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Child Care Subsidy Generosity and Child Maltreatment: The Moderating Effects of Administrative Burden

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Abstract

Purpose. Child maltreatment (CM) (i.e., neglect, emotional abuse, physical abuse, and/or sexual abuse) has profound and wide-ranging impacts on child development. A significant body of literature demonstrates robust links between poverty/financial hardship and risk for CM. The Childcare and Development Fund (CCDF) is the primary federal program which subsidizes child care costs for families, with children under age 13 (under age 19 for special needs), in the United States with lower-incomes. States have considerable discretion in determining policy options which can greatly impact both the generosity and adminstrative burden of the program.

Methods. At the state-level, using a moderated, two-way, fixed-effect approach, we investigate the association between the generosity of CCDF policies (e.g., copayment size, enrollment income, work requirements, etc.) and rates of child maltreatment investigations and substantiations involving children under the age of five. Furthermore, we examine how the effect of the generosity of child care subsidies on child maltreatment depends on the level of administrative burden (i.e., income cliffs and redetermination periods).

Results. In general, as subsidy generosity increases, rates of child maltreatment investigations and substantiations decrease, and these associations are strengthened when administrative burden is reduced.

Conclusions. Adminstrative burdens may diminish the impact that subsidies have on reducing family stress and financial hardship therefore reducing the potential preventive effect subsidies have on abuse and neglect of children, especially those most vulnerable-young children.

Keywords

Child Maltreatment; Child Maltreatment Prevention; Child Care Subsidies; Administrative Burden

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Child maltreatment (CM) (i.e., neglect, emotional abuse, physical abuse, and/or sexual abuse) involves caregiver experiences that directly harm and deprive children of their safety, intellectual stimulation, nutrition, and/or emotional support necessary for healthy development (Mehta et al., 2021). In 2021, nearly 4 million cases of CM were reported to child protective services (CPS) agencies across the United States, involving over 7 million individual children (U.S. Department of Health & Human Services, 2023). Of those cases, ~600,000 children were determined, through investigations, to be victims of abuse and/or neglect (i.e., substantiated or indicated). It is important to note that these prevalence rates likely grossly underestimate the true prevalence rate as most experiences of CM go unreported (Mehta et al., 2021). The adverse effects of abuse and neglect are profound and wide-ranging, impacting a broad range of mental and physical health outcomes across the lifespan (Russotti et al., 2021; Vizard, Gray, & Bentovim, 2022). Particularly concerning is the fatality rate associated with child maltreatment, which is 2.38 deaths per 100,000 children in 2020 (U.S HHS., 2023). This rate is striking when compared to the childhood cancer death rate in the U.S., which is 1.9 deaths per 100,000 children in 2020 (U.S. Mortality Data, 1969–2020). Moreover, the societal and economic tolls associated with child maltreatment are tremendous. In 2015, the estimated economic burden of substantiated cases in the United States was $428 billion and upwards of $2 trillion for all investigated cases (Peterson, Florence, & Klevens, 2018). The prevalence, etiological role, and cost associated with the abuse and neglect of youth therefore constitute a major public health concern (Merrick & Latzman, 2014). Continued efforts to improve CM prevention approaches are critical. strategy, highlighted in the CDC technical manual on CM prevention, involves strengthening economic supports for families (Fortson et al., 2016). Our research will focus specifically on child-care subsides, in which a growing body of research finds that CM rates to be vary depending on specific state, subsidy policies (Maguire-Jack et al., 2022). We introduce these concepts in the pages to follow.

Historically, CM research has focused largely on understanding: a) the consequences to normative development resulting from abuse/neglect, b) the protective/vulnerability factors which buffer or worsen outcomes in those exposed, c) risk factors for abuse/neglect, and d) treatment and selective/indicated intervention approaches (Cicchetti, 2013; Jones Harden, Simons, Johnson-Motoyama, & Barth, 2020; Merrick & Latzman, 2014; Toth & Cicchetti, 2013; Waid, Cho, & Marsalis, 2022). This important body of work has resulted in a widely accepted, ecological-transactional model of CM which emphasizes dynamic relations among risk and protective factors across systems (from biology-to-society) and development (from prenatal-to-adulthood) (Cicchetti, 2013;Toth & Cicchetti, 2013). This framework of understanding CM, and childhood adversity more broadly, through a developmental lens has been highly influential in models of CM prevention. Indeed, the Centers for Disease Control and Prevention (CDC) technical package on child abuse/neglect prevention emphasizes an ecological-transactional framework of prevention that considers the interactions of vulnerability and protective factors across four levels (individual, relationship, community, and societal) (Fortson, Klevens, Merrick, Gilbert, & Alexander, 2016).

Likewise, many in the prevention field have advocated for a public health approach to CM prevention (Higgins, Lonne, Herrenkohl, Klika, & Scott, 2022; Prinz, 2016; Whitaker, Lutzker, & Shelley, 2005). Core to the public health approach to CM prevention

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are six guiding characteristics: 1) address known risk factors and enhance protective factors across ecological levels, 2) focus on ‘whole-of-population’ which emphasizes primary and universal preventive interventions while still recognizing varied levels of vulnerability through secondary and tertiary interventions, 3) developmentally-informed timing of interventions, 4) use of evidence-based approaches, 5) special consideration of where prevention programing is based in order to maximize uptake and accessibility while reducing stigma, and 6) how to best bring about change in a sustained, scalable manner (Higgins et al., 2022). While efforts in adopting ecological-transactional, public health models of CM prevention (which consider timing, context, risk/protective factors, ‘whole-of-population’ etc.) continue to grow, the bulk of CM prevention research involves secondary (selective interventions) and tertiary (indicated preventive) preventive intervention (Jones Harden et al., 2020; Waid et al., 2022). Significant gaps in our understanding of primary and universal CM prevention strategies still remain, both in terms of volume of published research, but also methodological rigor (Jones Harden et al., 2020; Waid et al., 2022).

