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US shelter in place policies and child abuse Google search volume during the COVID-19 pandemic

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ABSTRACT

The COVID-19 pandemic has led to unemployment, school closures, movement restrictions, and social isolation, all of which are child abuse risk factors. Our objective was to estimate the effect of COVID-19 shelter in place (SIP) policies on child abuse as captured by Google searches. We applied a differences-in-differences design to estimate the effect of SIP on child abuse search volume. We linked state-level SIP policies to outcome data from the Google Health Trends Application Programming Interface. The outcome was searches for child abuse-related phrases as a scaled proportion of total searches for each state-week between December 31, 2017 and June 14, 2020. Between 914 and 1512 phrases were included for each abuse subdomain (physical, sexual, and emotional). Eight states and DC were excluded because of suppressed outcome data. Of the remaining states, 38 introduced a SIP policy between March 19, 2020 and April 7, 2020 and 4 states did not. The introduction of SIP generally led to no change, except for a slight reduction in child abuse search volume in weeks 8–10 post-SIP introduction, net of changes experienced by states that did not introduce SIP at the same time. We did not find strong evidence for an effect of SIP on child abuse searches. However, an increase in total search volume during the pandemic that may be differential between states with and without SIP policies could have biased these findings. Future work should examine the effect of SIP at the individual and population level using other data sources.

1. Background

COVID-19 has had widespread health, social, and economic effects across US society. Families have faced a combination of challenges including increased unemployment or precarious employment, school closures, movement restrictions, and social isolation. Each of these disruptions is a risk factor for child abuse and neglect (jointly termed maltreatment) (Risk and Protective Factors [Internet], 2022). Early in the pandemic, UNICEF cautioned about secondary effects of the pandemic on children including neglect and limited parental care, and increased exposure to several forms of maltreatment including physical violence, sexual violence, and emotional maltreatment (Technical Note: Protection of Children during the Coronavirus Pandemic, 2020). Babvey et al. found that posts on the subreddits r/survivorsofabuse and r/abuse

increased more than two-fold after shelter-in-place restrictions were introduced, indicating that abuse may have increased during this time (Babvey et al., 2021).

At the same time, COVID-19 created challenges in systems for monitoring child maltreatment (Katz et al., 2021). Educational professionals make up 21% of all child maltreatment referrals to Child Protective Services (CPS), thus school closures likely disrupted typical referral processes (Sciamanna, 2022). Likewise, reductions in routine pediatric care may have also decreased contact between healthcare mandated reporters and children. Thus, this period of increased familial stress and economic uncertainty may have been paired with decreased identification of child abuse (Welch and Haskins, 2020).

Between March 19 and April 7, 2020, 45 states introduced partial or statewide shelter in place (SIP) policies to reduce infection transmission

Abbreviations: API, application programming interface; COVID-19, coronavirus disease 2019; CPS, child protective services; SIP, shelter in place.

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(Mervosh et al., 2020). By April 2020, the United States (US) was experiencing its highest unemployment rates on record (National Employment Monthly Update [Internet], 2022; Unemployment Rates During the COVID-19 Pandemic [Internet], 2022). Previous research has found that economic policies or recessionary trends that decreased family income, created financial uncertainty, and increased unemployment were associated with increased self-reported physical abuse or emotional maltreatment and increased reports to CPS (Schneider et al., 2017; Brooks-Gunn et al., 2012; McLaughlin, 2022a; McLaughlin, 2022b; Kovski et al., 2021). In addition to these economic changes, SIP shifted family and community interactions, by increasing contact between household members and greatly reducing contact outside of the household. Such circumstances raised concerns about maltreatment, as risk factors (i.e., unemployment, parental stress, isolation/disconnection) for maltreatment increased (Abramson, 2020) but the ability to detect it decreased. Because of the challenges of measuring child maltreatment using CPS data during the COVID-19 pandemic, novel sources such as online search data merit consideration as alternative measures. Previously, Stephens-Davidowitz investigated how searches related to child maltreatment changed over the course of the Great Recession and found that places where CPS referrals went down had the largest increases in both child mortality and Google searches related to child maltreatment (Stephens-Davidowitz, 2013). We employed a similar approach with an objective of identifying the effect of state-level SIP policies during the COVID-19 pandemic on child maltreatment in the US. We used a difference-in-differences study design, a type of controlled pre-post design that estimates changes in searches related to child maltreatment after the introduction of SIP relative to states that did not undergo SIP at the same point in time (Strumpf et al., 2017). The major strength of the design is that it eliminates confounding from secular trends over time that are shared across states and from time-invariant risk factors for child abuse that vary across states. However, it requires a set of assumptions, such as parallel trends in the outcomes before the policy change across states that do and do not implement SIP, and that these parallel trends would have continued if SIP had not been implemented. We detail the method and our assessment of the assumptions in the statistical analysis section.

