Health & Place 77 (2022) 102885

Contents lists available at ScienceDirect

Health and Place

journal homepage: www.elsevier.com/locate/healthplace

# Location matters: Regional variation in association of community burden of COVID-19 with caregiver and youth worry

Andrew T. Marshall [a,*], Daniel A. Hackman [b], Eric Kan [a], Shermaine Abad [c], Fiona C. Baker [d], Arielle Baskin-Sommers [e], Gayathri J. Dowling [f], Marybel R. Gonzalez [g], Mathieu Guillaume [h], Orsolya Kiss [d], Connor J. McCabe [i], Bruce D. McCandliss [h], William E. Pelham III [g], Susan F. Tapert [g], Amandine Van Rinsveld [h], Elizabeth R. Sowell [a,**]

[a] Children's Hospital Los Angeles, and the Department of Pediatrics, University of Southern California, Los Angeles, CA, USA
[b] USC Suzanne Dworak-Peck School of Social Work, University of Southern California, Los Angeles, CA, USA
[c] Department of Radiology, University of California, San Diego, CA, USA
[d] Center for Health Sciences, SRI International, Menlo Park, CA, USA
[e] Department of Psychology, Yale University, New Haven, CT, USA
[f] Division of Extramural Research, National Institute on Drug Abuse, Rockville, MD, USA
[g] Department of Psychiatry, University of California, San Diego, CA, USA
[h] Graduate School of Education, Stanford University, Stanford, CA, USA
[i] Department of Psychiatry, University of Washington, Seattle, WA, USA

ARTICLE INFO

*Keywords:*
COVID-19
Adolescent
Caregivers
Anxiety
Residence characteristics

ABSTRACT

Our study characterized associations between three indicators of COVID-19's community-level impact in 20 geographically diverse metropolitan regions and how worried youth and their caregivers in the Adolescent Brain Cognitive Development℠ Study have been about COVID-19. County-level COVID-19 case/death rates and monthly unemployment rates were geocoded to participants' addresses. Caregivers' (vs. youths') COVID-19-related worry was more strongly associated with COVID-19's community impact, independent of sociodemographics and pre-pandemic anxiety levels, with these associations varying by location. Public-health agencies and healthcare providers should avoid adopting uniform "one-size-fits-all" approaches to addressing COVID-19-related emotional distress and must consider specific communities' needs, challenges, and strengths.

## 1. Introduction

The SARS-CoV-2 (COVID-19) pandemic has more strongly impacted the physical and mental health of lower-than higher-income populations in the United States (Karmakar et al., 2021), likely due to the social determinants of and inequities in risk of exposure, healthcare access, and abilities to engage in COVID-19-preventative behaviors (Okonkwo et al., 2021). Nonetheless, we have shown that despite greater risks of COVID-19 exposure, lower-income populations (and/or those living in lower-income neighborhoods) report engaging in more preventative behaviors to combat its spread (Marshall et al., 2022).

Beyond the influence of family- and neighborhood-level socioeconomic status on COVID-19-related health outcomes, behaviors, and perceptions, different U.S. regions and metropolitan areas have been differentially affected by COVID-19. For example, COVID-19 infection/death rates and the concurrent economic impact has varied widely across the US (Udalova, 2021), partially due to disparate responses to the pandemic (e.g., stay-at-home policies/behaviors, mask mandates, vaccination rates) (Zang et al., 2021; Lyu and Wehby, 2020). Further, individuals' worry about COVID-19 was related to self-reported community factors (general perceived sense-of-community, strictness of COVID-19 lockdown policies) (Zhou and Guo, 2021), and anxiety levels in adults in China were greater if they knew of more COVID-19-related deaths and cases among friends/family or in their neighborhood (Zhong et al., 2020; Liu et al., 2020a).

Although adult's COVID-19-related emotional distress and children's caregiver-reported intra-pandemic behavioral health differ across U.S. census regions (Fitzpatrick et al., 2020; Patrick et al., 2020), little is

* Corresponding author. Department of Pediatrics, Children's Hospital Los Angeles, 4650 Sunset Blvd., Mailstop #130, Los Angeles, CA, 90027, USA.
** Corresponding author. Department of Pediatrics, Children's Hospital Los Angeles, 4650 Sunset Blvd., Mailstop #130, Los Angeles, CA, 90027, USA.
*E-mail addresses:* amarshall@chla.usc.edu (A.T. Marshall), esowell@chla.usc.edu (E.R. Sowell).

https://doi.org/10.1016/j.healthplace.2022.102885
Received 2 February 2022; Received in revised form 10 June 2022; Accepted 23 July 2022
Available online 9 August 2022

known as to (1) whether COVID-19's community-level impact on health and unemployment is associated with the pandemic's evolving emotional toll on caregivers and children, independently of families' characteristics or risk of COVID-19 exposure and (2) whether such associations differ by region. Collectively considering the severity of COVID-19's regional impact and how such impact is associated with the behavioral/emotional responses within the region's population may promote regionally specific practices to better address the potential impact of community health and economic conditions (Hackman et al., 2021).

In May 2020, the Adolescent Brain Cognitive Development℠ Study (ABCD Study®, hereafter "ABCD") began surveying its participants on how COVID-19 has influenced daily life (Marshall et al., 2022; Pelham et al., 2021). Here, we report on caregivers' and youths' COVID-19-related worry levels. Using county-level geocoded data of COVID-19 incidence and unemployment, we report, for the first time, the extent to which several community-level variables at 21 data-collection sites in 20 geographically diverse metropolitan regions are associated with caregivers' and youths' COVID-19-related emotional well-being. Given our past research suggesting that caregivers may be serving as buffers for youth's COVID-19-related worry (Marshall et al., 2022), we hypothesized that caregiver (vs. youth) COVID-19-related worry would be more strongly influenced by community-level variables. Further, given regional differences in COVID-19-related burden (Udalova, 2021), we hypothesized that these associations would differ by region. Lastly, we hypothesized that if an immediate-household member was at greater risk of exposure to COVID-19 given their job or public-transit use, then the associations between community burden and COVID-19-related worry would be more pronounced (i.e., COVID-19-related community burden would be more strongly associated with COVID-19-related worry given a family member's greater exposure to the community).

## 2. Methods

### 2.1. Participants

ABCD is a 10-year longitudinal study incorporating identical protocols across 21 U.S. study sites (Fig. 1A; Tables A1-A2). Primarily using school-based enrollment (Garavan et al., 2018), ABCD enrolled 11,878 9- and 10-year-old children from 22 initial sites. Recruitment processes and derivation of the demographically and geographically diverse target sample are described elsewhere (Garavan et al., 2018). In May 2020, ABCD began collecting data via questionnaires on COVID-19's impact on youths' and caregivers' lives. Data from the questionnaires (disseminated by email at each of five timepoints: May 16–22, 2020, June 24–27, 2020, August 4–5, 2020, October 8, 2020, and December 13, 2020, via unique links from ABCD, with email/text-message reminders) are available through the National Institute of Mental Health Data Archive. Analyses incorporated additional data on participant characteristics and anxiety that were collected pre-pandemic as part of the ongoing main-study protocol (November 2020 ABCD 3.0 data release (The ABCD Consortium, 2020)).

Centralized IRB approval was obtained from the University of California, San Diego. Study sites obtained approval from their local IRBs. For the main ABCD protocol, caregivers provided written informed consent; children provided written assent. Accessing the COVID-19 questionnaires (clicking on the secure link) indicated willingness to participate. Data collection and analysis complied with all ethical regulations. The numbers of participants in analyses from each site are provided in Table A2). Following application of exclusionary criteria (Table A3), which generally incorporated excluding data due to missing demographic information, delayed returns of COVID-19 questionnaire responses, and inconsistency of the caregiver respondent throughout data collection, analysis included 18,128 caregiver-worry data points (i.e., questionnaire responses) (n = 5143) and 15,840 youth-worry data points (n = 5078) across 5 timepoints.

### 2.2. COVID-19 questionnaires

Caregiver and youth participants were compensated $5 for completing each questionnaire. Youth questionnaires were provided in English; caregiver questionnaires, in English and Spanish.

**Youth and caregiver worry**. Youth and caregiver participants rated how worried they had been about COVID-19 in the past week (5-point Likert scale: Not at All, Slightly, Moderately, Very, Extremely): "How worried have you been about coronavirus (COVID-19)?"

**COVID-19 family-exposure risk**. COVID-19 family-exposure risk was based on caregivers' responses to, "Was anyone in your household at increased risk for COVID-19 due to work in healthcare or other essential jobs (such as grocery store, factory, gig economy) or use of public transit?" (Responses: No, Yes, Don't Know).