A significant body of literature demonstrates robust links between poverty/financial hardship and risk for CM (Austin, Lesak, & Shanahan, 2020; Bullinger, Lindo, & Schaller, 2021; Hunter & Flores, 2021; Marie-Mitchell & Kostolansky, 2019). Under a family stress model (FSM), families facing financial hardship are likely enduring tremendous psychological stress which in turn may negatively impact parental mental health, actions, and decisions which could lead to CM perpetuation (Maguire-Jack, Johnson-Motoyama, & Parmenter, 2022; Masarik & Conger, 2017). Consequently, easing financial hardship via economic support programs for low-income families may reduce incidents of CM. In this prevention model, lessened family stress and improved parental mental health, combined with the potential for families to invest more money into their children’s well-being, lowers the likelihood of family violence (Maguire-Jack et al., 2022). Caregivers of young children, particularly infants, are at the greatest risk for perpetrating CM, as evidenced by high rates of substantiated abuse reports; the additional stressors of caring for a new child may exacerbate additional anxieties families may have, such as concerns about paying bills or for child care services (Paxson & Waldfogel, 2002). Infancy, and early childhood in general, represents a ‘sensitive period’ in development, wherein the impacts of adverse experiences can have the most profound and long lasting impacts (Vizard et al., 2022). Policies which ease financial burden, especially those policies that focus on economic supports for growing families, may have the greatest impacts on preventing CM for young children. Indeed, evidence supporting the preventive role of economic support programs for CM has begun to emerge in recent years. Variations in the generosity of state and federal polices related to the Earned Income Tax Credit (EITC) (Berger, Font, Slack, & Waldfogel, 2017; Kovski, Hill, Mooney, Rivara, Morgan, & Rowhani-Rahbar, 2022a; Kovski, et al., 2022b)., Child Care Tax Credit (Kovski, et al., 2022b), Temporary Assistance to Needy Families (TANF) (Spencer, Livingston, Komro, Sroczynski, Rentmeester, & Woods-Jaeger, 2021) and to a lesser extent the Supplemental Nutrition Assistance Program (SNAP) programs have been linked with reductions in child welfare reports of abuse/neglect. For review, see Maguire-Jack, Johnson-Motoyama, and Parmenter (2022).

Child care subsidies represent another type of economic support for families. Not only do child care subsides provide some immediate financial relief for families, lowering the

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out-of-pocket expenses for a family, but they also support families in working standard hours, maintaining full-time jobs, and potentially earning more income (Ha, 2009; Ha, Collins, & Martino, 2015; Marshall, Robeson, Tracy, Frye, & Roberts, 2013; Press, Fagan, & Laughlin, 2006). Furthermore, simply having child care relief for some parents has the potential to reduce family stress levels and increase the capacity for nurturing parenting (Ha et al., 2015). Child care is costly for many families. The annual average cost of child care, in 2022 dollars, ranged from $5,357 for school-age home-based care (in small counties) to $17,171 for infant center-based care in large counties (Landivar, Graf, & Rayo, 2023). In fact, the cost of center-based child care is more expensive than public university tuition in 28 states (Child Care Aware. 2018).

The Childcare and Development Fund (CCDF) is the primary federal program which subsidizes child care costs for families, with children under age 13 (under age 19 for special needs), in the United States with lower-incomes. The CCDF is a block grant provided to states, and each state has considerable discretion in determining policies related to eligibility requirements (i.e., which families can get into the program), subsidy and copayment amounts (i.e., child care cost relief to families), and re-determination requirements (i.e., burdens placed on families to remain in program). A handful of studies have linked variation in the generosity of state-specific CCDF policies and rates of CPS reports of CM. Klika et al. (2022) found one standard deviation increase in initial maximum income allowed for a family of three in order to qualify for subsidies, associated with a 3% decrease in neglect investigations and a 4% decrease in physical abuse investigations. In another study by Maguire-Jack et al. (2022), high levels of employment requirements (30 hours or more per week) were found to be related to higher rates of neglect. Finally, Rochford, Zeiger, and Peek-Asa (2022) found decreases in CM substantiations in states with higher initial enrollment income threshold and when states counted fewer sources of income when determining eligibility. There are several other, potentially impactful child care subsidy implementation rules that have not been studied as predictors of CM. These include a.) variation in copayment amounts required by families to pay towards the cost of subsidized care, b.) the proportion of those copayments to the maximum reimbursement rates (i.e., subsidy amounts plus copayment amounts), and c.) the difference between the maximum reimbursement rate that states allow to cover costs of child care and the actual market value of child care. It is recommended that states' maximum reimbursement rate be at least at the 75% percentile of current market rates to ensure equitable access to child care (Minton & Durham, 2016). States vary considerably in terms of what amount each family is required to pay in terms of a copayment, but also the amount of actual subsidy given. For example, starting in 2019, in South Dakota, families (size three) at or below 150% of the federal poverty level were exempt from paying any copayment amount. Whereas, in 2019, Oregon and Hawaii required families at 150% of the FPL to pay over $500 a month in copayments, which is roughly 20% of their income (https://nwlc.org/). All of which contributes to large differences, across state policies, in the cost endured by participating families. These costs, of course, impact family financial burden, and therefore are likely to impact rates of CM.