2. Methods

2.1. Exposure

We linked COVID-19 SIP data from Boston University and the New York Times to outcome data measured using the Google Health Trends API. We abstracted the dates that states introduced SIP from a database maintained by Boston University, along with information reported by the New York Times (Mervosh et al., 2020; Raifman et al., 2021). Both sources assembled dates based on state-issued health mandates, executive orders, and local news reports (Mervosh et al., 2020; Raifman et al., 2021; Tracking COVID-19 Policies [Internet], 2020).

2.2. Outcome

The volume of searches for child abuse was obtained from the API (Health Trends API Getting Started Guide [Internet], 2022; Stocking and Masta, 2017). To identify search terms potentially used by children who experienced abuse, we reviewed qualitative literature on children reporting maltreatment (Lavi and Katz, 2016; Williams, 2017; Jackson et al., 2015; Foster and Hagedorn, 2014; Foster, 2017; Katz and Barnett, 2014; Brennan and McElvaney, 2020) and validated scales for self-report of child maltreatment (Felitti et al., 1998; Bernstein et al., 1994). We then created search terms generally following the format “perpetrator” + “verb” + “me/my” (or “their” for sexual abuse), where perpetrator included an individual from a list of common abuse perpetrators and “verb” was the action against the child. For quality control, we searched each term in a Google Chrome incognito window and

discarded terms that recovered results not related to the specified child abuse domain (Masta et al., 2017). The final search terms encompassed three domains: physical abuse, sexual abuse, and emotional maltreatment. We attempted to create accurate search terms for neglect, but these terms uncovered many unrelated searches and were discarded.

Supplementary material 2 contains the final list of search terms. We included between 914 and 1512 abuse phrases for each abuse sub-domain (e.g., physical: “mom hit me,” emotional: “stepfather yells at me,” sexual: “uncle makes me touch their”), incorporating various spellings and tenses. In an effort to capture searches indicative of child abuse incidence, the majority of the search terms contained the words “me” or “my” combined with a caretaker perpetrator, to prioritize searches made by children about an abuse experience. Additionally, we included the term “child abuse hotline” to capture children or caregivers looking for this resource. We also investigated the term “signs of child abuse”; however, it returned low search volume, and may be more likely to be searched by individuals interested in learning about child abuse rather than by children experiencing abuse or witnesses, so we discarded it.

Google maintains a random sample of all Google searches that can be queried by researchers using the API (Masta et al., 2017). When a query is performed, a random sample of the overall sample is pulled for the requested geography and time frame. From this second sample, the API returns a scaled proportion equal to the number of searches for the specified search terms as a proportion of total searches multiplied by a constant (10 million) (Health Trends API Getting Started Guide [Internet], 2022). We used the Google Health Trends API to query the volume of Google searches performed that contained words matching each of the phrases in the list of abuse search terms, as a proportion of total searches performed. For the main analysis, we pulled state-level data for each week between December 31, 2017 and June 14, 2020. If the number of searches is below a threshold (not made public by Google) it is suppressed by the API leading to missing data (returned as zeroes), an issue that was more common for smaller states (Masta et al., 2017). To reduce missingness and improve search volume stability, we pulled ten random samples (Masta et al., 2017). Our final measure was the average of non-missing values from the random samples for each state-week. States with >55% of their data missing were excluded.

To adjust for the possibility of the outcome measure changing in response to changes in the total number of searches during the pandemic (COVID-19: How Cable's Internet Networks Are Performing. Metrics, Trends, and Observations, 2022), we conducted a sensitivity analysis using a normalized outcome. More information about the normalized outcome is contained in the supplementary material 1. A detailed description of the process we followed to use Google search terms is included elsewhere (Neumann et al., unpublished data, 2022).