### 2.3. COVID-19 community burden

County-level metrics of COVID-19-related disease burden (incidence, death rates) and economic burden (unemployment change) were geocoded to the most recent primary residential address.

**Incidence and death rates**. Cumulative cases and deaths were obtained from Johns Hopkins University's public repository (Dong et al., 2020). The calculated 7-day average of new cases and deaths, adjusted for the county's estimated 2019 population (https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-total.html), was based on the day of and six days prior to survey release (e.g., case and death rates per 100,000 people). Negative values (due to potential inaccuracies in the database's raw data, as described in the database's notes) were recoded to equal zero.

**Unemployment**. Monthly, non-seasonally-adjusted unemployment rates were available from the U.S. Bureau of Labor Statistics (https://www.bls.gov/lau/). An intra-pandemic change-in-unemployment-rate variable was created by subtracting the 2019 rate from the 2020 rate for each month of survey dissemination.

### 2.4. Participant characteristics

Caregiver-reported annual household income (before taxes, including all wages/benefits and other sources) was a 10-level continuous factor (1=<$5000; 2 = $5000-$11,999; 3 = $12,000-$15,999; 4 = $16,000-$24,999; 5 = $25,000-$34,999; 6 = $35,000-$49,999; 7 = $50,000-$74,999; 8 = $75,000-$99,999; 9 = $100,000-$199,999; 10 = ≥$200,000). Children's and caregivers' race and ethnicity were categorical factors derived from caregivers' baseline reports. Race had 6 levels: "White", "Black", "Asian", "American Indian/Alaska Native", "Native Hawaiian/Other Pacific Islander", or "Other" (e.g., multiracial). Ethnicity had 2 levels: "Hispanic/Latino/Latina" or "Not Hispanic/Latino/Latina." Maximum caregiver education across primary and secondary caregivers was a 5-level continuous factor (1 = ≤12th grade/no diploma; 2 = high-school graduate/GED or equivalent; 3 = Some college, no degree/Associate's degree; 4 = bachelor's degree; 5 = master's/professional degree, doctorate). Each participant's income, education, and caregivers' age (continuous) data were the most recent, non-missing data from annual ABCD visits. Youths' age (continuous) and sex at birth (categorical) were available in the COVID-19 data release.

To account for pre-pandemic anxiety levels, analyses controlled for the most recent, non-missing data of the anxious/depressed syndrome scale (standardized, norm-based t-scores to facilitate cross-study comparison) from the caregiver-completed Child Behavior Checklist (CBCL; for youth behavior) and Adult Self-Report (ASR; for caregiver's own behavior). (Barch et al., 2018).

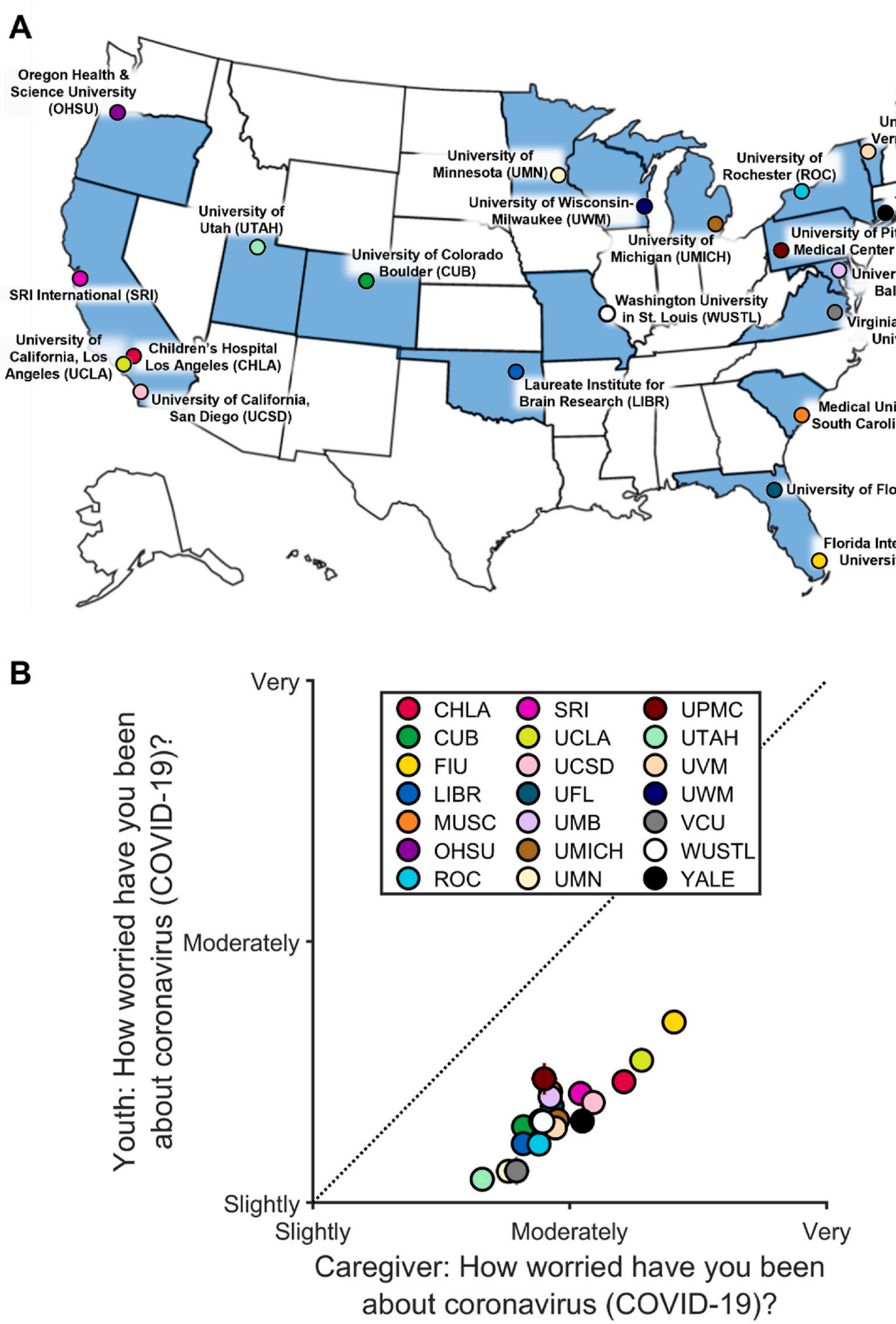


**Fig. 1. Mean COVID-19-related worry levels in caregivers and their children in the Adolescent Brain Cognitive Development Study**. (**A**) United States map of the locations of the ABCD Study data-collection/study sites. Each state with an ABCD data-collection site is shaded, and the full name and abbreviation of that site accompanies a circular marker of the location of that site within the state. (**B**) Each data point of mean COVID-19-relatd worry refers to an ABCD study site. Error bars are ±1 between-subjects standard error of the means. The dotted-line is the unit diagonal. CHLA = Children's Hospital Los Angeles (Los Angeles, California). CUB = University of Colorado Boulder (Boulder, Colorado). FIU = Florida International University (Miami, Florida). LIBR = Laureate Institute for Brain Research (Tulsa, Oklahoma). MUSC = Medical University of South Carolina (Charleston, South Carolina). OHSU = Oregon Health & Science University (Portland, Oregon). ROC = University of Rochester (Rochester, New York). SRI = SRI International (Menlo Park, California). UCLA = University of California, Los Angeles (Los Angeles, California). UCSD = University of California, San Diego (San Diego, California). UFL = University of Florida (Gainesville, Florida). UMB = University of Maryland, Baltimore (Baltimore, Maryland). UMICH = University of Michigan (Ann Arbor, Michigan). UMN = University of Minnesota (Minneapolis, Minnesota). UPMC = University of Pittsburgh Medical Center (Pittsburgh, Pennsylvania). UTAH = University of Utah (Salt Lake City, Utah). UVM = University of Vermont (Burlington, Vermont). UWM = University of Wisconsin – Milwaukee (Milwaukee, Wisconsin). VCU = Virginia Commonwealth University (Richmond, Virginia). WUSTL = Washington University in St. Louis (St. Louis, Missouri). YALE = Yale University (New Haven, Connecticut).

