sevilla (2014) and construct two aggregate measures. Basic care or management activities include the time spent in taking physical care of children, organizing and planning for children and, looking after children and travel related to childcare. Educational or

[34] In an earlier version of the paper Brown and De Cao (2020), we use a state-year level dataset on Personal Consumption Expenditures (PCE) available from the Bureau of Economic Analysis. We find evidence that unemployment leads to a decrease in real expenditure on basic goods such as food and beverages, and on gasoline, energy and transportation. Part of these results align with Ganong and Noel (2019) who show that consumer spending on necessities like groceries declines during economic busts, and Griffith, O'Connell and Smith (2016) who find that during the Great Recession households cut real food expenditure but maintain the number of calories purchased. The data used in Brown and De Cao (2020) do not allow to identify the precise expenditure on children, but their results may indicate an effect of unemployment on other forms of neglect, such as physical neglect.

recreational activities include reading to children, teaching children, attending meetings at a child's school, playing games, playing outdoors, attending a child's events, and taking walks with children. Total care includes all activities combined (sum of time spent on basic or management, educational or recreational). We also derive an extra outcome which corresponds to age-appropriate activities as in Schneider, Hastings and LaBriola (2018). This variable includes childcare activities by age of the youngest household child (basic childcare and play for respondents with a child under age 2; time spent in learning activities for respondents with a child age 3 to 5; and time spent in management for parents with a child age 6 to 13).

In Table VII we report the estimates of a regression model where we study the causal impact of the predicted unemployment on each of these time use variables. Our empirical model is as Equation 3 except for the outcomes which here reflect time allocation. Every column includes state and survey year fixed effects. In the even columns, we also adjust for the following ATHUS controls: gender, age and age squared, race and college degree of the respondent, number of adults in the household, age of the youngest child, and a weekend diary dummy. Regressions are weighted using ATHUS individual sampling weight. The standard errors are clustered at the state level in all regressions.

All point estimates are negative indicating a reduction in time allocation to each of these activities. Parental time investment in basic care or management activities goes down by 2-7 minutes per day or between 4 and 14 percent (columns (1)-(2)), albeit not in a statistically significant way. Highly statistical significant decreases are found in educational or recreational activities where a one percentage point increase in unemployment leads to a reduction in the daily parental time spent in these activities by 6-8 minutes or about 20-30 percent. This finding is the main driver of the overall effect on total care which goes down by 10-20 percent. When individual controls are added into the regressions the impact of unemployment remains negative but less significant. Interestingly, the time spent in age-appropriate activities is also reduced (columns (5)-(6)), suggesting that economic downturns affect the availability and adequate time investment on children.

To further understand how investments change we disaggregate the activities and study how they are affected by the recession in Table A10. Basic care and management activities comprise physical care of respectively infants (column (1)) or older children (column (2)), medical care inside or outside the home (column (3)), and any other childcare activities such as unpaid babysitting and travel related to childcare (column (4)). Educational or recreational activities instead include time spent supervising school work (column (5)), playing with household children (column (6)), and time spent reading to or talking with the child, as well as, listening to children (column (7)). In every column we control for state and survey year fixed effects and the individual and diary characteristics ad in the even columns of Table VII. Except for medical care and supervision, the time spent in all other activities is reduced when unemployment increases. Nevertheless, none of these estimates are statistically significant, except for a relevant and substantial decrease in the time spent reading, taking or listening to children where a one point percentage increase in unemployment results in a drop in this type of parental time investment by more than 50 percent (from 5 minutes on average per day to 2.4). While our child maltreatment data do not allow to observe the sub-categories of neglect, these results suggest the importance of time investments to prevent emotional or educational neglect.

Who are the most affected children? In Table VIII, we ask whether the causal impact of unemployment differs by the victim's age. We see that while the point estimates for the effect on overall abuse are similar across the two age groups, the effect of the predicted unemployment on neglect of young children (0-4 years) is more than double that for older children (5-17 years). A one percentage point increase in the predicted unemployment rate leads to a 15 percent increase in neglect of children aged 0-4 which is highly statistically significant.

In summary, these results indicate that toddlers are particularly at risk of neglect in a recession, and one of the reasons could be a decrease in parental time allocated to childcare. Parents may be physically present but mentally preoccupied, reducing the attention and engagement with their children. Lindo, Schaller and Hansen (2018) instead find that higher paternal employment lowers abuse rates, in contrast to maternal employment, which increases them, attributing this difference to fathers being more often the main perpetrators. Although our study focuses on informal childcare by parents, our findings are consistent with Sandner, Thomsen and Gonzales (2023), who show that increasing public childcare availability reduces child maltreatment in Germany. This suggests that inadequate childcare may lead to a higher risk of maltreatment.

4.3 Substance Abuse and Mental Health

Substance abuse, including drug or alcohol consumption, as well as inadequate mental health, can hinder parents from providing proper care for their children. Related research indicates a surge in drinking and smoking, potentially stemming from reactions to job loss or uncertainty, frequently among more vulnerable demographic segments (Charles and DeCicca, 2008; Deb et al., 2011; Currie, Duque and Garfinkel, 2015).

To investigate these channels we employ data sourced from the Selected Metropolitan/Micropolitan Area Risk Trends (SMART) Behavioral Risk Factor Surveillance System (BRFSS) City and County Database.[35] The BRFSS serves as an annual health-related telephone survey of households within the United States, comprising one of the world's largest continuously conducted health survey systems. The SMART subset of the BRFSS is produced to yield localized estimates, and for our research objectives, it is representative at the county level.

We aggregate individual-level data spanning the years 2005 to 2012. To refine our understanding of parental behavior, we restrict the data to households with children, constituting approximately 40 percent of the initial sample, while also excluding respondents below the age of 18. Notably, in nearly 90 percent of these child-present households, the main respondent is a parent or step-parent.

Subsequently, we create two distinct outcome variables to address substance abuse, alongside two variables to characterize mental health status. Specifically, the individual outcomes are: (i) the mean count of alcoholic beverages consumed on a monthly basis, (ii) a binary indicator signifying heavy drinking or otherwise[36], (iii) a binary variable taking a value of one when the individual experienced poor mental health for at least 10 days within the past month[37], and (iv) a distress indicator, represented as a binary variable set to one if the number of days with unsatisfactory mental health within the last month equals or exceeds 14 (CDC, 2001).

We estimate the following equation:

$$Health_{icst} = \tau + \pi Bartik_{cst} + X'_{icst}\iota + \varpi_c + \zeta_t + \xi_{cst} \tag{4}$$

where $Health_{icst}$ indicates one of the four outcomes defined above for individual i living in county c, state s and interviewed in year t. $Bartik_{cst}$ is the Bartik as in our baseline Equation (1), ϖ_c and ζ_t contain county and year fixed effects, and the vector X_{icst} include a set of individual controls

[35] Additional information can be found at: `http://www.cdc.gov/brfss/`.

[36] Heavy drinking entails exceeding one daily drink for women or two daily drinks for men (Dwyer-Lindgren et al., 2015).

[37] The question in the BRFSS is: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?"

which are the respondent's age and age squared, gender, race, college degree and income ban.

In Table IX, we report the estimates of Equation (4). Odd columns report the results without individual controls, while even columns include also individual characteristics. Standard errors are clustered at the county level, and SMART BRFSS county sampling weights are applied. Our findings in columns (1)-(4) suggest a decrease in alcohol consumption with rising unemployment, albeit only marginally statistically significant when focusing on heavy drinking. A one percentage point increase in unemployment is linked to a 0.7 percentage point reduction in heavy drinking, equivalent to a 15 percent drop with respect to the mean (0.048).

In columns (5)-(8), the focus shifts to mental health, where recessions appear to exacerbate distress and overall mental health degradation. The impact remains consistent even after adjusting for individual controls, with a one percentage point rise in unemployment leading to a 1.2-1.4 percentage point increase in the likelihood of experiencing distress, an approximate 11-13 percent increase. This trend is mirrored in the poor mental health outcome, showing similar magnitudes of effect as the distress outcome.

