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Child health care coverage and reductions in child physical abuse

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Abstract

Children in the United States suffered almost 118,000 cases of physical abuse in 2015. One factor that might help decrease child physical abuse is health care coverage. This paper presents a justification for a link between health care coverage and reductions in child physical abuse and, though it does not assess specific causal mechanisms, examines evidence for such a connection. The paper uses panel data linear regression analysis to explore state level physical abuse and health care coverage rates. Findings indicate a statistically significant relationship between increases in child health care coverage rates, including both private coverage and Medicaid coverage, and decreases in child physical abuse.

Keywords: Pediatrics, Sociology, Economics

1. Introduction

In 2015, an estimated 117,772 children were physically abused ([U.S. Dept. of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2017](#)). Though trends may have decreased over time ([Child Trends, 2016](#)), this still represents a significant public policy problem: in addition to the immediate pain and suffering that every case of abuse represents, there are substantial long-term costs as well. Children who suffer physical abuse will spend the rest of their lives at a higher risk for a host of adverse

health effects and chronic diseases including, but not limited to, heart disease, obesity, high blood pressure, and cancer (Gilbert et al., 2015; Danese et al., 2009; Felitti et al., 1998). The deleterious consequences go beyond physical symptoms: children who suffer abuse are also at higher risk for low academic achievement, abuse of illicit substances, alcoholism, juvenile and adult criminality, and a variety of psychological disorders (Felitti et al., 1998; Lansford et al., 2002; Silverman et al., 1996). The average lifetime cost associated with each case of child maltreatment, when considering long-term impacts, amounts to hundreds of thousands of dollars in economic losses for society (Fang et al., 2012).

Given the wide-ranging consequences of child abuse, prevention is the optimal policy response. One policy that is “proposed but unproven” to prevent abuse is “making health care more accessible and affordable,” such as via health care coverage (Betha, 1999, p. 1581). As child uninsured rates have decreased over the last two decades, so have physical abuse rates; uninsured rates are decreasing further since the passage of the Affordable Care Act, opening of the insurance exchanges, and Medicaid expansions. This article explores a justification for a link between health care coverage and reductions in child physical abuse and evaluates evidence of a correlation via statistical analysis of U.S. state-level child abuse and health care coverage rates. The analysis assesses only the presence of a connection between coverage and physical abuse, but, due to a lack of causal estimation strategy, not any specific causal mechanism. Results indicate an association between increases in child health care coverage rates, including both private and public coverage, and decreases in child physical abuse.

2. Background

2.1. What is child physical abuse?

2.1.1. Definition

In the United States, child physical abuse is defined by both state and federal laws. More specifically, the “Federal Child Abuse Prevention and Treatment Act provides minimum standards to the states for defining maltreatment, but each state defines child physical abuse within its own civil and criminal statutes” (Christian & Committee on Child Abuse and Neglect, 2015, p. e1338). As such, no single definition can capture the totality of what constitutes physical abuse across all states in the U.S. However, physical abuse can be generally characterized as “‘any nonaccidental physical injury to the child’ and can include striking, kicking, burning, or biting the child, or any action that results in a physical impairment of the child” (U.S. Dept. of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children’s Bureau, 2016, p. 2). Additionally, child abuse is typically understood as activity meeting

the above definition perpetrated “on the part of a parent or caretaker” (U.S. Dept. of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children’s Bureau, 2016, p. 1) against children in their care. Children are understood to be people less than 18 years old, for the most part, though child abuse data does include a small number of cases of abuse reported against children between 18 and 21 years of age.

2.1.2. Trends

Data from both the National Incidence Study (NIS) and the National Child Abuse and Neglect Data System (NCANDS) indicate that physical abuse has declined since the early 1990s (Olson and Stroud, 2012). NIS data are survey results designed specifically to capture rates and trends over time, and NCANDS data are based on actual Child Protective Services (CPS) reports from across the country. However, these data are far from a complete picture: even as NIS and NCANDS indicate that child physical abuse is on the decline, NCANDS data also seems to show increases in the rate of children dying due to child maltreatment (child maltreatment fatalities), and examinations of hospitalization data show that the rate of children hospitalized due to physical abuse is not declining and may be on the rise (Finkelhor and Jones, 2012). An additional complication in examining child physical abuse trends is that changes in trends might not be due just to changes in the actual rates of child physical abuse — rather, trends based on CPS data are also subject to variation based on CPS resources and capacity to review and substantiate abuse reports.

2.1.3. Etiology

Child physical abuse is a complex phenomenon to study, and researchers have acknowledged for decades that any explanation of the causes of physical abuse that focuses solely on individual or family characteristics will be limited in efficacy (National Research Council, 1993). Rather, the causes of physical abuse go beyond family characteristics; a more thorough model for analyzing abuse will instead consider individual, relationship, community, and societal factors — i.e., an ecological model (MacKenzie et al., 2011). The theoretical justification for a link between health care coverage and reductions in physical abuse that this paper offers will include both individual and societal factors.

2.2. Health care coverage

This paper uses the term “health care coverage” to encompass both private health insurance coverage, including individual and employer sponsored plans, and public health insurance coverage via Medicaid. Health insurance is understood as a system that helps to pay for some portion of expenses associated with medical and surgical

services (Fernandez and Uberoi, 2015). It is important to clearly delineate the difference between actual health care and health care coverage/health insurance. “Health insurance is a financial mechanism for paying for health care. It is not the care itself, or even a guarantee of care” (Katz, 2014, p. 859). This paper examines specifically the effect of health care coverage, and not just health care utilization – though actual utilization of health care is part of the theoretical explanation for why health care coverage might be associated with reductions in child physical abuse.

2.3. Theoretical model

Some child maltreatment literature indicates a link between health care coverage, neglect (Prevent Child Abuse America, n.d.), and medical neglect (Klevens et al., 2015), but that literature does not appear to consider a relationship between coverage and specifically physical abuse. One recent paper found that child Medi-Cal eligibility shows a negative association with risk of becoming a child maltreatment case (Thurston et al., 2017) and another found that Medi-Cal enrollment was associated with lower odds of serious maltreatment (Miyamoto et al., 2017); those papers used Medi-Cal (California’s Medicaid program) as a proxy for low socioeconomic status and also discussed the potential for Medi-Cal to reduce family stress. This paper appeals to the financial stress argument and presents additional theoretical perspectives, including a novel explication of how coverage, access to care, and exposure to the health care system might be associated with decreases in physical abuse. In its statistical analyses, this paper will also attempt to control for socioeconomic variables in order to isolate any effect Medicaid might have independent of its purely socioeconomic implications. Fig. 1 offers a visual representation of the theoretical model proposed by this paper.