### 2.5. Statistical analyses

**COVID-19-Related Worry**. These analyses employed MATLAB's Statistics and Machine Learning Toolbox 12.1 (R2021a; https://www.mathworks.com/products/statistics.html). To account for repeated within-participants observations, data were analyzed using general linear mixed-effects models via MATLAB's fitlme function (with random initial values for iterative optimization instead of internally defined, default initial values), which, for each model, tests the statistical significance of regression coefficients against a t-distribution; the fixed- and random-effects structures for these models are specified below. Categorical factors within each model were effect-coded (i.e., dummy-coded values within each level sum to 0); continuous factors within each model were centered. Effect sizes for the continuous factors (e.g., for conveying the strength of the association between the geocoded predictors and COVID-19-related worry, while controlling for other factors in the model) are represented by partial correlation coefficients ($r_p$) (Nakagawa and Cuthill, 2007). Comprehensive details of the full model output, effect-coding values, and model-fit characteristics for all sets of models are provided in Appendix B (Tables B1-B14).

For each of caregiver and youth COVID-19-related worry, three sets of hierarchical analyses were conducted to determine change in model fit given inclusion of each geocoded predictor (i.e., change [Δ] in the Akaike information criterion [AIC], with ΔAIC values exceeding 10 reflecting substantial support for the candidate model (Burnham and Anderson, 2004), with lower AIC values reflecting better model fit). Thus, for each of the three geocoded predictors, the goal of its analysis series was to evaluate whether model fit substantially improved when the geocoded predictor was first included solely as a fixed effect (relative to a baseline model, described below) and then, whether model fit was substantially improved by the inclusion of site-by-site ("SiteXSite") random slopes of the geocoded predictor to the model, while also including a fixed effect of that same geocoded predictor.

First, baseline caregiver/youth worry models included fixed-effects structures of caregiver education, household income, questionnaire number (continuous; questionnaires 1–5) to account for changes in worry through the pandemic (i.e., questionnaires were longitudinally administered to participants), pre-pandemic caregiver (or youth) anxiety (for the respective models), COVID-19 family-exposure risk, and caregiver (or youth) age, race, and ethnicity (for the respective models). These models were performed to provide a baseline comparison to which the models with each of the three geocoded predictors could be compared. Youth-data analyses also included youth sex-at-birth. Random-effects structures included random intercepts for participant and study site, as well as random slopes for questionnaire number per participant to account for participant-specific changes in COVID-19-related worry over time.

The second set of models (hereafter, "fixed-effects models") determined change in model fit ($\Delta AIC_{\text{Baseline-Fixed}}$) when adding fixed effects of each geocoded predictor (case rates, death rates, and changes in unemployment) and the interaction between that geocoded predictor and family-exposure risk to the baseline model. Specifically, these models were performed to evaluate both whether inclusion of geocoded predictors provided a significant improvement in model fit of COVID-19-related worry relative to the baseline models (i.e., did inclusion of the geocoded predictors substantially reduce model AIC?) and whether each geocoded predictor was significantly associated with COVID-19-related worry. To minimize multicollinearity, the geocoded predictors were analyzed separately, such that there were three different fixed-effects models (i.e., one per geocoded predictor). As in the caregiver and youth baseline models, random-effects structures included random intercepts for participant and study site and random slopes for questionnaire number per participant.

The third and final set of models (i.e., those reported below; hereafter, "site-specific random-slopes models") added random study-site-specific slopes of each geocoded predictor to the corresponding fixed-effects model to determine if there was evidence that model fit improved when allowing the parameters for COVID-19 geocoded predictors to vary by site ($\Delta AIC_{\text{Fixed-SiteXSiteRandom}}$). In other words, these models were performed to evaluate whether there were meaningful differences between sites (i.e., whether they would differ by region) with respect to associations between the geocoded predictors and COVID-19-related worry (i.e., did allowing associations between COVID-19-related worry and geocoded predictors to differ by study site substantially reduce model AIC?). As in the fixed-effects models, the geocoded predictors were analyzed separately, such that there were three different site-specific random-slopes models (i.e., one per geocoded predictor) for both caregiver and youth worry. As in the baseline and fixed-effects models, the site-specific random-slope models' random-effects structures also included random intercepts for participant and study site and random slopes for questionnaire number per participant.

**Site-by-site differences**. To further explore site-by-site differences, we performed dominance analyses for each site (Azen and Budescu, 2003). Intuitively, dominance analyses measure the relative importance of predictors to a model by determining the added variance accounted for by each predictor within the full model and all lower-level models. Accordingly, dominance analyses permit within-model comparison of predictors' predictive abilities by parsing the variance accounted for by individual predictors, even when the predictors are intercorrelated (Azen and Budescu, 2003). Here, predictor importance of the three geocoded factors (here, all in the same model) within each site was assessed relative to the baseline model (described above, except for random effects of study site, as well as some site-specific adjustments described below) using the R v3.6.3 package dominanceanalysis (Version 2.0). The fit index for each geocoded factor was the change in marginal $R^2$ (Nakagawa and Schielzeth, 2013). The directions and p-values of geocoded-factor associations in the full mixed-effects model (baseline + geocoded data) were derived using the R package lmerTest (Version 3.1–3).

## 3. Results

### 3.1. Sample demographics

Compared to the ABCD cohort, our current sample was more likely to have higher incomes, identify the youth's race as white, and identify the youth's ethnicity as non-Hispanic/Latino/Latina (Table A1). At the first questionnaire, youth participants were ~12.7 years old (range: 10.6–15.1).

### 3.2. COVID-19-related worry

#### 3.2.1. Caregiver-youth differences

While caregiver worry covaried with youth worry (Fig. 1), as reported previously (Marshall et al., 2022), caregivers were generally more worried than youth about COVID-19 (Caregivers: $M = 2.94$, $SEM = 0.01$; Youth: $M = 2.31$, $SEM = 0.01$).

#### 3.2.2. Baseline models

Caregiver worry decreased with questionnaire number (i.e., time), $t(18{,}115) = -8.95$, $p < .001$, $r_p = -0.07$, increased with education level, $t(18{,}115) = 3.09$, $p = .002$, $r_p = .02$, increased with age, $t(18{,}115) = 4.88$, $p < .001$, $r_p = .04$, decreased with household income, $t(18{,}115) = -2.53$, $p = .011$, $r_p = -0.02$, and was higher given family-exposure risk (No/Yes), $t(18{,}115) = 4.42$, $p < .001$. Caregiver COVID-19 related worry was elevated in those with greater levels of pre-pandemic anxiety (ASR), $t(18{,}115) = 8.25$, $p < .001$, $r_p = .06$.

Youth worry also decreased over time, as the pandemic continued (i.e., questionnaire number), $t(15{,}826) = -4.23$, $p < .001$, $r_p = -0.03$, and increased with caregiver education level, $t(15{,}826) = 2.68$, $p = .007$, $r_p = .02$. Youth COVID-19-related worry was greater in those with higher levels of pre-pandemic anxiety (CBCL), $t(15{,}826) = 6.65$, $p <$

.001, $r_p = .05$.

*3.2.3. Geocoded predictors: fixed-effects and site-specific random-slopes models*

*3.2.3.1. COVID-19 cases.* Caregivers. Across sites and time, COVID-19 case rates ranged 0.00–161.71 per 100,000 people per day (Mdn = 10.07). Caregiver-worry model fit improved with inclusion of case-rate data at both the population ($\Delta AIC_{Baseline\text{-}Fixed} = 255.48$) and site-by-site levels ($\Delta AIC_{Fixed\text{-}SiteXSiteRandom} = 56.49$). Caregiver worry was positively associated with case rates, t (18,113) = 8.70, p < .001, $r_p = .06$ (Fig. 2A and B), which was more pronounced given family-exposure risk (Case