2.3. Statistical analysis

We used a difference-in-differences design to estimate the extent that changes in child abuse search volume after the introduction of SIP policies were greater (or less) in states that introduced SIP in a given week vs. those that did not in that same week (Angrist and Jörn-Steffen, 2022). For each week that SIP was introduced, “treated” states were those with the policy and “untreated” states were those without.

We regressed the child abuse search volume as a function of: 51 indicators for calendar week; 2 indicators for calendar year; 41 indicators for included state; 82 interaction terms between state and year to capture state-specific time trends; and indicators for week since SIP, where the reference group represented no SIP in a given state-week, and time before or after SIP was coded as indicators for each of the ten weeks before SIP (leads), the week of SIP's introduction, and the ten weeks after SIP (lags). We included lead effects as negative controls and rejected models that detected leads. We hypothesized that any effects of SIP would occur in the 2.5 months after its introduction, and did not estimate effects beyond ten weeks to limit confounding introduced by

changes over a longer period. The coefficients for the treatment terms (time before or after the policy change) are the estimated additional changes in child abuse search volume in states with SIP net of the change over the same week in states not introducing SIP. Robust standard errors were specified to account for the clustering of data over time within states, and we applied analytic weights for state average population size in 2018 and 2019 from the American Community Survey ([ACS Demographic and Housing Estimates \[Internet\], 2022a](#); [ACS Demographic and Housing Estimates \[Internet\], 2022b](#)).

The difference-in-differences design assumes that: i) pre-policy trends in child abuse were parallel in treated and untreated states and would have continued to be parallel in the absence of the policy/intervention, ii) that there are no unmeasured time-varying confounders (i.e., no factors that varied within states over time affecting child abuse that also affected which states introduced the policy), and iii) that there are no other changes at the time of the policy change that affect the outcome differentially in states introducing and not introducing SIP. We plotted trends of the outcome in the time period before SIP was introduced and visually compared treated and untreated state trends to assess the plausibility of the parallel trends assumption. As a robustness check, we conducted a falsification test, repeating the analysis with the SIP dates shifted to occur in 2019 and adding an additional year of pre-period outcome data ([Lipsitch et al., 2010](#)).

We ran six post-hoc sensitivity analyses to address concerns that arose during data exploration. First, we noticed a reduction in the percentage of state-weeks with suppressed outcome data returned by the Google Health Trends API from the pre- to post-policy periods, particularly in states with small populations. At the same time, the magnitude of the search volume in these states decreased, suggesting that the outcome was “detecting” lower search volumes, which would previously have been below the suppression threshold. We were concerned that this pattern might result from an increase in total searches, whereby even if the absolute number of child maltreatment searches were increasing (to push above the suppression threshold) it would appear as a decline in the outcome (abuse searches as a proportion of total searches). Thus, we re-ran the models, restricting the data by dropping nine states that had any missing outcome data. Second, we also ran a more restrictive sensitivity analysis on the 15 states (dropping 27 states) with no change in missingness/suppression of the outcome variable in the two months before vs. two months after SIP’s introduction.

Third, we recoded the exposure to stop counting weeks since SIP once the SIP policy ended within each state. Fourth, we created an exposure defined by level of restrictiveness: one level that indicates more restrictive SIP enforcement and the other that indicates less restrictive enforcement (compared with no SIP). Bans that do not strictly enforce movement or only applied to a subset of the population (e.g., those who are at increased risk from Covid, those over the age of 65, etc.) were encoded as less restrictive, and all other bans were coded as more restrictive. Fifth, we removed the interaction between state and year from the analysis.

Sixth, recent economics literature has shown that implementing difference-in-differences designs with two-way fixed effects models and a binary indicator variable for a policy change can lead to biased estimates under certain conditions ([Callaway and Sant’Anna, 2020](#); [Baker et al., 2022](#)). Using multiple indicators to model dynamic changes during the post-policy period, as we have done, partially addresses these concerns. However, to ensure robustness to the biases recently identified, we also ran models using the method proposed by Callaway and Sant’anna ([Callaway and Sant’Anna, 2020](#)). These models did not point to different findings.