2.4. Health care coverage as access to affordable health care

2.4.1. Coverage increases accessibility, affordability, and utilization of health care

Health care coverage makes care more accessible and affordable (Nyman, 1999), leading to increased utilization of services including outpatient visits, preventive care, inpatient visits, and ambulatory admissions (Buchmueller et al., 2005). Expansions in child coverage lead to increased access to doctors, more well-child visits, and more children having usual sources of care (Larson et al., 2016). Enrollment in the State Children’s Health Insurance Program (SCHIP) increases access by allowing families to more quickly see providers for routine care. After enrolling children in SCHIP, the percentage of families reporting it was “very easy or easy to get ... health care for their child” increased 36 percent; this included when children were sick, for specialty care, and for all health care needs (Kempe et al., 2005, p. 365). After SCHIP enrollment, children are also more likely to have seen a provider for

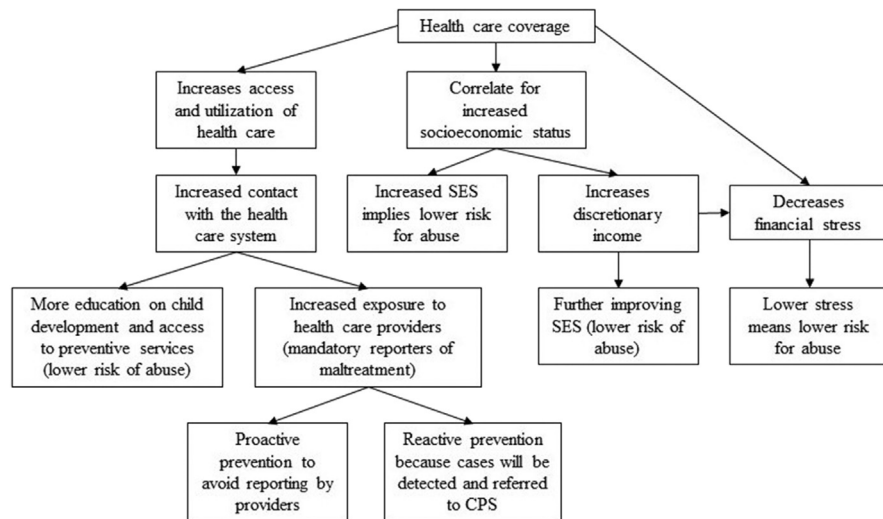


Fig. 1. Visual representation of hypothesized theoretical model.

routine care than before they enrolled. Research consistently finds that expansion of public insurance for children “unambiguously improves current utilization of preventive care” (Currie et al., 2008, p. 1567). Conversely, being uninsured makes children less likely to have a regular source of care (Newacheck et al., 1998), and uninsured children are “consistently the least likely to have access to a usual source of care” (Berdahl et al., 2013, p. 191). Coverage may be a more powerful predictor of access to and utilization of health care than factors like income or race (Olson et al., 2005).

2.4.2. More education on child development and referrals to preventive programs

More exposure to the health care system increases the likelihood that parents/caregivers will get additional information from doctors that might prevent abuse. Providers are in a unique position to offer advice to parents/caregivers and to refer them to additional parenting or child development classes (Mayo Clinic, 2015). In survey of pediatricians, 70 percent said that “they can help prevent child abuse by providing anticipatory guidance” and 91 percent “agreed that pediatricians should screen for parenting problems during health supervision visits” (Flaherty and Stirling, 2010, pp. 833–834).

In addition to referring patients to external preventive services such as home visitation programs, some providers are participating in other prevention initiatives. Examples include the Safe Environment for Every Kid (SEEK) model, the Connected Kids: Safe, Strong, Secure office intervention, and the Practicing Safety program (Gwirtzman Lane, 2014). The American Academy of Pediatrics has a

program called Bright Futures which aims to inform primary care providers about recommendations to prevent maltreatment, including continuing medical education, providing family support, counseling parents/caregivers, developing and participating in community support programs, and working with family members to assess family function (Fussell, 2011). Like pediatricians, children's hospitals also share a commitment to the prevention of child abuse and neglect (National Association of Children's Hospitals and Related Institutions, 2011). These examples are not intended to be an exhaustive list of preventive programs used by primary care providers, but are intended to illustrate ways that providers are working to prevent child abuse before it has the chance to occur.

2.4.3. Mandatory reporting: preventive and reactive

All U.S. states legally require health care providers to be mandatory reporters of suspected child maltreatment (Child Welfare Information Gateway, 2015). There are two effects that might follow from this requirement: first, an increase in parental/caregiver accountability. Parents/caregivers whose children have regular physicians may be less likely to commit physical abuse because physicians would tend to observe evidence of the abuse. Second, in cases where abuse has occurred, providers can detect those cases and refer them to Child Protective Services to keep situations from escalating or proceeding further. This line of reasoning regarding detection of abuse is highlighted by the National Research Council: "Health professionals in private practice, community health clinics, and hospitals are often the first point of contact for abused children and their families when physical injuries are sustained" (National Research Council, 1993, p. 20). The Council points out that the absence of access to preventive care actually increases the risk of child abuse cases going undetected, untreated, and unreported.

One study on reporting finds that "Primary care providers report most, but not all, cases of suspected child abuse that they identify" (Flaherty et al., 2000, p. 489), and a follow up study finds that clinicians report about 73 percent of cases that are "likely or very likely caused by child abuse" (Flaherty et al., 2008, p. 611). Another study found that over 80 percent of physicians reported receiving continuing medical education on child abuse and over 60 percent were confident they could identify and manage abuse (Flaherty et al., 2006). One survey of physicians in Kentucky found higher levels of confidence: 89.9 percent were comfortable recognizing child abuse, 85.9 percent knew the process to report abuse, and 83.6 percent knew who to call locally to report suspicions of abuse (Brenzel et al., 2007). Nurse practitioners report even higher proportions of suspected cases of abuse: according to one 2014 study of pediatric nurse practitioners, 80 percent reported every case of suspicious injuries to authorities (Herendeen et al., 2014).