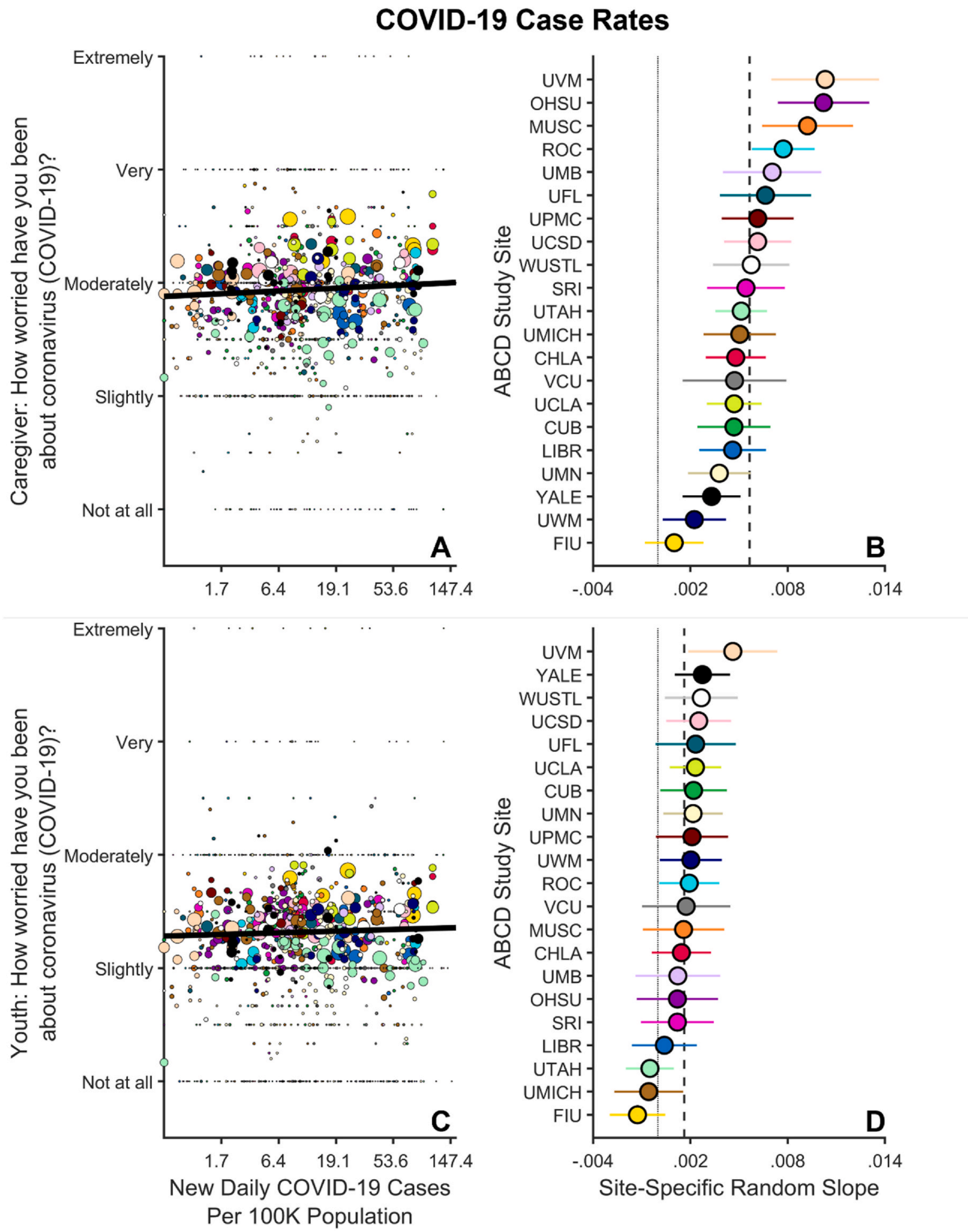


**Fig. 2. Mean COVID-19-related worry levels and COVID-19 case rates.** (**A, C**) Caregiver and youth worry levels as a function of new daily county-level COVID-19 cases per 100,000 people (case rates). The size of the data marker refers to the number of data points used to compute the corresponding mean. (**B, D**) Site-specific random slopes of case rates with 95% confidence intervals of the mixed-effects models of caregiver and youth COVID-19-related worry. (**A, C**) The thick line refers to the best fit simple regression line, not controlling for other fixed effects. For graphing, the abscissa is log-scaled for ease of interpretation. (**B, D**) The thin, gray, dotted line refers to x = 0. The thicker dashed line refers to the population-level estimate from the mixed-effects model.

Rates × Family-Exposure Risk), t (18,113) = 2.24, p = .025. Regression coefficients indicated that caregiver worry would increase by 1 unit for every 163.0 new daily cases (per 100,000) given family-exposure risk and for every 193.6 new daily cases given no family-exposure risk.

Youth. Youth-worry model fit also improved with inclusion of case-rate data at the population ($\Delta AIC_{Baseline\text{-}Fixed} = 11.64$) and site-by-site levels ($\Delta AIC_{Fixed\text{-}SiteXSiteRandom} = 17.29$), as youth worry was positively associated with increased case rates, t (15,824) = 3.08, p = .002, $r_p$ = .02 (Fig. 2C and D). Model estimates indicated that youth worry would increase by 1 unit given an additional 616.3 new daily cases (per 100,000). Family-exposure risk did not moderate this association, t (15,824) = 0.15, p = .879.

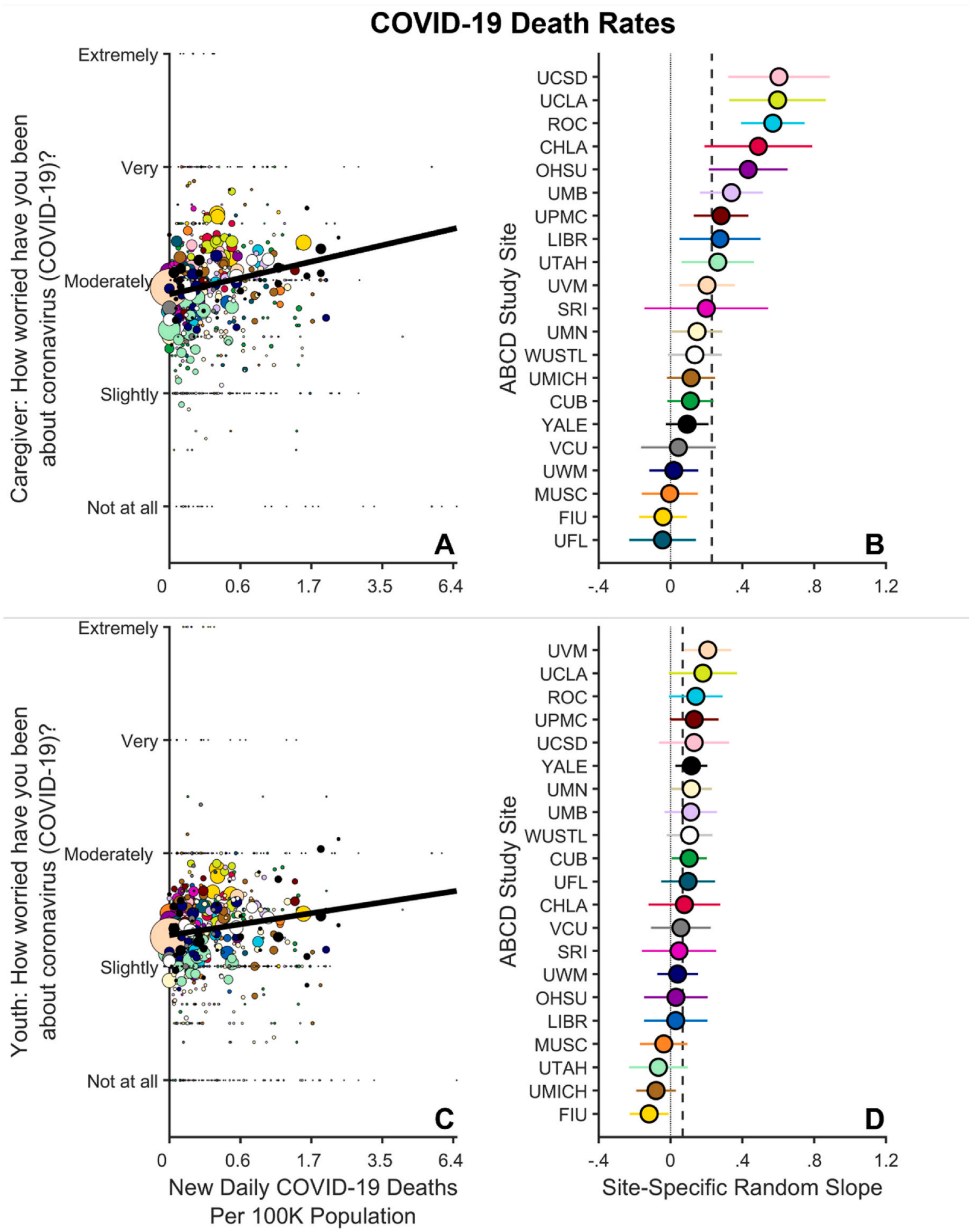


**Fig. 3. Mean COVID-19-related worry levels and COVID-19 death rates**. (**A, C**) Caregiver and youth worry levels as a function of new daily county-level COVID-19 deaths per 100,000 people (death rates). The size of the data marker refers to the number of data points used to compute the corresponding mean. (**B, D**) Site-specific random slopes of death rates with 95% confidence intervals of the mixed-effects models of caregiver and youth COVID-19-related worry. (**A, C**) The thick line refers to the best fit simple regression line, not controlling for other fixed effects. (**B, D**) The thin, gray, dotted line refers to x = 0. The thicker dashed line refers to the population-level estimate from the mixed-effects model.