Similar to findings by Currie, Duque and Garfinkel (2015), Lindo, Schaller and Hansen (2018), De Cao, McCormick and Nicodemo (2022), and Dettling and Kearney (2023), our study corroborates the negative effects of recession on parental health found both in the United States and the UK. Echoing Lindo, Schaller and Hansen (2018), our results suggest that deteriorating parental mental health due to unemployment could contribute to increased neglect. Notably, our analysis is based on self-reported measures, in contrast to Lindo, Schaller and Hansen (2018), who focus on more severe outcomes like hospitalizations and fatalities from poisonings and self-harm, indicative of extreme substance abuse and psychological distress.

4.4 Family Structure and Family Income

Family structure can significantly influence the susceptibility to child maltreatment (Berger, 2004). Single-parent households frequently encounter distinctive challenges owing to their exclusive responsibility for childcare. This translates to fewer financial resources and available time, potentially resulting in a less favorable caregiving environment and an increased risk of child neglect. In the subsequent analysis, we explore whether unemployment impacts the composition of households and their income.

We leverage data from the American Community Survey (ACS), which is accessible via IPUMS and spans the period from 2004 to 2012. The ACS is a nationally representative household survey that gathers annual information about the US population and housing dynamics. Our sample selection narrows down to families with underage children, where the respondent is aged 18 or older. We concentrate on four categorical outcomes: (i) married, (ii) apart (comprising divorced, separated, or married individuals living separately), (iii) widowed or single, and (iv) previous annual household income.[38] It is noteworthy that families categorized under outcome (ii) where both parents potentially contribute to the child's care, even if living apart, might exhibit an economic advantage in contrast to families classified under outcome (iii) with only one parent present.

The findings of our analysis are presented in Table X. Our regressions include survey year and state fixed effects, and are weighted using the household ACS sampling weights, similarly to the empirical Equation 3. Columns (2), (4), and (6) incorporate additional controls, namely family size, the count of children below five years of age, respondent's gender, ethnicity and race (White or Hispanic), educational attainment (college degree), age, and age squared.

Examining columns (1) and (2), we identify a negative and significant impact of unemployment on the likelihood of being married. Specifically, a one percentage point rise in the unemployment rate is associated with a 1.5 percentage point decrease in the likelihood of being married, which corresponds to a 2.1 percent reduction relative to the mean (0.72). This reduction is 2.6 percent when individual controls are added to the regression. The probability of being married with the spouse living apart, or being separated or divorced increases by 4.7-6.9 percent when the unemployment rises by one percentage point, albeit the effect is only marginally statistically significant. Contrarily, an economic downturn appears to increase the probability of being single or widowed but this is insignificant. Family income decreases by 13-14 percent with an increase of the predicted unemployment by one percent.

Taken together, our findings suggest that the recession dissuades marriage, favors parents who live apart or have legally dissolved marriages, and decreases the available financial resources. While a decrease in income does not translate into a reduction in expenditure on children, it could operate indirectly via increasing parental stress. Our result concerning marriage aligns with a prevailing pattern in the literature, which typically demonstrates its pro-cyclical nature (Bellido and Marcén,

[38]Family income is adjusted to 2014 dollars with CPI-U-RS.

2021).[39] Further research has shown an increase in divorce rates associated with a spouse's job displacement (Charles and Stephens, 2004).[40] Our result on family income reconciles with a booming literature showing how income increases from various programs such as minimum wages, tax benefits, EITC or child support pass-throughs reduce the child protection system involvement and child maltreatment (e.g., Schneider, Bullinger and Raissian, 2021; Kovski et al., 2022; Bullinger and Boy, 2023; Bullinger, Packham and Raissian, 2023; Rittenhouse, 2023). In particular, Bullinger, Packham and Raissian (2023) show that higher cash transfer early in a child's life results in a more stable home environment and in higher parental or relative caregiving which in turn reduce child maltreatment.

5 Conclusion

Child neglect has received the least scientific and public attention, yet mounting evidence suggests its consequences are equally damaging as sexual or physical abuse (Gilbert et al., 2009; Bullinger et al., 2020). Despite the critical repercussions of neglect, our understanding of its underlying causes remains limited. This knowledge gap hinders the effective design of child protection interventions. Our paper unveils the impact of a macroeconomic determinant: unemployment. We use a new dataset containing every reported incident of child abuse and neglect made to the Child Protective Services for nearly every state in the U.S. from 2004 to 2012. To avoid endogeneity, we use a predicted county-level unemployment rate, a Bartik instrument, which is formed by interacting initial county industry shares and national industry unemployment rates. Reduced form estimates show that a one percentage point increase in the unemployment rate leads to a 14 percent increase in neglect, but no significant changes in the other forms of maltreatment.

As neglect is the failure to provide for a child's basic needs risking their health and well-being, we primarily explore a direct pecuniary channel. The likelihood of neglect might be higher if there is a decrease in income as a consequence of the recession. Although suggestive evidence shows a drop in family income, we do not find lower expenditure on children's goods and services. A decline in economic resources induced by the recession may then indirectly heighten neglectful parenting.

[39] Recent research highlights the decline in marriage rates in the US as a significant contributor to economic inequality and the deterioration of children's educational and behavioral outcomes (Kearney, 2023).

[40] Conversely, other studies show a decline in divorce and separation during economic downturns (Cherlin et al., 2013; Schaller, 2013), which contrasts with our findings.

In sum, the rise in one-parent families (including divorcees, separated or married but living apart), the decline of married parents as well as, less parental childcare investment and worse mental health could potentially lead to child neglect.

Financial support might help preventing or reducing child neglect in difficult economic times. The existing literature highlights the successful poverty-reducing impact of welfare programs (e.g., Ben-Shalom, Moffit and Scholz (2012); Moffitt (2013); Bitler, Hoynes and Kuka (2017)). Safety net programs may prevent children from being neglected when a parent is made unemployed, which may in turn have positive long-lasting consequences for those children. However, over the past 20 years, substantial changes to the U.S. welfare programs have led to increased spending on children near and above the poverty line, and less on the poorest ones (Hoynes and Schanzenbach, 2018). This might imply that the most disadvantaged children who are at greater risk of child maltreatment may have been left behind. It also emphasizes how replacing lost income during an economic downturn might benefit children and society in general.

Given that childhood experiences are known to affect a large set of outcomes throughout the lifecycle (Almond, Currie and Duque, 2018), more research is needed to evaluate the impact of poverty reduction programs on children protection, understanding why some low-income families are able to provide adequately for their children despite economic difficulties versus others whose economic conditions may lead to child neglect (Slack et al., 2011; Doyle and Aizer, 2018).

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Tables and Figures

Table I: Summary Statistics

	Mean	SD	25th percentile	Median	75th percentile
Number of Incidents of Physical Abuse	42.20	135.40	3	10.70	29
Number of Incidents of Sexual Abuse	22.58	67.79	2	7	20
Number of Incidents of Emotional Abuse	19.69	176.17	0	1	6
Number of Incidents of Neglect	185.21	621.47	11	43	126
Unemployment Rate %	6.85	2.99	4.6	6.1	8.5
Observations	24,181	24,181	24,181	24,181	24,181
Counties	2,803	2,803	2,803	2,803	2,803
States	46	46	46	46	46

Notes. In this Table, we present summary statistics for the full sample of 24,181 county-years included in the baseline regressions. All the summary statistics are unweighted and refer to substantiated cases.

Table II: The Effect of the Bartik on Unemployment Rate: First Stage Estimates

	Unemployment Rate	
	Overall/Emotional sample	Physical/Neglect/Sexual sample
	(1)	(2)
	OLS	OLS
Bartik	0.60***	0.63***
	(0.10)	(0.11)
State-Year Fixed Effects	Yes	Yes
County Fixed Effects	Yes	Yes
Controls for Ethnic Group	Yes	Yes
ln(Child Population)	Yes	Yes
Observations	23,468	24,181
Counties	2,771	2,803
States	45	46
Kleibergen-Paap F-stat	34.5	34.9

Notes. In this Table, we regress the unemployment rate on the Bartik. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. There are fewer observations for overall and emotional abuse because some state-years are missing observations for emotional abuse. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table III: The Effect of Unemployment on Child Maltreatment: Reduced Form Estimates

	Overall	Physical	Neglect	Sexual	Emotional
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Bartik	0.057***	0.038	0.128***	0.002	0.017
	(0.028)	(0.038)	(0.038)	(0.039)	(0.146)
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes
ln(Child Population)	Yes	Yes	Yes	Yes	Yes
Observations	23,468	24,181	24,181	24,181	23,468
Counties	2,771	2,803	2,803	2,803	2,771
States	45	46	46	46	45