The impact of the generosity of a state's child care subsidy program may only be as good as the length of time, or subsidy spell, that a family enrolled in the program is allowed to continue receiving benefits. The CCDF program has several *administrative burdens*,

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which are policies that can cause undue burden on families wishing to both begin and continue receiving benefits (Jenkins & Nguyen, 2022). These policies vary across states and are known to dramatically influence subsidy spells. One such policy is referred to as a redetermination period, or the length of time between when a family initially enrolls and when a family must recertify their income and other eligibility criteria in order to continue receiving benefits. In 2014, the CCDF reauthorization required states to have at least a 12-month period of redetermination, as several states only had a maximum 6-month redetermination period. However, to date, only two states have redetermination periods longer than 12 months, Nebraska, and New Jersey. Even a one-month increase in the redetermination period makes a significant difference in a family's subsidy spell length. Jenkins and Nguyen (2022) found that for every one month increase in redetermination period, there was a 1.4 week increase in a state's median subsidy spell length. If, for example, states increased their redetermination period from 12 to 18 months, families would continue to save thousands of dollars on child care costs for an additional 6 months and perhaps increase their spell length even further beyond that for a predicted increase of over two months on average. Moreover, and perhaps most concerning, there is a great deal of added stress placed on families when faced with more frequent administrative work related to re-certifying their eligibility (Jenkins & Nguyen, 2022).

Another policy that can have a significant burden on families who wish to continue receiving child care benefits is known as an income cliff, or the 'cliff effect (Isaacs, Katz, & Kassabian, 2016; Roll & East, 2014). When the redetermination period is up, families must recertify their income in order to continue receiving benefits. States may choose to set this redetermination income eligibility amount to be the same or a higher amount than the initial income eligibility amount. For states who choose to set the same income eligibility thresholds at redetermination, this effectively means that *any* increase in a family's income level between initially enrolling and recertifying their eligibility, above the threshold, would result in a discontinuation of benefits. Therefore, even if a state had a generous set of CCDF policies, such as low-to-zero copayment amounts and a high reimbursement rate (saving the family several thousands of dollars a year in child care costs), yet imposed an income cliff at redetermination, families would potentially go from paying next to nothing in child care costs to paying the full price for child care if their income increased even a small amount over the course of their enrollment period. For many families facing an income cliff, the potential increase in out-of-pocket expenses related to having to pay the full price for child care costs far outweighs the minor increase in their income which caused the ineligibility (Jenkins & Nguyen, 2022).

To date, there have been no studies examining the impact of variation in administrative burden policies on child maltreatment. We hypothesize that the effect of state variation in the generosity of their CCDF programs (i.e., maximum initial income eligibility, work requirements, copayment size, reimbursement rate, etc.) on rates of abuse and neglect are likely moderated by policy variation in administrative burden. That is, the economic supports the CCDF program provides families may have less of an impact on reducing rates of child maltreatment when families are only able receive those benefits for a short amount of time (either because of shorter redetermination periods or income cliffs at redetermination). In the current study, we aim to examine the association between a

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composite of several indicators of subsidy policy generosity and rates of child maltreatment. Furthermore, we will examine the degree to which that association varies depending on the level of administrative burden.

Methods

Data

All study methodology was approved via an independent review board. State-level, child care subsidy policy data related to the Child Care Development Fund (CCDF) was obtained from two publicly available sources: the Urban Institute's CCDF policies database (ccdf.urban.org, May 2023) and the National Women's Law Center's State Child Care Assistance Policies annual reports (https://nwlc.org/, May 2023). These data were linked (by state, year, and quarter from Yr2009 Q1 to Yr2020 Q1) with child maltreatment reports obtained from the National Child Abuse and Neglect Data System (NCANDS) across the same timeframe. Next, additional data used as control variables and cost-of-living adjustments were added from the American Community Survey (ACS), the U.S. Census Bureau, and The Council for Community and Economic Research (C2ER).

Measures

Child care subsidy generosity composite: Six continuous child care subsidy policy variables were used to create one composite variable representing variation in the overall generosity of each state's CCDF policies from 2009–2020. Each indicator was z-score transformed, summed to form a single score, and finally the summed-composite variable itself was z-scored to aid interpretability, resulting in an overall z-score composite (Song et al., 2013). The first indicator, 'enrollment income,' was indexed as the maximum monthly countable income to initially qualify for CCDF subsidies for a family size of three divided by cost-of-living (state-by-year estimates) with higher values considered more generous (or higher ratio of enrollment income to cost-of-living). C2ER provides quarterly estimates of the relative cost of living for various cities across the United States to provide a cost-of-living index. For the quarters of study, we averaged the index for all available cities within each state to obtain a state index.

The second indicator 'what counts as enrollment income' was a count of whether a state included various types of income in determining eligibility. These types of potential income included Temporary Assistance for Needy Families (TANF), Supplemental Security Income (SSI), Supplemental Security Disability Income (SSDI), net self-employment, Child Support, Supplemental Nutrition Assistance Program (SNAP) benefits, general assistance programs, value of housing assistance, Low Income Home Energy Assistance Program (LIHEAP), foster care income, state Earned Income Tax Credit (EITC), non-recurring lump sum income, and non-recurring gifts. The sum of these types of income counted by each state (up to 13) was reverse scored before z-score transformation such that higher values (or fewer types of income counted) are more generous.

