The Impact of Unemployment on Child Abuse and Neglect in the United States*

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Abstract

In this paper, we show that unemployment increased the neglect and physical abuse of children in the United States during the period from 2004 to 2012. A one percentage point increase in the unemployment rate led to a 25 percent increase in neglect and a 12 percent increase in physical abuse. We identify these effects by instrumenting for the county-level unemployment rate with a predicted county-level unemployment rate, which we create by combining national level unemployment rates across industries with differences in the initial industrial structure across counties. We tested whether the unemployment effects can be explained by changes in alcohol abuse or divorce, but failed to find consistent evidence with those mechanisms. However, we find that results for neglect are consistent with the poverty mechanism. By exploiting variation in unemployment policies over time within states, we find that the extension of unemployment benefits mitigates the effect of unemployment on neglect.

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Keywords: violence against children, child maltreatment, child abuse and neglect, unemployment rate, recession.

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1 Introduction

Child maltreatment is the abuse and neglect of children under 18 years old. In the United States, child maltreatment is still a major problem. The U.S. Department of Health and Human Services estimate that there were approximately 679,000 victims in 2013 alone (US Department of Health and Human Services, 2013). Child maltreatment can have long-term consequences on the victims including mental health problems, substance abuse, lower levels of education, productivity or earnings, and a higher probability of engaging in crime (e.g., Dube et al., 2003; Springer et al., 2007; Currie and Widom, 2010; Currie and Tekin, 2012).

Many scholars propose that unemployment is one of the main causes of child maltreatment (e.g., Gillham et al., 1998). However, causal empirical evidence is scarce and presents mixed findings. Early economic studies found only a weak relationship between economic conditions and child maltreatment (Paxson and Waldfogel, 2002; Bitler and Zavodny, 2004; Seiglie, 2004). More recently, Lindo et al. (2013) find that male layoffs increase child maltreatment whilst the opposite is true for female layoffs. Stephens-Davidowitz (2013) finds that the Great Recession caused a decrease in reporting of child maltreatment but an increase in actual incidences.

In this paper, we investigate the relationship between unemployment and child maltreatment. We make three main contributions. First, we use a new dataset containing every reported incident of child abuse and neglect made to the state Child Protective Services for nearly every state in the U.S. for nine years from 2004 to 2012. Unique feature of the data is information about the county of the report. A handful of previous papers have used an earlier and more limited version of this dataset, with information available only at a state level and for the mid 1990s (Paxson and Waldfogel, 1999, 2002, 2003). Our dataset comes from the National Child Abuse and Neglect Data System (NCANDS), produced by the National Data Archive on Child Abuse and Neglect (NDACAN) within the U.S. Department of Health and Human Services. This dataset enables us to examine the whole of the U.S., improving upon recent articles that consider only one state (Lindo et al., 2013; Frioux et al., 2014; Raissian, 2015).

Second, we identify the casual impact of unemployment on child maltreatment using an instrumental variables approach. We instrument for the county-level unemployment rate using a predicted county-level unemployment rate, which we create by combining national level unemployment rates across industries with differences in the initial industrial structure across counties. This type of instrument has been widely used in the labour economics literature, and is referred to as the Bartik instrument (Bartik, 1991a; Blanchard et al., 1992). Our approach improves on previous work (see Paxson and Waldfogel, 1999, 2002; Bitler and Zavodny, 2004; Seiglie, 2004; Stephens-Davidowitz, 2013) where the authors assume that area-level unobservable characteristics related to child maltreatment are not correlated with the economic variable considered. The Bartik instrument has also been used in a related literature that investigates the effect of economic conditions on intimate partner violence (e.g., Aizer, 2010; Anderberg et al., 2016).

Third, we investigate if the effect of unemployment on neglect and physical abuse is driven by changes in substance abuse, family structure, or poverty. Individuals may increase substance abuse to cope with the stress of unemployment, which may increase physical abuse or neglect. Unemployment can lead to divorce, which may lead to abuse if children are exposed to new adults (new partners of the parents) who may be prone to abusive behaviour, whilst single parent households may have fewer resources to provide for a child's basic needs. Finally, an increase in poverty due to an increase in unemployment can result in a failure to meet a child's basic physical and/or physiological needs.

We find that a one percentage point increase in the unemployment rate leads to a 15 percent increase in overall abuse. We look at the effect of unemployment on different types of abuse, and find that the effect on overall abuse is mainly driven by an increase in neglect and physical abuse. A one percentage point increase in the unemployment rate leads to a 25 percent increase in neglect and a 12 percent increase in physical abuse. We demonstrate that the results are robust to several checks and, in particular, they are not driven by an increase in reporting as a result of a re-allocation of labour to high reporting sectors. Heterogeneous effects show that unemployment has a larger impact on neglect amongst young children (0-4 years), and has a larger impact on neglect among female perpetrators. When testing whether the unemployment effects can be explained by changes in alcohol abuse or divorce, we fail to find consistence evidence with those mechanisms. However, we find that results for neglect are consistent with the poverty mechanism. By exploiting variation in unemployment policies over time within states, we find that the extension of unemployment benefits mitigates the effect of unemployment resulting in a reduced number of children who are neglected.

The paper is structured as follows. In Section 2, we describe the Child Protective Services and the process of child abuse reporting in the United States. We present our empirical strategy and outline the NCANDS dataset in Section 3. In Section 4, we show the main results, and the heterogenous impact. In Section 5, we test three mechanisms that can explain our results. Robustness checks are presented in Section 6. Section 7 concludes the paper.

2 Context: Child Protective Services and the Process of Child Abuse Reporting in the United States

At the Federal level, child abuse and neglect is 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. Physical abuse is generally defined as 'any nonaccidental physical injury to the child'. 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. 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, and 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[1]. The process of child abuse reporting varies by state, but typically works as follows[2]. All but ten states have a centralised statewide hotline that reporters can call if they suspect child abuse or neglect[3]. Individuals in some professions, such as teachers and doctors, are mandated to report any suspicion of child abuse, but reports can come from any member of the public, for example neighbours, family or friends[4]. Trained specialists receive the

[1]The CPS falls under different departments in different states, for example the Department of Health and Welfare in Idaho, the Department of Social Services in Missouri, or the Office of Children and Family Services in New York.

[2]We have contacted every Child Protective Services agency in the United States by phone and email to understand the process of child abuse reporting. The information provided in Section 2 is based on those phone calls and emails. A useful review of procedures is available for New York state, at the website of the Office of Children and Family Services: `http://ocfs.ny.gov/ohrd/ccg/`, which is similar to procedures in many other states. Recommended procedures for CPS caseworkers can be found at Children's Bureau (2003).

[3]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 specific county offices in the county in which the child resides.

[4]In some states, such as New Hampshire, everyone is a mandated reporter by law.

call, attain 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. This often requires that the specialists call other agencies, such as law enforcement and schools, to gather additional information.

The case is then sent to the CPS office in the county in which the child resides[5]. A CPS caseworker makes initial face to face contact with the family, before undertaking an investigation[6]. During the investigation, the caseworker may talk to the child, to the child's family, 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-behavioural therapy, school-based training, or counselling 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.

In 2012, the CPS agencies received approximately 3.4 million reports of child abuse or neglect involving approximately 6.3 million children. Of these, 62.0% were investigated leading to a national rate of investigated reports of 28.3 per 1,000 children (US Department of Health and Human Services, 2012). Professionals made 58.7% of reports, with 16.7% made by legal and law enforcement personnel, 16.6% by education personnel and 11.1% by social services personnel (US Department of Health and Human Services, 2012). Of the child-reports that were investigated, 19% of cases were found to be substantiated[7].

3 Identification Strategy and Data

3.1 Identification Strategy: The Bartik Instrument

We wish to understand the effect of unemployment on the incidence of child abuse and neglect. Unobservable worker characteristics within a county might be correlated with both the unemployment rate in that county, and the incidence of child abuse or neglect.

[5]If it is decided that an investigation is not needed, details about the report are nonetheless kept on file in case of future calls.

[6]For example, in New Hampshire initial face to face contact must be made within 24, 48 or 72 hours, depending on the degree of emergency of the report, after which an investigation has to be concluded within 60 days.

[7]These figures apply to the Federal Fiscal Year 2012, which runs from 1st October 2011 until 30th September 2012.

To deal with this concern, we use an instrumental variables approach. We instrument for the county-level unemployment rate using a predicted county-level unemployment rate, which combines national level unemployment rates across industries with differences in the initial industrial structure across counties. This approach was introduced by Bartik (1991b). It has been used many times in the labour economics literature (e.g., Blanchard and Katz, 1992; Luttmer, 2005; Wozniak, 2010), and has been used recently in papers on violence against women (e.g., Aizer, 2010; Anderberg et al., 2016).

Our instrument is a weighted average of the national level unemployment rates across each of twenty industries[8], where the weights are the fraction of the employed working-age population in each industry in 2003 in the given county. National level unemployment rates are plausibly exogenous to county-level worker characteristics in any individual county, since counties are small in size relative to the whole of the United States (the U.S. consists of 3,143 counties). The initial industrial structure in a county is likely correlated with its workers' characteristics, which is a threat to the validity of the instrument. However, the initial industrial structure is by definition time invariant at the county level, and so we can deal with this threat by controlling for county-level fixed effects, which we do in all regressions. We estimate the following, where equation (2) is the first stage of the IV procedure:

$$Y_{cst} = \beta Unemp_{cst} + X'_{cst}\phi + year'_t + \psi_{st} + \eta_c + \epsilon_{cst} \tag{1}$$

$$Unemp_{cst} = \delta(\Sigma_j w_{csj} N_{tj}) + X'_{cst}\theta + year'_t + \pi_{st} + \tau_c + \upsilon_{cst} \tag{2}$$

Here, Y_{cst} is the natural logarithm of the number of abuses per year in county c, in state s, in year t, for the type of abuse of interest[9]. We count only allegations that were found to be substantiated.[10] $Unemp_{cst}$ is the unemployment rate in county c, in state s, in year t. The instrument comprises of the weights, w_{csj}, which are the fraction of employed working-age individuals in each industry, j, at the start of the sample period in county c, in state s; and the national level unemployment rate, N_{tj} in each industry, j, in each time period, t. We control for county fixed effects through η_c, to ensure the validity of our instrument as discussed above. We also control for year fixed effects through $year'_t$.