Notes. In this Table, we regress the Bartik on a different outcome of child maltreatment. In each case, the dependent variable is the natural logarithm of the number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. There are fewer observations for overall and emotional abuse because some state-years are missing observations for emotional abuse. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table IV: The Role of the Manufacturing Industry

	Overall	Physical	Neglect	Sexual	Emotional
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Manufacturing Bartik	0.052*	0.037	0.125***	-0.005	-0.013
	(0.027)	(0.036)	(0.036)	(0.041)	(0.141)
Non-Manufacturing Bartik	0.084*	0.040	0.143**	0.043	0.174
	(0.045)	(0.059)	(0.057)	(0.043)	(0.232)
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes
ln(Child Population)	Yes	Yes	Yes	Yes	Yes
Observations	23,468	24,181	24,181	24,181	23,468
Counties	2,771	2,803	2,803	2,803	2,771
States	45	46	46	46	45
Test for equality of coefficients (p-value)	0.299	0.929	0.628	0.0944	0.240

Notes. In this Table, we regress the Manufacturing Bartik IV and the Non-Manufacturing Bartik IV on a different outcome of child maltreatment. In each case, the dependent variable is the natural logarithm of the number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. There are fewer observations for overall and emotional abuse because some state-years are missing observations for emotional abuse. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table V: The Main Results Capture an Effect on the Actual Incidence of Maltreatment, Not Reporting

	Control Reporting		Professional/Parent Reporters		Unsubstantiated Reports		All Reports	
	Overall	Neglect	Overall	Neglect	Overall	Neglect	Overall	Neglect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bartik	0.055*	0.115***	0.056*	0.137***	0.021	0.050	0.029	0.048**
	(0.028)	(0.036)	(0.028)	(0.045)	(0.043)	(0.055)	(0.021)	(0.023)
Fraction Employed in Schools	0.493	-0.307						
	(0.536)	(1.076)						
Fraction Employed in Social Services	0.814	0.952						
	(2.423)	(2.823)						
Fraction Employed in Health Care	0.221	0.946						
	(0.351)	(0.940)						
Fraction Employed in Police	-3.244	-1.045						
	(4.379)	(3.749)						
Fraction Employed in Clergy	3.838**	0.665						
	(1.637)	(3.014)						
Fraction Employed in Child Care	-0.437	-1.512						
	(1.407)	(1.638)						
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(Child Population)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,766	21,354	22,686	23,399	23,468	24,181	23,468	24,181
Counties	2,767	2,799	2,736	2,768	2,771	2,803	2,771	2,803
States	45	46	43	44	45	46	45	46
Mean of outcome	3.75	3.04	3.35	2.53	4.71	4.13	5.35	4.85

Notes. In this Table, we ask whether the main results capture an effect on the actual incidence of child maltreatment or reporting behaviour. In columns (1) and (2), we control for the fraction of the working-age population employed in high-reporting sectors. In columns (3) and (4), we only count incidents that are reported by a professional or the victim's parent. We restrict the regressions in columns (3) and (4) to state-years for which more than 80% of reports had a non-missing reporter. In columns (5) and (6), we count unsubstantiated reports, while in columns (7) and (8) we include all reports, substantiated and unsubstantiated. In each case, we present the results from the second stage. The dependent variable is the natural logarithm of the relevant number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. Standard errors (in parentheses) are clustered at the state level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table VI: Parental Expenditure on Children

	Schooling		Lessons		Childcare		Consumption goods	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bartik	-0.0374	0.1409	-0.2424	-0.1511	-0.5012	-0.3910	-0.0539	0.0125
	(0.1669)	(0.1331)	(0.2229)	(0.1759)	(0.3032)	(0.2936)	(0.1226)	(0.1214)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEX Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	24,679	24,679	9,461	9,461	13,256	13,256	40,341	40,341
Mean Outcome	4.713	4.713	5.022	5.022	5.990	5.990	4.550	4.550
Mean Unemployed	6.087	6.087	6.106	6.106	6.097	6.097	6.160	6.160

Notes. In this Table, we ask whether unemployment decreases parental expenditure on children that could in turn lead to child neglect. We use individual data from the Consumer Expenditure Survey (CEX) for the period 2004-2012. Schooling includes expenditure on student room and board, school meals, books, supplies, and equipment, tuition, and any other school-related expenses. Lessons includes fees for recreational lessons and other instruction. Childcare includes all costs for babysitting, nannies, daycare centers, and nursery schools. Consumption goods include spending on clothes, children's furniture and equipment. Every column includes state and survey year fixed effects. In columns (2), (4), (6) and (8) we also adjust for the following CEX controls: household size, age of the oldest parent and age-squared, race of each parent, and work hours of each parent. Regressions are weighted using CEX individual sampling weight. We restrict the sample to the 400 state-years that are included in the baseline regressions. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table VII: Parental Time Investment in Childcare

	Basic/Management		Educational/Recreational		Age-appropriate		Total care	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bartik	-7.0195	-2.4118	-8.1401**	-5.5907	-11.9887***	-2.8755	-15.1596**	-8.0024*
	(4.7513)	(3.4086)	(3.0318)	(3.3529)	(4.1187)	(4.4663)	(5.6497)	(4.5309)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATHUS Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	48,245	48,245	48,245	48,245	39,304	39,304	48,245	48,245
Mean Outcome	49.28	49.28	27.37	27.37	47.20	47.20	76.66	76.66
Mean of Bartik	6.183	6.183	6.183	6.183	6.194	6.194	6.183	6.183

Notes. In this Table, we ask whether unemployment decreases parental time investment on childcare activities that could in turn lead to child neglect. We use individual data from the American Heritage Time Use Study (AHTUS) for the period 2004-2012. The outcomes represent minutes spent in different activities. In columns (1)-(4) we consider aggregated measures of time as in Amuedo-Dorantes and Sevilla (2014). Basic care or management includes the physical care of children, organizing and planning for children and, looking after children and travel related to child care. Educational or recreational includes reading to children, teaching children, attending meetings at a child's school, playing games, playing outdoors, attending a child's events, and taking walks with children. Age-appropriate is defined in Schneider, Hastings and LaBriola (2018) and it includes childcare activities by age of the youngest household child (basic childcare and play for respondents with a child under age 2; time spent in learning activities for respondents with a child age 3 to 5; and time spent in management for parents with a child age 6 to 13). Total care includes all activities combined (sum of time spent on basic or management, educational or recreational). Every column includes state and survey year fixed effects. In columns (2), (4), (6) and (8) we also adjust for the following ATHUS controls: gender, age and age squared, race and college degree of the respondent, number of adults in the household, age of the youngest child, and a weekend diary dummy. Regressions are weighted using ATHUS individual sampling weight. We restrict the sample to the 400 state-years that are included in the baseline regressions. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table VIII: Heterogeneous Effects by Age

	Age 0-4		Age 5-17	
	Overall	Neglect	Overall	Neglect
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Bartik	0.073**	0.151***	0.060**	0.074
	(0.035)	(0.047)	(0.026)	(0.068)
State-Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes
ln(Child Population)	Yes	Yes	Yes	Yes
Observations	23,468	24,181	23,468	24,181
Counties	2,769	2,801	2,545	2,577
States	45	46	45	46
Mean of outcome	2.57	2.12	3.24	2.27

Notes. In this Table, we test whether there are heterogenous effects of unemployment by age. In columns (1) and (2), we consider maltreatment among 0-5 year old children, while in columns (3) and (4) we focus on 5-17 year old children. In each case, the dependent variable is the natural logarithm of the number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population in each respective age group (0-4 in columns (1)-(2) or 5-17 in columns (3)-(4)) and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the county-year 0-4 child population in columns (1)-(2) and by the county-year 5-17 child population in columns (3)-(4). Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table IX: Alcohol Consumption and Mental Health

	Drinks per month		Heavy drinker		Being in distress		Poor mental health	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bartik	-0.6619	-0.7483	-0.0072*	-0.0074*	0.0143**	0.0122**	0.0198**	0.0175*
	(0.5163)	(0.5188)	(0.0040)	(0.0040)	(0.0060)	(0.0061)	(0.0086)	(0.0090)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BFRSS Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	357,498	357,498	357,498	357,498	360,339	360,339	360,339	360,339
Mean Outcome	10.33	10.33	0.048	0.048	0.109	0.109	0.141	0.141
Mean of Bartik	6.062	6.062	6.062	6.062	6.058	6.058	6.058	6.058