The third indicator 'minimum required work hours' was indexed as the minimum number of hours per week families are required to work. In states that require a different number of

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hours for full- or part-time child care, the maximum value was counted. This indicator was also reverse scored prior to z-scoring such that higher values (or fewer work requirements) are considered more generous. These first three indicators used data collected from the CCDF policies database.

Indicator four, the 'difference between state reimbursement rate and 75th percentile rate' was calculated as the percent difference between the maximum base child care reimbursement rate for center care for a four-year old and the cost of center care for a four-year old at the 75% percentile of a recent market rate survey (if conducted within 2 years of when the reimbursement rate policy was last in effect). There were 79 instances (out of N=2295) where there was not a recent market rate survey. In those cases, an inflation calculator (https://www.bls.gov/data/inflation_calculator.htm) was used to estimate the adjusted 75% percentile of market rate value based on the next most recent market rate survey for that state.

The fifth indicator, 'copayment size as a percent of income,' was indexed as the percent of income that a copayment amount is for each state, for a hypothetical family of three, living at 150% of the federal poverty level (calculated by year), seeking center-based care for a four-year old. This indicator was reverse-scored such that larger values (lower percent of income) are considered more generous.

Finally, the sixth indicator, 'share of child care cost,' was the copayment size used in indicator five divided by the reimbursement rate used in indicator four. The reimbursement rate is comprised of a families' copayment plus the actual subsidy provided by the state. A large copayment, proportional to the reimbursement rate, would indicate a large share of the cost of care paid by families versus the state. This indicator is also reverse-scored prior to z-score transformation. These last three indicators were gathered from data obtained in the NWLC annual report tables.

Redetermination period: Child care recipients only receive benefits for a set amount of time, or redetermination period. After which, recipients' eligibility and subsidy level must be re-evaluated if a family desires to continue receiving benefits. The longer the redetermination period, the more likely families are to stay in the subsidy program for longer, as it requires less burden in terms of having families' income and other eligibility be re-evaluated (Jenkins & Nguyen, 2022). Moreover, in the case of income cliffs, families may become ineligible if they make any additional income above the initial income eligibility threshold. As of 2014, CCDF guidelines require states to have a minimum 12-month redetermination period (however, in these data redetermination periods range from 6–18 months). However, states may have longer periods if they wish. Redetermination period data was pulled from the CCDF policies database. This variable is treated as continuous and represents the redetermination period, in months, for a given state, in a given year-quarter.

Income cliff: When families first apply for CCDF subsidies, their monthly income must be at or below an initial monthly income eligibility threshold in order to qualify for benefits. When the redetermination period is up, families' income must be at or below a redetermination income eligibility threshold. Furthermore, during a redetermination period,

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families' income must be at or below a continuing income eligibility threshold. For states who chose to set their continuing or redetermination income eligibility thresholds to be the same as their initial income eligibility thresholds, an income cliff is more likely to occur within participating families. An income cliff is a sudden, total loss of child care subsidies because a families' income increased (even one dollar more per month) above the continuing or redetermination thresholds. Income cliffs are much less likely to occur when states choose to set the continuing or redetermination thresholds at a higher value than the initial monthly income eligibility threshold. Data on whether or not states increase those thresholds were collected from the CCDF policies database. This is a dichotomous variable, if the continuing or redetermination income eligibility amount was higher than the initial income threshold in a given state and year-quarter, then this variable was coded as 'no cliff', and if the amount was the same it was coded 'cliff'.

Child maltreatment. Four child maltreatment rate variables were used. The first was the rate of substantiated reports of infant (under age 1) abuse and/or neglect per 100,000 (population of infants under age 1 by state and year). The second was the rate of all investigations of infant abuse and/or neglect per 100,000. The third was the rate of substantiated reports of abuse/neglect in children aged 1–5 years of age per 100,000. The final maltreatment variable was the rate of all investigations of abuse and/or neglect in 1–5 year old children per 100,000.

Control variables: Using data from the US Census Bureau and the ACS, we included state-level, time-varying control variables known to associate with child maltreatment including race compositions of children (proportion Black, proportion White, proportion some other racial group, and proportion non-White Hispanic), proportion of state considered urban, state unemployment rate, and the poverty rate. Rooted in legacies of racism and socio-economic inequities, racial identify and poverty both influence how families interact with the child welfare system as evidence from disparity work (Maguire-Jack et al., 2015). For these reasons we control for variation in racial composition and measures of poverty.

Analysis: A series of eight two-way, linear fixed-effects, moderated regressions were modeled (4 outcomes × 2 moderators). The outcomes included the four child maltreatment variables (rate per 100,000), the primary predictor was the child care subsidy generosity composite (z-score scale), the moderators included redetermination period (in months) and income cliff (−1 = income cliff, 0 = no income cliff), and the control variables (mentioned above). State and quarterly (year-quarter, e.g., 2008q1, 2008q2) fixed effects were included to remove state time-invariant effects as well as time shocks. Clustered (by state level), robust standard errors were modeled.