Most of these studies also note that providers face barriers to reporting, including concerns about certainty regarding suspicions, effectiveness of CPS in confirming and managing cases, damaging patient relationships, harming families if suspicions are ultimately unfounded, or making situations worse for children. In addition, research from the Crimes Against Children Research Center shows that maltreatment reporting procedures need to be improved substantially; many providers believe their training in reporting processes is inadequate and that they have too little information about what happens after reports are filed (Walsh and Jones, 2015). It is absolutely the case that the current reporting system is imperfect and needs to be improved. However, despite the shortcomings of the current reporting system, the findings in the literature seem clear: when confident in their identification of child abuse, providers are likely to report their suspicions to CPS for further investigation.

2.5. Health care coverage and socioeconomic status

Health care coverage relates to socioeconomic status in multiple ways. First, it might be a correlate for higher socioeconomic status. People with health care coverage generally have higher incomes (Bernard et al., 2009), and “children in low-income families are... more likely to be at risk of maltreatment” (Berger, 2004, p. 744). If coverage correlates with higher incomes, then this could explain a connection with reduced physical abuse. However, public coverage does not correlate with incomes, because programs are means tested; families who get Medicaid or SCHIP benefits must have lower incomes relative to people above those income thresholds. The relationship is additionally complicated because families with higher incomes are likely to have private coverage, and families with low incomes may have access to public coverage for their children via Medicaid and/or SCHIP. Families with incomes just above Medicaid/SCHIP thresholds, however, may not have access to either public or affordable private coverage (Barry-Jester and Casselman, 2015) — especially in states where Medicaid has not been expanded (Garfield and Damico, 2016).

Second, health care coverage might affect discretionary incomes, though whether that effect tends to be positive or negative is not clear. Health care coverage might decrease discretionary incomes, because families pay premiums to get private coverage (Claxton et al., 2015). Insofar as public health coverage does not require premium payments from recipients, this effect will not exist for public coverage. Coverage might also increase discretionary incomes. Because demand for health care is relatively inelastic, both by price and by income (Ringel et al., 2002), families consume some health care regardless of their incomes. Health care coverage offsets the cost of care, freeing up resources and increasing discretionary income. Both private and public coverage increase discretionary income in this way. This is borne out empirically: “families with uninsured members are more likely to have higher health

expenditures as a proportion of family income than are insured families” (Coleman et al., 2002, p. 69).

This paper’s statistical models will include median income and several other socio-economic variables, which will allow an examination of the effect health care coverage might have on child physical abuse independent of socioeconomic effects that are already well documented in the literature.

2.6. Health care coverage as a stress reliever

Economic stress is associated with significantly higher rates of abuse; children in low socioeconomic status households are three times more likely to be abused (Sedlak et al., 2010; Thurston et al., 2017). Access to and affordability of health care are sources of significant financial stress. Fourteen percent of all American families cite health care costs as their most important financial problem (Swift, 2015). Fifty-three percent of uninsured Americans face problems dealing with medical debt (Hamel et al., 2016). Health care coverage decreases stress associated with health care because it decreases volatility of consumption and offers a peace of mind effect (Haushofer et al., 2017). That effect extends to Medicaid: Oregon’s expansion was associated with reduced financial strain and lower rates of depression (Baicker et al., 2013).

As summarized in Fig. 1, this paper posits a several-pronged connection between health care coverage and reductions in physical abuse. First, coverage increases access to and utilization of health care. That means proactive prevention via program referrals and education. Further, more exposure to healthcare providers may imply a level of proactive prevention to prevent reporting, and reactive prevention because cases will be more likely to be detected and reported. Second, coverage is associated with increased SES, which is itself correlated with reduced risk for physical abuse. Coverage also increases discretionary incomes, which further improves SES and reduces risk of physical abuse. Third, coverage reduces financial stress, which is associated with physical abuse. Reductions in such stress might lead to reductions in risk of physical abuse.

3. Methods

This paper utilizes panel data linear regression to analyze state-level data on child physical abuse, income, poverty, labor force participation, marriage, education, race, WIC receipt, and child health care coverage. The panel includes data for all U.S. States and the District of Columbia from 2000–2015, yielding a preliminary $n = 816$. Due to missing values in state level child physical abuse counts, in the final analyses, $n = 667$. Data are compiled from three datasets, including the Current Population Survey Annual Social and Economic Supplement (Flood et al., 2015), the

Kids Count Data Center's child and adult population file based on U.S. Census Bureau data (KIDS COUNT Data Center, 2017b), and the Kids Count Data Center's child maltreatment by type file based on data from the National Child Abuse and Neglect Data System (KIDS COUNT Data Center, 2017a).

In order to check for robustness of results, this paper checks results several ways. First, it considers results of panel data linear regression using increasingly robust specifications: fixed state effects; fixed state effects with population weights applied; fixed state and year effects with population weights applied; fixed state and year effects with population weights applied and standard errors clustered by state; and fixed state effects with Census division-specific linear time trends with population weights and standard errors clustered by state.

Second, the paper considers alternative forms of the model with different dependent variables: panel data Poisson regressions performed on the dependent variable left in raw count form and panel data log-linear regressions performed on a log-transformed version of the raw counts of child abuse by state with independent variables left in rate form.

Note that the paper uses Census division-specific linear time trends instead of state-specific linear time trends. Linear regression requires a certain number of observations for each predictor variable included in the model – the model must maintain sufficient degrees of freedom – and the inclusion of state-specific time trends may add too many predictor variables relative to the total sample size. If too many degrees of freedom are removed, “we also will reduce the power to detect true relations” (Babyak, 2004, p. 414). One rule of thumb for linear regression is “to have a minimum base sample size of 50 observations and then roughly 8 additional observations per predictor” (Babyak, 2004, p. 414). Following that rule illustrates why the addition of state-specific linear time trends is inappropriate in this model. Due to missing data, there is a maximum of 667 observations. In version four of the model (as shown in Table 3) there are nine variables and then an additional 51 state dummy variables and 16 year dummy variables, yielding 76 total variables. With eight observations per variable and a base of 50, this specification requires at least 658 observations, which falls under the model's max of 667. However, adding in state-specific time trends removes the 16 year dummies and adds in 51 new state-time trend variables and one continuous year variable, resulting in a total of 112 variables. That number of variables would require 946 observations – 41 percent more than the model's max of 667. This gives good reason to be skeptical of the results of such a specification: there would be too few observations to consider the results of a specification with this many variables reliable, and the model's capacity to detect true relationships between the variables would be inhibited.