Notes. In this Table, we ask whether unemployment changes alcohol consumption and mental health in a way that could in turn lead to child neglect. We use individual data from the SMART Behavioural Risk Factor Surveillance System (BRFSS) City and County database for the period 2005-2012. Drink per month represents the average number of alcoholic beverages consumed per month; heavy drinker is a dummy equal to one if the individual is a heavy drinker; being in distress is a dummy variable equal to one if the number of days when the individual's mental health was not good in the last month is equal or above to 14; poor mental health is a dummy variable equal to one if the number of days when the individual's mental health was not good in the last month is equal or above to 10. Every column includes county and survey year fixed effects. In columns (2), (4) and (6) we also adjust for the following BFRSS controls: respondent's age and age squared, gender, race, college degree and income ban. Regressions are weighted using SMART BFRSS county sampling weight. We restrict the sample to the county-years that are included in the baseline regressions. Standard errors (in parentheses) are clustered at the county level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table X: The Impact of Unemployment on Family Structure and Income

	Married		Apart		Widowed/Single		Family Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bartik	-0.0153***	-0.0187***	0.0111*	0.0076*	0.0042	0.0112	-11.8884***	-12.7894***
	(0.0047)	(0.0066)	(0.0055)	(0.0045)	(0.0051)	(0.0069)	(1.6374)	(1.8470)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ACS Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2,509,762	2,509,762	2,509,762	2,509,762	2,509,762	2,509,762	2,297,175	2,297,175
Mean Outcome	0.719	0.719	0.160	0.160	0.121	0.121	91.29	91.29
Mean of Bartik	6.293	6.293	6.293	6.293	6.293	6.293	6.294	6.294

Notes. In this Table, we ask whether unemployment affects family formation and dissolution which could in turn lead to child neglect. We use individual data from the American Community Survey (ACS) for the period 2004-2012. Married is a dummy variable equal to one if the respondent is married; apart is a dummy variable equal to one if the respondent is married but the spouse is living apart, separated or divorced; the outcome widowed or single corresponds to a respondent who is either widowed or single; family income is the annual family income adjusted to 2014 dollars with CPI-U-RS and expressed in thousands. Every column includes state and survey year fixed effects. In columns (2), (4), (6), (8) and (10) we also adjust for the following ACS controls: family size, number of children below five, whether the respondent is male, white, hispanic, has a college degree, his/her age and age squared. Regressions are weighted using ACS household sampling weight. We restrict the sample to the 400 state-years that are included in the baseline regressions. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For online publication

Appendix A: Additional Tables and Figures

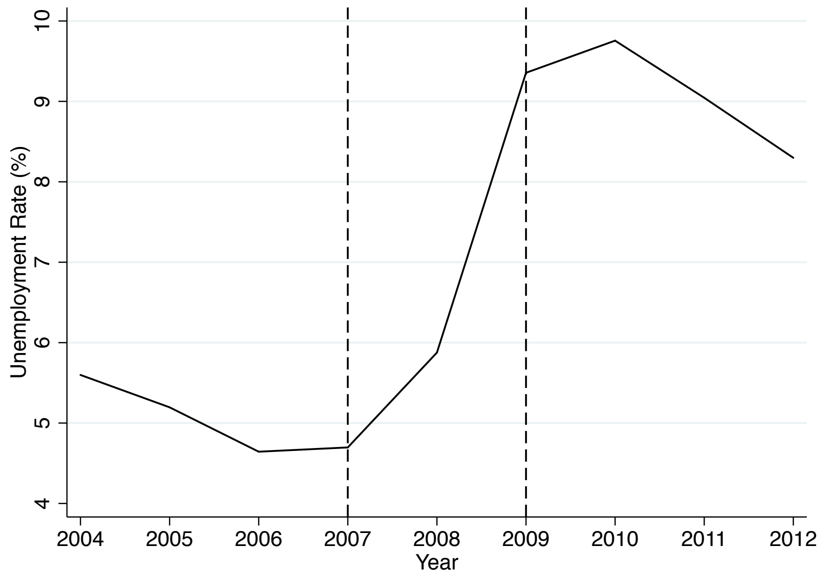

Figure A1: *Notes.* **Trend in the Unemployment Rate**. In this Figure, we present the trend in the weighted average unemployment rate across the 2,803 counties in our final sample. We weight observations by the child population, so that the unemployment rate is representative of where children reside in the U.S. Unemployment rates jumped during the period from 2007 to 2009, with the onset of the recession.

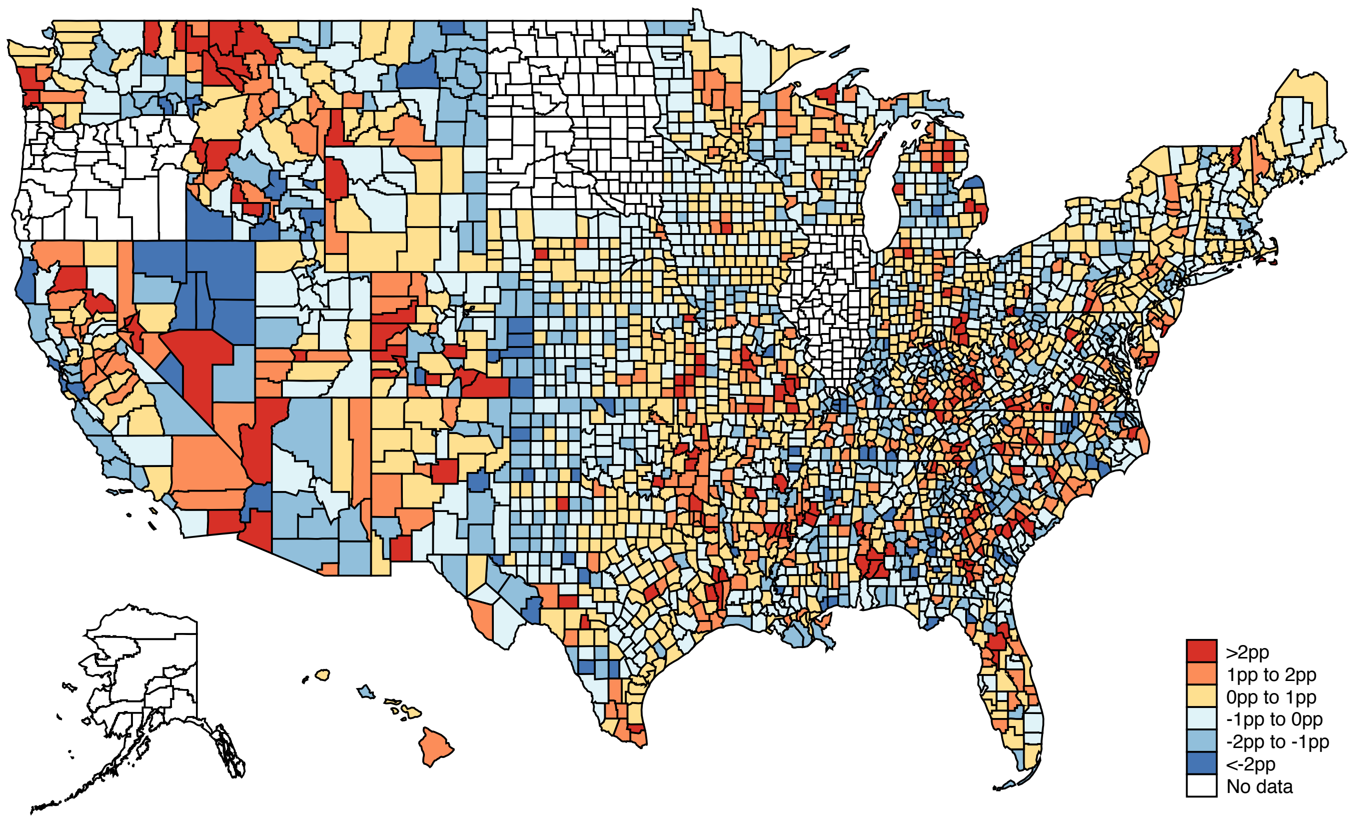

Figure A2: *Notes.* **Change in the Unemployment Rate Before and After the Recession**. This map presents the change in the unemployment rate before and after the recession. We regress the unemployment rate on state-year fixed effects. We take the residuals from this regression, and calculate the average for the pre-recession period 2004-2006 and for the post-recession period 2010-2012. We then subtract the pre-recession average from the post-recession average. Alaska and Hawaii are in the bottom left of the figure.