Results

Descriptive statistics are outlined in Table 1. The CCS generosity composite variable (primary predictor) is Z-scored, with a mean of 0 and a standard deviation of 1. One generosity value was constructed for each state in each year-quarter (e.g., 2018q1, 2018q2, etc). Supplemental figures and tables are also provided, which present data on within state variation in CCS generosity. Across all states and year-quarters, the minimum value was

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−3.13 (i.e., one state, in a given year-quarter had a CCS generosity value 3.13 standard deviations below the mean), the maximum value was 3.89 (i.e., one state, in a given year-quarter had a CCS generosity value 3.89 standard deviations above the mean). Eight two-way, fixed-effects regressions were conducted, one for each moderator (2) – outcome (4) combination (see Table 2 and Table 3)

Income cliff moderations

The interaction between child care subsidy generosity and income cliff was significant when predicting infant substantiated reports of abuse and/or neglect (b= −92.02; p<.001). To interpret that interaction, when the income cliff moderator was centered at ‘no income cliff’ (i.e., the continuing or redetermination income eligibility amount was higher than the initial income threshold in a given state and year-quarter), the effect of child care subsidy generosity on infant substantiations was negative and significant (b= −76.68; p=.01). In order words, for states with no income cliff, for every 1 standard deviation increase in overall child care subsidy generosity, there are roughly 76 fewer infant substantiation reports per quarter, on average. That amounts to a roughly 11.8% decrease in infant substantiations per 100,000 infants, per quarter, on average. When re-centered at ‘income cliff’ (i.e., continuing or redetermination income eligibility amount was the same as the initial income threshold in a given state and year-quarter), the effect of subsidy generosity on infant substantiations was not significant (b=15.34; p=.30). The interaction effect can therefore be interpreted in the following way: the overall generosity of a state’s child care policies have a more pronounced effect on reducing substantiated infant maltreatment reports in states that choose not to place income cliff burdens on families during redetermination of subsidy benefits.

The interaction between child care subsidy generosity and income cliff was also significant when predicting infant total referral rates of abuse and/or neglect (b= −167.53; p=.003). Probing the interaction, the effect of subsidy generosity on infant referrals was negative and significant with no income cliff (b= −219.26 p=.003) but not significant for states with income cliffs. This corresponds to an approximately 10.3% decrease in total infant maltreatment referrals for every one-standard-deviation increase in child care subsidy generosity in states without income cliffs, per quarter, on average. Similar results were found for ages 1–5, See table 3. A ~10% reduction in age 1–5 substantiations and 9.96% reduction in age 1–5 overall rates was found. Moreover, similar results were found for these models without control variables (not presented). As an example, the interaction between child care subsidy generosity and income cliff was significant when predicting infant total referral rates of abuse and/or neglect (b= −172.04; p=.003).

Redetermination period moderations

The interaction between child care subsidy generosity and redetermination period was significant when predicting infant substantiated reports of abuse and/or neglect (b= −9.43; p=.01). To interpret that interaction, when the redetermination period moderator was centered at 18,15,12,11,8, and 6 months (the range of redetermination periods across states), the effect of child care subsidy generosity on infant substantiations was negative and significant (b=−96.49; p=.01). For states with an 18-month period between the start of

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subsidy benefits until redetermination of benefits, for every 1 standard deviation increase in overall child care subsidy generosity, there are roughly 96 fewer infant substantiation reports per quarter, on average. That amounts to a ~15% decrease in infant substantiations per 100,000 infants, per quarter, on average. When re-centered at a redetermination period of 12 months, the effect of subsidy generosity on infant substantiations was not significant, but in the expected direction (b=−39.92; p=.07). The interaction effect can therefore be interpreted in the following way: the overall generosity of a state's child care policies have a more pronounced effect on reducing substantiated infant maltreatment reports in states that choose to have longer redetermination periods. Additional simple slopes are

The interaction between child care subsidy generosity and redetermination period was not significant when predicting infant total referral rates of abuse and/or neglect (b=−11.24; p=.15). However, the main effect of child care subsidy generosity on infant maltreatment referrals was significant (b=−106.42; p=.03). This corresponds to an approximately 5% decrease in total infant maltreatment referrals for every one-standard-deviation increase in child care subsidy generosity in states, regardless of redetermination period. Similar results were found for ages 1–5 for referral rates (5.3% decrease via a main effect) but no significant main effects or interactions were found for age 1–5 substantiations.

It should be noted that each of the interaction terms found to be significant at the nominal p-value cut-off of .05 was also significant when using a false-discovery rate (FDR) of q<.05, thereby adjusting for test multiplicity, with the noted exception of the interaction between redetermination period and generosity predicting age 1–5 substantiations.

Discussion

The effects of CM are profound, substantially increasing the risk for a variety of mental health problems and physical maladies alike as well as causing great cost to society at large (Vizard et al., 2022; Peterson et al., 2018). Few population-level prevention strategies exist and even fewer have been studied using rigorous evidence-based methodologies. A clear link exists between poverty/financial hardship and risk for CM (Austin et al., 2020); a promising CM prevention strategy involves strengthening economic supports for families (Fortson et al., 2016). By reducing family stress via the lessening of financial hardship, the risk for maltreatment is likely to go down (Maguire-Jack et al., 2022; Masarik & Conger, (2017). This study leveraged longitudinal data on variation in child care subsidy policy generosity to examine changing rates of child maltreatment (both substantiations and total investigations) and to understand the degree to which the effect of child care subsidy generosity depends on administrative burden. Three indicators of child care policy generosity (i.e., higher initial subsidy income eligibility, lower work hour requirements, and fewer types of income counted as sources of income for eligibility) have been studied previously as predictors of reduced child maltreatment (Maguire-Jack et al., 2022; Maguire-Jack, Park, Feely, Schneider, Pace, Klika, & Thibodeau, 2023; Klika et al., 2022). This study examined those three indicators as well as three additional generosity policy indicators (copayment size as a percentage of income at 150% of the federal poverty level, share of child care costs-or the ratio between copayment size and reimbursement rate, and the percent difference between the reimbursement rate and the 75% percentile of market rate surveys). A

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composite of overall child care subsidy generosity was formed from these six indicators and examined as a predictor of child maltreatment. It was hypothesized that the effect of overall child care generosity would be moderated by indicators of administrative burden. That is, reductions in child maltreatment (both for substantiations and total investigations) would be greatest, in terms of predicting reduced CM, when there were both high levels of subsidy generosity and low levels of administrative burden. Indeed, both redetermination period length and the presence/absence of an income cliff moderated the association between child care subsidy generosity and child maltreatment across both age groups (age 0/infants and ages 1–5 years, see tables 2 and 3).