[8]For the industry classification, we use the North American Industry Classification System (NAICS), see www.census.gov/eos/www/naics.

[9]Some counties have zero abuses for particular abuse types in a given year. This varies by the type of abuse and year, but, for example, 9.7% of counties have no reported cases of physical abuse in 2004. To deal with zeros, we add 0.01 abuses before taking the natural logarithm. We later check the robustness of results to adding 0.001 abuses.

[10]In the Robustness section 6, we also consider unsubstantiated cases.

The coefficient of interest is β. This coefficient tells us the percent change in the number of abuses in a county as a result of an increase in the unemployment rate by one percentage point.

A further identification concern comes from the measurement of the left hand side variables. The measurement of abuse differs across states and may change over time within states. If the unobservable reasons for these differences are correlated with unemployment, our estimate of β will be biased. Differences in measurement arise from several sources. First, the definitions of child abuse and neglect vary across states and may vary over time within states. Whilst the Child Abuse Prevention and Treatment Act (CAPTA) provides federal definitions, state definitions can differ (Child Welfare Information Gateway, 2014). For example, Washington state does not recognise emotional abuse[11]. Second, some states include specific exceptions in their definitions of child abuse and neglect. For example, in twelve states and D.C., financial inability to provide for a child is exempt from the definition of neglect. 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. Since these differences only occur at the state level, we can deal with this concern by controlling for state-year fixed effects through ψ_{st}.

In X'_{cst}, we control for the total child population in county c, in state s, in year t, and the fractions of the population that are Black, Hispanic, and Other race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight regressions by the child population at the start of the sample period, because the child population varies considerably across counties and we wish to estimate an effect that is representative for children in counties across the whole of the U.S.[12] We cluster standard errors at the state level. Our main concern here is that the investigation of child abuse is controlled at the state level, and so the number of substantiated incidents may be correlated across counties within the same state. This is true even though we control for state-year fixed effects. For example, if CPS workers are re-allocated within the state from one county office to another, changes in the quality of investigation (and so perhaps the number of incidents found to be

[11]There are several other examples, which are summarised in Child Welfare Information Gateway (2014). For example, seven states explicitly include human trafficking in their definition of child sexual abuse. Twenty-five states and D.C. include a failure to educate a child as required by law in the definition of neglect. Thirty-eight states include acts that threaten a child with harm or create a substantial risk of harm to the child's health or wellbeing in the definition of physical abuse.

[12]Of the 3,143 counties in the U.S. in 2003, 1% of counties had 222 or fewer children. By contrast, 25% of counties had a child population of greater than or equal to 15,297, whilst the largest county, Los Angeles, had 2,678,788 children.

substantiated) may be correlated across those two counties. We later demonstrate the robustness of results to clustering at a county level (in Section 6).

3.2 Data

3.2.1 Outcome Variables: Child Abuse and Neglect

We use a dataset from the National Child Abuse and Neglect Data System (NCANDS), produced by the National Data Archive on Child Abuse and Neglect (NDACAN) within the U.S. Department of Health and Human Services[13]. The dataset contains all reported incidents of child abuse and neglect made to state Child Protective Services in nearly every state in the U.S. for the years 2004-12[14]. In this paper, we focus on reports of neglect, physical, sexual, and emotional abuse. For each child abuse report, we observe the gender, age and ethnic group of the perpetrator and victim, the county of report, the report date, the type of abuse alleged and the outcome of the investigation.

In each year a small number of states do not submit information to NCANDS, which is a voluntary reporting system. The median number of states reporting in each year is 49 (including D.C.), and the lowest is 45 in 2004. Our analysis focuses on a final sample of 2,803 counties from forty six states[15]. For each county and year, we create a count of the total number of incidents of each abuse type[16]. We count only incidents where that specific type of abuse was found to be substantiated by the Child Protective Services[17].

[13]The NCANDS was established in response to the Child Abuse Prevention, Adoption and Family Services Act of 1988 (NDACAN, 2006). The dataset is processed and published by Cornell University.

[14]Some states do not submit data for some years during the sample period, as explained further in the Data Appendix.

[15]We exclude Alaska, South Dakota, Illinois, North Dakota and Oregon. Alaska is organised by boroughs, which have different boundaries to the FIPS counties used in all federal reporting systems including NCANDS. The county of report that Alaska submits to NCANDS is created after the fact, based on computer codes that have changed over time and has a tenuous link to the borough boundaries in which the Child Protective Services is organised. Only 25 out of 66 counties in South Dakota are included in the NCANDS data, whilst in Illinois the fraction of counties reporting decreases from all to less than one third between 2010 and 2011. Finally, North Dakota and Oregon do not report any information before 2009, and so are not observed before the start of the financial crisis, the time at which the big changes in the unemployment rate occur in our sample period.

[16]Emotional abuse is not recognised in some state-years. Emotional abuse is not recorded in Washington state in any year, or in: D.C. in 2004, Idaho in 2006, Indiana in 2004-7, Rhode Island 2007, or Vermont in 2012.

[17]Specifically, we count incidents that are coded as ‘substantiated’, ‘indicated or reason to suspect’, and ‘alternative response disposition - victim’ for the given abuse type, since states differ slightly in the way that they classify the outcome of investigations.

3.2.2 Unemployment Rate

We focus on the annual unemployment rate at a county level, using data from the Local Area Unemployment Statistics (LAUS) produced by the Bureau of Labour Statistics (BLS)[18]. The BLS calculates unemployment rates using information collected in the Current Population Survey, Current Employment Statistics survey, and state Unemployment Insurance systems.

3.2.3 Control Variables

We measure the total population of children using the Population and Housing Unit Estimates (PHUE), produced by the Census Bureau. The Census Bureau uses data on births, deaths and migration to update decennial census data to produce these estimates[19]. We define a child as any individual between the ages of 0 and 17. We also use the PHUE to measure the fraction of the population that are of each ethnic group (Black, Hispanic and Other race).

3.2.4 Summary Statistics

In Table 1, we present unweighted means and standard deviations for the main variables we use in the regression analysis. Neglect is considerably more common than the other three types of abuse, with the mean number of incidents of neglect (183) more than four times greater than the mean number of incidents of physical abuse (42), the next most common form of abuse. The variance in the number of incidents of all abuse types per year is large, but particularly so for emotional abuse.

Figure 1 shows the abuse rates by victim's age. We can see that young children (aged 0-4) are more commonly the victims of neglect than children aged 5-17. The rate of neglect amongst children aged 0-4 is nearly twice the rate amongst children aged 5-17. Children aged 5-17 are more commonly the victims of sexual abuse than young children (aged 0-4). The rate of sexual abuse amongst children aged 5-17 is more than three times greater than the rate amongst 0-4 year olds.

Figure 2 shows the overall abuse rate by perpetrator and victim's gender. Women are relatively more likely to abuse, but they usually spend more time with children. In analysis not reported here we find that conditional on the time spent with children, men

[18] This series can be downloaded from `http://www.bls.gov/lau/home`, where the reader can find more information about the procedures used to calculate these unemployment rates.

[19] The PHUE can be downloaded from `http://www.census.gov/popest/index`, where the reader can find more information about the procedures used to estimate population.

physically, sexually and emotionally abuse children at a greater rate. The rate of female perpetrated neglect is instead approximately double the rate of male perpetrated neglect.

Figure 3 shows the overall abuse rate trends for the least and the poorest 10% of counties. It is important to notice that the differences in abuse rates between the poorest and least poor counties may be partly driven by differences in definitions of abuse at the state level,[20] or by changes in definitions of abuse over time, or by differences in which counties are included in the calculation of the weighted mean in each year[21]. With those caveats in mind, the Figure clearly shows that overall abuse is more common in the poorest 10% of counties than the richest 10% of counties. This is true also for neglect, sexual and physical abuse rates (statistics not reported).

In Figure 4, we plot the unweighted average unemployment rate across counties over the sample period. Figure 4 demonstrates that unemployment rates jumped between 2007 and 2009 with the onset of the financial crisis. The median county in our sample experienced an increase in the unemployment rate of 3.9 percentage points between 2007 and 2009. In Figure 5, we split the sample of counties into those with a below and above median increase in the predicted unemployment rate between 2007 and 2009, using our instrument. We plot the trends in the unweighted average number of incidents of abuse. We normalise the trends for each group of counties such that the number of abuses is 100 in the year 2007[22]. We see that overall abuse, physical abuse and neglect increased from 2008 onwards for the counties that experienced a greater than average predicted unemployment shock during the financial crisis, which was not true of the counties experiencing a below average shock. Although sexual abuse declined throughout the sample period for both groups of counties, that decline was slower from 2008 onwards for the

[20]The poorest 10% of counties come from the following 24 states: Alabama, Arkansas, Arizona, California, Colorado, Florida, Georgia, Kentucky, Louisiana, Missouri, Mississippi, Montana, North Carolina, Nebraska, New Mexico, New York, Oklahoma, Pennsylvania, South Carolina, Tennessee, Texas, Utah, Virginia and West Virginia. The least poor 10% of counties come from the following 31 states: Alabama, California, Colorado, Connecticut, Florida, Georgia, Iowa, Idaho, Indiana, Kansas, Kentucky, Massachusetts, Maryland, Michigan, Minnesota, Missouri, Nebraska, New Hampshire, New Jersey, New Mexico, Nevada, New York, Ohio, Pennsylvania, Tennessee, Texas, Utah, Virginia, Vermont, Wisconsin, and Wyoming. Therefore, fifteen states have counties in both the richest and poorest 10%.