Python 2.7 was used to query the Google Health Trends API, R 4.0.5 and Stata 16.1 were used to clean, visualize, and perform the statistical analysis.

2.4. Ethics approval and patient and public involvement

This study was exempt from approval by the institutional review board because it is not considered human subjects research. Patients or the public were not involved in the design, or conduct, or reporting, or dissemination plans of our research.

3. Results

Eight states (Alaska, Delaware, Montana, North Dakota, Rhode Island, South Dakota, Vermont, Wyoming) and DC were excluded because of complete or high rates of suppression by the Google Health Trends API. Of the remaining 42 states, 38 introduced a SIP policy between March 19, 2020 and April 7, 2020 and 4 states (Arkansas, Iowa, Nebraska, Utah) did not ([Fig. 1](#)).

States that introduced SIP had on average larger populations, higher median incomes, were less rural, voted republican in lower proportions, and were more racially and ethnically diverse than states that did not introduce SIP ([Table 1](#)). Trends in child abuse search volume in SIP and non-SIP states appeared parallel between January 2018 and February 2020, supporting the plausibility of the parallel trends assumption ([Supplemental Fig. S2](#)).

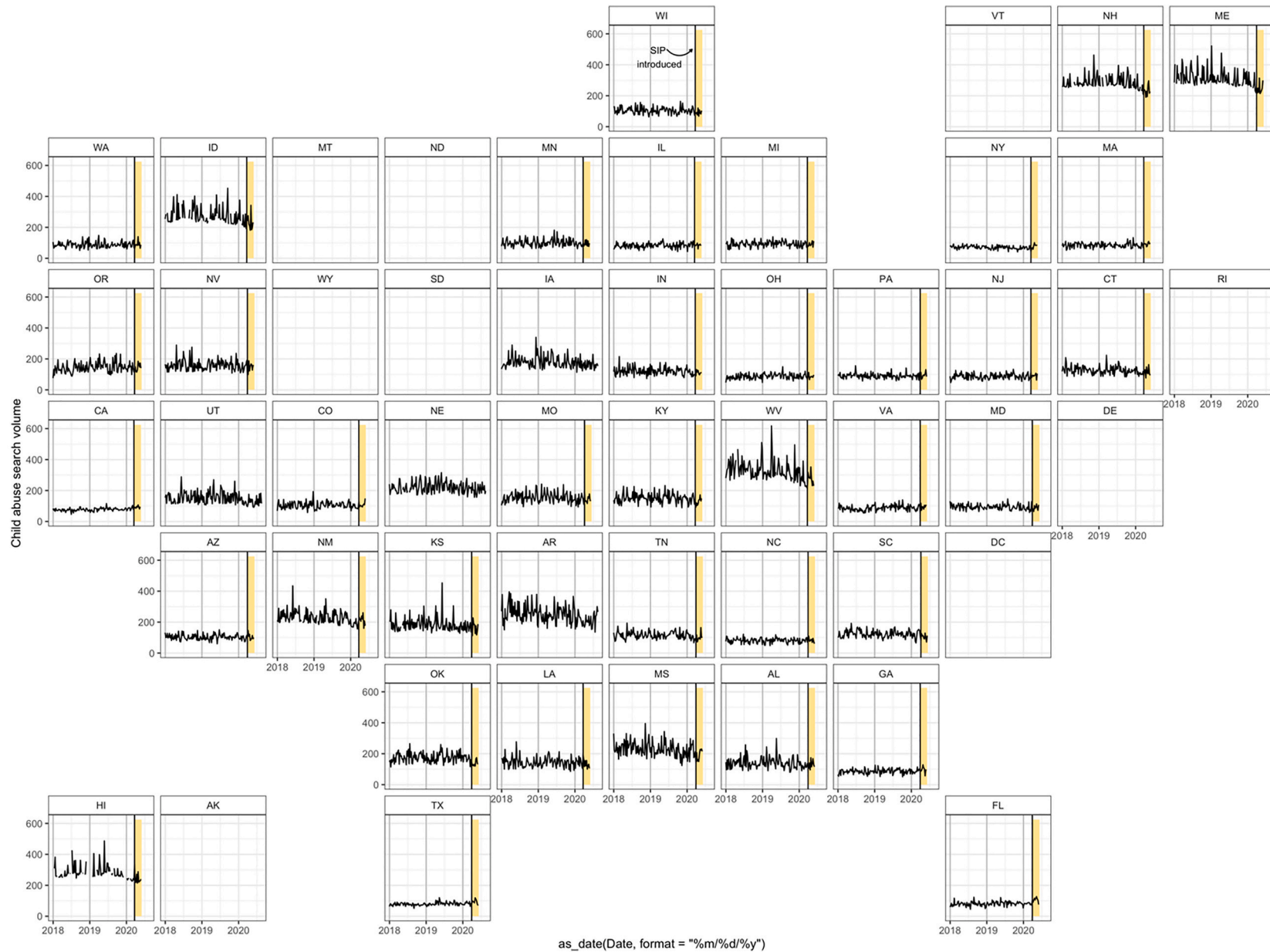
Searches related to emotional and sexual abuse contributed the most to child abuse search volume, followed by searches related to physical abuse. Searches of “child abuse hotline” contributed least to the measure ([Supplemental Fig. S3](#)).