One resolution to this problem recommended by Babyak (2004) is to reduce the total number of variables. Thus the model uses Census division-specific linear time trends

instead of state-specific trends. Because there are only nine Census divisions, this reduces the total number of variables added to the model while still allowing for the inclusion of time trends that vary by Census division, though not by state. This specification includes the nine variables shown in the table, 51 state dummies, one year trend variable, and nine Census division-time trend variables. This specification requires a threshold of at least 610 observations, which the model meets.

3.1. Data

The primary dependent variable is the child physical abuse rate per thousand children, which is calculated by dividing the total number of children physically abused (KIDS COUNT Data Center, 2017a) by the Census Bureau's estimate of the total number of children in each state, each year (KIDS COUNT Data Center, 2017b), and multiplying by 1000. Total physical abuse numbers for each state are based on unique counts of substantiated and indicated, but not unsubstantiated, cases in the NCANDS Child File from FFY 2000–2015. This variable contains 667 out of a possible 816 values, due to missing values in child abuse counts. The only clear pattern in the missing data is that the first four years of the panel contained most of the missing values. Starting in 2005, there were only 3 missing values per year, on average. Two additional versions of the dependent variable are used in alternative specifications: raw counts for Poisson regression, and log-transformed counts for log-linear regression. One item to note: effective 2015, a methodological change in NCANDS data shifted how “alternative response” cases are coded, which might influence results. Analyses were performed using only data from before 2015 and again including data from 2015, and results are the same in either specification. In the interest of including as many state-years as possible into the sample, results are reported based on the specifications which include 2015 data.

Time effects are controlled for by including dummies for each year of observation, ranging from 2000 to 2015, and by adding in Census division-specific linear time trends. Each state has a minimum of five years of child physical abuse data, with an average of 13.1 and a maximum of 16 years total. Refer to Fig. 2 to see the relationship between time, child physical abuse rates, and child health care coverage at the national level, and Figs. 3 and 4 to see those relationships at the state level.

Additional variables, drawn from Current Population Survey's Annual Social and Economic Supplement (CPS ASEC) 2000–2016 data (Flood et al., 2015), are included to control for socioeconomic effects. Median income is included to capture, as directly as possible at the state-level, the impact of income on child physical abuse (Cancian et al., 2010). Other variables include population living below the poverty threshold, percent of adult population participating in the labor force (LFP), percent of adults that are married, and percent of the state population receiving Women, Infants, and Children benefits (Joo Lee et al., 2006).

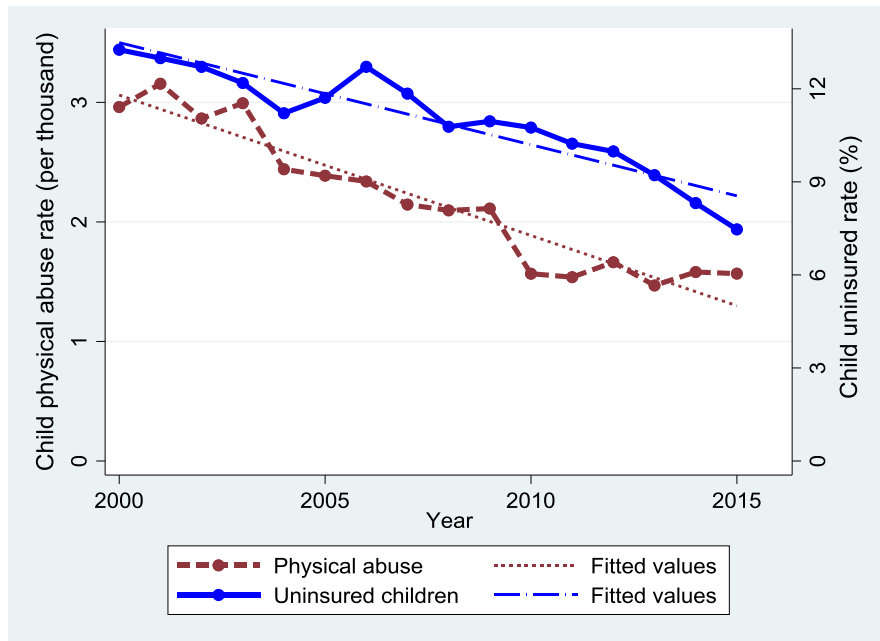


Fig. 2. Changes in child physical abuse and uninsured rates over time, national.

Demographic variables drawn from CPS ASEC include education and race. Education level is measured as the number of working age adults with a high school education or higher. Race is reported as the number of children in each state who identify as white. This variable is included because there are racial disparities in child abuse reporting (Dakil et al., 2011). Both variables are converted into population rates.

Health care coverage is also captured via two variables from CPS ASEC data (Flood et al., 2015): child Medicaid coverage, which is the total number of children in each state with Medicaid coverage; and child private coverage, which is the total number of children in each state with private coverage. Coverage is broken down into private and public to see if the effect of coverage varies depending on type of coverage and to account for the effect of any transition or substitution between child private and Medicaid coverage (Gresenz et al., 2012).

All CPS ASEC variables were extracted in whole numbers and transformed into rates using CPS ASEC population estimates and appropriate weights. Kids Count maltreatment data were transformed into rates using Census population data (KIDS COUNT Data Center, 2017b). Creating population-level rates allows the model to account for variation in population size, both by state and over time.

Table 1 contains basic descriptive statistics for the final variables input into the model. Note in particular difference in overall, between, and within standard