[21]Not all counties are included in the calculation in every year because not all states submit information to NCANDS in every year.

[22]Since we normalise the abuse trends in this way, we should not compare the changes in incidents across abuse types. The changes in the incidence of physical and sexual abuse are exaggerated compared to the changes in neglect as a result of the normalisation, because neglect is much more common than physical or sexual abuse. To see this, see Figure A.1, which demonstrates that neglect is much more common.

counties experiencing a greater than average predicted unemployment shock. This Figure therefore provides suggestive evidence that the increase in unemployment associated with the financial crisis may have increased abuse. We investigate this more formally in the regression analysis, presented in Section 4.

4 Results

In Table 2, we present the main results. In columns (1) and (2), we look at the effect of unemployment on overall abuse, combining any incident of neglect, physical, sexual or emotional abuse. We find that the coefficients on unemployment are positive, and for the IV regression the effect is statistically significant at the 1% level. A one percentage point increase in the unemployment rate leads to a 15 percent increase in overall abuse. In columns (3) to (8), we separate out these three different types of abuse, and present OLS and IV results. The IV results in columns (4) and (6) demonstrate that the effect in column (2) is driven by an effect on neglect and physical abuse. A one percentage point increase in the unemployment rate leads to a 25 percent increase in neglect and a 12 percent increase in physical abuse. There is no statistically significant effect of unemployment on the incidence of sexual abuse, though the coefficients on unemployment are again positive. Our results, which are for the U.S. as a whole, contrast with the estimates presented in Lindo et al. (2013) for California. In that single state, they do not find a robust statistically significant effect of the overall predicted employment rate on either neglect or physical abuse.

The OLS estimate of the effect on physical abuse is also positive and statistically significant, but one fifth the size of the IV results. The OLS estimate of the effect on neglect is not statistically significant, and is considerably smaller than the IV estimate. This difference may exist because the instrumental variables procedure removes the omitted variable bias in the OLS estimates. One source of omitted variables bias in the OLS estimates could derive from individuals' unobservable preference for work versus family. During a recession, workers' bargaining power decreases and so workers with a strong preference for work, who are more likely to go the extra mile for their employer (for example working unpaid overtime), are more likely to remain in employment. Yet these individuals are ceteris paribus more likely to neglect their family. At a county level, this unobservable is time variant. Areas with an increasing population of individuals with an unobservable preference for work over family will observe both a smaller increase in unemployment and a larger increase in neglect. Alternatively, part of the difference between the OLS and IV could be explained by the removal of attenuation bias due to measurement error in the unemployment rates at a county level.

4.1 Heterogeneity

In this section, we ask whether the effect of unemployment on abuse and neglect differs by victims' age, and by perpetrators' gender. We only report the IV results for overall and physical abuses, and neglect.

The results in Table 3 (columns (1) and (2)) show that there is little difference in the effect of unemployment on overall abuse across young (0-4 years) and older (5-17 years) children. Whilst the effect of unemployment on physical abuse is not statistically significant for either age group, and nor is the effect on neglect of 5-17 year old children, the p-values associated with the coefficients on the unemployment rate are close to 0.100 in each case. The p-value for the coefficient of interest is 0.141, 0.101 and 0.120 in columns (3), (4) and (6) respectively. The greatest difference in the point estimates is for neglect, where there is a larger effect amongst young children. A one percentage point increase in unemployment rate leads to 26 percent increase in neglect across 0-4 years old children.

The results in Table 4 are suggestive that the effect of unemployment on female perpetrated neglect is greater than the effect on male perpetrated neglect. The point estimate for female perpetrated neglect is double the size of that for male perpetrated neglect, and suggests that a one percentage point increase in the unemployment rate increases female perpetrated neglect by 32 percent.

5 Mechanisms

Why does unemployment increase physical abuse and neglect? Three main mechanisms have been proposed in the existing literature. We can undertake tests of each of these mechanisms, as in each case we have a U.S. dataset covering the same sample period as the NCANDS data. We focus on the two outcomes that are affected by unemployment: physical abuse and neglect.

5.1 Alcohol consumption

The first mechanism is substance abuse. Individuals may increase alcohol consumption or drug use to cope with stress after being made unemployed (e.g., Boardman et al. (2001); Eliason and Storrie (2009)). Substance abuse can in turn increase child maltreatment.

Previous evidence has demonstrated that substance abuse can lead to violent behaviour within the household (e.g., Lee Luca et al. (2015)), and so this might explain the increase in physical abuse. Further, alcohol and drug use can limit a parent's ability to care for their child, or drain resources that could otherwise be used to pay for the child's basic needs, and so this may also explain the increase in neglect. To explore this mechanism, we used data on the estimated county-level prevalence of heavy and binge drinking over the period from 2004 to 2012[23]. These measures of alcohol consumption are estimated in a paper by Dwyer-Lindgren et al. (2015), using the Behavioural Risk Factor Surveillance System (BRFSS) dataset. The BRFSS is a health-related telephone survey of U.S. households, conducted by the Centre for Disease Control and Prevention (CDC), which samples approximately 400,000 adults each year and is the largest continuously conducted health survey system in the world[24].

In Table 5, we test whether unemployment increases overall, physical abuse and neglect by increasing alcohol consumption. In columns (1) to (6), we ask whether unemployment increases heavy or binge drinking. We look at the prevalence rate of heavy and binge drinking at the county level, overall and for men and women separately. We use the same Bartik IV strategy as in the baseline regressions. We weight the observations by the 2003 child population as in the baseline regressions because we want to know the effect of unemployment on alcohol consumption where the children of the United States reside. We in fact find that unemployment causes a decrease in binge drinking. This result is in line with previous studies where economic downturns have been found to be positively correlated with health, mainly because of an improvement in healthy behaviours (Ruhm, 2000, 2003, 2005; Ruhm and Black, 2002). Further, we find that unemployment causes a decrease in female heavy and binge drinking, effects that are statistically significant at a 1% level. This is inconsistent with the alcohol explanation for the main results. An increase in the unemployment rate equivalent to one standard deviation of the within county variation is associated with a 0.27 standard deviation decrease in the overall prevalence of binge drinking, a 0.37 standard deviation decrease in the prevalence of female heavy drinking and a 0.58 standard deviation decrease in the prevalence of female binge drinking. When we control for the prevalence of overall binge and heavy drinking in the baseline regressions in columns (7) to (9), there is virtually no change in the size or statistical significance of the effect of unemployment on overall,

[23]Heavy drinking is classified as more than one drink per day for women, or more than two drinks per day for men. Binge drinking is classified as having more than four drinks for women or five drinks for men on a single day at least once in the previous thirty days.

[24]For details see: `http://www.cdc.gov/brfss/`.

physical abuse or neglect. We can therefore rule out that unemployment causes a change in abuse and neglect through an increase in alcohol consumption.

5.2 Divorce

The second mechanism is family structure, and in particular divorce. Unemployment can lead to divorce (e.g., Kofi Charles and Stephens (2004); Doiron and Mendolia (2012); Eliason (2012)). Divorce can in turn increase child abuse and neglect, for three reasons (Lindo et al., 2013). Divorce might increase the time that children spend with unrelated adults (the new partners of their parents), who may be particularly prone to abusive behaviour (Sedlak et al., 2010). The children of divorced parents may grow up in single parent households, which may have fewer resources to provide for those children's basic needs, leading to an increase in neglect. Finally, divorce may lead to stress, mental health problems or substance abuse, which as previously explained can lead to physical abuse or neglect. In the case of family structure, we use the American Community Survey, available for the period from 2005 to 2012, to measure the prevalence of divorce at a county-level.

In Table 6 we test whether divorce is a potential mechanism. As in the regressions for alcohol consumption, we again weight the observations by the total child population in 2003, such that the effect of unemployment on divorce that we estimate is representative of that relationship where the children of the United States reside. Column (1) demonstrates that there is a large, positive and statistically significant effect of unemployment on divorce. A one percentage point increase in the unemployment rate is associated with an increase in the divorce rate by 0.5 percentage points. A one standard deviation increase in the unemployment rate is associated with a 0.83 standard deviation increase in the rate of divorce (using the within county variation). This is consistent with the claim that unemployment causes an increase in abuse and neglect through an increase in divorce. Since unemployment might trigger divorce with a lag, because divorce procedures can be time consuming, we allow for an effect at a one year lag in column (2). As we might expect, the effect is greater at a one year lag than the contemporaneous effect. In columns (3) to (5), we control for the divorce rate in the baseline regression. If divorce is driving the effect of unemployment on abuse and neglect, we would expect the coefficient of interest on unemployment to fall to zero and become statistically insignificant, whilst the coefficient on divorce would be positive and significant. However, controlling for divorce has virtually no effect on the size or statistical significance of the effect of unemployment on overall, physical abuse or neglect. Further the coefficients on the divorce rate are not statistically significant for any type of abuse and are even negative in the case of overall abuse and neglect. This suggests that our results are not being driven by divorce.

5.3 Poverty

The forth mechanism is poverty. Families who cannot cope with the negative income shock failure to meet a child's basic physical and/or psychological needs (e.g., provide adequate food, clothing, shelter or medical care), simply because they cannot afford to meet those needs. We test this mechanism indirectly, by asking whether state policies intended to mitigate the effects of unemployment on poverty also reduced the effect of unemployment on child abuse and neglect.

During the Great Recession, unemployment increased dramatically in the U.S.. Several policies were implemented to support people who lost their jobs. The duration of the unemployment benefits was extended from the standard 26 weeks to as long as 99 weeks. In addition, eligibility criteria for the Supplemental Nutritional Assistance Program (previously known as the food stamps program) were relaxed, expanding its reach.