[Fig. 2](#) displays SIP-related changes in child abuse search volume, where each estimate is interpreted as the change in the volume of the outcome (at a specified week before or after the introduction of SIP vs. earlier weeks) experienced by states that introduced SIP net of the changes experienced over the same time period by states that did not introduce SIP. As expected, no differences were detected in the weeks preceding the policy change. Weeks 5–7 after the policy change had small estimated increases in the outcome, and weeks 8–10 had estimated decreases, though most confidence intervals overlapped the null. The model passed the falsification test, and did not detect pre- or post-policy changes when fictitious 2019 dates were used for SIP’s introduction ([Fig. S4](#)).

Compared to the main analysis, analysis of the normalized outcome showed point estimates for the post-policy period shifted downward, most notably for weeks 8–10 after the policy change ([Fig. S5](#)). These point estimates are consistent with a reduction in child abuse search volume for those weeks. The model that excluded 9 states with the most missing data resulted in nearly identical results as the main model ([Fig. S6](#)). The model that excluded 27 states and kept states with no discernible change in the proportion of missing data did not detect an effect of the policy change on the outcome, though only a shorter post-policy period could be investigated ([Fig. S7](#)). The model that incorporated SIP end dates into the analysis detected lead effects and was rejected from further consideration ([Fig. S8](#)). Less restrictive SIP policies were introduced in 5 states (Connecticut, Georgia, Kentucky, Oklahoma, and Texas) and the remaining states were encoded as having more restrictive policies. This analysis did not support a relationship between either policy strength and child abuse search volume ([Fig. S9](#)). The analysis that removed state-year interaction terms detected policy effects in the lead period so it was not considered for interpretation ([Fig. S10](#)).

4. Discussion

In this study, we found evidence consistent with no association of SIP with child abuse search volume. Using a normalized outcome, findings indicated a reduction in search volume associated with SIP in weeks 8–10. These findings were contrary to our hypothesis of an increase in child abuse due to SIP. SIP orders may have had no impact on child abuse on average. The impact of the pandemic on family life is likely



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Fig. 1. Child abuse search volume before and up to ten weeks after the introduction of shelter in place policies (yellow shaded area). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Eight states (Alaska, Delaware, Montana, North Dakota, Rhode Island, South Dakota, Vermont, Wyoming) and DC were excluded. Of the remaining states, four did not introduce shelter in place policies (Arkansas, Iowa, Nebraska, and Utah). Child abuse search volume is more variable and has a higher average magnitude in states with smaller populations. Because the API suppressed data below an unknown threshold, it is possible that for smaller states only the right-hand side of a distribution of search volumes is returned by the API where the data is above the threshold. For example, in New Hampshire, the data is more variable in the upwards direction and appears bounded at a lower value. The bound appears to move downward shortly before shelter in place is introduced, possibly as a function of changing total search volume. Thus, we don't recommend comparing the magnitude of the outcome across states.

different according to economic factors, such as essential work status, remote work options, and accumulated wealth. It may be that some families experienced reductions in stress (and downstream reductions in abuse) that outweighed increases in stress and abuse experienced by other families (Pallsson et al., 2020). However, children with previous adverse childhood experiences including household violence or witnessing caregiver intimate partner violence may have been at higher risk during SIP, and the effects of these experiences may accumulate and compound (Bryce, 2020). In another study, we found that searches for child abuse and child-witnessed intimate partner violence increased during the COVID-19 pandemic in the US overall (Riddell et al., 2022). Combined with this study, this may suggest that an increase in child abuse occurred during the COVID-19 pandemic, and is not isolated to states that introduced SIP.