*3.2.3.2. COVID-19 deaths.* Caregivers. Across sites and time, COVID-19 death rates ranged 0.00–6.56 per 100,000 people per day (Mdn = 0.17), the inclusion of which improved caregiver-worry model fit at the population ($\Delta AIC_{Baseline\text{-}Fixed}$ = 72.93) and site-by-site levels ($\Delta AIC_{Fixed\text{-}SiteXSiteRandom}$ = 66.57). Caregiver worry increased with death rates, t (18,113) = 4.28, p < .001, $r_p$ = .03 (Fig. 3A and B), which was more pronounced given family-exposure risk (Death Rates × Family-Exposure Risk), t (18,113) = 2.30, p = .022. Given family-exposure risk, a 1-unit increase in worry would be predicted given an additional 3.8 deaths per day (per 100,000); without family-exposure risk, 5.0 additional deaths per day.

Youth. Inclusion of COVID-19 death rates improved model fit at the

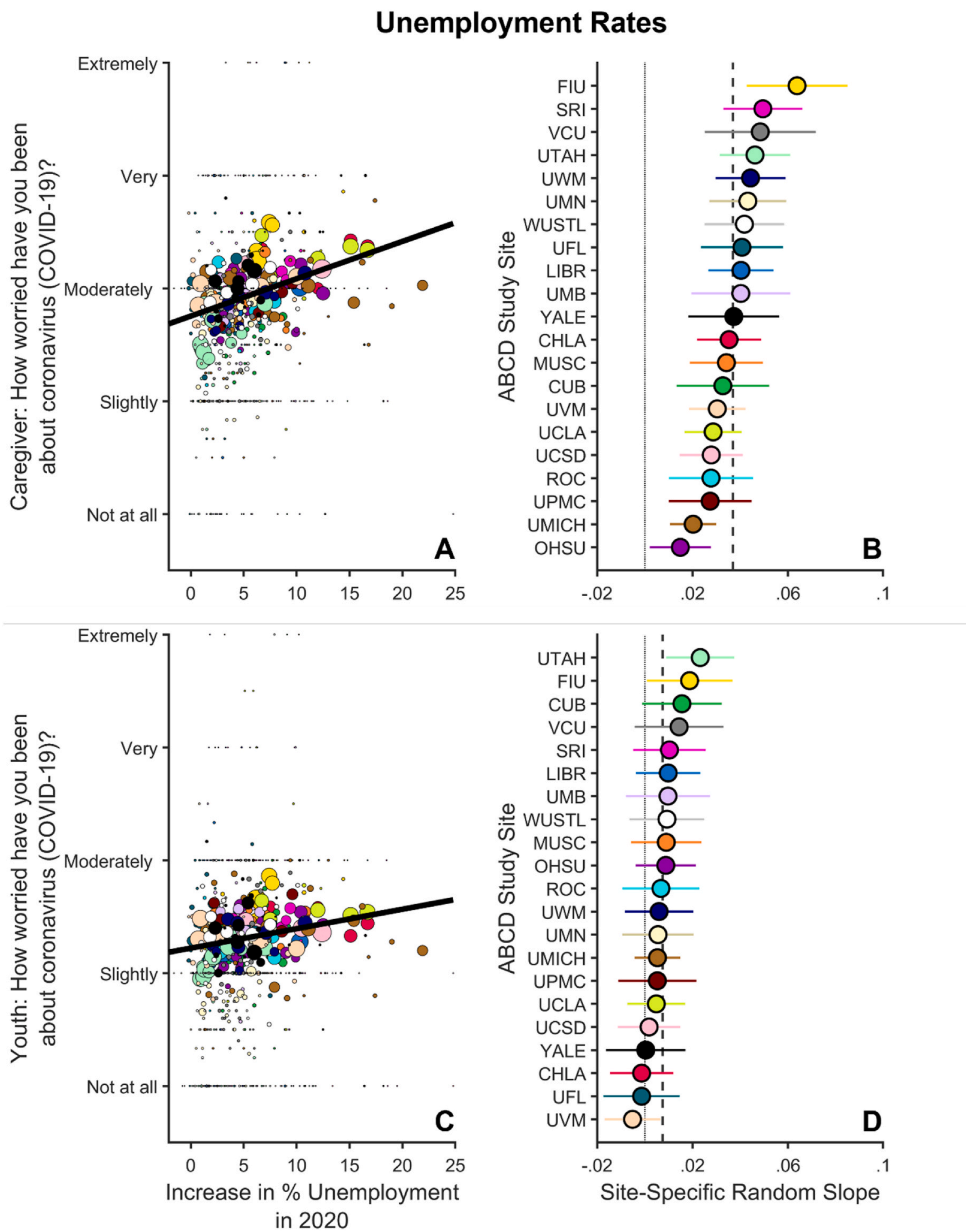


**Fig. 4. Mean COVID-19-related worry levels and change in unemployment rates during the COVID-19 pandemic.** (**A, C**) Caregiver and youth worry levels as a function of the county-level change in monthly unemployment rates from 2019 to 2020. The size of the data marker refers to the number of data points used to compute the corresponding mean. (**B, D**) Site-specific random slopes of unemployment change with 95% confidence intervals of the mixed-effects models of caregiver and youth COVID-19-related worry. (**A, C**) The thick line refers to the best fit simple regression line, not controlling for other fixed effects. (**B, D**) The thin, gray, dotted line refers to x = 0. The thicker dashed line refers to the population-level estimate from the mixed-effects model.

population ($\Delta AIC_{Baseline\text{-}Fixed} = 11.80$) and site-by-site levels ($\Delta AIC_{Fixed\text{-}SiteXSiteRandom} = 20.41$), with youth worry being associated with increased death rates, $t\ (15{,}824) = 2.04$, $p = .042$, $r_p = .02$ (Fig. 3C and D). A 1-unit increase in youth worry would be predicted given an additional 14.8 COVID-19 deaths per day (per 100,000). There was no Death Rates × Family-Exposure Risk interaction, $t\ (15{,}824) = 1.55$, $p = .121$.

*3.2.3.3. Unemployment.* Caregivers. Across sites and time, median unemployment change was +4.8% (i.e., an additional 4.8% of individuals were unemployed in 2020; range = −2.1% to +24.8%). For caregivers, including unemployment change improved model fit at the population ($\Delta AIC_{Baseline\text{-}Fixed} = 86.46$) and site-by-site levels ($\Delta AIC_{Fixed\text{-}SiteXSiteRandom} = 18.72$). Increased unemployment was positively associated with increased worry, $t\ (18{,}113) = 8.06$, $p < .001$, $r_p = .06$ (Fig. 4A and B). Here, a 1-unit increase in caregiver worry would be expected given a +27.1% change in unemployment. There was no Unemployment-Change × Family-Exposure Risk interaction, $t\ (18{,}113) = -1.27$, $p = .204$.

Youth. There was neither an association between unemployment change and youth's worry levels, $t\ (15{,}824) = 1.64$, $p = .101$, $r_p = .01$ (Fig. 4C and D), nor an Unemployment-Change × Family-Exposure Risk interaction, $t\ (15{,}824) = 0.54$, $p = .589$. Accordingly, including unemployment change did not improve model fit ($\Delta AIC_{Baseline\text{-}Fixed} = -2.40$; $\Delta AIC_{Fixed\text{-}SiteXSiteRandom} = 1.83$).

### *3.3. Site-by-site differences*

Dominance analyses further evaluated site-by-site differences (Fig. 5). The most dominant predictor (i.e., the predictor accounting for the most variance in caregiver/youth worry within each site with all predictors in the model) varied widely across sites and between caregivers and youth. For caregivers, case rates reflected the most dominant predictor at 7 sites; death rates, 5 sites; and, unemployment change, 9 sites. In contrast, for youth, case rates reflected the most dominant predictor at 5 sites; death rates, 9 sites; and, unemployment change, 7 sites. For caregivers, the direction of the association between worry and the most dominant predictor at each site matched the population-level analyses above. Similar patterns were apparent in the youth analyses with some exceptions (e.g., FIU), in which the dominant predictor was inversely associated with worry. However, these inverse associations were not statistically significant given Bonferroni correction ($p < .017$); those that passed Bonferroni correction within the caregiver-worry analyses were not the within-site dominant predictors. Accordingly, whether the dominant predictor was significantly associated with worry levels was also site-specific. While there were two instances in which a site's dominant predictor of youth worry constituted statistically significant relationships after Bonferroni correction (OHSU, UMB), there were stronger relationships between the dominant predictor and worry levels in the caregiver analyses, further corroborating the mixed-effects analyses above (Figs. 2–4).

