Population Health Metrics

RESEARCH

Open Access

Investigating the impact of the COVID-19 pandemic on the nutritional status of infants and toddlers: insights from China

Lijuan Gu[1*], Linsheng Yang[1,2] and Hairong Li[1]

Abstract

Background A comprehensive understanding of the impact of the COVID-19 pandemic on childhood nutrition is crucial for devising effective mitigation strategies. However, existing knowledge regarding the pandemic's effect on childhood nutritional status remains limited. Furthermore, research focusing on young children aged 0–3 years is scarce.

Methods Leveraging the outbreak that originated in Wuhan in Dec 2019, the epicenter of China's first and largest outbreak, and national survey and statistical yearbook data, this study conducted a natural experimental analysis with the consideration of geographical exposure, temporal exposure and survey cohort effects to investigate the pandemic's impacts on varying nutritional indicators of infants and toddlers aged 0–36 months. A comprehensive set of sensitivity analyses, robustness checks and falsification tests were conducted. The potential heterogeneities across socioeconomic and age groups were also examined.

Results The pandemic was robustly predictive of a higher weight-for-age z-score (WAZ) and length/height-for-age z-score (HAZ), and a lower likelihood of underweight. The effects of the pandemic on increasing WAZ and reducing underweight were more pronounced among children from economically disadvantaged backgrounds or aged 0–12 months. Additionally, the increasing HAZ was primarily among children from households with lower family income. Moreover, the pandemic was negatively linked to the body mass index (BMI)-for-age z-score (BAZ) of children residing in more developed cities, and positively linked to overweight/obesity among children aged 13–24 months.

Conclusions This study adds to a more comprehensive understanding of the impact of the COVID-19 pandemic on childhood nutrition. Notably, the findings highlight that weight gain attributable to the pandemic was predominantly among vulnerable children from disadvantaged backgrounds and younger age groups, who were already at a higher risk of overweight/obesity before the pandemic. Consequently, our findings imply the necessity of greater caution to the widened gap in childhood malnutrition post-pandemic. Furthermore, the study emphasizes the importance of implementing adaptable strategies with the consideration of social justice to safeguard all children's right to optimal growth from exogenous shocks and to achieve the children-related SDGs by 2030.

Keywords COVID-19 pandemic, Impact, Heterogeneity, Nutritional status, Young children, Natural experimental analysis

*Correspondence:
Lijuan Gu
gulj@igsnrr.ac.cn
Full list of author information is available at the end of the article

Background

The effects of the COVID-19 pandemic extend far beyond that of a virus infection. Indirectly, the pandemic could pose grave risks to nutritional status through a steep decline in household income and a potential disruption of food system, routine health services and social protections, with children from less favorable backgrounds bearing the worst consequences [1, 2]. The prospect of increased child malnutrition triggered by the pandemic is of paramount concern [3]. According to tentative assumptions, because of their accompanying mobility and food systems disruptions, even comparatively moderate and fairly short lockdown measures could lead to an average 7.9% decrease in GNI per capita in LMICs, which could subsequently translate into a shocking 14.3% increase in global wasting among young children aged 0–5 years, with 80% of them being from sub-Saharan Africa and south Asia [3, 4]. Besides wasting, the pandemic is argued to heighten the risk of other forms of child malnutrition, even in the short term [5]. Given the lifelong consequences of early-life malnutrition on personal growth and development [6] and the interconnectedness of individual development, national well-being and global sustainability [7], to deny the COVID-19 crisis a potentially intergenerational legacy of malnutrition and to preserve children's rights to optimal development, a thorough understanding of the pandemic's impacts on childhood nutritional status is urgently needed.