Data on unemployment benefit durations come from state-specific trigger reports and they are provided by the Department of Labor[25]. The reports contain information on the eligibility and adoption of the Extended Benefit program and the Emergency Unemployment Compensation program. The federal government decides when states can adopt extended benefits based on a set of triggers related to the insured and total unemployment benefit rates. The Extended Benefit program is a joint state and federal program which allows for an extension of 13 up to 20 weeks of benefits in states where unemployment rate is high. Half of the cost is payed by the federal government. From February 2009 the program became a federally funded program and as a consequence many states joined it and adopted lower triggers to qualify for it. The Emergency Unemployment Compensation program was implemented in June 2008. It initially allowed for 13 extra weeks of benefits and was then expanded to have four tiers, providing up to 53 weeks of federally financed additional benefits.

Together with the unemployment policies also the Department of Agriculture's food-stamp program, now called the Supplemental Nutrition Assistance Program (SNAP) was expanded following the economic recession (Mulligan, 2012). The Federal government allowed states broader eligibility criteria and as a consequence by 2010 half of non-elderly households with an unemployed head or spouse participated in the program.

[25]See http://ows.doleta.gov/unemploy/trigger/ and http://ows.doleta.gov/unemploy/euc trigger/.

We have data on when each state was eligible and activated the Extended Benefit program and different tiers of the Emergency Unemployment Compensation program. The USDA's SNAP Policy Database contain information on each state policy choice at monthly level. We then created a variable 'food stamps' which tells us the fraction of months in the year for which the state had relaxed asset tests for food stamps eligibility[26].

We use the variation in unemployment policies over time within states to identify their effect on unemployment[27]. Table 7 shows how the two state policies, unemployment benefit extension and food stamps programs, affect the impact of unemployment on child abuse and neglect.

In particular, in Table 7, we interact the unemployment rate with the policy variable. In columns (1) to (4), the policy variable is the duration of unemployment benefits (number of weeks) in the state-year, and in columns (5) to (8), it is a dummy variable that takes the value 1 if the state relaxed asset tests for food stamps in that year. Since there are two endogeneous variables, unemployment and unemployment interacted with the policy variable, we interact the policy variable with the instrument to create the second instrument. The negative coefficient on the interaction instrument in the first stages might indicate that states with food stamps policies or long benefits have counties whose unemployment rates are less badly affected by national shocks.

The most interesting result is the coefficient on the benefit duration and unemployment rate interaction term in column (3) (point estimate = -0.0028, SE=0.0011). The effect of unemployment on neglect decreases as the state raises the duration of unemployment benefits. Thus the extended benefits or emergency unemployment compensation schemes, which drive the increases in benefits duration in this sample period, seem to have successfully reduced the impact of unemployment on child neglect. This in turn provides indirect evidence that the mechanism underlying the effect of unemployment on neglect is related to poverty. Benefits allow individuals to weather short-term income shocks from unemployment, and prevent them from neglecting their children. The size of the effect is large. A one percentage point increase in the unemployment rate at the 25th percentile of benefits duration (26 weeks) causes a 32 percent increase in neglect, while a one percentage point increase in the unemployment rate at the 75th percentile of benefits duration (74.7 weeks) causes only an 18 percent increase in neglect.

[26] The food stamp policy variable is not available in 2012, and the benefits duration variable is not available for Hawaii.

[27] Hagedorn et al. (2013) study the effect of unemployment benefit extensions on labor market implications. They find that benefit extensions raise equilibrium wages and lead to large decrease in vacancy creation and employment and to an increase in unemployment.

We cannot learn much about the effect of the food stamp policy, because the instruments do not identify separate variation in each of the endogenous variables very well. The SW F-stat on the interaction variable's first stage is just 2.57.

Given the potential policy endogeneity (states with an increase in unemployment expand benefit eligibility versus increases in benefits lead to higher unemployment), we will exploit the policy discontinuity at state borders comparing unemployment in bordering counties that belong to different states (Hagedorn et al., 2013)[28].

However, these results so far are consistent with the idea that poverty is a mechanism through which a raise in unemployment leads to an increase in neglect.

6 Robustness

6.1 Changes in Actual Incidence or Reporting?

In the paper we have only considered substantiated reports. However, the share of substantiated reports in all reports is quite low (19 percent). In Table 8 we add substantiated and unsubstantiated reports and test if unemployment has an effect on all reports. If our main results capture an effect on reporting behaviour, then we would expect a similar effect on substantiated and unsubstantiated reports. If our main results really capture an effect on actual incidence, we would expect a stronger effect on substantiated reports, and so accordingly we would expect to see a smaller effect on the measure of all reports. This is indeed what we find in Table 8. The point estimates of the effects of unemployment on overall, physical abuse and neglect are smaller than the effects on substantiated reports alone. For physical abuse and neglect respectively, the point estimates are between one half and three quarters the size of the effects on substantiated alone.

An unemployment shock may result in a reallocation of labour to high-reporting sectors, such as schools, health care, social services, police, clergy and childcare. The increase in reports of physical abuse and neglect might then simply capture an increase in reporting rather than an increase in the actual incidences of abuse. To address this issue, we follow Lindo et al. (2013). In columns (1) to (3) of Table 9, we control for the fraction of the working age population employed in six high-reporting sectors. We wish to test whether the effects are driven by a re-allocation of labour to high reporting sectors following the unemployment shock, and so reflect an increase in reporting rather than actual incidence. The coefficients on the unemployment rate barely change in any regression, and the fraction employed in high-reporting sectors variables are statistically

[28] See for example Holmes (1998) and Dube et al. (2010) who adopted similar identification strategies.

insignificant in all but one case (clergy). These results suggest that the effects capture an effect on actual incidences, not reporting behaviour.

6.2 Other Robustness Tests

In Table 9, in columns (4)-(6), we also test the robustness to dropping the two largest counties with a population of more than one million children in 2003. In columns (7)-(9), we test the robustness to dropping the counties in the smallest 10 percent in terms of 2003 child population. In columns (10)-(12), we test if our results are robust to clustering standard errors at a county level, and in columns (13)-(15), we test if our results are robust to controlling for linear county trends[29]. The coefficients of interest change very little in size or statistical significance in nearly every case. The main exception is the effect on overall abuse once controlling for linear county trends.

Finally, in Tables 10 and 11, we instead add 0.01 and 0.0001 to all county-years before taking the natural logarithm when constructing the dependent variable. Doing so has little effect on the size or statistical significance of the results.

Broadly, the effects of unemployment on overall abuse, physical abuse and neglect are robust.

7 Conclusion

Child maltreatment is a severe public health problem with long-term consequences, and is still very prevalent in the United States. Studying the determinants of child abuse and neglect has potentially large benefits, for this generation and the next. However, very little robust empirical evidence exists on the economic determinants of child maltreatment.

In this paper, we study the causal effect of unemployment on child abuse and neglect. We use a unique dataset containing every reported incident of child abuse and neglect made to the state Child Protective Services for nearly every state in the U.S. from 2004 to 2012. We identify the effect of unemployment by instrumenting for the county-level unemployment rate with a predicted county-level unemployment rate, which we create by combining national level unemployment rates across industries with differences in the initial industrial structure across counties.

[29] The two counties with a child population of more than one million in 2003 are: Los Angeles, California (2,678,788 children), and Harris, Texas (1,043,580 children). In columns (7)-(9), we drop the counties with a population of less than 1,231 children in 2003 (the 10th percentile among all counties in the U.S. in that year).

We find that an increase of one unit in the unemployment rate leads to a significant increase in all abuses (15 percentage points), and in particular in physical abuses (12 percentage points) and neglect (25 percentage points). We show that our results are robust to several robustness checks.

We test three potential mechanisms through which an increase in unemployment leads to an increase in physical abuse and neglect: substance use, divorce, and poverty. While we do not find consistent evidence with the first two mechanism, we find that results for neglect are consistent with the poverty channel. By exploiting variation in unemployment policies over time within states, we find that extension of unemployment benefit mitigates the effect of unemployment on neglect. A one percentage point increase in the unemployment rate at the 25th percentile of benefits duration (26 weeks) causes a 32 percent increase in neglect. But a one percentage point increase in the unemployment rate at the 75th percentile of benefits duration (74.7 weeks) causes only an 18 percent increase in neglect. We believe that this is a very important result for policy. Poor economic conditions are often associated with child maltreatment, hence, policies designed to enhance parents' employment security, for example, could prove an important contributor to child maltreatment reduction.

This is the first paper to causally identify the effect of unemployment on child maltreatment using data for all the United States at county level and for over a decade, and to confirm poverty to be one of the main mechanism causing child neglect.

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8 Tables and Figures

Table 1: Summary Statistics

	Mean
Number of Incidents of Physical Abuse	42.22
	(135.39)
Number of Incidents of Sexual Abuse	22.60
	(67.80)
Number of Incidents of Emotional Abuse	19.68
	(176.13)
Number of Incidents of Neglect	182.51
	(616.47)
Unemployment Rate (%)	6.85
	(2.99)
Fraction Black (%)	9.69
	(14.87)
Fraction Asian (%)	1.13
	(2.39)
Fraction Hispanic (%)	8.42
	(13.59)
Fraction American Indian (%)	1.48
	(4.89)
Child Poverty Rate 2003 (%)	19.34
	(7.57)
Child Population	24,386
	(79,772)
Observations	24,181
Counties	2,803
States	46

Notes. In this Table, we present summary statistics for the full sample of counties included in the baseline regressions. We present unweighted means, with unweighted standard deviations in parentheses.