Post hoc analyses were conducted to determine whether the magnitude and distribution of case rates, death rates, and unemployment change impacted the corresponding dominance analyses' increase-in-marginal $R^2$ value for both caregiver and youth worry. First, across the 21 study sites, there were no between-site correlations between the dominance-analyses values (Fig. 5) and mean case rates, death rates, or unemployment change, $|r|s \leq 0.36$, $ps \geq .110$. Next, to determine whether the dominance-analyses results were dependent on how variable the corresponding geocoded data were at each site, we correlated the within-site standard deviations of case rates, death rates, and unemployment change with the corresponding increase-in-marginal $R^2$ value for both caregiver and youth worry (Fig. 5). None of these correlations were significant either, $|r|s \leq 0.30$, $ps \geq .184$.

## 4. Discussion

Our goals were twofold: (1) characterize the associations between COVID-19-related worry levels and three geocoded indicators of the community-level impact of COVID-19, and (2) examine variability in these associations between caregivers and youth across U.S. metropolitan regions. Overall, community-level case rates, death rates, and unemployment were associated with increased worry, independent of sociodemographics and general anxiety. As hypothesized, caregiver (vs. youth) worry levels were more highly associated with these geocoded factors. Further, caregiver associations for case and death rates were

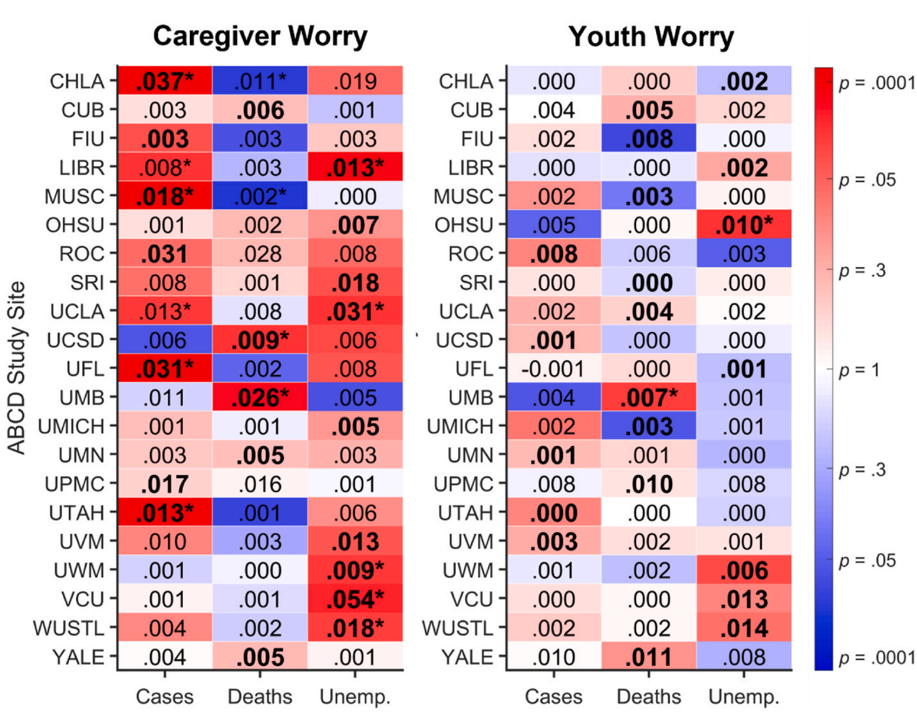


**Fig. 5. Site-by-site dominance analyses for the three geocoded factors predicting COVID-19-related worry in caregivers and youth.** With all three factors (case rates, death rates, unemployment change) entered into the same model, each numerical value refers to the increase in marginal $R^2$ by that factor in the model. The bolded value on each line refers to the relatively most dominant predictor for that site in that analysis. The shading of each box corresponds to the direction and statistical significance of the corresponding factor in the full mixed-effects model (see color bar on right; blue = inverse associations, red = positive associations). Asterisks indicate that the statistical significance was maintained after correction for multiple comparisons (i.e., 0.05 divided by 3). For 10 of the 42 site-by-site analyses, mixed-effects model structure was modified given convergence errors: (1) The caregiver MUSC and youth VCU models did not include random slopes of questionnaire number, and (2) small cell sizes for certain races were collapsed as "Other" in the caregiver SRI, caregiver UMICH, caregiver UPMC, caregiver UWM, caregiver VCU, youth CUB, youth SRI, and youth UFL.

more pronounced if an immediate family member was at risk of COVID-19 exposure (i.e., job, public transit use), suggesting that caregiver COVID-19 worry (statistically adjusting for pre-pandemic general anxiety) was not only sensitive to COVID-19's community impact but also the extent to which COVID-19 may more directly impact the family.

Allowing the associations between worry and geocoded factors to vary by site represented substantial improvements in model fit. In short, location matters. Given regional differences in COVID-19 incidence and response (Udalova, 2021; Zang et al., 2021; Lyu and Wehby, 2020), these region-specific associations highlight that although there are overall relationships between community burden and caregiver and youth worry, the most salient community-level COVID-19-related conditions, in terms of worry, differ by location. For example, per the population-level random-effects patterns (Figs. 2–4) and the dominant predictors that passed Bonferroni correction (Fig. 5), some sites' caregiver worry levels were primarily associated with case rates (e.g., MUSC), whereas other sites' caregiver worry levels were primarily associated with death rates (e.g., UCSD) or unemployment change (e.g., SRI). Interestingly, the relative dominance of each geocoded predictor on either caregiver or youth worry was not associated with the mean or variability of the data of the geocoded predictors, suggesting that the neighborhood-level factors that may best predict COVID-19-related emotional distress may not be driven by the severity of those factors in each region. Indeed, that associations differed with respect to case rates and death rates may partially reflect regional differences in COVID-19 testing capacity (i.e., more testing, higher case rates) or the frequency/extent to which deaths are reported (Balog-Way and McComas, 2020), the extent to which such individuals actually think they will contract and/or die from COVID-19,[3] and/or the extent to which individuals trust their public health systems (Gopichandran et al., 2020). In contrast to caregivers, while youth's COVID-19-related worry was generally less sensitive to COVID-19's community impact, analysis did reveal model improvement when allowing site-by-site variation in these associations. Accordingly, it may be disadvantageous for public-health agencies and healthcare providers to uniformly adopt the same general approaches to addressing COVID-19-related emotional distress across regions. Ultimately, these results highlight the necessity for future research to investigate and consider the needs, challenges, COVID-19-related burden, and strengths of specific communities.

Multiple studies have described the pandemic's effects on adolescent mental health (Racine et al., 2021). However, none have done so with respect to the relationship between COVID-19-related community burden and caregiver/youth worry, which may have considerable implications for mental health. Indeed, worry about COVID-19 infection was associated with elevated depressive symptoms in 2nd-6th-graders in China (Xie et al., 2020), and COVID-19 worry was associated with symptoms of depression, anxiety, distress, and post-traumatic stress disorder in U.S. adults (Liu et al., 2020b) and adults in Norway (Blix et al., 2021). Further, COVID-19-related worry was shown to be elevated in U.S. adults who initiated substance use (e.g., alcohol, stimulants) during the pandemic (Rogers et al., 2020). In turn, in individuals in China, COVID-19 worry was shown to be positively associated with how supportive these individuals were to prevention measures, with worry also being positively associated with how much COVID-19-related information they had consumed (Liao and Wang, 2021). Accordingly, with respect to such potential benefits of higher COVID-19-related worry levels, our results demonstrate that the type of information that is most effective at eliciting adherence to preventative measures (i.e., cases, deaths, unemployment) may depend on locality; the mechanisms driving preventative behavior (e.g., health belief model (Rosenstock, 1974; Janz and Becker, 1984)) may be regionally dependent. Unfortunately, excess emotional distress may then contribute to individuals' not trusting such risk communication (Glik, 2007). Thus, much like how risk communication strategies may require modification for vulnerable populations or given cultural differences (Vaughan and Tinker, 2009), different regions (for any number of reasons) may be more or less responsive to different types and sources of COVID-19-related information. Indeed, past research has suggested that such messaging may, for example, need to dynamically account for whether individuals live in urban versus rural U.S. communities (Callaghan et al., 2021). In other words, different aspects of community COVID-19-related burden may translate quite differently into worry depending on region. Therefore, if COVID-19-related data (e.g., case rates) are conveyed in order to ultimately promote preventative action, then it will be critical to know which information is most effective at doing so, while also ensuring that such information does not induce excess emotional burden, which may then have the inverse effect.