Substantive existing studies have explored the associations between the pandemic and childhood weight status. Primarily because of the increased food insecurity, decreased daily physical activity and heightened unhealthy dietary behaviors due to the pandemic [8], excessive weight gain, increased body mass index (BMI) or a higher prevalence of overweight/obesity among children had been reported. Comparing the pooled mean differences in nutritional indicators between pre- and post-pandemic stages was frequently used as the analytic strategy [9–11]. Clear deprivation differentials were found with children from disadvantaged socioeconomic backgrounds being particularly vulnerable [8, 12]. Moreover, preventative interventions have been highlighted to mitigate the possibly exacerbating disparities in health and education attainment in years to come [2, 12]. Preschool-aged children (3–6 years) [10, 13], children and adolescents (7–18 years) [14] and young adults (18–25 years) [15] have been the primary research groups. Although 0–3 years is a critical development stage for dietary and behavioral pattern formation and the growth of numerous nutritional parameters [6], little is known of the impact on this age range.

Although understanding the impacts of the pandemic on other forms of malnutrition is equally important [1, 3], only several studies have examined empirically the potential change in other nutritional parameters. For instance, in their comparative study of kindergarten children using multi-city data, Wen, Zhu and Ji found that during COVID-19 school closures, height growth was more severely affected than weight growth [16]. Similarly, Rahman et al.'s purposive sampling study in Selangor Malaysia observed a rising stunting prevalence among children aged 0–5 years [3]. In contrast, Cai et al. in their comparison of annual height and weight data of 3–6-year-old children living in Southwestern China, failed to detect any significant change in height growth during the lockdown [13]. Existing evidence is limited and more studies are needed to understand comprehensively the impacts of the pandemic on various nutritional indicators besides weight status. Moreover, as highlighted by Seth, Gupta and Pingali [17], changes in weight and height status could be attributed to different normal growth processes between survey times, underscoring the importance of teasing out these factors in future studies.

Because of the government's prompt implementation of countermeasures during the early stage of virus transmission, China experienced a rapid diffusion process alongside an effective control process in 2020 [18]. There was a clear timeline for outbreak and control. Ever since the official report of the first identified case in Wuhan in late Dec 2019 [18], with early symptom onset dating back to Dec 1st [19] and a lack of effective countermeasures until the lockdown of Wuhan city on Jan 23rd, 2020, the virus rapidly spread across cities, countries and continents, leading to a pandemic wreaking global havoc. The detection of the first case in Shenzhen on Jan 19th in mainland cities beyond Wuhan marked the gradual reporting of newly confirmed cases across cities (Fig. 1a and b). By Jan 23rd, 117 cities from 29 out of the 31 mainland provincial-level administrative units had confirmed cases. On Jan 24th, the majority of provinces announced the activation of the first-level public health emergency response. By Jan 29th, 288 cities from all 31 provincial-level administrative units had confirmed cases (Fig. 1b). With the governments' swift and comprehensive implementation of countermeasures upon recognizing the virus as a human-to-human infectious disease, on Feb 16th, controls started to rein in the virus. On March 12th, the peak of this outbreak originating from Wuhan was officially declared to be over. By March 16th, curbing imported cases had become the top priority. Subsequently, occasional resurgences were reported in local areas throughout 2020 (Fig. 1c). However, because of their limited transmission range and the implementation of differential suppression and mitigation strategies such as self-isolation and contact tracing [20], these outbreaks primarily affected local populations.