These results highlight the importance of increasing the length of time families may receive benefits by reducing administrative burdens. For example, our models predict that if a given state increased the overall generosity of its program (e.g., large changes to a few policies or moderate changes to several policies) by 1 standard deviation (i.e., going from the mean to standard deviation above the mean, or going from 1 standard deviation above the mean to 2 standard deviations above average generosity levels) across time, there would be an accompanying ~ 12% percent drop in infant substantiated maltreatment reports, only if there is no 'cliff effect.' Similarly, with respect to total infant maltreatment referrals, a 10% reduction in reports is observed with a 1 standard deviation increase in overall subsidy generosity only when families are not faced with income cliffs. When income cliffs exist, wherein families who earn slightly more in income can become ineligible to continue receiving benefits, there is no statistically significant reduction observed in child maltreatment rates when a state increases its subsidy generosity.

Similar effects were observed with respect to redetermination periods. The longer the redetermination period, or time families have in a subsidy program before having to recertify to continue benefits, the greater the reduction in CM as subsidy generosity is increased. These effects complement findings from studies examining the impact of administrative burdens on subsidy spells (Jenkins & Nguyen, 2022). As more administrative burdens are placed on families, the less likely they are to continue receiving benefits. If families are unable to continue to receive benefits because administrative burden is so high, then the generosity of the program is less likely to have meaningful impacts on reducing child maltreatment. Families facing shorter redetermination periods may have increased stress due to anticipating the potential loss of care/need to re-certify eligibility. These anticipation effects may explain lower abuse rates in infancy with longer redetermination periods beyond 12 months. Jenkins and Nguyen (2022) found that for every additional month of a redetermination period, there was a 1.4 week increase in the amount of time families were predicted to continue receiving benefits, which is over 2 months of additional financial help in paying for child care when redetermination length is increased by 6 months. Even small changes to the generosity of a subsidy program are much more likely to have impacts on family financial hardship when families are able to maintain such economic supports for longer periods. Indeed, our models show that the effect of increasing subsidy generosity on reductions in child maltreatment changes by 1% for every additional month of extra redetermination period length.

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In summary, states have considerable discretion in how their CCDF program is administered. Making significant changes to the number of eligible individuals allowed to be eligible (by setting higher initial eligibility income thresholds), lowering the number of required number of work hours, lowering the number of sources of income counted towards eligibility, lowering the cost to families through smaller copayment sizes, and increasing access to child care through higher reimbursement rates are all implementation rules that can increase the generosity of a subsidy program. Such changes have the potential to dramatically lower family stress related to financial burdens surrounding the high cost of child care, and thus reduce risk for conditions that may lead to child abuse and neglect. However, increasing the generosity of such policies is only as good as a family's ability to maintain eligibility and receive benefits for a sustained amount of time. These findings are critical for policymakers who are interested in leveraging economic support programs to reduce child maltreatment. The findings specifically suggest that a policy change to increase the overall generosity of the child care subsidy program, such as an increase in the amount of monthly income a family can have to become eligible, is not likely to have much of an impact on child maltreatment if there are significant administrative burdens for the program. As such, policy changes must include both increasing generosity and reducing administrative burden simultaneously.

This study has a number of important limitations that should be noted when considering the results. The primary limitation is the lack of child care recipient data at the individual-level. That is, we do not report on variations in the number of families that enroll in the CCDF program nor the length of time any one family stays in the program. Relatedly, we do not link data at the individual-level between CCDF recipients and families engaged in the child welfare system. Therefore, we cannot show that the same families who participated in CCDF state programs which had a high level of generosity and/or low levels of administrative burden engaged less frequently with child protective services. Additionally, while we utilize strict statistical controls including state and quarterly fixed effects (removing time-invariant variation that exists between groups) as well as six time-varying controls, we are relying on correlational not experimental data. Child maltreatment is only measured using officially reported, administrative data which only involves acts of abuse/neglect that have been a.) observed by an outside party and b.) reported to child welfare agencies. Two-way fixed effects models can be confounded with the presence of heterogenous treatment effects (Callaway, Goodman-Bacon, & Sant'Anna, 2021). To overcome these challenges, alternative estimation methods for binary treatments exist and are growing in popularity (e.g., Callaway & Sant'Anna, 2021). We also acknowledge the challenge in supporting a parallel trends assumption with our design. With a continuous policy variable such as ours, it is not straightforward to test 'pre-policy trends'. For example, we would need to derive a cut-off, or threshold, at which a state's generosity score was low enough to be considered, by us to be 'not treated'. It is for this reason that we choose TWFE, as this general approach, albeit having limitations, freely allows for continuous treatment effects where state's can take any value at any time. We also acknowledge the existence of unobserved, time-varying potential confounders that we did not adjust for. An attempt was made to include as many covariates as possible with data that was available. Alternative approaches for continuous variables (e.g,, Callaway et al., 2021) (child care subsidy generosity is considered a continuous

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'treatment') are not currently designed to handle interaction effects and time-varying covariates. Moreover, by testing for interaction effects, we are modeling potential treatment heterogeneity directly, at least with respect to administrative burden. Only two states had redetermination period of 15 months or greater (Nebraska and New Jersey). Therefore, the model results when re-centered at 15 or 18 months may not generalize beyond Nebraska and New Jersey.