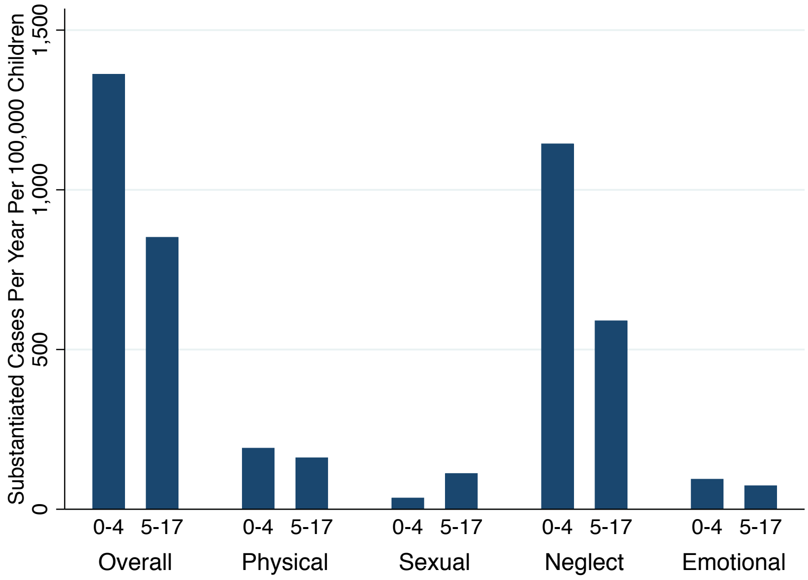

Figure 1: *Notes.* **Abuse Rates by Child Age.** In this Figure, we plot the weighted mean abuse rate per year per 100,000 children for children aged 0-4 years old and 5-17 years old, for each abuse type. We calculate the weighted mean abuse rate as follows. In each county-year, we calculate the abuse rate by dividing the number of incidents for each age group by the number of children of that age group, using population estimates from the Population and Housing Unit Estimates. We then take a weighted mean of the abuse rates across all county-years, where the weights are the child population of the relevant age group in each county-year. We use all available county-years for the entire sample period 2004-12 to calculate this weighted mean. If a child is abused in multiple ways, we count the case only once in the overall abuse measure, which is why the sum of abuse rates across all individual abuse types exceeds the overall abuse rate.

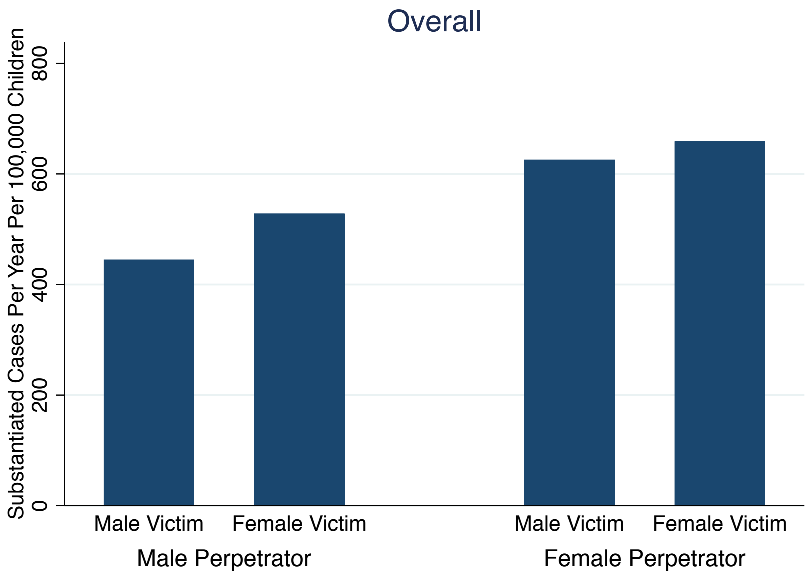

Figure 2: *Notes.* **Overall Abuse Rate by Perpetrator and Victim Gender.** In this Figure, we plot the weighted mean overall abuse rate per year per 100,000 children for each perpetrator and victim gender combination. We calculate the weighted mean abuse rate as follows. In each county-year, we calculate the abuse rate by dividing the number of incidents of overall abuse in each perpetrator-victim gender group by the number of children of the victim's gender aged 0-17, using population estimates from the Population and Housing Unit Estimates. We then take a weighted mean of the abuse rates across all county-years, where the weights are the population of children of the victim's gender aged 0-17 in each county-year. We use all available county-years for the entire sample period 2004-12 to calculate this weighted mean.

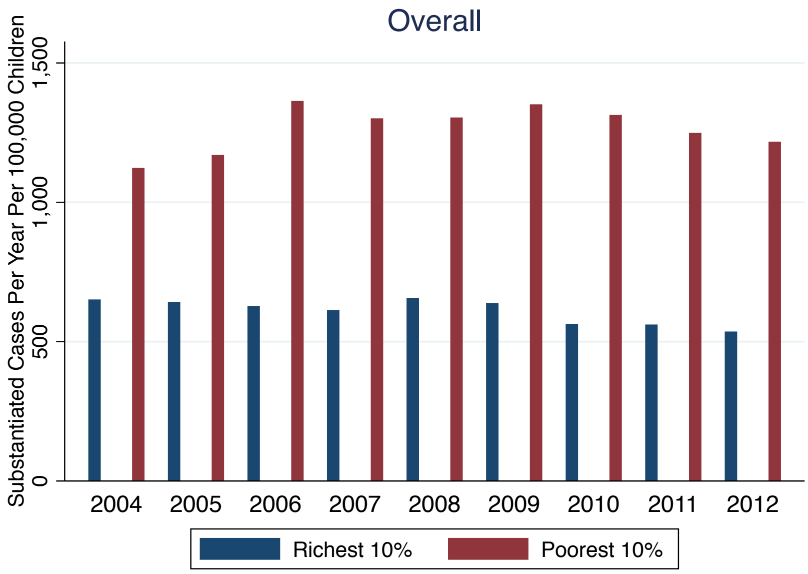

Figure 3: *Notes.* **Overall Abuse Rate Trends for the Least and Most Poor**. In this Figure, we present the weighted mean overall abuse rate in each year for the initially poorest and least poor 10% of counties in the U.S. We do this as follows. We take the 2,803 counties that are included in the final regression analysis, and classify the poorest 10% and least poor 10% in 2003 using the poverty rate taken from the Small Area Income and Poverty Estimates. The poorest 10% of counties are the 273 counties that had a 2003 poverty rate of greater than 20.1%, and the least poor 10% of counties are the 269 counties that had a 2003 poverty rate of less than 7.8%. In each county-year, we calculate the abuse rate by dividing the number of incidents of overall abuse by the number of children aged 0-17, using population estimates from the Population and Housing Unit Estimates. We then take the weighted mean of the abuse rates across all county-years among the least poor or poorest 10% of counties respectively, where the weights are the child population in each county-year. We use all available county-years in any given year to calculate this weighted mean.

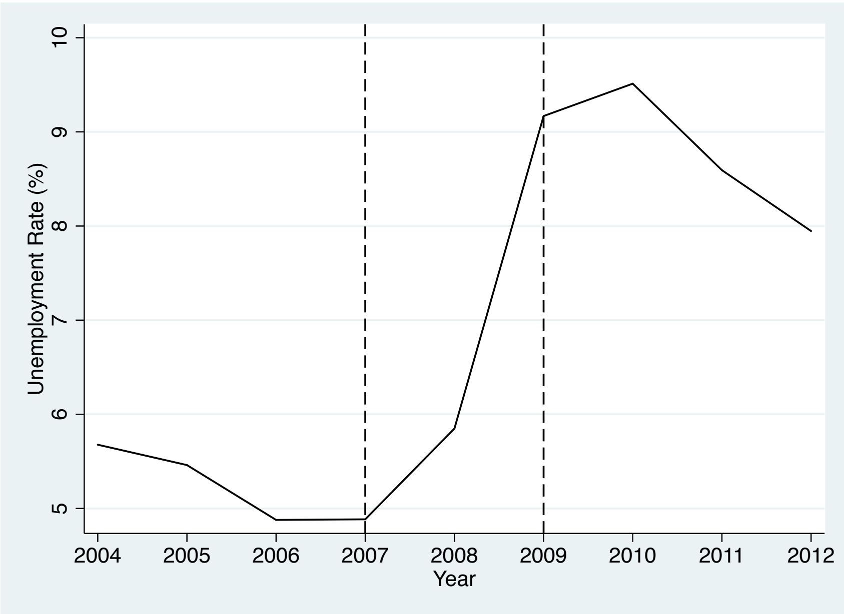

Figure 4: *Notes.* **Trends in Unemployment**. In this Figure we present the trend in the unweighted average unemployment rate across the 2,803 counties in our final sample. Not all counties are observed in every year in the final sample, as some states do not report to NCANDS in some years, as explained in Section 3.2.1. Unemployment rates jumped during the period from 2007 to 2009, with the onset of the financial crisis.