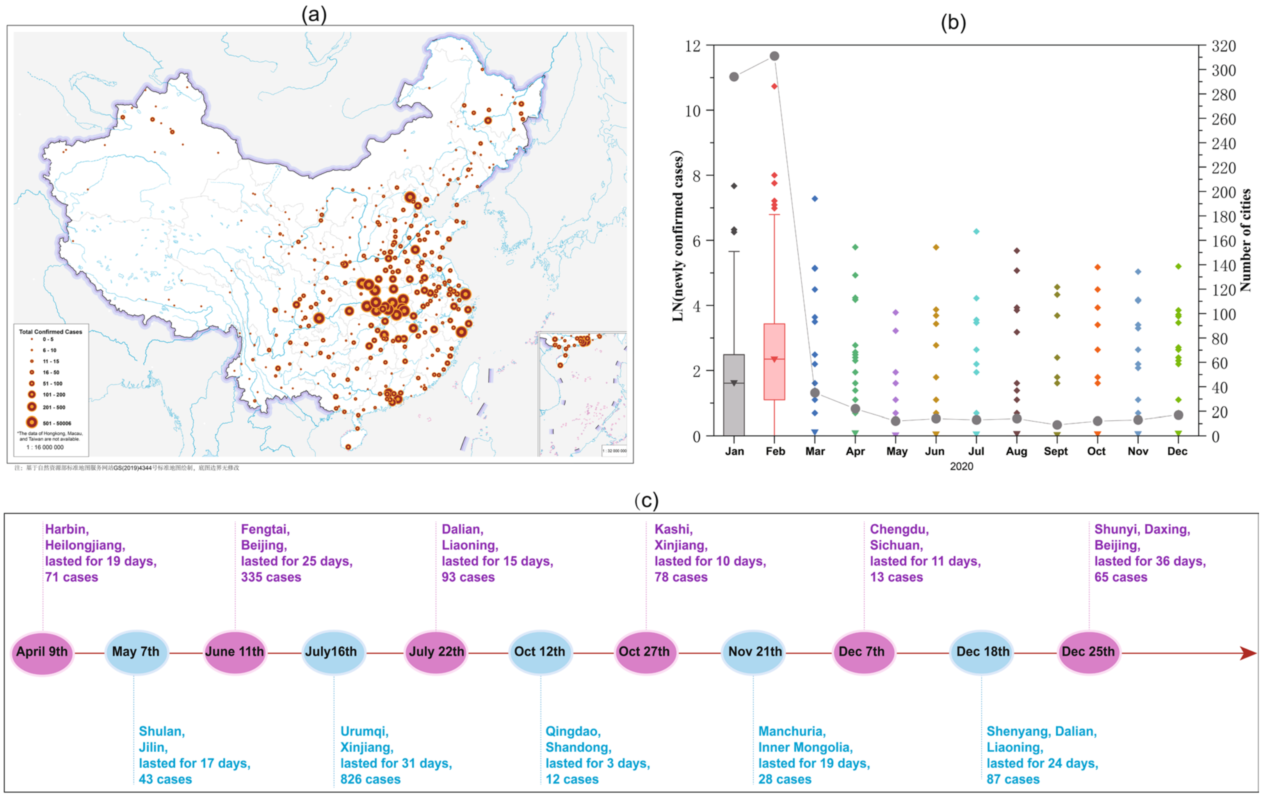

Fig. 1 **a** City-level accumulated confirmed cases by Mar 31st, 2020. **b** Box charts of newly confirmed cases across cities by month in 2020 (including both imported and local cases). **c** Timeline of multiple outbreaks from Apr to Dec 2020 (including mainly cities with local cases)

As the first epicenter, this wave originating in Wuhan and lasting from Jan to Mar 2020 was the earliest and largest outbreak in China, exerting a distinct timeline and global influence. Given the scattered small outbreaks that occurred subsequently throughout 2020, in our natural experimental study aiming to capture the pandemic's effect on child nutrition, this initial wave serves as a feasible research case. Leveraging nationwide survey data conducted in 2016, 2018 and 2020, along with daily recorded epidemic data in 2020 and statistical yearbook data, we set out to to do a preliminary natural experimental analysis to assess whether this outbreak imposed any causal effect on varying nutritional status of infants and toddlers aged 0–3 years. By distinguishing between treated and control groups and simultaneously considering geographical exposure, temporal exposure and survey cohort effects, we apply the Difference-in-Difference-in-Differences estimator (DDD) technique to investigate the pandemic's effect on nutritional status. For sensitivity check, a set of individual, parental, household and city-level characteristics are included as covariates and varying thresholds of epidemic risk areas are used. For robustness check, DDD analyses with a multilevel framework are conducted. Moreover, two falsification tests using survey data from 2016 and 2020, and 2016 and 2018, respectively, are performed. Additionally, we explore the potential heterogeneities of the effects between varying age groups, family income groups and city economic development groups. The originality of this study lies in utilizing natural experimental analysis to empirically evaluate the pandemic's impact on various nutritional indicators of infants and toddlers aged 0–3 years. Our main findings will provide informative guidance for adaptable strategies aimed at mitigating the deteriorating impacts of the pandemic and safeguarding children's right to optimal development from future exogenous shocks.