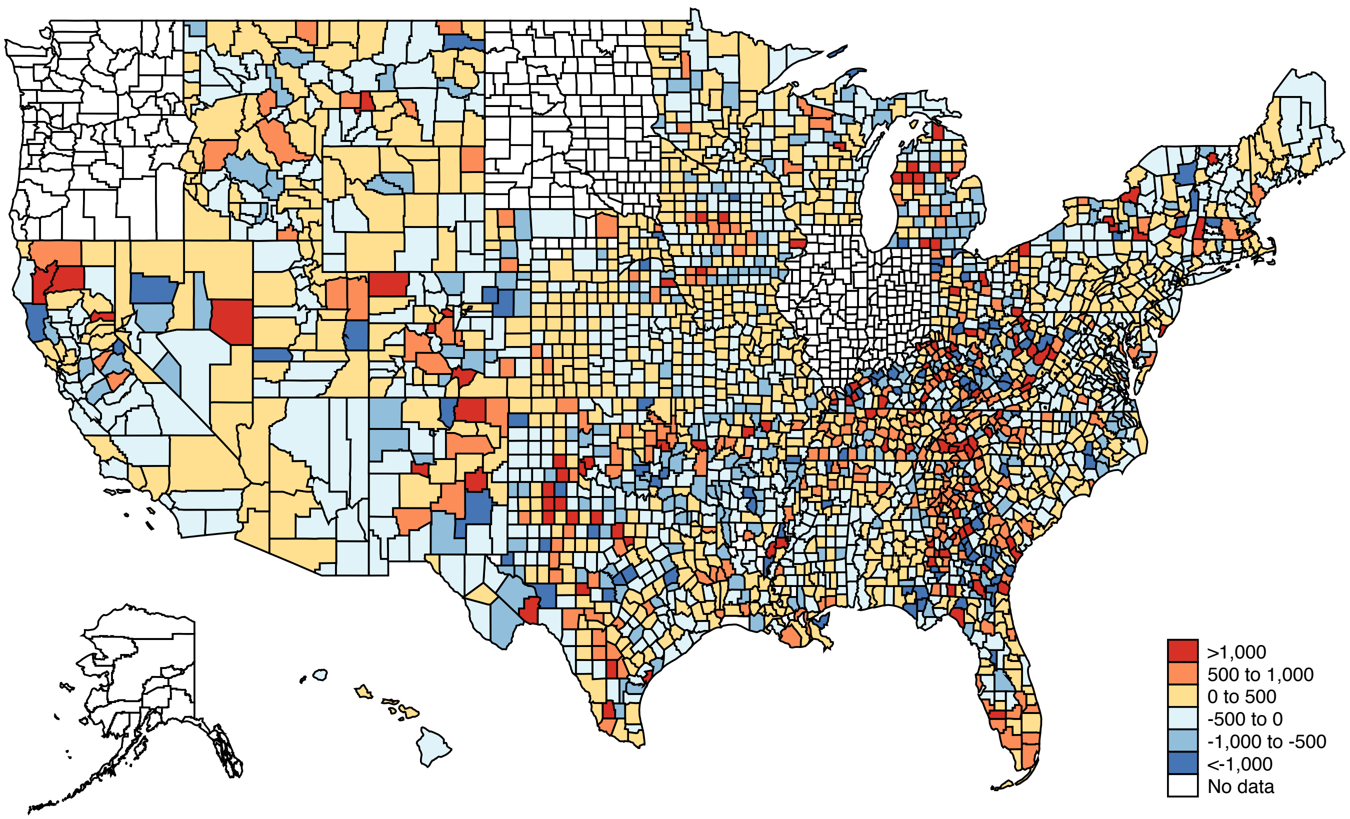

Figure A3: *Notes.* **Change in the Overall Abuse Rate Before and After the Recession**. This map presents the change in the overall abuse rate before and after the recession. We regress the overall abuse rate per 100,000 children on state-year fixed effects. We take the residuals from this regression, and calculate the average for the pre-recession period 2004-2006 and for the post-recession period 2010-2012. We then subtract the pre-recession average from the post-recession average. Alaska and Hawaii are in the bottom left of the figure. Washington does not record emotional abuse in any year, and Indiana does not record emotional abuse for the years 2004-7. Therefore, we cannot calculate the change in the overall abuse rate for either state and so they are missing from this map.

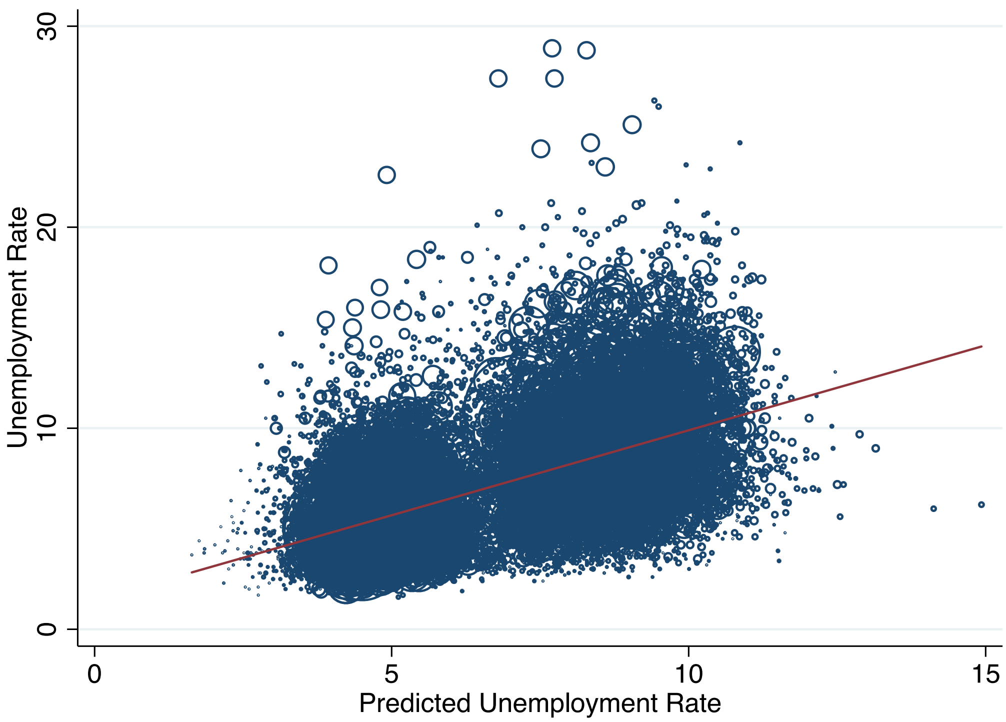

Figure A4: *Notes.* **Unemployment Rate and Predicted Unemployment Rate** The figure shows a scatterplot of unemployment rate and predicted unemployment rate (Bartik instrument) for the period 2004-2012 for all counties included in our main analysis, along with a regression line. Observations are weighted by child population.