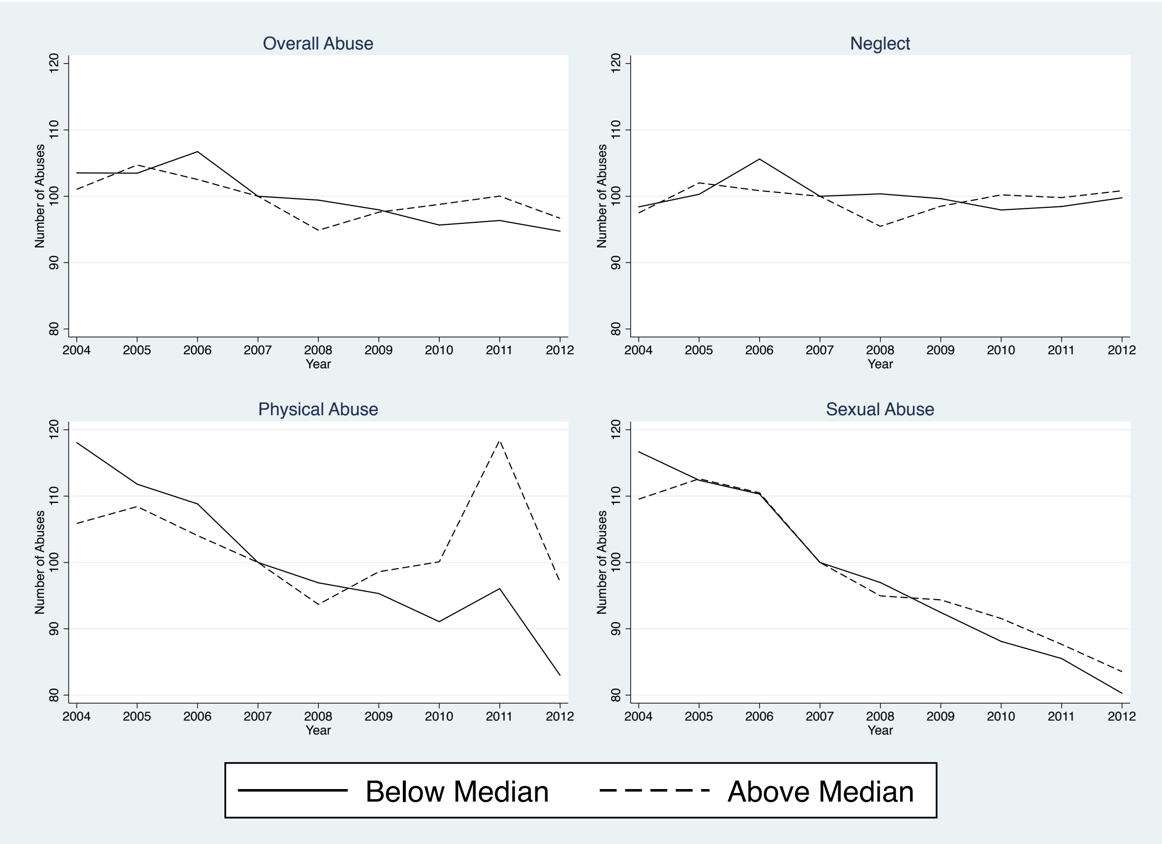

Figure 5: *Notes.* **Abuse Trends Below and Above the Median Bartik Shock**. In this Figure, we present trends in the unweighted average number of abuses across counties, for overall, physical, sexual abuse and neglect. We split the 2,803 counties in the final sample into those that experienced a below and above median increase in the predicted unemployment rate (using our instrument) between 2007 and 2009. The median increase in the predicted unemployment rate from 2007 to 2009 was 4.72 percentage points. For each abuse type, we normalise the unweighted average number of abuses to equal 100 in the year 2007 for both the below and above median shock counties. We therefore should not compare the size of the changes across abuse types, since the normalisation means that changes in physical and sexual abuse (which are much less common than neglect) are exaggerated relative to changes in neglect. To see this, see Figure A.1 in the Appendix, which demonstrates that neglect is much more common. Not all counties are observed in every year in the final sample, as some states do not report to NCANDS in some years, as explained in Section 3.2.1.

Table 2: Main Results

	Overall		Physical		Neglect		Sexual		Emotional	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Unemployment Rate	0.0051	**0.15*****	**0.019***	**0.12****	-0.0049	**0.25*****	0.0013	0.053	-0.059	0.14
	(0.010)	**(0.045)**	**(0.0096)**	**(0.053)**	(0.013)	**(0.068)**	(0.014)	(0.061)	(0.045)	(0.20)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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
Total Child Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,468	23,468	24,181	24,181	24,181	24,181	24,181	24,181	23,468	23,468
Counties	2,771	2,771	2,803	2,803	2,803	2,803	2,803	2,803	2,771	2,771
States	45	45	46	46	46	46	46	46	45	45
Mean of outcome	3.77	3.77	1.65	1.65	3.05	3.05	0.94	0.94	-2.19	-2.19
Mean of Unemployment Rate	6.86	6.86	6.85	6.85	6.85	6.85	6.85	6.85	6.86	6.86
Kleibergen-Paap F-stat		33.3		33.9		33.9		33.9		33.3

Notes. Standard errors (in parentheses) are clustered at the state level in all regressions. This Table contains the results of the OLS and IV 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 in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

Table 3: By Victim Age

	Overall		Physical		Neglect	
	Age 0-4	Age 5-17	Age 0-4	Age 5-17	Age 0-4	Age 5-17
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
Unemployment Rate	**0.16*****	**0.16*****	0.14	0.099	**0.26*****	0.17
	(0.053)	**(0.045)**	(0.092)	(0.060)	**(0.077)**	(0.11)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes	Yes
Total Child Population	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,468	23,468	24,181	24,181	24,181	24,181
Counties	2,771	2,771	2,803	2,803	2,803	2,803
States	45	45	46	46	46	46
Mean of outcome	2.57	3.24	-0.24	1.06	2.12	2.27
Mean of Unemployment Rate	6.86	6.86	6.85	6.85	6.85	6.85
Kleibergen-Paap F-stat	33.3	33.3	33.9	33.9	33.9	33.9

Notes. Standard errors (in parentheses) are clustered at the state level in all regressions. This Table contains the results of the IV regressions which look at the effect of unemployment on the incidence of overall, physical abuse and neglect by victim age. In each case, the dependent variable is the natural logarithm of the number of incidents of abuse of that type per year for a victim of the given age group, after first adding 0.001 incidents to every county-year to ensure that no county-years have zero incidents. We look at two age groups: children aged 0-4 years and children aged 5-17 years. We control for county fixed effects in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

Table 4: By Perpetrator Gender

	Overall		Physical		Neglect	
	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
Unemployment Rate	0.077	**0.23******	0.026	0.10	**0.16***	**0.32******
	(0.051)	**(0.065)**	(0.068)	(0.13)	**(0.089)**	**(0.081)**
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes	Yes
Total Child Population	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,893	20,893	21,606	21,606	21,606	21,606
Counties	2,509	2,509	2,541	2,541	2,541	2,541
States	42	42	43	43	43	43
Mean of outcome	2.89	2.97	0.73	0.29	1.59	2.58
Mean of Unemployment Rate	6.87	6.87	6.85	6.85	6.85	6.85
Kleibergen-Paap F-stat	28.9	28.9	29.8	29.8	29.8	29.8

Notes. Standard errors (in parentheses) are clustered at the state level in all regressions. This Table contains the results of the IV regressions which look at the effect of unemployment on the incidence of overall, physical abuse and neglect by perpetrator gender. In each case, the dependent variable is the natural logarithm of the number of incidents of abuse of that type per year perpetrated by someone of the given gender, 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 in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

Table 5: Testing the Alcohol Mechanism

	Alcohol Consumption						Abuse and Neglect		
	Both		Male		Female		Overall	Physical	Neglect
	Heavy	Binge	Heavy	Binge	Heavy	Binge			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	IV	IV	IV	IV	IV	IV	IV	IV	IV
Unemployment Rate	-0.079	**-0.12***	-0.046	-0.00088	**-0.12*****	**-0.24*****	**0.13*****	**0.11****	**0.23*****
	(0.052)	**(0.064)**	(0.070)	(0.10)	**(0.045)**	**(0.060)**	**(0.043)**	**(0.055)**	**(0.065)**
Heavy Drinking Prevalence							**0.061***	0.011	**0.10****
							(0.036)	(0.039)	**(0.051)**
Binge Drinking Prevalence							-0.049	**-0.061****	-0.040
							(0.039)	**(0.030)**	(0.044)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total Child Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,370	24,172	21,370	24,172	21,370	24,172	20,782	21,370	21,370
Counties	2,802	2,802	2,802	2,802	2,802	2,802	2,770	2,802	2,802
States	45	45	45	45	45	45	44	45	45
Mean of outcome	7.20	16.6	9.71	23.5	4.77	9.99	3.75	1.62	3.04
Mean of Unemployment Rate	7.00	6.85	7.00	6.85	7.00	6.85	7.02	7.00	7.00
Kleibergen-Paap F-stat	32.1	33.9	32.1	33.9	32.1	33.9	26.9	27.7	27.7

Notes. Standard errors (in parentheses) are clustered at the state level in all regressions. In this Table, we test the alcohol mechanism. In columns (1) to (6), we use the same Bartik IV strategy to look at whether unemployment causes an increase in alcohol consumption. In columns (1), (3) and (5) we look at the prevalence of heavy drinking, which is defined as consuming more than one drink per day for women and two drinks per day for men for the last thirty days. In columns (2), (4) and (6), we look at the prevalence of binge drinking, which is defined as consuming more than four drinks in a single day for women or five drinks for men, at least once during the past thirty days. In columns (1) and (2) we look at the prevalence rate across genders, in columns (3) and (4) we look at the male prevalence and in columns (5) and (6) female prevalence. In columns (7) to (9), we then control for the prevalence of heavy and binge drinking across genders in the baseline regression. There are no measures of alcohol for D.C. (and so we lose one state, with one county), and heavy drinking is only measured from 2005 onwards. 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 in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

Table 6: Testing the Divorce Mechanism

	Divorce		Abuse and Neglect		
			Overall	Physical	Neglect
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
Unemployment Rate	**0.0050*****	**0.0017****	**0.14*****	**0.11****	**0.22*****
	(0.0014)	**(0.00085)**	**(0.044)**	**(0.055)**	**(0.065)**
Lag Unemployment Rate		**0.0051*****			
		(0.0017)			
Divorce Rate			-0.082	0.51	-0.12
			(0.36)	(0.58)	(0.57)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
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
Total Child Population	Yes	Yes	Yes	Yes	Yes
Observations	21,354	21,352	20,766	21,354	21,354
Counties	2,799	2,799	2,767	2,799	2,799
States	46	46	45	46	46
Mean of outcome	0.12	0.12	3.75	1.63	3.04
Mean of Unemployment Rate	7.00	7.00	7.02	7.00	7.00
Kleibergen-Paap F-stat	32.5		30.7	31.3	31.3
SW F-stat for Unemployment Rate		42.7			
SW F-stat for Lag Unemployment Rate		39.2			