Although Google searches are challenging to analyze, more traditional measures of child abuse pose challenges that warrant use of nontraditional measures. For example, a CDC analysis of emergency room visits for child maltreatment over the pandemic found that visits for child maltreatment were much lower in weeks 11–24 of 2020 (weeks beginning March 8–June 7) compared to the same weeks in 2019 (Swedo et al., 2020). Yet the number of severe visits that resulted in hospitalization was similar to 2019. At the same time, the total number of child emergency visits greatly decreased, demonstrating a large reduction in healthcare-seeking behavior during the pandemic. Thus, it is difficult to determine from healthcare utilization data whether child maltreatment truly decreased, or if maltreatment detection decreased because caretakers were less likely to seek medical care and only came to the hospital in the most severe cases. Likewise, two studies of CPS reports found that allegations of child maltreatment in New York City dropped between 29% and 52% (depending on report source) during the first three months of the pandemic and by 27% in Florida during the first two months of the pandemic (Rapoport et al., 2021; Baron et al., 2020). Thus, detection of maltreatment using hospitalizations and CPS reports appear to have been heavily affected during the pandemic, making it difficult to know whether rates of child maltreatment had changed using traditional measures. On the other hand, a recent study examining texts and calls to the hotline *Childhelp* increased following school closures and SIP mandates, suggesting that maltreatment may have increased during this time (Ortiz et al., 2021).

One recent study used Google Trends data (as opposed to the Google Health Trends API) to study child maltreatment during the COVID-19 pandemic (Riem et al., 2021). The authors estimated total maltreatment searches by multiplying the returned measure by an estimated number of desktop Google searches per day (only available for the two most recent months at the time of abstraction), and found that 28 out of the 33 abuse-related search terms considered increased during lockdown in “many countries worldwide” (Riem et al., 2021). This is in contrast to this study’s results, though the studies have many differences (e.g., geographic scope, large difference in number of search terms considered, focus on SIP vs. pandemic overall).

Previous studies that have looked at exposures that affect income related to child maltreatment referrals have some relevance to our findings. One possible mechanism through which SIP might affect child abuse is stress due to SIP-related employment cuts and ensuing financial hardship. McLaughlin found that state-level increases in cigarette taxes, sales taxes, and the price of gasoline were associated with higher child maltreatment referral rates (McLaughlin, 2022a; McLaughlin, 2022b). A recent study by Kovski et al. found that state-level increases in earned income tax credits were associated with fewer reports of child neglect (Kovski et al., 2021). These studies suggest that policies that decreased income led to increases in child maltreatment, and that the inverse is also true. However, these studies rely on CPS reports. CPS data pose unique challenges because state funding of CPS varies both across states and within states over time. Of particular concern during the pandemic is the possibility that recessionary budget cuts can lead to reduced interactions with mandated reporters as well as CPS workforce and

protocol changes that may lead to spurious appearance of changes in maltreatment that do not reflect the true underlying incidence. This concern is demonstrated in a previous study that found that places most affected by the Great Recession had the largest reductions in child maltreatment referral rates but that these places had the largest increases in child mortality and child maltreatment-related Google searches (Stephens-Davidowitz, 2013). These findings are consistent with the possibility that referrals to CPS decreased during the Great Recession while maltreatment incidence actually increased. Two studies of the effects of decreased consumer confidence during the Great Recession on self-reported maltreatment by mothers also estimated increases in maltreatment (Schneider et al., 2017; Brooks-Gunn et al., 2012). Thus, exposures like the Great Recession and the COVID-19 pandemic that may directly affect reports to CPS pose challenges to using these data to measure abuse.