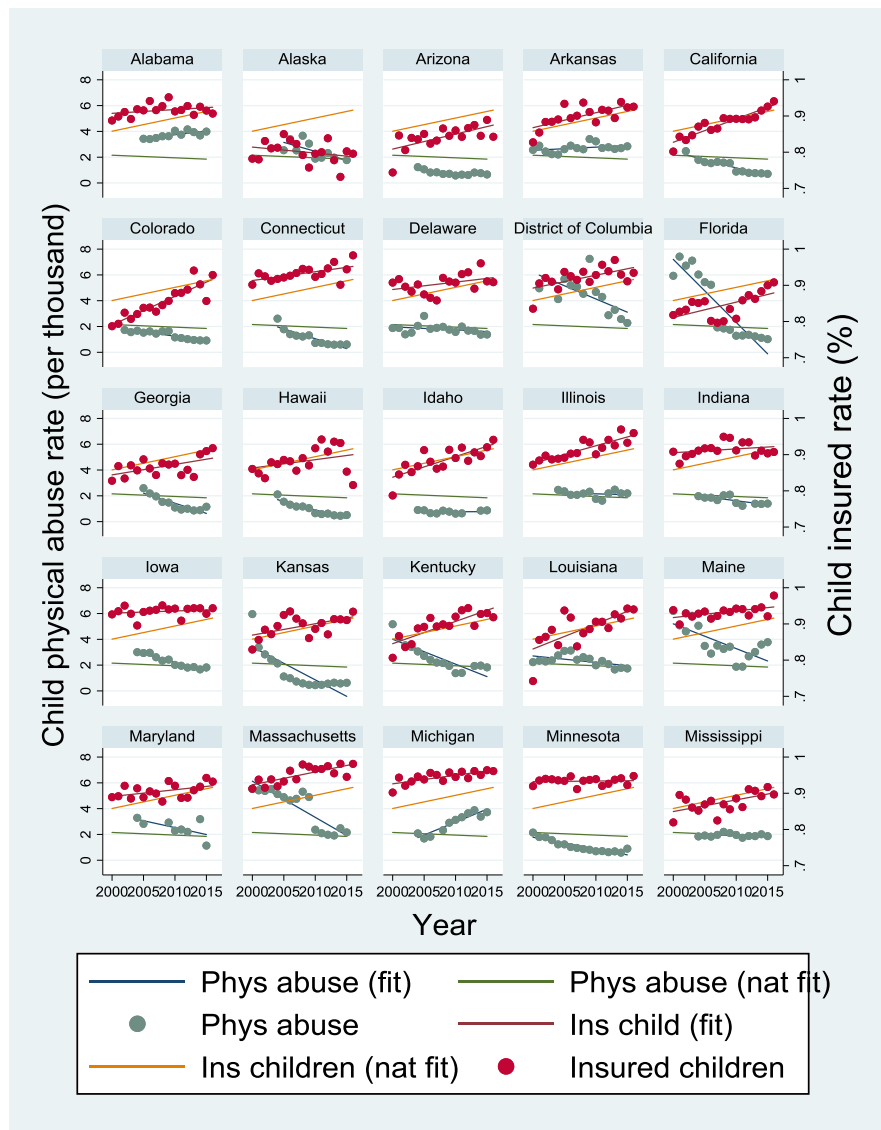


Fig. 3. Changes in child physical abuse and insurance coverage over time, by state with national fit lines (Alabama – Mississippi).

deviations. These differences are one reason that this paper's panel data linear regression will use fixed effects.

Fig. 2 shows the U.S.-level child physical abuse rate alongside the child uninsured rate from 2000–2015, with trend lines added. The child physical abuse rate, shown on the left axis, is calculated by dividing state-level maltreatment reports (KIDS COUNT Data Center, 2017a) by the child population (KIDS COUNT Data Center, 2017b) of states who reported child physical abuse numbers each year. The child uninsured rate, shown on the right axis, is based on CPS ASEC data on children covered by either Medicaid or private insurance (Flood et al., 2015). For ease of presentation, state-level data were aggregated up to the national level. This illustration is

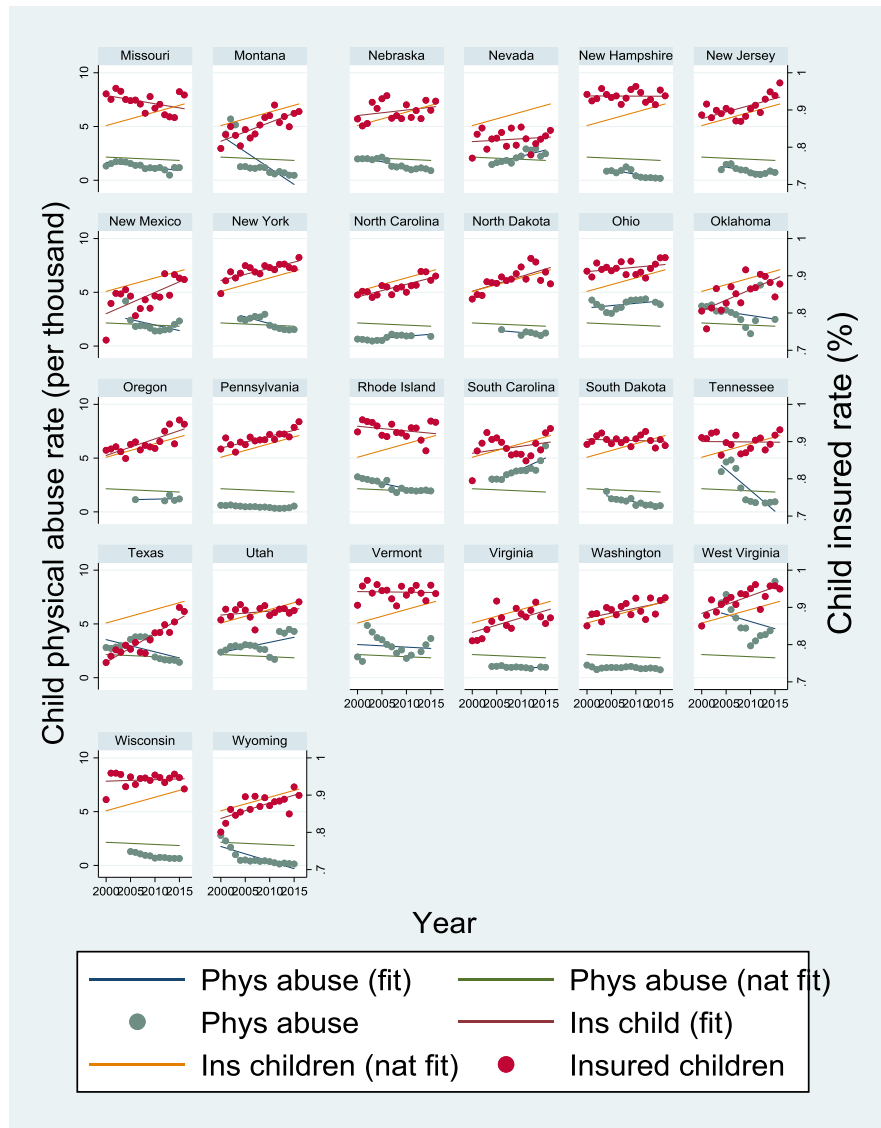


Fig. 4. Changes in child physical abuse and insurance coverage over time, by state with national fit lines (Missouri - Wyoming).

compelling: as the child uninsured rate has decreased by half, the child physical abuse rate has declined to a similar degree – the trend lines are almost parallel.