Data and analytical strategies

Data source

Survey data. Individual characteristics of infants and toddlers and corresponding parental and household information came from Wave 4 (2016), Wave 5 (2018) and Wave 6 (2020) of the China Family Panel Studies (CFPS) (http://www.isss.pku.edu.cn/cfps/en/index.htm). CFPS is a nationally representative longitudinal study conducted every 2 years since 2010 focusing on the evolution of Chinese society, economy and population. CFPS is hierarchically designed to collect representative samples and information at multiple levels. Covering 25 out of the 31 mainland China provincial-level administrative units and representing 95% of the population, CFPS offers the most high-quality and comprehensive contemporary China data [21].

Epidemic data. City-level epidemic data including daily accumulated confirmed cases and newly confirmed cases from the detection of the first confirmed cases outside Wuhan city in Shenzhen in Guangdong Province from Jan 19th, 2020 to Dec 31st, 2020 were used. Epidemic data of municipal, prefecture-level and vice-provincial cities were mainly provided by China Data Lab (CDL) (https://projects.iq.harvard.edu/chinadatalab), which collects data from Ding Xiang Yuan (https://ncov.dxy.cn/ncovh5/view/pneumonia), a professional platform in the medical field supplying authoritative information [18]. Epidemic data of county-level cities were derived primarily by scraping the official notifications of local health commission. Given the constant report of imported cases since late Feb 2020, city-level epidemic data were cross-checked with the COVID-19 data repository operated by the Center for System Science and Engineering at Johns Hopkins University (JHU CSSE)(https://github.com/CSSEGISandData/COVID-19), which aggregates local media and government reports to provide provincial level near real-time epidemic data [22]. Any contraction was subjected to official statistics for accuracy.

Statistical yearbook data. The 2017, 2019 and 2021 China Statistical Yearbook (County-level) [23], the 2017, 2019 and 2021 China City Statistical Yearbook [24], and the 2016, 2018 and 2020 statistical communiqué on national economic and social development from the official websites of local governments were collected to provide city-level socioeconomic information.

Outcomes

Both the continuous measurements and the categorical measurements of nutritional status were considered. Weight-for-age z-score (WAZ), length/height-for-age z-score (HAZ), and BMI-for-age z-score (BAZ), which were calculated in reference to the WHO Child Growth Standards (0–5 years) [25], were used to enable an exploration of the nutritional status at even the extreme ends. To acquire a more straightforward relationship, the categorical measurements of nutritional status based on WAZ, HAZ and BAZ, i.e., underweight, stunting, wasting and overweight/obesity, were also used. According to the WHO reference, WAZ with less than −2 Standard Deviation (SD) was defined as "underweight", HAZ with less than −2 SD was defined as "stunting", BAZ with less than −2 SD was defined as "wasting", and BAZ with more than +2 SD was defined as "overweight/obesity".

Exposures

Definition of exposure. Although COVID-19 has wreaked global havoc, we assume that its impact on child nutrition is restricted to mainly children residing in medium- and high-risk areas, where tight countermeasures were implemented to combat the spread of the virus. In this study, being exposed to the pandemic for any duration of time was defined as exposure. We measure it both geographically according to the risk area categorization of residential areas during the transmission stage, and temporally considering simultaneously the survey time and children's birth time relative to the outbreak of the pandemic. Our research objects were limited to infants and toddlers aged 0–36 months who hadn't been infected by the survey time. Children who had changed their place of residence or who were born between Apr to Dec 2020 in areas with any resurgence of infections were excluded.

Definition of the treated and the control group. Children who were born in or before Mar 2020 and aged 0–36 months during the survey window (born between Mar 2017 and Mar 2020 and surveyed between July 2020 and Dec 2020), and children who were born in or before Mar 2018 and aged 0–36 months during the survey window (born between Mar 2015 and Mar 2018 and surveyed between June 2018 and May 2019) were defined as the treated group. Children who were born between Apr 2020 and Dec 2020 (aged 0–7 months during the survey window between July 2020 to Dec 2020), and children who were born between Apr 2018 and Dec 2018 (also aged 0–7 months during the survey window between June 2018 and May 2019) were defined as the control group (Supplementary Fig. 1).