While individuals' intra-pandemic general and COVID-19-specific emotional distress may depend on location (as shown here, as well as in adolescents and adults in Italy (Lenzo et al., 2020; Buzzi et al., 2020) and adults in China (Ren et al., 2020; Lei et al., 2020)), with the potential for complex geotemporal patterns (Zhang et al., 2020), it is possible that these patterns may also be partially explained by sociodemographic differences of regional populations (Fitzpatrick et al., 2020; Patrick et al., 2020; McKnight-Eily et al., 2021). Accordingly, as done here, it is critical to analytically control for such factors. If research can identify how environmental factors correlate with emotional distress, then public-health agencies could develop regionally specific information campaigns so their constituents can appropriately respond to natural disasters (e.g., pandemics) without experiencing excessive emotional tolls (Abraham, 2009). Along with regional sociodemographics, such campaigns may depend on what types of COVID-19-related information regional populations want to know (e.g., total infected vs. how to identify infection) (Kwok et al., 2020) or, more generally, social media use (Zhong et al., 2020), cultural environments (Abraham, 2009), and local politics (Gollust et al., 2020). Thus, it will be critical for research to identify underlying mechanisms of site-specific associations with caregivers' and youths' worry levels. Future ABCD data releases will include data on policy changes across sites and counties (e.g., mask mandates, gathering bans) to further inform such investigations.

The consistently weaker associations between geocoded factors and worry levels in youth versus caregivers suggests that, at least in relation to COVID-19, youth's worry levels (independent of pre-pandemic anxiety levels) may be relatively less sensitive to event-related, dynamically changing community-level factors. This may be because COVID-19-related incidence, death rates, and unemployment change are less pertinent to adolescents (e.g., case- and death-rate associations in caregivers but not youth were moderated by family-exposure risk). Alternatively, adolescents may be more resilient to external COVID-19-related stressors, in part because caregivers, teachers, and/or mentors may serve as supportive buffers for youth. Indeed, in a previous study, we showed that caregivers of families at greater risk of COVID-19 exposure were engaging in more frequent conversations with their children about COVID-19 risk/prevention and reassurance, with these youth also engaging in more preventative behaviors (Marshall et al., 2022). Associations between family-level COVID-19-related stressors and youth's caregiver-reported externalizing and internalizing symptomatology were also more pronounced when their caregivers showed greater stress and anxiety (Cohodes et al., 2021). Thus, targeted support for families and caregivers, especially those at greater risk of experiencing COVID-19 stressors (Westrupp et al., 2021), may ultimately buffer against potential COVID-19-induced detriments on adolescent mental health.

While our results illuminate caregiver-youth and region-specific differences in COVID-19-related worry, our data are observational, prohibiting establishment of causality. However, it is unlikely that individuals' COVID-19-related worry directly caused county-level COVID-19 case rates, death rates, and unemployment change. While county-level data may preclude understanding of more local associations between COVID-19 worry and community-level impact, especially in larger counties (e.g., Los Angeles), to our knowledge, such data at greater resolution (e.g., census tract) are not available. However, as public-health policy and decisions are frequently managed and implemented at the county level (Bryant, 2018), our results offer accessibility to policy makers and healthcare providers in informing potential techniques to alleviate natural-disaster-induced emotional distress.

Overall, we highlight that increased COVID-19 community burden is associated with increased worry, independent of COVID-19 exposure risk and prior anxiety levels, and we provide novel insight into how the strength and nature of these associations vary by U.S. region. While there are several possibilities for explaining individual differences in perceptions of COVID-19 (Boyd, 2021), it is likely that regional variations in associations between COVID-19 community burden and COVID-19-related worry (and the extent to which these relationships may influence preventative action) could partially account for the geographic asymmetries in the plethora of ways that communities have been impacted by COVID-19. Properly communicating risk in the wake of natural disasters, like disease outbreaks, is essential to minimizing both the corresponding health and economic impacts (Smith, 2006; Abrams and Greenhawt, 2020). However, the effectiveness of well-intended risk messaging, whether in terms of cases, deaths, or economic effects (e.g., unemployment), may have inadvertent negative side effects (e.g., excessive worry, uncertainty as to proper preventative action) (Balog-Way and McComas, 2020), such that the content and framing of risk communication may need to account for regional differences in order to both convey risk while also minimizing excess anxiety/worry. In other words, information dissemination that is specifically tailored for targeted ages or regional audiences (e.g., case rates in Rochester, New York, but death rates in Boulder, Colorado; Fig. 5) may be more effective at encouraging preventative action than generic boiler-plate messaging in nationally distributed press releases (Kreuter and Wray, 2003). Thus, it may be unwise for public health agencies and healthcare providers to endorse a "one-size-fits-all" approach to aiding their constituents and patients in coping with traumatic events (e.g., natural disasters), like COVID-19 (Lodder et al., 2021). Greater understanding of how and why regional populations are influenced by different event-related data may ultimately promote more optimal information dissemination, intervention, and resilience in adults and adolescents.

## Author contributions

Conception and design of experiments and analysis: ATM, DAH, FCB, GJD, MRG, BDM, SFT, ERS. Data collection: ATM, EK, SA, FCB, ABS, MRG, MG, OK, CJM, WEP, SFT, AV, ERS. Analysis and interpretation: ATM, DAH, FCB, ABS, GJD, MRG, MG, OK, CJM, BDM, WEP, SFT, AV, ERS. Writing of the paper: ATM, DAH, ERS.

## Declaration of competing interest

The authors declare no competing financial interests.

## Acknowledgements

We would like to thank the ABCD participants and their families for their time and dedication to this project.

ABCD Acknowledgement. Data used in the preparation of this article were obtained from the Adolescent Brain Cognitive DevelopmentSM (ABCD) Study (https://abcdstudy.org/), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10,000 children age 9–10 and follow them over 10 years into early adulthood. The ABCD Study® is supported by the National Institutes of Health and additional federal partners under award numbers U01DA041048, U01DA050989, U01DA051016, U01DA041022, U01DA051018, U01DA051037, U01DA050987, U01DA041174, U01DA041106, U01DA041117, U01DA041028, U01DA041134, U01DA050988, U01DA051039, U01DA041156, U01DA041025, U01DA041120, U01DA051038, U01DA041148, U01DA041093, U01DA041089, U24DA041123, U24DA041147. A full list of supporters is available at https://abcdstudy.org/federal-partners.html. Addition support for this work was made possible from supplements to U24DA041123, U24DA041147, and U01DA041048, the National Science Foundation (NSF 2028680), and Children and Screens: Institute of Digital Media and Child Development Inc. A listing of participating sites and a complete listing of the study investigators can be found at https://abcdstudy.org/consortium_members/. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in analysis or writing of this report. Dr. Gayathri Dowling was substantially involved in all of the cited grants. All other Federal representatives contributed to the interpretation of the data and participated in the preparation, review, and approval of the manuscript, consistent with their roles on the ABCD Federal Partners Group. This manuscript reflects the views of the authors and may not reflect the opinions, views, and official policy or position of the U.S. Department of Health and Human Services or any of its affiliated institutions or agencies or other ABCD consortium investigators. The ABCD data repository grows and changes over time. The ABCD data repository grows and changes over time. The ABCD data used in this report came from [NIMH Data Archive Digital Object Identifier (DOI)]. DOIs can be found at [DOI URL].

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2022.102885.