In addition to the graphical representation, the correlations between each variable were also identified: year is 95.54 percent negatively correlated with the child physical abuse rate and 93.48 percent negative correlated with the child uninsured rate, and the child uninsured rate is 85.06 percent positively correlated with the child physical abuse rate. All correlations were statistically significant. Uninsured rates and physical abuse decrease over time, and physical abuse decreases as the uninsured rate decreases. There are reasons that uninsured rates might decrease at the same time the abuse rate decreases - one might be an increased social emphasis

Table 1. Descriptive statistics.

Variable description	Mean	Standard deviation overall	Standard deviation between	Standard deviation within	Min	Max
Child physical abuse rate per thousand	2.095	1.415	1.138	0.851	0.131	8.959
Median income (in \$1000s)	51.102	9.057	7.826	5.218	30	84.248
Poverty rate: percent of population in poverty	0.127	0.035	0.029	0.017	0.045	0.237
Labor force participation rate	0.650	0.043	0.038	0.020	0.514	0.767
Marriage rate: percent of adults who are married	0.515	0.047	0.043	0.019	0.243	0.611
Education: percent of adults with high school education or higher	0.820	0.036	0.029	0.021	0.721	0.908
Race: percent of child population that is white	0.809	0.139	0.139	0.021	0.178	0.986
WIC: percent of population receiving WIC benefits	0.071	0.023	0.014	0.019	0.020	0.141
Child Medicaid coverage: percent of children with coverage via Medicaid	0.308	0.101	0.068	0.074	0.067	0.615
Child private coverage: percent of children with private coverage	0.642	0.088	0.075	0.047	0.365	0.863

on child welfare in the 1990s and early 2000s (Olson and Stroud, 2012). However, this is a useful way to, at a high level, examine that relationship, and this does add evidence to a connection between increases in health care coverage and reductions in physical abuse. Next, statistical analysis was performed on state-level data.

4. Results

Table 2 shows results of three versions of bivariate panel data regressions of child physical abuse and child health insurance coverage using state and year fixed effects. Each column displays the results of one model, and each row shows the coefficient and standard errors for variables included in each model. Bivariate results indicate that private coverage is statistically significant and negatively related to child physical abuse. In bivariate analysis, Medicaid is statistically insignificant, but when run

Table 2. Bivariate regression analyses, child physical abuse and health care coverage variables.

	Bivariate private	Bivariate Medicaid	Private and Medicaid
Private	-3.127** (0.955)		-4.522*** (1.170)
Medicaid		0.194 (0.829)	-2.067* (1.007)
Observations	667	667	667
Adjusted R ²	0.173	0.158	0.177

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

alongside private coverage, as is necessary to account for any impact of children transitioning between private and Medicaid coverage (Gresenz et al., 2012), Medicaid is also statistically significant and negatively related to child physical abuse. These regressions provide preliminary support for the theory that health care coverage may be related to reductions in child physical abuse and justify further multivariate and more robust analyses.

Next, data are examined using inferential methods that control for the effect of each variable and differences between states: panel data linear regression analysis with state fixed effects. In addition to being necessary for statistical reasons (refer to Table 1 for between and within standard errors), fixed effects are also theoretically justified: the addition of fixed effects for each state allows the model to control for factors that vary by state but not over time (Kohler and Kreuter, 2009). As such, the addition of fixed effects allows the model to control for factors that would otherwise be left out as unmeasured, such as by-state variations in the legal definition of child physical abuse.

Results of five regressions are summarized in Table 3. The first examines the effect of child private and insurance coverage rates using panel data linear regression with state fixed effects, without year fixed effects or any population weighting or clustering of standard errors by state. The second adds in population weighting. The third adds in year fixed effects. The fourth includes state and year fixed effects, population weighting, and standard errors clustered by state. The fifth model removes year fixed effects and adds in Census division-specific linear time trends, with population weights and standard errors clustered by state. Each model has a total 667 observations and includes all 51 states with between five and 16 years of data and an average of 13.1 years of data.

Tables 4 and 5 offer results of four additional versions of the model with different forms of the dependent variable. Table 4 shows results from panel data Poisson regressions performed on a form of the dependent variable left in raw counts. Table 5 shows results from panel data log-linear regressions performed on a log-transformed version of the raw counts of child abuse by state, with independent variables left in rate form. Each table includes two forms of the regressions: one with state and year fixed effects and one with state fixed effects and division-specific linear time trends.

In all models, both child private coverage and child Medicaid coverage have statistically significant negative relationships with child physical abuse.

5. Discussion

The key takeaway of these regression results is that child health care coverage, including both private and public coverage, is associated with declines in child physical abuse.

Table 3. Linear regression results, primary model.

	(1)	(2)	(3)	(4)	(5)
	Fixed state effects	Fixed state effects, pop weighted	Fixed state and year effects, pop weighted	Fixed state and year effects, pop weighted with by-state cluster	Fixed state effects with division-specific linear time trends, pop weights and by-state cluster
Race (% child pop = white)	3.829 (2.152)	9.819*** (2.790)	7.159* (3.102)	7.159 (4.570)	7.082 (4.736)
Marital status (% adult pop married)	2.242 (2.194)	2.141 (2.630)	2.115 (2.901)	2.115 (3.616)	0.536 (2.820)
Education (% adults with HS+)	-8.497** (2.643)	-13.88*** (3.195)	-12.34*** (3.588)	-12.34 (10.29)	-5.717 (5.230)
LFP (% adults in labor force)	-3.004 (2.237)	-8.418** (2.734)	-8.030** (3.002)	-8.030 (4.004)	-11.23* (5.136)
Poverty (% population in poverty)	-4.300 (2.740)	-5.291 (3.295)	-2.946 (3.686)	-2.946 (4.232)	-1.063 (3.176)
WIC (% population receiving WIC)	-4.546* (1.844)	-3.749 (2.130)	-2.028 (3.057)	-2.028 (3.082)	-1.895 (2.832)
Median income (family income, in 1000s)	-0.0419*** (0.0108)	-0.00605 (0.0133)	-0.0156 (0.0203)	-0.0156 (0.0255)	0.0270 (0.0221)
Child private coverage (% children with private insurance)	-3.146** (1.125)	-3.140* (1.300)	-4.383** (1.437)	-4.383** (1.564)	-3.592** (1.088)
Child Medicaid coverage (% children with Medicaid)	-2.496** (0.946)	-3.279** (1.073)	-3.523** (1.278)	-3.523* (1.721)	-3.805** (1.288)
Constant	12.63*** (3.253)	14.04*** (4.165)	15.76*** (4.298)	15.76 (9.297)	168.0 (109.7)
Observations	667	667	667	667	667
Adjusted R^2	0.152	0.236	0.242	0.301	0.419

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Poisson regression results.