D1: Survey cohort effect measured the difference of the control group between two survey waves and implied the temporal nutritional variation that could be caused by macro-environmental changes (D1). A binary variable, "survey cohort", implying whether a child was born between Apr 2020 and Dec 2020, or was born between Apr 2018 and Dec 2018, was implemented. It is worth mentioning that in this part, sampled child respondents from Harbin, Shulan, Beijing, Urumqi, Dalian, Qingdao, Kashi, Manchuria, Chengdu and Shenyang were excluded for the resurgence of local outbreaks.

D2: Temporal exposure effect measured the difference of the treated group between two waves and implied the nutritional change caused by whether a child had been temporally exposed to the pandemic and the macro-environmental changes between two survey waves (D2). Subsequently, a binary variable "temporal exposure", indicating whether a child was surveyed before the occurrence of this outbreak (i.e., CFPS 2018, surveyed between June 2018 and May 2019) or after this outbreak (i.e., CFPS 2020, surveyed between July 2020 and Dec 2020), was created.

D3: Geographical exposure effect measured the nutritional change caused by whether a child had been geographically exposed to the pandemic (D3). A binary variable, "geographical exposure", i.e., being exposed to the pandemic for residing in the medium-/high-risk areas, which had a large number of cases, or not being exposed to the pandemic for living in the low-risk areas, which had null or minimal cases, were generated.

To combat the rapid transmission of the virus, Wuhan city was locked down on Jan 23rd, 2020. Subsequently, on Jan 24th, the majority of provinces announced the activation of the first-level public health emergency response. By Feb 12th, Chinese authorities emphasized the need for precise countermeasures and the adoption of differentiated strategies based on specific regional conditions [26]. According to the State Council's guideline issued on Feb 18th [20], a threshold of 50 accumulated cases in county/city regions was set to differentiate between the low-risk and medium-/high-risk areas. In low-risk areas, the focus was on forestalling imported cases and restoring normalcy to production and daily life. Medium-risk areas should gradually resume work and production, while high-risk areas should be committed to prevent further transmission. Thus, in this study, we applied 50 accumulated confirmed cases as our threshold for categorizing low-risk and medium/high-risk areas. Given that as the pandemic evolved, the threshold for defining risk areas occasionally changed (e.g., 10 accumulated confirmed cases had been used as the threshold during May 2021). To ensure the robustness of our analysis, besides 50 accumulated confirmed cases, we further conducted additional checks using the thresholds of 15 and 10 accumulated confirmed cases.

Covariates

Individual-level sociodemographic information including age, gender, birth weight, gestational age, and months of breastfeeding were used as covariates. Moreover, parental characteristics including age, height, body mass index (BMI), International Standard Classification of Occupation (ISEI) and educational attainment, characteristics of households including urban/rural residence, family size and quartiles of average family income, and characteristics of cities including GDP per capita and urbanization rate, were incorporated into the analysis (see Table 1 for details).

Analytical strategies

Descriptive and regression analyses. One-way ANOVA and cross-tabulations were used to examine if significant differences existed between different survey years in childhood nutrition and demographic characteristics, and paternal, household and city-level characteristics. To visualize the age trajectories of nutritional status across waves, local polynomial regressions were used to regress children's WAZ, HAZ and BAZ on their ages in months.

The Difference-in-Difference-in-Differences estimator (DDD), which applies an appropriate counterfactual quasi-experimental design to derive causal effects, was employed [27]. Besides a comparison of the outcomes before and after an event between the control group without any exposure and the treated group with exposure, DDD simultaneously considers the group effect of a third key dummy variable. In this study, to estimate more accurately the effect of the pandemic on child nutritional status, the variations in nutritional indicators between groups from different geographical areas with different epidemic risks (D3: geographical exposure effect) from varying temporal exposures (D2: temporal exposure effect), and belonging to different survey cohorts (D1: survey cohort effect) were simultaneously investigated. Consequently, the impact of the pandemic on childhood nutrition could be reasonably obtained through the difference between children with varying geographical exposures in the difference between children with varying temporal exposures in the difference between children belonging to varying survey cohorts (D3-(D2-D1)) (Supplementary Fig. 1).