## References

Abraham, T., 2009. Risk and outbreak communication: lessons from alternative paradigms. Bull. World Health Organ. 87, 604–607.
Abrams, E.M., Greenhawt, M., 2020. Risk communication during COVID-19. J. Allergy Clin. Immunol. Pract. 8 (6), 1791–1794.
Azen, R., Budescu, D.V., 2003. The dominance analysis approach for comparing predictors in multiple regression. Psychol. Methods 8 (2), 129–148.
Balog-Way, D.H.P., McComas, K.A., 2020. COVID-19: reflections on trust, tradeoffs, and preparedness. J. Risk Res. 23 (7–8), 838–848.
Barch, D.M., Albaugh, M.D., Avenevoli, S., et al., 2018. Demographic, physical and mental health assessments in the adolescent brain and cognitive development study: rationale and description. Developmental Cognitive Neuroscience 32, 55–66.
Blix, I., Birkeland, M.S., Thoresen, S., 2021. Worry and mental health in the Covid-19 pandemic: vulnerability factors in the general Norwegian population. BMC Publ. Health 21, 928.
Boyd, K., 2021. Beyond Politics: additional factors underlying skepticism of a COVID-19 vaccine. Hist. Philos. Life Sci. 43, 12.
Bryant, B., 2018. Managing Disasters at the County-Level: A Focus on Public Health. https://www.naco.org/featured-resources/managing-disasters-county-level-focus-public-health. August 23, 2021.
Burnham, K.P., Anderson, D.R., 2004. Multimodal inference: understanding AIC and BIC in model selection. Socio. Methods Res. 33 (2), 261–304.
Buzzi, C., Tucci, M., Ciprandi, R., et al., 2020. The psycho-social effects of COVID-19 on Italian adolescents' attitudes and behaviors. Ital. J. Pediatr. 46, 69.
Callaghan, T., Lueck, J.A., Trujillo, K.L., Ferdinand, A.O., 2021. Rural and urban differences in COVID-19 prevention behaviors. J. Rural Health 37 (2), 287–295.
Cohodes, E.M., McCauley, S., Gee, D.G., 2021. Parental buffering of stress in the time of COVID-19: family-level factors may moderate the association between pandemic-related stress and youth symptomatology. Research on Child and Adolescent Psychopathology 49, 935–948.
Dong, E., Du, H., Gardner, L., 2020. An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect. Dis. 20 (5), P533–P534.
Fitzpatrick, K.M., Drawve, G., Harris, C., 2020. Facing new fears during the COVID-19 pandemic: the state of America's mental health. J. Anxiety Disord. 75, 102291.
Garavan, H., Bartsch, H., Conway, K., et al., 2018. Recruiting the ABCD sample: design considerations and procedures. Developmental Cognitive Neuroscience 32, 16–22.
Glik, D.C., 2007. Risk communication for public health emergencies. Annu. Rev. Publ. Health 28, 33–54.
Gollust, S.E., Nagler, R.H., Fowler, E.F., 2020. The emergence of COVID-19 in the US: a public health and political communication crisis. J. Health Polit. Pol. Law 45 (6), 967–981.
Gopichandran, V., Subramanian, S., Kalsingh, M.J., 2020. COVID-19 pandemic: a litmus test of trust in the health system. Asian Bioethics Review 12, 213–221.
Hackman, D.A., Cserbik, D., Chun, J.-C., et al., 2021. Association of local variation in neighborhood disadvantage in metropolitan areas with youth neurocognition and brain structure. JAMA Pediatr. 175, e210426.

Janz, N.K., Becker, M.H., 1984. The health belief model: a decade later. Health Educ. Q. 11 (1), 1–47.
Karmakar, M., Lantz, P.M., Tipirneni, R., 2021. Association of social and demographic factors with COVID-19 incidence and death rates in the US. JAMA Netw. Open 4 (1), e2036462.
Kreuter, M.W., Wray, R.J., 2003. Tailored and targeted health communication: strategies for enhancing information relevance. Am. J. Health Behav. 27, S227–S232.
Kwok, K.O., Li, K.K., Chan, H.H.H., et al., 2020. Community responses during early phase of COVID-19 epidemic, Hong Kong. Emerg. Infect. Dis. 26 (7), 1575–1579.
Lei, L., Huang, X., Zhang, S., Yang, J., Yang, L., Xu, M., 2020. Comparison of prevalence and associated factors of anxiety and depression among people affected by versus people unaffected by quarantine during the COVID-19 epidemic in Southwestern China. Med. Sci. Mon. Int. Med. J. Exp. Clin. Res. 26, e924609.
Lenzo, V., Quattropani, M.C., Musetti, A., et al., 2020. Resilience contributes to low emotional impact of the COVID-19 outbreak among the general population in Italy. Front. Psychol. 11, 576485.
Liao, H.-P., Wang, J.-L., 2021. The impact of epidemic information on the public's worries and attitude toward epidemic prevention measures during the COVID-19 outbreak. Curr. Psychol.
Liu, M., Zhang, H., Huang, H., 2020a. Media exposure to COVID-19 information, risk perception, social and geographical proximity, and self-rated anxiety in China. BMC Publ. Health 20, 1649.
Liu, C.H., Zhang, E., Wong, G.T.F., Hyun, S., Hahm, H., 2020b. Factors associated with depression, anxiety, and PTSD symptomatology during the COVID-19 pandemic: clinical implications for U.S. young adult mental health. Psychiatr. Res. 290, 113172.
Lodder, G.M.A., Van Halem, S., Bülow, A., van Scheppingen, M.A., Weller, J., Reitz, A.K., 2021. Daily fluctuations in occupation with and worry about COVID-19. Pers. Indiv. Differ. 182, 111078.
Lyu, W., Wehby, G.L., 2020. Community use of face masks and COVID-19: evidence from a natural experiment of state mandates in the US. Health Aff. 39 (8), 1419–1425.
Marshall, A.T., Hackman, D.A., Baker, F., et al., 2022. Resilience to COVID-19: socioeconomic disadvantage associated with higher positive caregiver-youth communication and youth preventative actions. Front. Public Health 10, 734308.
McKnight-Eily, L.R., Okoro, C.A., Strine, T.W., et al., 2021. Racial and ethnic disparities in the prevalence of stress and worry, mental health conditions, and increased substance use among adults during the COVID-19 pandemic - United States, April and May 2020. MMWR (Morb. Mortal. Wkly. Rep.) 70 (5), 162–166.
Nakagawa, S., Cuthill, I.C., 2007. Effect size, confidence interval and statistical significance: a practical guide for biologists. Biol. Rev. 82, 591–605.
Nakagawa, S., Schielzeth, H., 2013. A general and simple method for obtaining $R^2$ from generalized linear mixed-effects models. Methods Ecol. Evol. 4 (2), 133–142.
Okonkwo, N.E., Aguwa, U.T., Jang, M., et al., 2021. COVID-19 and the US response: accelerating health inequities. BMJ Evidence-Based Medicine 26 (4), 176–179.
Patrick, S.W., Henkhaus, L.E., Zickafoose, J.S., et al., 2020. Well-being of parents and children during the COVID-19 pandemic: a national survey. Pediatrics 146 (4), e2020016824.
Pelham III, W.E., Tapert, S.F., Gonzalez, M.R., et al., 2021. Early adolescent substance use before and during the COVID-19 pandemic: a longitudinal survey in the ABCD Study cohort. J. Adolesc. Health 69 (3), 390–397.
Racine, N., McArthur, B.A., Cooke, J.E., Eirich, R., Zhu, J., Madigan, S., 2021. Global prevalence of depressive and anxiety symptoms in children and adolescents during COVID-19: a meta-analysis. JAMA Pediatr. 175, 1142–1150.
Ren, Y., Qian, W., Li, Z., et al., 2020. Public mental health under the long-term influence of COVID-19 in China: geographical and temporal distribution. J. Affect. Disord. 277, 893–900.
Rogers, A.H., Shepherd, J.M., Garey, L., Zvolensky, M.J., 2020. Psychological factors associated with substance use initiation during the COVID-19 pandemic. Psychiatr. Res. 293, 113407.
Rosenstock, I.M., 1974. The health belief model and preventative health behavior. Health Educ. Monogr. 2 (4), 354–386.
Smith, R.D., 2006. Responding to global infectious disease outbreaks: lessons from SARS on the role of risk perception, communication and management. Soc. Sci. Med. 63 (12), 3113–3123.
The ABCD Consortium, 2020. Dataset: Release 3.0.
Udalova, V., 2021. Pandemic Impact on Mortality and Economy Varies across Age Groups and Geographies. https://www.census.gov/library/stories/2021/03/initial-impact-covid-19-on-united-states-economy-more-widespread-than-on-mortality.html. August 25, 2021.
Vaughan, E., Tinker, T., 2009. Effective health risk communication about pandemic influenza for vulnerable populations. Am. J. Publ. Health 99 (S2), S324–S332.
Westrupp, E.M., Bennet, C., Berkowitz, T., et al., 2021. Child, parent, and family mental health and functioning in Australia during COVID-19: comparison to pre-pandemic data. Eur. Child Adolesc. Psychiatr.
Xie, X., Xue, Q., Zhou, Y., et al., 2020. Mental health status among children in home confinement during the coronavirus disease 2019 outbreak in Hubei province, China. JAMA Pediatr. 174 (9), 898–900.
Zang, E., West, J., Kim, N., Pao, C., 2021. U.S. regional differences in physical distancing: evaluating racial and socioeconomic divides during the COVID-19 pandemic. PLoS One 16, e0259665.
Zhang, S.X., Huang, H., Wei, F., 2020. Geographical distance to the epicenter of Covid-19 predicts the burnout of the working population: ripple effect or typhoon eye effect? Psychiatr. Res. 288, 112998.
Zhong, B., Jiang, Z., Xie, W., Qin, X., 2020. Association of social media use with mental health conditions of nonpatients during the COVID-19 outbreak: insights from a national survey study. J. Med. Internet Res. 22 (12), e23696.
Zhou, M., Guo, W., 2021. Social factors and worry associated with COVID-19: evidence from a large survey in China. Soc. Sci. Med. 277, 113934.