	(1)	(2)
	Fixed state and year effects, controlling for population size	Fixed state effects with division-specific linear time trends, controlling for population size
Race (% child pop = white)	4.333 (2.310)	3.316 (2.274)
Marital status (% adult pop married)	0.977 (1.672)	0.533 (1.153)
Education (% adults with HS+)	-3.892 (3.587)	-2.807 (2.078)
LFP (% adults in labor force)	-3.990* (1.641)	-3.881* (1.600)
Poverty (% population in poverty)	-2.751 (2.051)	-2.054 (1.364)
WIC (% population receiving WIC)	-0.688 (1.369)	0.226 (1.241)
Median income (family income, in 1000s)	-0.0124 (0.0109)	0.00801 (0.00891)
Child private coverage (% children with private insurance)	-2.059** (0.742)	-1.349** (0.516)
Child Medicaid coverage (% children with Medicaid)	-1.385* (0.665)	-1.367** (0.446)
Observations	667	667

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Child private coverage and child Medicaid coverage are both statistically significant, which indicates that child health coverage is associated with reductions in child physical abuse. Interpreting the size of the coefficients from Table 3, specification 5 yields an interesting result. A one percentage point increase in the child private coverage rate is associated with a decrease of 3.6 children per thousand physically abused and a one percentage point increase in child Medicaid coverage rate is associated with a decrease of 3.8 children per thousand physically abused. However, it is important to put these in context: the national child physical abuse rate was around 1.5 children per thousand in 2014, three children per thousand in 2000, and over the span of the study was around 2.1 children per thousand. So, these coefficients are larger than the national mean value of the dependent variable in question.

There are a few items to note: first, the most likely explanation for the size of the coefficients is the nature of this paper's statistical model, ordinary least squares (OLS) panel data regression. OLS coefficients can be influenced by large values in the dependent variable. In the case of this research, there are some states with child physical abuse rates substantially higher than the national average — these states may be influencing the coefficients to be larger than the national rate. Refer to Figs. 3 and 4 for graphs that examine the change in child physical abuse and child insured rates over time, along with lines fitted to national means for comparison. Note specifically states like Alabama, Connecticut, the District of Columbia, Maine, Massachusetts, Minnesota, Ohio, Oklahoma, South Carolina, Utah, and West Virginia, whose

Table 5. Log-linear regression results.

	(1)	(2)
	Fixed state and year effects, controlling for population size, by-state cluster	Fixed state effects with division-specific linear time trends, controlling for population size, by-state cluster
Race (% child pop = white)	4.003 (2.149)	3.334 (2.050)
Marital status (% adult pop married)	0.617 (1.461)	0.690 (1.267)
Education (% adults with HS+)	-1.931 (3.023)	-2.946 (2.061)
LFP (% adults in labor force)	-3.046* (1.456)	-3.716* (1.581)
Poverty (% population in poverty)	-2.687 (1.661)	-3.052* (1.383)
WIC (% population receiving WIC)	0.181 (1.459)	0.323 (1.135)
Median income (family income, in 1000s)	-0.00819 (0.0110)	0.00980 (0.00931)
Child private coverage (% children with private insurance)	-1.932* (0.733)	-1.173* (0.512)
Child Medicaid coverage (% children with Medicaid)	-1.448* (0.677)	-1.367* (0.606)
Constant	10.25** (3.203)	61.78 (40.32)
Observations	667	667
Adjusted R ²	0.422	0.477

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

mean child maltreatment rates are substantially higher than the national mean. These states with higher rates are not necessarily outliers and this is not an argument to exclude them. Rather, they may simply have larger influences on the coefficients than states with smaller rates. These coefficients are also based on data from 2000–2015, and rates were higher at the beginning of the time span than at the end, so higher values in earlier years will also raise the value of the coefficients. In order to test this theory, a simple sub-group analysis was performed: panel data regressions were run for states with mean child physical abuse rates above and below 1.8 per thousand (the median value). Refer to Table 6 for results of this analysis. For states with mean values over 1.8, the coefficient of private insurance was -6.03, but for states with mean values under 1.8, the coefficient for private insurance was 2.37. In the sub-group analysis, Medicaid was not statistically significant – this is probably due to the limited sample size in analysis (each model's n was under 350). Future research should include more complex sub-group analysis to see how coefficients vary between states with high and low child physical abuse rates, how that effect has changed over time, and whether under other specifications Medicaid might be statistically significant.

Second, this paper is not examining specific causal mechanisms underlying the association at interest. The size of the coefficients, while interesting, should not be the

Table 6. Above and below median child physical abuse regression results.

	Fixed state and year effects, pop weighted with by-state cluster: above median physical abuse rate	Fixed state and year effects, pop weighted with by-state cluster: below median physical abuse rate
Race (% child pop = white)	9.210 (7.523)	2.557 (4.288)
Marital status (% adult pop married)	4.149 (5.326)	-1.283 (2.904)
Education (% adults with HS+)	-18.01 (14.39)	0.374 (5.114)
LFP (% adults in labor force)	-12.16* (5.822)	-4.375 (3.312)
Poverty (% population in poverty)	-11.17 (8.268)	-2.751 (2.874)
WIC (% population receiving WIC)	-5.912 (5.058)	0.697 (2.242)
Median income (family income, in 1000s)	-0.0888* (0.0326)	0.0333 (0.0192)
Child private coverage (% children with private insurance)	-6.028* (2.393)	-2.370* (0.880)
Child Medicaid coverage (% children with Medicaid)	-4.469 (2.764)	-1.134 (1.018)
Constant	-26.44 (13.23)	3.571 (5.874)
Observations	346	321
Adjusted R^2	0.313	0.457

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

primary focus of this research. Rather, this paper is examining the existence of an association between child health care coverage and reductions in physical abuse and recommending future research on the identified association.

Thus, the most important result from this research is not the size of the coefficients; rather, the most important result is that the variables have a statistically significant association. A second related question is why Medicaid coverage's measured effect is smaller than the effect of private insurance in the first four specifications, before Census division-specific time trends are added.