Normally, DDD is included as an interaction term between the dummy variables of differences in various models. In this study, we used multivariate regressions in our analyses of continuous nutritional indicators (i.e., WAZ, HAZ and BAZ), and logistic regressions in our analyses of categorical nutritional indicators (i.e., underweight, stunting, wasting and overweight/obesity). Taking the analyses of continuous indicators as an example, the equation is:

$$\begin{aligned} \mathrm{y} = \beta_0 + \beta_1 E + \beta_2 T + \beta_3 A + \gamma_1 E * T \\ + \gamma_2 E * A + \gamma_3 T * A + \delta E * T * A + \alpha X \end{aligned}$$

where y could be WAZ, HAZ, or BAZ, β_0 is the intercept, E is the dummy for geographical exposure, T is the dummy for temporal exposure, A is the dummy for survey cohort, X denotes the covariates; β_1, β_2, β_3 and γ_1, γ_2, γ_3 are the coefficients of the dummy variables and their interactions;α is the coefficient of covariates; δ, the coefficient of the interactions between geographical exposure, temporal exposure and survey cohort, is the DDD estimator of the impact of the pandemic on childhood nutrition. For each outcome, a set of 3 models were conducted. Model 1 s were the null model. In Model 2 s, individual, parental and household information were included. In Model 3 s, city-level socioeconomic characteristics were

Table 1 Descriptive statistics of research samples by wave (Mean(SD), %)

Variables	2016	2018	2020	All	*P* value
Childhood nutritional information					
WAZ	0.08 (1.49)	0.23 (1.43)	0.28 (1.39)	0.19 (1.45)	0.000
HAZ	−0.58(2.33)	−0.24 (2.23)	−0.05 (2.18)	−0.32 (2.26)	0.000
BAZ	0.45 (2.00)	0.38 (1.91)	0.36 (1.80)	0.44 (1.93)	0.059
Underweight	7.3	5.4	4.5	5.9	0.005
Stunting	15.7	10.0	6.0	11.1	0.000
Wasting	21.0	20.7	23.0	20.7	0.083
Overweight/obesity	32.6	36.1	33.5	34.4	
Childhood demographic information					
Age (month)	19.30 (10.51)	18.53 (10.03)	20.43 (10.64)	19.29 (10.39)	0.000
Male	52.7	53.1	51.9	52.6	0.812
Birth weight (kg)	3.26 (0.56)	3.24 (0.52)	3.23 (0.52)	3.25 (0.54)	0.295
Gestational age (month)	9.49 (0.64)	9.47 (0.67)	9.49 (0.82)	9.47 (0.69)	0.263
Months of breastfeeding	9.59 (5.89)	8.97 (5.87)	8.89 (6.34)	9.30 (6.08)	0.013
Paternal sociodemographic information					
Paternal age	30.76 (5.51)	31.21 (5.30)	31.42 (4.79)	31.08 (5.28)	0.010
Paternal height (m)	1.71 (5.39)	1.72 (5.87)	1.72 (5.66)	1.72 (5.70)	0.137
Paternal BMI	23.33 (3.44)	23.55 (3.42)	23.73 (3.36)	23.55 (3.41)	0.095
Paternal ISEI	36.47 (15.44)	35.42 (19.18)	37.13 (18.67)	36.26 (17.63)	0.083
Maternal sociodemographic information					
Maternal age	28.58 (5.16)	29.10 (4.69)	29.67 (4.59)	29.04 (4.87)	0.000
Maternal height (m)	1.60 (5.23)	1.60 (5.45)	1.60 (5.50)	1.60 (5.40)	0.340
Maternal BMI	21.94 (3.46)	22.34 (3.48)	22.39 (3.31)	22.24 (3.43)	0.007
Maternal ISEI	30.10 (21.32)	37.44 (19.14)	33.67 (22.78)	33.39 (21.28)	0.000
Parental educational attainment (Paternal, maternal)					
No formal education	8.5, 11.0	3.9, 5.7	2.8, 4.0	5.3, 7.0	0.000, 0.000
Primary school	19.8, 18.3	13.2, 11.7	7.0, 6.0	14.1, 12.4	
Middle school	35.6, 36.3	35.7, 35.7	35.0, 33.7	35.5, 35.4	
High school	17.8, 17.1	20.9, 20.7	21.6, 21.4	20.0, 19.7	
College or higher	18.3, 17.3	26.3, 26.3	33.7, 34.9	25.2, 25.6	
Household information					
Rural residence	54.5	50.4	47.3	51.2	0.001
Family size	5.61 (2.16)	5.40 (2.11)	5.31 (2.07)	5.46 (2.12)	0.000
Average income-1st quartile	28.3	25.9	23.4	26.2	0.006
Average income-2nd quartile	31.0	31.3	30.3	30.9	
Average income-3rd quartile	24.3	27.0	26.0	25.8	
Average income-4th quartile	16.3	15.9	20.3	17.1	
City-level information					
GDP per capita (10,000 yuan)	4.90 (4.69)	5.34 (4.77)	5.45 (4.48)	5.29 (4.55)	0.538
Urbanization rate	53.18 (12.89)	55.46 (13.16)	60.57 (13.97)	57.65 (13.01)	0.008
Medium-/high-risk region	33.6	31.4	31.1	32.2	0.301