We do not account for the quality and availability of child care in various regions across the United States. Instead, what we demonstrate are links between policy variation and child maltreatment rates at the state-level. Such findings do have important implications for policy, especially when considering administrative burden. We recommend additional research, especially those that take advantage of quasi-experimental designs. For example, taking a deeper dive into states that make significant improvements to child care subsidy policies (compared to similar states with similar demographics), or those that take steps to lessen administrative burden and examining potential prospective changes to rates of CM. Administrative burdens are a well-known problem in the social welfare system, as evidenced by quantitative and qualitative methods evaluating the negative impact that administrative burdens have on up-take within programs, even programs that are otherwise considered generous (Henly, Kim, Sandstrom, Pilarz, & Claessens, 2017; Herd, DeLeire, Harvey, & Moynihan. 2013; Isaacs et al., 2016; Roll & East, 2014). Lastly, there may be other policies (separate from child care subsidies) that my be confounding these effects. However, because child care subsides change frequently across and within states, any policy that may be a confounder would likely need to show the same degree of variation across time and be associated with both child care subsidies and our outcomes. However, this is an important limitation and we encourage future work on this topic to better isolate these effects using quasi-experimental methods or through the study of 'the combined effects' of multiple policies.

A primary strength of this study was a focus on the critical role that administrative burdens have on modulating the overall impact of child care generosity on rates of abuse and neglect. Minimizing burdens such as income cliffs and short redetermination periods are actionable, relatively straightforward, and potentially powerful ways to boost the impact of any means-tested social welfare program. Recent quasi-experimental research provides evidence that burdens decrease up-take not only for child care subsidy programs but also other means-tested programs like Medicaid (Herd et al., 2013). The new rules, imposing a minimum 12-month redetermination period, from 2014 reauthorization of CCDF increased subsidy spell length of 30% for families (Rochford et al., 2022). However, currently, only a few states have longer redetermination periods. This is a limitation of the study, for example, when our effects are recentered at the 18 month redetermination period, we may be underpowered to detect an effect. Cliff effects, which can be exacerbated by short redetermination periods, are another well-known issue for families struggling to afford child care (Roll & East, 2014). Take an example from New Mexico (FY2017), a family of three with one child in care living at 200% of the FPL, receiving CCDF subsidies would be paying roughly $7,488 per year in child care costs at a subsidized rate. However, once that family increases their income to 201% of the FPL, that family would no longer be eligible for CCDF subsidies and be paying the full, average cost of center-based care

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amounting to nearly $15,569 a year (Fox, Feng, & Reynolds, 2023). Such an example highlights, that even with generous subsidies, administrative burdens can be so immense as to cause families to not benefit from subsidies at all. As our preliminary data points to, these burdens may diminish the impact that subsidies have on reducing family stress and financial hardship therefore reducing the potential preventive effect subsidies have on abuse and neglect of children, especially those most vulnerable-young children. No single policy, however, will be successful in preventing all cases of abuse or neglect. The most productive preventive strategies will be those that tackle not only economic stress for families, but a comprehensive set of community and individual-level factors, benefiting the most people.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1.

Descriptive Statistics

Variable	Mean	Standard Deviation
Generosity Z-Score Composite (Z-scored)	0	1
Redetermination Period (# of months)	10.01	2.89
Income Cliff (cliff = −1, no cliff = 0)	−0.54	0.50
Age 0 Referral Rate (inv. per 100,000)	2124.13	1040.92
Age 0 Substantiation Rate (inv. per 100,000)	647.46	396.31
Age 1–5 Referral Rate (inv. per 100,000)	1586.80	744.69
Age 1–5 Substantiation Rate (inv. per 100,000)	341.55	203.23
Avg. state proportion of child population- White	60.00	17.88
Avg. state proportion of child population- Black	12.72	12.32
Avg. state proportion- other (not Black, not White)	10.75	9.82
Avg. state proportion of population- urban	73.94	14.79
Avg. state unemployment rate	6.00	2.34
Avg. State poverty rate	13.00	3.52

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Table 2.

Two-Way Fixed Effect Moderated Regressions Results: Does the association between CCS Generosity and CM Rates Depend on Redetermination Period Length?