This study has several strengths. This study created a metric for child abuse search volume based on a comprehensive set of thousands of searches that children who experienced abuse or witnesses may perform. Search terms were informed by qualitative literature, and tested to ensure their validity in leading to child abuse-related sites. Importantly, the specific searches we performed should not be sensitive to media coverage of child abuse cases, which is often a concern with Google search analyses (Cervellin et al., 2017). We pulled multiple samples to improve measure stability and reduce missingness. Lastly, we used a quasi-experimental design that eliminates confounding from variables that differ across states and confounding from variables that change over time.

This study also has several limitations. First, Google searches related to child abuse is a proxy measure for child abuse incidence and future research should investigate how the measure tracks with other measures of abuse such as emergency room hospitalizations related to abuse and calls to the hotline *Childhelp*. While there are no studies validating this specific measure, a recent study found that seasonal peaks in Google searches for domestic violence tracked with peaks in police calls for domestic violence in Finland, suggesting that Google searches may provide important insights on the incidence of violence (Koutaniemi and Einiö, 2021). Second, while SIP policies may vary at levels smaller than the state, such as the county or city level, Google search data is not available at these smaller scales. Third, a key assumption of the difference-in-differences design is that no risk factors for the outcome change at the time of SIP implementation in treated states but not in untreated states. SIP policies were introduced at a period of unprecedented change to daily life; our effect estimates may therefore be capturing the effect of SIP combined with these other changes (e.g., school closures, unemployment). If these changes were all downstream of SIP, then we may have estimated a total effect of SIP and downstream changes rather than SIP in isolation. Another concern is related to evidence that internet usage changed markedly during the pandemic (COVID-19: How Cable’s Internet Networks Are Performing. Metrics, Trends, and Observations, 2022), possibly due to remote work and schooling, changes in how individuals connect with family and friends, and increased interest in news coverage related to the pandemic, among others (Koeze and Popper, 2020). If total search volume increased, then the same (or even increases in) in number of child abuse related searches could translate into decreases in relative search volume when taken as a proportion of total searches. Further, if there was a greater increase in total searches in treated vs. untreated states, this could spuriously create the appearance of a SIP-related decrease in child abuse that is actually due to changes in total search volume. Normalization is designed to eliminate this bias, insofar as the absolute number of searches for the normalizing term (here, “and”) do not change with SIP. However, if SIP was associated with increased searches of the normalizing term, then normalization cannot remove this bias and may exacerbate it. Google does not give access to the total search volume, and methods to estimate total search volume involve untenable assumptions. Finally, child abuse search volume only reflects the subgroup

Table 1
Comparison of states introducing shelter-in-place policies with states not introducing shelter in place policies.

Week of 2020 that shelter in place was introduced	Week 12 (Mar 15)	Week 13 (Mar 22)	Week 14 (Mar 29)	Week 15 (Apr 5)	Total Across All States with shelter in place	States without shelter in place
States	CA, IL, NJ, NY	CO, CT, HI, ID, IN, KY, LA, MA, MI, MN, NH, NM, OH, OR, WA, WI, WV	AL, AZ, FL, GA, KS, MD, ME, MS, NC, NV, OK, PA, TN, TX, VA	MO, SC	CA, IL, NJ CO, CT, HI, ID, IN, KY, LA, MA, MI, MN, NH, NM, NY, OH, OR, WA, WI, WV AL, AZ, FL, GA, KS, MD, ME, MS, NC, NV, PA, TN, TX, VA MO, SC	AR, IA, NE, UT
Number of States	4	17	15	2	38	4
Average of State Populations, 2018–2019	20,140,104	5,019,139	8,778,809	5,622,980	8,126,681	2,818,844
Sum of State Populations, 2018–2019	241,745,139	85,325,360	131,682,139	11,245,961	469,998,598	11,275,378
% of Study Population¹ Population	50.2%	17.7%	27.4%	2.3%	97.7%	2.3%
Characteristics						
Median Age²	38	39	39	39	39	36
Median Income²	\$73,038	\$63,649	\$59,353	\$54,330	\$62,451	\$60,295
% Rural^{3,4}	8.5%	24.7%	26.9%	31.6%	24.2%	29.0%
Educational Attainment²						
High school/GED	24.9%	28.4%	28.3%	28.3%	29.9%	28.1%
Associate's Degree	7.8%	9.0%	8.4%	8.4%	8.9%	8.6%
Bachelor's Degree	21.8%	19.5%	18.6%	18.6%	17.9%	19.3%
Graduate/Professional	14.5%	12.1%	11.5%	11.5%	10.8%	12.1%
Race/Ethnicity²						
Non-Hispanic Asian, Native Hawaiian, or Pacific Islander	9.5%	5.8%	3.5%	1.9%	5.1%	2.5%
Hispanic or Latino (any race)	23.8%	11.1%	13.8%	5.0%	13.2%	9.6%
Non-Hispanic Black	11.6%	7.2%	16.4%	19.0%	11.9%	6.2%
Non-Hispanic White	52.4%	71.3%	62.4%	71.6%	65.8%	78.9%
Other (includes one or more races)	2.7%	4.5%	3.9%	2.7%	4.0%	3.0%
Political Leaning						
Average % voted Republican in 2016 Presidential Election	36.9%	47.3%	50.0%	55.7%	47.7%	53.9%