There are three primary explanations. First, it's possible that the difference reflects a socioeconomic effect not already controlled for by the model – higher private coverage might be associated with higher incomes, higher employment, and lower poverty rates, and higher Medicaid coverage might be associated with lower incomes, higher unemployment, and higher poverty rates. However, this model includes controls for median income, poverty rate, labor force participation rate, education, and even WIC receipt, so a hidden socioeconomic effect as an explanation is probably insufficient. Second, maybe the difference reflects some real difference in the effect of private versus Medicaid coverage. Maybe it is the case that private coverage has some effect that Medicaid coverage does not. This could be due, for example, to longer wait times associated with Medicaid relative to private coverage (Ostrom et al., 2017) or other factors. It is important to note, however, that research

generally shows “that the Medicaid program, while not perfect, is highly effective” and in many metrics shows similar outcomes to private coverage (Paradise and Garfield, 2013, p. 10). Third, the difference between Medicaid and private insurance shrinks significantly once Census division-specific time trends are added, indicating that once the specification includes geographically-specific time trends, there is not much difference between Medicaid and private coverage.

That Medicaid’s effect is comparable, and even slightly larger, than the effect of private coverage in specification five of the model is to be expected. Remember that factors related to increased risk for child physical abuse include low socioeconomic status and financial stress. As a program targeted toward families with lower incomes, Medicaid is intended for families facing those higher risk factors. As such, it would be reasonable to expect that Medicaid coverage would have a stronger negative effect on child physical abuse risk than would private coverage.

These regression results are even stronger because the model is checked for robustness with multiple alternative specifications. As demonstrated in Figs. 2, 3, and 4, both child physical abuse and the child uninsured rate have declined over time. The general decline in child physical abuse is probably due to many different factors, of which only a few are accounted for in this model. Inclusion of year fixed effects and time trends is a way to control for otherwise excluded variables, and the findings indicate that child health care coverage, including both private and Medicaid coverage, has a statistically significant negative relationship with child physical abuse, even controlling for the passage of time and other changes that have occurred during the span of the study.

This finding is relevant given recent occurrences in health policy: in 2010, the Affordable Care Act was passed with the intention of decreasing the U.S. uninsured rate; that rate is unambiguously lower now, especially since Medicaid expansion and insurance exchanges opened in 2013 (Nekvasil, 2016). Adult uninsured rates started dropping quickly in 2013, when Medicaid expansions began and insurance exchanges opened. Though child uninsured rates had already been on a decline previously, they have continued to decrease further since 2013. Medicaid expansion appears to have substantially decreased children’s uninsured rates, even though expansion was primarily for uninsured adults: “States that extended Medicaid coverage to more uninsured adults saw nearly double the rate of decline in uninsured children as compared to states that didn’t accept the ACA’s Medicaid option” (Chester and Alker, 2015, para. 3). Previous expansions led to similar outcomes: expanded Medicaid eligibility for adults also meant significant decreases in uninsured rates for children (Dubay and Kenney, 2003). One reason for this is the welcome mat effect, where parents/caregivers of eligible children signed up their children when they enrolled; many of the remaining children who are uninsured are eligible for coverage and will be more likely to get coverage if their caregivers also enroll (Alker, 2016).

Though this research is insufficient to assess a causal link between child health care coverage and reductions in physical abuse, there is a clear and statistically significant negative association.

5.1. Limitations and future research

There are several limitations to this study. First, the results are sufficient only to suggest a statistically significant association between increased child health care coverage and reductions in child physical abuse. The analysis is insufficient to assess any causal relationship between the dependent and independent variables. This paper offers a potential explanation for why coverage and abuse might be related and assesses if they are; whether the explanatory mechanisms offered are correct is beyond the scope of the analysis.

Assessing this relationship using causal methods is a critical next step. While beyond the scope of this research, next steps should attempt to identify appropriate causal estimation strategies. One such strategy might be using ACA Medicaid expansion as an exogenous policy shift associated with increased Medicaid enrollment for children to perform difference in difference analysis (though a substantial weakness in such analysis is that expansion was primarily for adults, so child coverage growths will be due mostly to the welcome mat effect rather than real expansions in child eligibility). An additional method which might be useful for such analysis might be synthetic controls (Abadie et al., 2010, 2015; Kreif et al., 2016).

Second, this is a study of state-level data. These results cannot be extrapolated to apply to the individual or local/county level; results from this study can only inform state-level analysis.

Third, the abuse variable is based on counts of children with substantiated abuse cases rather than counts of each case of substantiated abuse. This does not account for the impact of children with multiple cases of abuse. Substantiated cases also undercount the actual prevalence of abuse, and many children in unsubstantiated cases face similar risk of abuse to children in substantiated cases (Olson and Stroud, 2012). Future research should replicate this analysis on unsubstantiated cases as well. This variable is also based on data from the National Child Abuse and Neglect Data System, which can vary based on state definitions of abuse and how each state reports their data (Olson and Stroud, 2012). By-state definition variation, however, is controlled for via state fixed effects in the regression models, assuming those definitions did not change substantively over the time span of the study.

Fourth, if health care coverage does lead to improved reporting, then even as actual instances of abuse decrease, reporting of abuse might go up; thus, this paper's results

are probably underestimating the extent to which health care coverage reduces child physical abuse.

Fifth, this paper's statistical analyses do not include controls for Medicaid expansions and the creation of state insurance marketplaces which occurred due to the ACA. As additional years of data become available, the impact of state Medicaid expansions and establishment of the federal and state health insurance exchanges should be assessed.

Future research should also include sub-group analysis to examine variation by state child physical abuse rate. It should also examine the relationship between child physical abuse and health care coverage at more granular levels of analysis, such as at the level of individual cases or at the county-level. Such analyses might be more able to assess specific causal mechanisms beyond the capacity of this paper.

6. Conclusion

Prior to this paper, research into health care coverage and child maltreatment focused on neglect and medical neglect, not specifically on physical abuse. This paper offers several justifications for a connection between increases in child health care coverage and reductions in child physical abuse. Panel data linear regression analysis on state-level data over 16 years, with state and year fixed effects and Census division-specific linear time trends, controlling for a variety of socioeconomic and demographic factors, and using several different specifications to check for robustness, suggests a statistically significant relationship between increases in state-level child health care coverage rates and reductions in child physical abuse. That observed negative relationship exists for both private and Medicaid coverage. Though the results of this paper are insufficient to assess the causal pathways for the connection, results do indicate an association between increases in child health care coverage and reductions in child physical abuse.

Declarations

Author contribution statement

Neil McCray: Conceived and designed the analysis; Analyzed and interpreted the data; Contributed analysis tools or data; Wrote the paper.

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Additional information

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