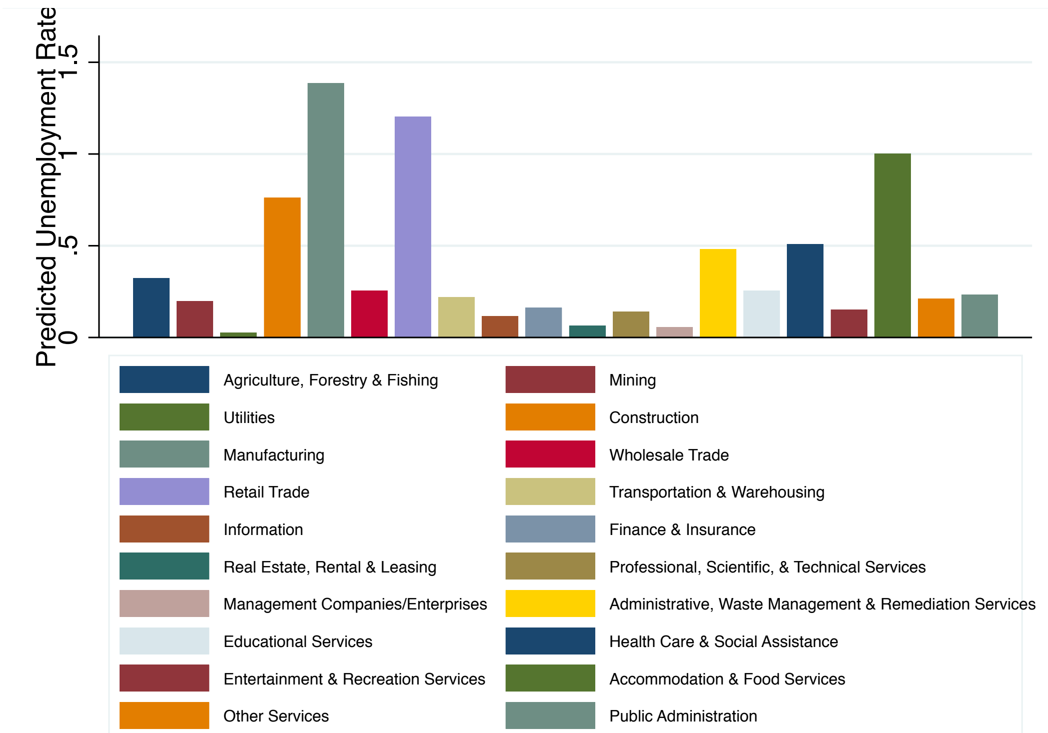

Figure A5: *Notes.* **Predicted Unemployment Rate by Industry.** The figure plots the predicted unemployment rate (Bartik instrument) for the period 2004-2012 for all the 20 industries.

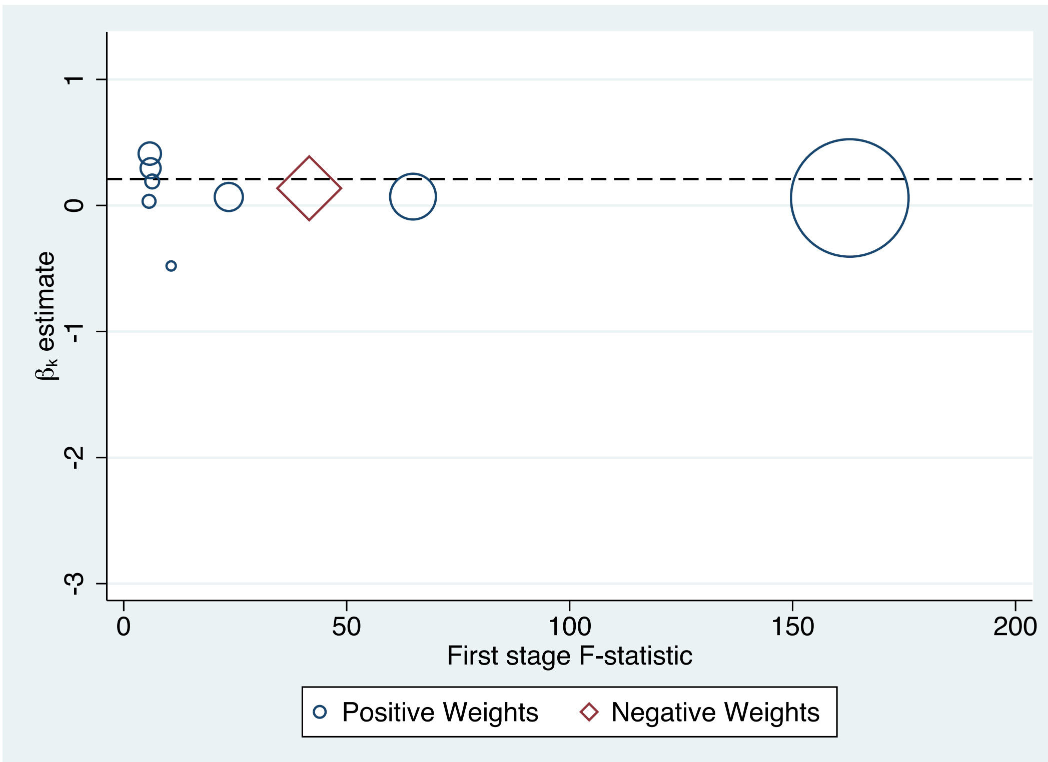

Figure A6: *Notes.* **Just-identified IV estimates based on the industry share instruments.** This figure plots the relationship between each industry share IV estimate $\hat{\beta}_k$, its first stage F-statistic, and its Rotemberg weight. Each point is a separate industry share instrument. The estimated $\hat{\beta}_k$ for each instrument is reported on the y-axis, while its estimated first-stage F-statistic is on the x-axis. The regressions outcome is neglect. Only instruments with first-stage F-statistics above five are reported. The size of the points corresponds to the magnitude of the Rotemberg weights, the circles indicate positive Rotemberg weights and the diamonds indicate negative weights. The horizontal dashed line corresponds to the overall second stage $\hat{\beta}$ reported in column (2) of Table A4. For more details refer to footnote 25 and Goldsmith-Pinkham, Sorkin and Swift (2020).

Table A1: The Effect of Unemployment on Child Maltreatment: OLS Estimates

	Overall	Physical	Neglect	Sexual	Emotional
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Unemployment Rate	0.013	0.026**	0.002	0.010	-0.045
	(0.010)	(0.010)	(0.012)	(0.014)	(0.044)
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes
ln(Child Population)	Yes	Yes	Yes	Yes	Yes
Observations	23,468	24,181	24,181	24,181	23,468
Mean of outcome	3.77	1.65	3.05	0.94	-2.19
Mean of Unemployment Rate	6.86	6.85	6.85	6.85	6.86

Notes. This Table contains the results of the OLS regressions which look at the effect of unemployment on the incidence of overall, physical, sexual, emotional abuse and neglect. In each case, the dependent variable is the natural logarithm of the number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. There are fewer observations for overall and emotional abuse because some state-years are missing observations for emotional abuse. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: The Effect of Unemployment on Child Maltreatment in California

	Overall	Physical	Neglect	Sexual	Emotional
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Bartik	-0.160	-0.143	-0.117	0.031	-0.613
	(0.166)	(0.201)	(0.162)	(0.167)	(0.387)
County Year Trend	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes
ln(Child Population)	Yes	Yes	Yes	Yes	Yes
Observations	522	522	522	522	522
Mean of outcome	5.983	3.491	5.727	2.265	3.320
Mean of Bartik	6.264	6.264	6.264	6.264	6.264

Notes. In this Table we regress the Bartik IV on a different outcome of child maltreatment. In each case, the dependent variable is the natural logarithm of the number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, county linear year trend, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. Standard errors (in parentheses) are clustered at the county level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Rotemberg Weights

	Top 5 Rotemberg weight industries	
	Overall	Neglect
Industry	(1)	(2)
Manufacturing	0.734	0.732
Professional, Scientific, and Technical Services	0.116	0.111
Construction	0.109	0.104
Public Administration	0.064	0.074
Finance and Insurance	0.044	0.042

Notes. The table presents Rotemberg weights for the industries used in the construction of the Bartik instrument, as explained in Goldsmith-Pinkham, Sorkin and Swift (2020). We report the Rotemberg weights for outcomes overall abuse and neglect, and only for industries with a weight above 3 percent.