¹ Based on the sum of state populations.

² American Community Survey 2019 5-year Survey, average of States in category.

³ 2010 Decennial Census Data, average of States in category.

⁴ 2016 election results from <https://www.nytimes.com/elections/2016/results/president>, average of States in category.

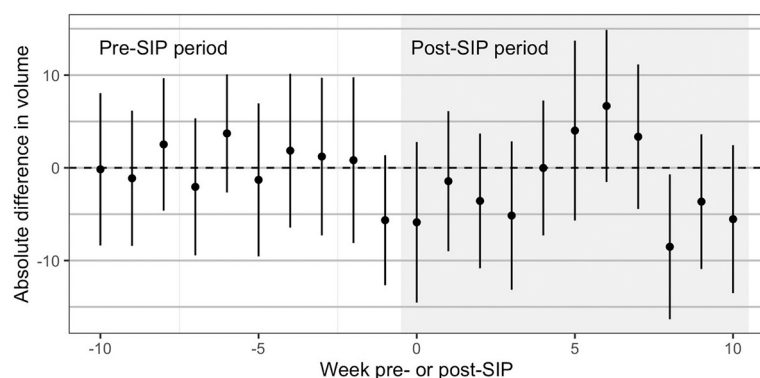


Fig. 2. Estimated effect of introduction of shelter in place on child abuse search volume.

This figure shows the change in child abuse search volume in states introducing SIP in each of the 10 weeks before and after policy introduction and in the week of the policy change compared with pre-policy weeks. These estimates control for shared time trends (on the month and year level), state-specific yearly trends, and additional changes experienced by states not introducing the policy over the same time period.

performing searches and does not capture changes among children not performing searches, such as those with limited internet access, and those very young.

5. Conclusions

Overall, we did not find evidence supporting our hypothesis that SIP policies led to increased child abuse search volume. The challenges identified in all available sources of data on child abuse/maltreatment

underline the importance for future work to use multiple measures of maltreatment/abuse with different strengths and weaknesses as a technique for triangulating evidence across multiple approaches to measure the outcome. Future work examining whether heterogeneous effects might underlie these results (e.g., if some families had reduced abuse while others increased) would be valuable.

Competing interests

There are no competing interests.

Ethics approval statements

This study was exempt from approval by the institutional review board because it is not considered human subjects research.

Contributorship statement

Corinne A Riddell: Conceptualization, Formal Analysis, Funding Acquisition, Investigation, Methodology, Supervision, Validation, Visualization, Writing - original draft. Kriszta Farkas Formal Analysis, Investigation, Methodology, Validation, Writing - review & editing. Krista Neumann: Data Curation, Investigation, Validation, Visualization, Writing - review & editing. N. Jeanie Santaularia: Data curation, Investigation, validation, Writing - review & editing. Jennifer Ahern: Conceptualization, Investigation, Methodology, Supervision, Writing - review & editing. Susan M. Mason: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing - review & editing.

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Data availability

Researchers affiliated with academic institutions and journal lists may request access to the Google Health Trends API through the request form: https://docs.google.com/forms/d/e/1FAIpQLSe_nHdGiG1YF-7rVDDmmulN8R-ra9MnGLLs7gIIaAX9VHPdPg/viewform. All analysis code can be found on (<https://github.com/corinne-riddell/SIP-and-abuse>).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ypmed.2022.107215>.

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