Notes. Standard errors (in parentheses) are clustered at the state level in all regressions. In this Table, we test the divorce mechanism. In column (1), we use the same Bartik IV strategy to look at whether unemployment causes a change in the divorce rate. We consider the divorce rate among individuals aged 18 and over. In column (2), we allow for an lagged effect of unemployment on divorce. To do so we add a second instrument, which is simply the lag of the original instrument. The divorce rate is only measured from 2005 and onwards, which is why we do not lose one year of data when we add the lagged unemployment rate. In columns (3) to (5), we then control for the divorce rate in the baseline regression. 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 in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

Table 7: Policy Analysis: Overall Sample

	Benefits Duration				Food Stamps			
	First Stage		Second Stage		First Stage		Second Stage	
	Unemployment Rate	Interaction	Neglect	Physical	Unemployment Rate	Interaction	Neglect	Physical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IV	IV	IV	IV	IV	IV	IV	IV
Bartik IV	1.39***	160.6***			0.85***	0.40**		
	(0.26)	(36.0)			(0.14)	(0.16)		
Benefit Duration x Bartik IV	-0.0078***	-1.30***						
	(0.0022)	(0.38)						
Food Stamp x Bartik IV					-0.35***	-0.51*		
					(0.13)	(0.28)		
Unemployment Rate			**0.39*****	0.11			**0.26*****	0.081
			(0.099)	**(0.090)**			(0.068)	**(0.060)**
Benefit Duration x Unemployment Rate			**-0.0028*****	0.0000052				
			(0.0011)	**(0.0010)**				
Food Stamp x Unemployment Rate							-0.048	0.047
							(0.15)	(0.16)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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
Total Child Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,145	24,145	24,145	24,145	21,833	21,833	21,833	21,833
Counties	2,799	2,799	2,799	2,799	2,083	2,083	2,083	2,083
States	45	45	45	45	46	46	46	46
Mean of outcome			3.05	1.64			3.07	1.69
Mean of Unemployment Rate			6.85	6.85			6.73	6.73
SW F-stat Unemprate	48.4		48.4	48.4	37.4		37.4	37.4
SW F-stat Interaction		10.5	10.5	10.5		2.57	2.57	2.57

Notes. Standard errors (in parentheses) are clustered at the state level in all regressions. This Table contains the results of IV regressions which allow the effect of unemployment on the incidence of physical abuse and neglect to differ by two state-level policies. In columns (1)-(4), we interact the unemployment rate with the duration of unemployment benefits that an individual can claim in the state-year. In columns (5)-(8), we interact the unemployment rate with a dummy variable that takes the value 1 if the state has relaxed asset tests for food stamps in that year. In columns (1), (2), (5) and (6), we present results from the first stage (which is identical for the physical abuse and neglect regressions, for a given policy of interest), and in columns (3), (4), (7) and (8), the results from the second stage. Food stamp policy data is available only from 2004-11, while data on benefits duration is not available for Hawaii. 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 in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

Table 8: All Reports: Substantiated + Unsubstantiated

	Overall		Physical		Neglect		Sexual		Emotional	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Unemployment Rate	-0.0034	**0.084****	0.00067	**0.094***	-0.010	**0.11****	0.00061	0.041	**-0.13*****	0.074
	(0.0060)	**(0.039)**	(0.0066)	**(0.049)**	(0.0069)	**(0.042)**	(0.013)	(0.049)	**(0.037)**	(0.21)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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
Total Child Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,468	23,468	24,181	24,181	24,181	24,181	24,181	24,181	23,468	23,468
Counties	2,771	2,771	2,803	2,803	2,803	2,803	2,803	2,803	2,771	2,771
States	45	45	46	46	46	46	46	46	45	45
Mean of outcome	5.35	5.35	3.85	3.85	4.85	4.85	2.83	2.83	0.89	0.89
Mean of Unemployment Rate	6.86	6.86	6.85	6.85	6.85	6.85	6.85	6.85	6.86	6.86
Kleibergen-Paap F-stat		33.3		33.9		33.9		33.9		33.3

Notes. Standard errors (in parentheses) are clustered at the state level in all regressions. This Table contains the results of the OLS and IV regressions which look at the effect of unemployment on the total reports of overall, physical, sexual, emotional abuse and neglect, including both substantiated and unsubstantiated reports. In each case, the dependent variable is the inverse hyperbolic sine transformation of the number of substnatiated and unsubstantiated reports of that abuse type per year. We control for county fixed effects in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

Table 9: Robustness of Main Results

	Control Reporting			Drop Large Counties			Drop Small Counties			Cluster County			Control County Trends		
	Overall	Physical	Neglect	Overall	Physical	Neglect	Overall	Physical	Neglect	Overall	Physical	Neglect	Overall	Physical	Neglect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
Unemployment Rate	**0.14*** **	**0.12** **	**0.22*** **	**0.14*** **	**0.12** **	**0.24*** **	**0.14*** **	**0.10* **	**0.24*** **	**0.15*** **	**0.12* **	**0.25*** **	0.04	**0.13* **	**0.10** **
	(0.043)	**(0.055)**	**(0.063)**	**(0.044)**	**(0.052)**	**(0.067)**	**(0.045)**	**(0.054)**	**(0.069)**	**(0.052)**	**(0.059)**	**(0.066)**	(0.042)	**(0.074)**	**(0.046)**
Fraction Employed in Schools	0.66	0.56	-0.028												
	(0.60)	(1.23)	(1.16)												
Fraction Employed in Social Services	1.16	1.10	1.15												
	(2.48)	(2.72)	(2.89)												
Fraction Employed in Health Care	0.54	-0.79	1.35												
	(0.37)	(0.85)	(0.98)												
Fraction Employed in Police	-3.21	-4.31	-0.55												
	(4.37)	(3.06)	(3.78)												
Fraction Employed in Clergy	3.56**	0.20	-0.068												
	(1.64)	(3.88)	(3.08)												
Fraction Employed in Child Care	-0.027	2.20	-1.04												
	(1.38)	(1.76)	(1.74)												
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Ethnic Group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total Child Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear County Trends	No	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	20,766	21,354	21,354	23,450	24,163	24,163	21,480	22,186	22,186	23,468	24,181	24,181	23,468	24,181	24,181
Counties	2,767	2,799	2,799	2,769	2,801	2,801	2,545	2,577	2,577	2,771	2,803	2,803	2,771	2,803	2,803
States	45	46	46	45	46	46	45	46	46	45	46	46	45	46	46
Mean of outcome	3.75	1.63	3.04	3.76	1.64	3.05	4.20	2.14	3.52	3.77	1.65	3.05	3.77	1.65	3.05
Mean of Unemployment Rate	7.02	7.00	7.00	6.86	6.85	6.85	7.02	7.00	7.00	6.86	6.85	6.85	6.86	6.85	6.85
Kleibergen-Paap F-stat	32.5	33.1	33.1	33.7	34.4	34.4	32.2	32.9	32.9	64.5	67.7	67.7	32.1	30.0	30.0

Notes. Standard errors (in parentheses) are clustered at the state level in the regressions in columns (1) to (9) and (13) to (15), and at the county level in columns (10) to (12). In this Table, we test the robustness of the main results for overall, physical abuse and neglect. In columns (1) to (3), we control for the fraction of the working age population employed in high-reporting sectors. In columns (4) to (6), we drop the two counties with a population of more than one million children in 2003 (Harris, Texas; and Los Angeles, California). In columns (7) to (9), 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 columns (10) to (12), we cluster standard errors at the level of the county. Finally, in columns (13) to (15), we control for linear county trends. 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 in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

Table 10: Robustness: Add 0.01 Before Taking Natural Logarithm

	Overall		Physical		Neglect		Sexual		Emotional	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Unemployment Rate	0.0054	**0.14*****	**0.017***	**0.090***	-0.0037	**0.22*****	0.0056	0.048	-0.056	0.087
	(0.0097)	**(0.044)**	**(0.0089)**	**(0.047)**	(0.011)	**(0.063)**	(0.014)	(0.052)	(0.035)	(0.16)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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
Total Child Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,468	23,468	24,181	24,181	24,181	24,181	24,181	24,181	23,468	23,468
Counties	2,771	2,771	2,803	2,803	2,803	2,803	2,803	2,803	2,771	2,771
States	45	45	46	46	46	46	46	46	45	45
Mean of outcome	3.77	3.77	1.88	1.88	3.23	3.23	1.27	1.27	-1.11	-1.11
Mean of Unemployment Rate	6.86	6.86	6.85	6.85	6.85	6.85	6.85	6.85	6.86	6.86
Kleibergen-Paap F-stat		33.3		33.9		33.9		33.9		33.3

Notes. Standard errors (in parentheses) are clustered at the state level in all regressions. This Table contains the results of the OLS and IV 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 0.01 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

Table 11: Robustness: Add 0.0001 Before Taking Natural Logarithm

	Overall		Physical		Neglect		Sexual		Emotional	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Unemployment Rate	0.0048	**0.15*****	**0.021****	**0.14****	-0.0062	**0.27*****	-0.0030	0.058	-0.063	0.18
	(0.011)	**(0.046)**	**(0.010)**	**(0.061)**	(0.014)	**(0.074)**	(0.015)	(0.070)	(0.055)	(0.25)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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
Total Child Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,468	23,468	24,181	24,181	24,181	24,181	24,181	24,181	23,468	23,468
Counties	2,771	2,771	2,803	2,803	2,803	2,803	2,803	2,803	2,771	2,771
States	45	45	46	46	46	46	46	46	45	45
Mean of outcome	3.68	3.68	1.41	1.41	2.87	2.87	0.61	0.61	-3.26	-3.26
Mean of Unemployment Rate	6.86	6.86	6.85	6.85	6.85	6.85	6.85	6.85	6.86	6.86
Kleibergen-Paap F-stat		33.3		33.9		33.9		33.9		33.3

Notes. Standard errors (in parentheses) are clustered at the state level in all regressions. This Table contains the results of the OLS and IV 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 0.0001 incidents to every county-year to ensure that no county-years have zero incidents. We control for county fixed effects in all regressions. We have therefore implicitly controlled for state fixed effects, and so control for small differences in definitions of abuse across states. We include state-year fixed effects to control for any changes in the definitions of abuse over time within states, and control for year fixed effects. Finally, we control for the total child population and the fraction of the overall population that is Black, Hispanic or Other Race (which includes individuals who are Asian, Alaskan Native, American Indian, Native Hawaiian or Other Pacific Islander and Two or More Races). We weight observations by the total child population in 2003, the year before the start of the sample period.