Table A4: The Effect of Unemployment on Child Maltreatment: Second Stage Estimates

	Bartik		Industry Shares	
	Overall	Neglect	Overall	Neglect
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
Unemployment Rate	0.096**	0.204***	0.023	0.064*
	(0.049)	(0.068)	(0.035)	(0.035)
State-Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes
ln(Child Population)	Yes	Yes	Yes	Yes
Observations	23,468	24,181	23,468	24,181
Counties	2,771	2,803	2,771	2,803
States	45	46	45	46
Mean of outcome	3.77	3.05	3.77	3.05
Mean of Unemployment Rate	6.86	6.85	6.86	6.85
Kleibergen-Paap F-stat	34.53	34.91		
Hansen Overid test p-value			0.000	0.007

Notes. In this Table, we report the second stage estimates of the effect of unemployment on overall abuse and neglect. In columns (1) and (2), we present the perfect identified model where the Bartik is used as instrument for the unemployment rate. In columns (3)-(4) we use the initial industry shares as instruments following Goldsmith-Pinkham, Sorkin and Swift (2020). In each case, we present the results from the second stage. The dependent variable is the natural logarithm of the relevant number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. Standard errors (in parentheses) are clustered at the state level in columns (1)-(2) and at county level in columns (9)-(10).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Robustness of Main Results: Alternative weights for the Bartik

	1995 Weight	
	Overall	Neglect
	(1)	(2)
	OLS	OLS
Bartik (1995 weights)	0.042*	0.103***
	(0.021)	(0.029)
State-Year Fixed Effects	Yes	Yes
County Fixed Effects	Yes	Yes
Controls for Ethnic Group	Yes	Yes
ln(Child Population)	Yes	Yes
Observations	23,459	24,172
Counties	2,770	2,802
States	45	46
Mean of outcome	3.77	3.05

Notes. In this Table, we check the robustness of the main results to using an alternative Bartik. In columns (1) and (2), we use the national-level unemployment rate by industry, weighted by the share of the employed working-age population at the county level in 1995. The dependent variable is the natural logarithm of the relevant number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. Standard errors (in parentheses) are clustered at the state level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Robustness of Main Results: Specification Changes

	Control County Trends		Drop State-Year FE		2003 Child Weight		Total Pop Weight		Cluster County Level	
	Overall	Neglect	Overall	Neglect	Overall	Neglect	Overall	Neglect	Overall	Neglect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bartik	0.026	0.067**	0.064	0.127**	0.056*	0.125***	0.060**	0.129***	0.060**	0.129***
	(0.028)	(0.033)	(0.051)	(0.057)	(0.028)	(0.037)	(0.027)	(0.037)	(0.030)	(0.037)
State-Year Fixed Effects	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear County Trends	Yes	Yes	No	No	No	No	No	No	No	No
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(Child Population)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,468	24,181	23,468	24,181	23,480	24,193	23,468	24,181	23,468	24,181
Counties	2,771	2,803	2,771	2,803	2,771	2,803	2,771	2,803	2,771	2,803
States	45	46	45	46	45	46	45	46	45	46
Mean of outcome	3.77	3.05	3.77	3.05	3.77	3.05	3.77	3.05	3.77	3.05
Mean of Unemployment Rate	6.86	6.85	6.86	6.85	6.86	6.85	6.86	6.85		

Notes. In this Table, we test the robustness of the main results for overall abuse and neglect. In columns (1) and (2), we control for linear county trends. In columns (3) and (4), we drop state-year fixed effects and add year fixed effects. In columns (5) and (6), we weight observations using the child population in the county in 2003. In columns (7) and (8), we weight observations using the total population in the county-year. Finally, in columns (9) and (10), we cluster standard errors at the level of the county. In each case, the dependent variable is the natural logarithm of the number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. In columns (1)-(4) and (9)-(10), we weight observations by the child population in the county-year. Standard errors (in parentheses) are clustered at the state level in the regressions in columns (1) to (8), and at the county level in columns (9) and (10).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Robustness of Main Results: Alternative Choices for the LHS Variable

	Ln(Rate)		IHS Rate		Add 0.01		Add 0.0001		Ln(Number of Children)	
	Overall	Neglect	Overall	Neglect	Overall	Neglect	Overall	Neglect	Overall	Neglect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bartik	0.057**	0.128***	0.057**	0.109***	0.055**	0.115***	0.059**	0.141***	0.058*	0.146***
	(0.028)	(0.038)	(0.027)	(0.035)	(0.027)	(0.035)	(0.028)	(0.041)	(0.035)	(0.045)
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(Child Population)	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,468	24,181	23,468	24,181	23,468	24,181	23,468	24,181	17,403	17,748
Counties	2,771	2,803	2,771	2,803	2,771	2,803	2,771	2,803	2,046	2,078
States	45	46	45	46	45	46	45	46	37	38
Mean of outcome	6.41	5.67	7.15	6.51	3.86	3.23	3.68	2.87	3.66	2.88
Mean of Unemployment Rate	6.86	6.85	6.86	6.85	6.86	6.85	6.86	6.85	6.84	6.86
Kleibergen-Paap F-stat	32.7	33.1	32.7	33.1	34.5	34.9	34.5	34.9	25.2	26.7

Notes. This Table contains the results of IV regressions which look at the robustness of the effect of unemployment on the incidence of overall abuse and neglect with respect to the choice of the dependent variable. In columns (1) and (2), we take the natural logarithm of the rate of abuse per 100,000 children. We first add 0.001 incidents to the number of abuses before taking the rate, to ensure that no county-years have a rate of zero before taking the natural logarithm. In columns (3) and (4), we take the inverse hyperbolic sine transformation of the rate of abuse per 100,000 children. In columns (1)-(4), we do not control for the natural logarithm of the child population, as the left hand side variable is already based on a rate per 100,000 children. In columns (5) and (6), the dependent variable is the natural logarithm of the number of incidents of overall abuse or neglect, after first adding 0.01. In columns (7) and (8), we again take the natural logarithm of the number of incidents, but now add 0.0001. In columns (9) and (10), we take the natural logarithm of the number of children who are victims of overall abuse and neglect (after adding 0.001), rather than the number of incidents. Only 38 states record a unique child ID variable, and so can be included in these two regressions. In columns (5)-(10), we control for the natural logarithm of the child population. We control for county fixed effects, state-year fixed effects, and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. We weight observations by the child population in the county-year. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Robustness of Main Results: Sample Changes

	Drop Large Counties		Drop Small Counties	
	Overall	Neglect	Overall	Neglect
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Bartik	0.076***	0.142***	0.053*	0.126***
	(0.023)	(0.035)	(0.028)	(0.038)
Observations	23,450	24,163	21,480	22,186
State-Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes
ln(Child Population)	Yes	Yes	Yes	Yes
Observations	23,450	24,163	21,480	22,186
Counties	2,769	2,801	2,545	2,577
States	45	46	45	46
Mean of outcome	3.76	3.05	4.20	3.52

Notes. In this Table, we test the robustness of the main results for overall abuse and neglect. In columns (1) and (2), we drop the two counties with a population of more than one million children in 2003 (Harris, Texas; and Los Angeles, California). In columns (3) and (4), we drop the counties in the smallest 10% of counties in the United States in terms of 2003 child population, which are the counties with fewer than 1,232 children. In each case, the dependent variable is the natural logarithm of the number of incidents of that abuse type per year, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects, state-year fixed effects, the natural logarithm of the child population and the fraction of the overall population that is Black, Hispanic or Other Race. We weight observations by the child population in the county-year. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Parental Expenditure on Children Adjusted by Income

	Schooling		Lessons		Childcare		Consumption goods	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bartik	0.2645*	0.2889**	0.2473	0.1864	-0.2935	-0.2232	0.2036	0.0454
	(0.1476)	(0.1394)	(0.2372)	(0.2390)	(0.2198)	(0.2330)	(0.1540)	(0.1164)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEX Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	24,472	24,472	9,357	9,357	13,108	13,108	39,835	39,835
Mean Outcome	-5.217	-5.217	-5.198	-5.198	-3.999	-3.999	-5.224	-5.224
Mean Unemployed	6.085	6.085	6.103	6.103	6.099	6.099	6.162	6.162

Notes. In this Table, we ask whether unemployment decreases parental expenditure on children that could in turn lead to child neglect. We use individual data from the Consumer Expenditure Survey (CEX) for the period 2004-2012. Schooling includes expenditure on student room and board, school meals, books, supplies, and equipment, tuition, and any other school-related expenses. Lessons includes fees for recreational lessons and other instruction. Childcare includes all costs for babysitting, nannies, daycare centers, and nursery schools. Consumption goods include spending on clothes, children's furniture and equipment. Each outcome represents a share of household income. Every column includes state and survey year fixed effects. In columns (2), (4), (6) and (8) we also adjust for the following CEX controls: household size, age of the oldest parent and age-squared, race of each parent, and work hours of each parent. Regressions are weighted using CEX individual sampling weight. We restrict the sample to the 400 state-years that are included in the baseline regressions. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Parental Time Investment in Childcare - Disaggregated Activities

	Infants	Older children	Medical	Other care	Supervision	Play	Read/talk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bartik	-1.1154	-1.1461	0.1081	-0.2583	1.1258	-3.9513	-2.7652***
	(2.3302)	(1.7117)	(1.2128)	(2.8720)	(1.5468)	(2.8140)	(0.8182)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,245	48,245	48,245	48,245	48,245	48,245	48,245
Mean Outcome	20.58	10.26	1.628	16.82	5.408	16.80	5.162
Mean of Bartik	6.183	6.183	6.183	6.183	6.183	6.183	6.183