Redetermination Period	**18m**	**15m**	**12m**	**11m**	**8m**	**6m**
Outcome:						
Age 0 Referral Rate						
Predictors:						
Generosity Composite −106.42* (main effect)	−203.18**	−169.46**	−135.73**	−124.48**	−90.76	−68.28
5.0% ▫	*9.6%* ▫	*8.0%* ▫	*6.4%*	*5.9%* ▫	*4.3%*	*3.2%*
Redetermination Period 24.52 (main effect)	22.88	--	--	--	--	--
Generosity*Redetermination	−11.24	--	--	--	--	--
Outcome:						
Age 0 Substantiation Rate						
Predictors:						
Generosity Composite −15.48 (main effect)	−96.49*	−68.20*	−39.92	−30.49	−2.21	16.65
2.4%	*14.9%* ▫	*10.5%* ▫	*6.2%*	*4.7%*	*0.3%*	*2.6%*
Redetermination Period 13.10* (main effect)	11.73	--	--	--	--	--
Generosity*Redetermination	−9.43*	--	--	--	--	--
Outcome:						
Age 1–5 Referral Rate						
Predictors:						
Generosity Composite −83.58* (main effect)	−162.30**	−134.91**	−107.51**	−98.38**	−70.99*	−52.72
5.3% ▫	*10.2%* ▫	*8.5%* ▫	*6.8%* ▫	*6.2%* ▫	*4.4%* ▫	*3.3%*
Redetermination Period 15.791 (main effect)	14.47	--	--	--	--	--
Generosity*Redetermination	−9.13	--	--	--	--	--
Outcome:						
Age 1–5 Substantiation Rate						
Predictors:						
Generosity Composite −13.96 (main effect)	−53.05*	−39.45*	−25.84*	−21.31	−7.71	1.34
2.4%	*15.6%* ▫	*16.5%* ▫	*7.6%* ▫	*6.2%*	*0.2%*	*.03%*
Redetermination Period 2.83 (main effect)	2.18	--	--	--	--	--
Generosity*Redetermination	−4.53*	--	--	--	--	--

Note: Redetermination period is a continuous moderator defined as the maximum number of months families may obtain CCS benefits before eligibility requires redetermination. In our data, redetermination periods take the value of 6,8,11,12,15, or 18 months, with a sample size of N = 760, 18, 16, 1487, 1, and 13, respectively. The total sample size is N = 2295 (51 regions × 45 quarter-years). Regression models that include interaction terms impact the interpretation of coefficients of the predictors involved in the interaction term. The ‘Generosity Composite’ coefficient always represents the effect of a 1SD unit increase in the generosity composite (z-score transformed) on CM outcome rates, when the value of ‘Redetermination Period’ equals 0 (i.e., zero months of redetermination). When you ‘recenter’ the data by subtracting a constant from each Redetermination Period value, the meaning of 0 changes. For example, if the constant ‘18’ was subtracted from each Redetermination Period values, then the value of 0, actually represents 18 months of redetermination. Consequently, the interpretation of the ‘Generosity Composite’ coefficient changes. The ‘Generosity Composite’ coefficient would then be interpreted as the effect of a 1SD unit increase in the generosity composite (z-score transformed) on CM outcome rates, when the value of ‘Redetermination Period’ equals 18m (i.e., a region in a given quarter-year had an 18m redetermination period policy in effect). The same logic applies to each ‘recentering’ we preformed. Interaction term coefficients (if statistically significant) can be tricky to interpret. An interaction effect refers to when the effect of one predictor on an outcome

depends (or varies) on the level of a second predictor (and vice-versa). One way to understand exactly how the ‘effect’ of the Generosity Composite varies depending on Redetermination Period length is to re-center data as described above. Looking at the results, the first thing to notice is that the ‘Generosity*Redetermination’ interaction effect is not statistically significant. The exact p-value of the interaction term coefficient was $p = 0.15$. A strict interpretation of a null interaction term means that the ‘effect’ of the Generosity Composite on Age 0 Referral Rate does not depend (i.e., is constant) on the length/value of the Redetermination Period (we ignore the varying effects and assume they are the same). For the purpose of instruction, imagine the interaction effect was significant. The effect of increasing generosity on the reduction of CM rates appears to be larger and more significant as Redetermination Periods get longer. In fact, Generosity is only significant for Redetermination Periods with months equal to or longer than 11 months. However, since the interaction coefficient was not statistically significant, we urge caution in over interpreting differences between the estimated ‘simple slopes’ (i.e., Generosity coefficients at different levels of Redetermination Period). The coefficient of Redetermination Period and the coefficient for the interaction term remain constant across the re-centered models (this is always the case) as the models are identical in terms of model fit. Main effect, percentage

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Table 3.

Two-Way Fixed Effect Moderated Regressions Results: Does the association between CCS Generosity and CM Rates Depend on Income Cliff?

Income Cliff	No Cliff	Cliff
Outcome:		
Age 0 Referral Rate		
Predictors:		
Generosity Composite −106.77* (main effect)	−219.26**	−51.73
5.0% ▫	*10.3%* ▫	*2.4%*
Income Cliff −13.22 (main effect)	20.88	--
Generosity*Income Cliff	−167.53**	--
Outcome:		
Age 0 Substantiation Rate		
Predictors:		
Generosity Composite −15.04 (main effect)	−76.68*	15.34
2.3%	*11.8%* ▫	*2.4%*
Income Cliff 29.2 (main effect)	48.07	--
Generosity*Income Cliff	−92.02**	--
Outcome:		
Age 1–5 Referral Rate		
Predictors:		
Generosity Composite −83.80* (main effect)	−158.19**	−47.64
5.3% ▫	*10.0%* ▫	*3.0%*
Income Cliff −5.48 (main effect)	17.06	--
Generosity*Income Cliff	−110.55**	--
Outcome:		
Age 1–5 Substantiation Rate		
Predictors:		
Generosity Composite −13.65 (main effect)	−34.98*	−3.28
4.0%	*10.2%* ▫	*0.96%*
Income Cliff 21.25 (main effect)	27.71	--
Generosity*Income Cliff	−31.69*	--

Note: Income Cliff is coded (cliff = −1, no cliff = 0)