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

A Appendix

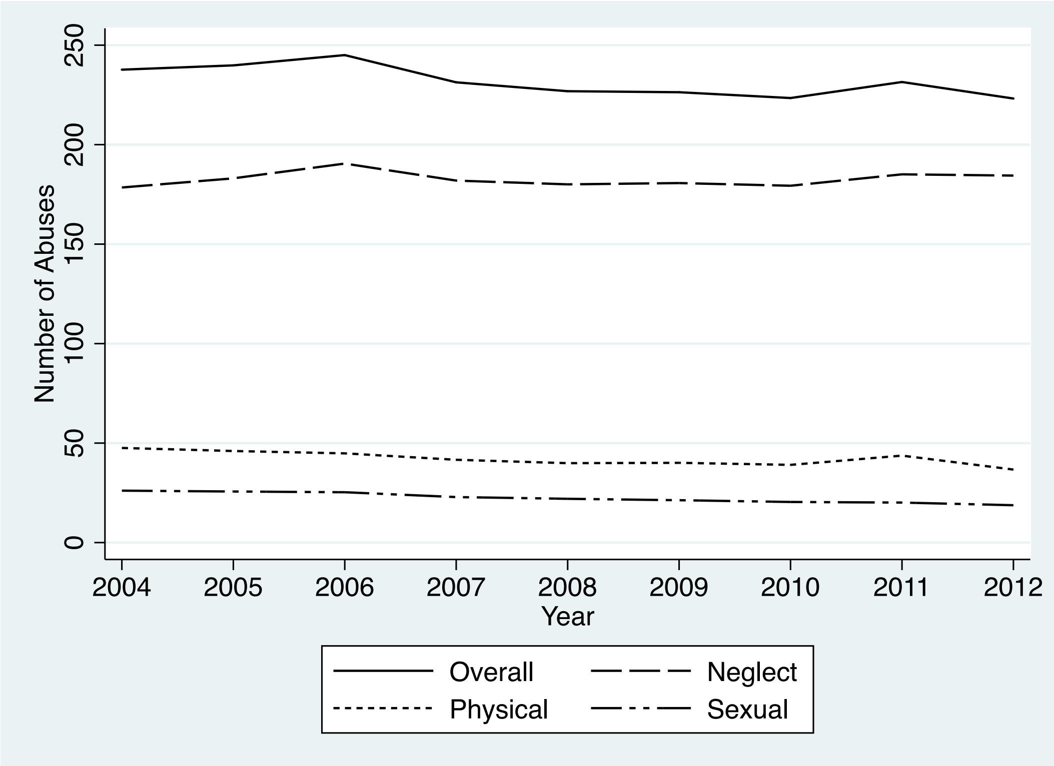

Figure A.1: *Notes.* **Abuse Trends**. In this Figure, we present trends in the unweighted average number of abuses across counties, for overall, physical, sexual abuse and neglect. Not all counties are observed in every year in the final sample, as some states do not report to NCANDS in some years, as explained in Section 3.2.1. This Figure demonstrates that neglect is considerably more common than physical and sexual abuse. The sum of neglect, physical and sexual abuses can be more than the total number of overall abuses, since we count a child-report where the child is maltreated in more than one way only once in the measure of overall abuse.

B Data Appendix

B.1 Creating the Left Hand Side Variables

B.1.1 Organising the Data by Calendar Year and Report Date

The NCANDS data is released annually, and is organised 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 organise the data by the date of incidence of abuse, but that is unobserved. The closest that we can get to the date of incidence is the date of report, which is also contained in the dataset. We therefore reorganise 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 B.2. Indiana missing the FFY 2012. Our dataset for this state then does not include any incident whose investigation was 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 was concluded more than 15 days after the report was 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 B.2, 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 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 3.2.1.

B.1.2 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

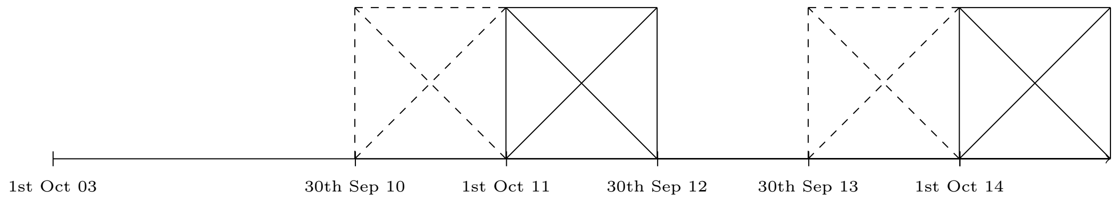

Figure B.2: Missing Years by Report Date for Indiana. The solid crosses indicate the missing periods of data for Indiana by investigation disposition date (the Federal Fiscal Year 2012, and from 1st October 2014 onwards). To organise the data by report date, I treat both the solid and dashed time periods as missing. In other words, I 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, I 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.

is missing from the dataset because there is no CPS office located in the county, rather than because there were 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.

B.2 Description of the Construction of the Variables

Table B.1: Data Appendix

Variable	Data Source	Method
Overall Abuse, Neglect, Physical Abuse, Sexual Abuse, Emotional Abuse	National Child Abuse and Neglect Data System (NCANDS)	We keep only child-reports where at least one allegation of child maltreatment is found to be substantiated. There can be up to four allegations of child maltreatment on any given child-report. To do this, we keep any child-report for which at least one of the variables Mal1Lev, Mal2Lev, Mal3Lev, Mal4Lev is equal to 1 (substantiated), 2 (indicated or reason to suspect), or 3 (alternative response victim). We keep only child-reports for which the child is aged from 0 to 17 years inclusive. Within each county-year we then sum the total number of substantiated incidents of each type of abuse. To do so we use the report date (RptDt) and calendar year, as explained in Section B.1.1. For the measures of overall abuse, we treat a child-report with more than one substantiated type of abuse as a single case. For example, if a child is both physically and sexually abused, we treat this as only one incident of overall abuse. We create a measure of the overall number of abuses per year as: $A^*_{cst} = A_{cst}/(O_{cst}/D_t)$, where A^*_{cst} is the 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. We then take the natural logarithm of the number of abuses per year. For county-years with zero abuses, we first add 0.01 to the number of abuses before taking the natural logarithm. Further explanation for the creation of the left hand side variables is given in Section B.1.
Unemployment Rate	Local Area Unemployment Statistics (LAUS)	We use the annual average unemployment rate at a county-level, produced by the Bureau of Labor Statistics.
Predicted Unemployment Rate (Instrument)	Quarterly Census of Employment and Wages (QCEW) and Current Population Survey (CPS-BLS)	The weights for the instrument are the fraction of all employed individuals working in each industry at the county-level in 2003. To calculate this, we use the QCEW. We first sum the annual average number employed 'annual_avg_emplvl' across all ownership sectors (government and private), for each of the 20 NAICS industries 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. We calculate national level unemployment rates in each year using the CPS-BLS. We divide the total unemployed by the sum of the total employed and unemployed in each of the 20 NAICS industries. To calculate the instrument we then take a weighted average of these national level unemployment rates across industries using the weights previously described, which capture the initial industrial structure in each county.

Data Appendix: Continued

Variable	Data Source	Method
Fraction Black, Asian, Hispanic and American Indian	Population and Housing Unit Estimates (PHUE)	First, we calculate the fraction of the population who are Black, Asian, and American Indian. The PHUE contains a breakdown of the total population by race, where an individual can be classified as Black Alone, White Alone, Asian Alone, American Indian Alone or Two or More Races. An individual who is Two or More Races is included in the base category with whites. The PHUE treats being Hispanic as an ethnic group, rather than a race. We therefore separately calculate the fraction of the population who identify with the Hispanic ethnic group. For this reason, the fractions Black, Asian, Hispanic and American Indian could sum to more than one, since a Hispanic individual can also classify a separate race. For the years 2004-9, we use the 2009 Vintage, and for the years 2010-12 we use the 2014 Vintage.
Fraction Employed in Schools, Health Care, Social Services, Police, Clergy, Childcare	American Community Survey (ACS)	For each high-reporting sector, we calculate the fraction of the working age (18-64) population who are employed in each sector. 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. The geographic identifier in the ACS is the PUMA, not the county. We therefore use the 2010 county to 2000 PUMA cross-walk provided by the Missouri Census Data Center. For counties that are entirely contained within a single PUMA, we assign to the county the value for the PUMA in which it is contained. For counties that cut across more than one PUMA, we assign a weighted average of the values for the PUMAs that intersect with that county, where the weights are the fraction of the county population in each PUMA. The ACS only contains PUMA information for the years 2005 to 2012, and so these variables are only defined for those years.
Total Children	Population and Housing Unit Estimates (PHUE)	We take the total number of boys and girls aged 0-17 from the PHUE. For the years 2004-9, we use the 2009 Vintage, and for the years 2010-12 we use the 2014 Vintage. This is also the dataset we use to create the weight for our regressions, for which we use the number of children (aged 0-17) in 2003. For this we again use the 2009 Vintage.