Notes. In this Table, we ask whether unemployment decreases parental time investment on childcare activities that could in turn lead to child neglect. We use individual data from the American Heritage Time Use Study (AHTUS) for the period 2004-2012. The outcomes represent minutes spent in different activities. Infants and older children indicate physical care of respectively infants or older children. Medical care includes medical care for children inside or outside the home. Other care is time spent in other childcare such as unpaid babysitting and travel related to child care. Supervision includes time spent supervising school work such as homework, exercises and lessons. Play comprises time spent playing with household children. Read or talk is time spent reading to/talking with child, listening to children. Every column includes state and survey year fixed effects. In columns (2), (4), (6) and (8) we also adjust for the following ATHUS controls: gender, age and age squared, race and college degree of the respondent, number of adults in the household, age of the youngest child, and a weekend diary dummy. Regressions are weighted using ATHUS individual sampling weight. We restrict the sample to the 400 state-years that are included in the baseline regressions. Standard errors (in parentheses) are clustered at the state level in all regressions.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix B: The Child Protective Services and the Process of Child Maltreatment Reporting

At the Federal level, child abuse and neglect are defined by the Child Abuse Prevention and Treatment Act (CAPTA) as: 'Any recent act or failure to act on the part of a parent or caregiver, which results in death, serious physical or emotional harm, sexual abuse or exploitation, or an act or failure to act which presents an imminent risk of serious harm' (Child Welfare Information Gateway, 2014). There exist some differences in the way that specific types of child abuse or neglect are defined across states. Neglect is generally defined as the failure of a parent or other caregiver to provide the necessary food, clothing, shelter, medical care or supervision to the point that the child's health, safety and well-being are threatened with harm. Physical abuse is generally defined as any non-accidental physical injury to the child. The definition of sexual abuse generally includes the encouragement or coercion of a child to engage in any sexually explicit conduct or simulation of such conduct for the production of child pornography, as well as rape, molestation, incest, or prostitution. Emotional abuse is generally defined as injury to the psychological capacity or emotional stability of the child, as evidenced by an observable or substantial change in behaviour, emotional response or cognition (Child Welfare Information Gateway, 2014).

All fifty states and the District of Columbia have a Child Protective Services (CPS) agency, which is responsible for investigating reports of child abuse and neglect. The process of child maltreatment reporting varies by state, but typically works as follows. All but ten states have a centralized statewide hotline that reporters can call if they suspect child abuse or neglect.[41] Trained specialists at either the state or county hotline receive the call, obtain as much information about the case as possible from the reporter, and make a judgement about whether the case warrants an investigation in accordance with state law.

After the initial phone call, the case is allocated to the CPS office in the county in which the child resides. A CPS caseworker makes initial face to face contact with the family, before undertaking an investigation. During the investigation, the caseworker may talk to the child, to the child's family,

[41] Alabama, California, Hawaii, Maryland, Minnesota, North Carolina, North Dakota, South Carolina, Wisconsin and Wyoming do not have a statewide hotline, and so reporters must call the specific county office in the county in which the child resides. In states with a statewide hotline, the initial call is often processed at the state level, but it can be directed to county hotlines.

as well as professionals who are involved in the child's life. The caseworker will decide whether there is sufficient evidence that child abuse or neglect has taken place. In the event that the report is substantiated, a range of actions can be taken. In extreme cases, the child can be removed from his or her family home for protection. More often, the caseworker will recommend a plan to the family involving, for example, cognitive-behavioral therapy, school-based training, or counseling and other supportive services (Children's Bureau, 2003). The CPS cannot directly prosecute the parents, but they can recommend cases to law enforcement agencies and the courts.

Online References

Children's Bureau. 2003. "Child Protective Services: A Guide for Caseworkers." Child Abuse and Neglect User Manual Series.

Child Welfare Information Gateway. 2014. "Definitions of Child Abuse and Neglect." U.S. Department of Health and Human Services.

Appendix C. Description of the Construction of the Outcomes Dataset

C.1. Organizing the Data by Calendar Year and Report Date

The NCANDS data is released annually, and is organized by Federal Fiscal Year (FFY) (running from 1st October to 30th September), and by the investigation disposition date (the date of the outcome of the CPS investigation). For example, the NCANDS dataset for 2012 contains every child-report for which the outcome of the investigation occurred between 1st October 2011 and 30th September 2012. We would ideally like to organize the data by the date of the incident of abuse, but that is unobserved. The closest that we can get to the date of the incident is the date of report, which is also contained in the dataset. We therefore reorganize the data by the date of report and calendar year. This seems straightforward. However, an issue arises because seventeen states are not observed in at least one year during the sample period. The problem is that one missing year of NCANDS data by the federal fiscal year and investigation disposition date does not translate into only one missing year by calendar year and report date. To see this, take the example of Indiana, as demonstrated in Figure C1. Indiana is missing the FFY 2012. Our dataset for this state then does not include any incident whose investigation is concluded between 1st October 2011 and 30th September 2012, as indicated by the solid cross. Now suppose that an incident is reported on 15th September 2011. Whilst this incident is reported within a 'non-missing' FFY of the dataset, if the investigation is concluded more than 15 days after the report is made, then the investigation disposition date falls in a missing FFY and this incident will be missing from the data. To deal with this, for each missing FFY of the data, we extend the missing dates to twelve months before the start of the missing FFY, as demonstrated by the dashed cross in the Figure. Over 99% of reports reach an investigation disposition within twelve months of the report date, and so doing this we can claim to capture over 99% of all cases of child abuse in the final sample period.

As can be seen in Figure C1, for some state-years we then only observe reports for part of the calendar year. For example, for Indiana in 2010 we only observe reports from 1st January until 30th September 2010. To deal with this, we firstly restrict the sample period to 2004 to 2012 (when the majority of states have a complete year's worth of data). Secondly, for the states with missing years, we calculate the number of abuses per year as: $A^*_{cst} = A_{cst}/(O_{cst}/D_t)$, where A^*_{cst} is the

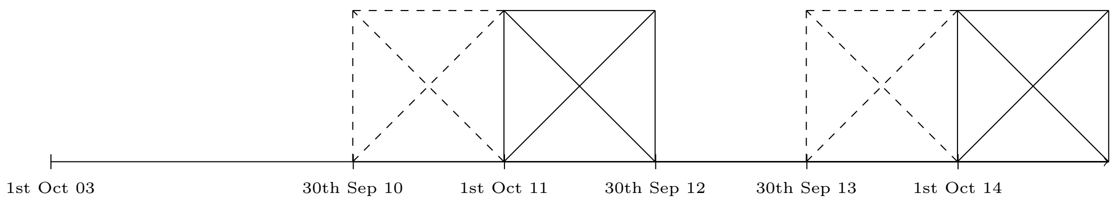

Figure C1: Missing Years by Report Date for Indiana. The solid crosses indicate the missing periods of data for Indiana by investigation disposition date (the Federal Fiscal Year 2012, and from 1st October 2014 onwards). To organize the data by report date, we treat both the solid and dashed time periods as missing. In other words, we extend the missing period by twelve months before the start of the missing FFY by investigation disposition date. To see the intuition: for the first missing year in the Figure, we know that more than 99% of all incidents reported before 30th September 2010 will have had their investigation disposition before the start of the missing year (1st October 2011), and will therefore appear in the dataset.

number of abuses per year for county c in state s in year t, A_{cst} is the number of abuses over the part of the year that we observe, O_t is the number of days in year t that we observe for county c in state s, and D_t is the total number of days in year t. After creating the measure of the number of abuses per year in this way, we take the natural logarithm transformation as explained in Section 2.2.

C.2. Dealing with Missing Counties

The county of report is typically the county in which the victim resides. However, in some states (for example Utah), it is the county where the office investigating the report of child abuse lies. In general, the two are the same. However it is possible that a county is missing from the dataset because there is no CPS office located in the county, rather than because there are truly no incidents of child abuse in that county. We assume that the former is true only if a county is missing from the dataset for every type of abuse for every year of the dataset, which the case for 54 counties. We treat these 54 counties as missing from the dataset throughout, and treat any other county that does not appear in the dataset in a particular year for a particular abuse type as having zero incidents of that abuse type in that year.