Note: Calculated based on complete data

considered. Through all models, inverse probability weighting, which were cross-sectional weights provided by the original databases from CFPS, was applied.

Sensitivity, robustness and heterogeneity check. Given that the data in this study were hierarchically structured with individual observations nested within cities, some unmeasurable macro-sociocultural or environmental factors could induce more similar childhood nutritional status within the same city. As such, to account for the potential intra-cluster correlation and achieve more accurate standard errors, multilevel regression analyses with individuals clustered within cities were performed to check the robustness of our results. Moreover, to check the specificity of our main results, two falsification tests were conducted. First, instead of the 2018 data, we used the 2016 data to investigate whether the associations persist. Second, instead of the 2018 and 2020 survey data, a DDD examination between the 2016 and 2018 data was performed. In addition, the potential heterogeneity in the associations caused by varying age groups (0–12 months vs. 13–24 months vs. 25–36 months), family income groups (lower average family income (1st and 2nd quartiles) vs. higher average family income (3rd and 4th quartiles)), and city economic development groups (lower GDP per capita (equals to or below the median value) vs. higher GDP per capita (higher than the median value)) were also explored.

Missing values. Considering the not missing completely at random pattern of several missing values and the presentation of both continuous and categorical variables, a combination of manual imputation, which indicated a convenient inference of missing values from previous or following survey waves, and multiple imputations using chained equations (MICE) with conditional imputations were used. We created 20 equally plausible imputations with MICE and applied Rubin's rule for scalar estimands to do combination [28]. The Stata MP 17 [29] was used for analysis.

Results

Descriptive information

After several rounds of data cleansing, in our main analysis of the CFPS 2018 and 2020 data, information of 3 049 infants and toddlers, 4 500 parental respondents and 2 345 households from 143 cities were finally included (see Fig. 2 for details). In our falsification test with the CFPS 2016 and 2020 data, information of 3 020 infants and toddlers, 5 203 adult respondents and 2 601 households from 143 cities were included (Supplementary Fig. 2). In our falsification test with the CFPS 2016 and 2018 data, information of 3 641 infants and toddlers, 5 382 adult respondents and 2 807 households in CFPS 2016 and 2018 from 147 cities were included (see Supplementary Fig. 3 for details).

Table 1 presents descriptive statistics of the included respondents in 2016, 2018 and 2020. Significant increases over time were observed in the mean values of WAZ and HAZ. In contrast, although it seems that the mean values of BAZ decreased with time, the differences across survey years were not significant. Similarly, as time went by, the proportions of young children being underweight or stunted significantly went down, and the proportions of young children being wasted or overweight/obese fluctuated with insignificant temporal patterns. Regarding childhood demographic information, the mean ages of child respondents varied slightly with differences of no more than 2 months across years. The proportions of male children were slightly higher, with no significant differences across

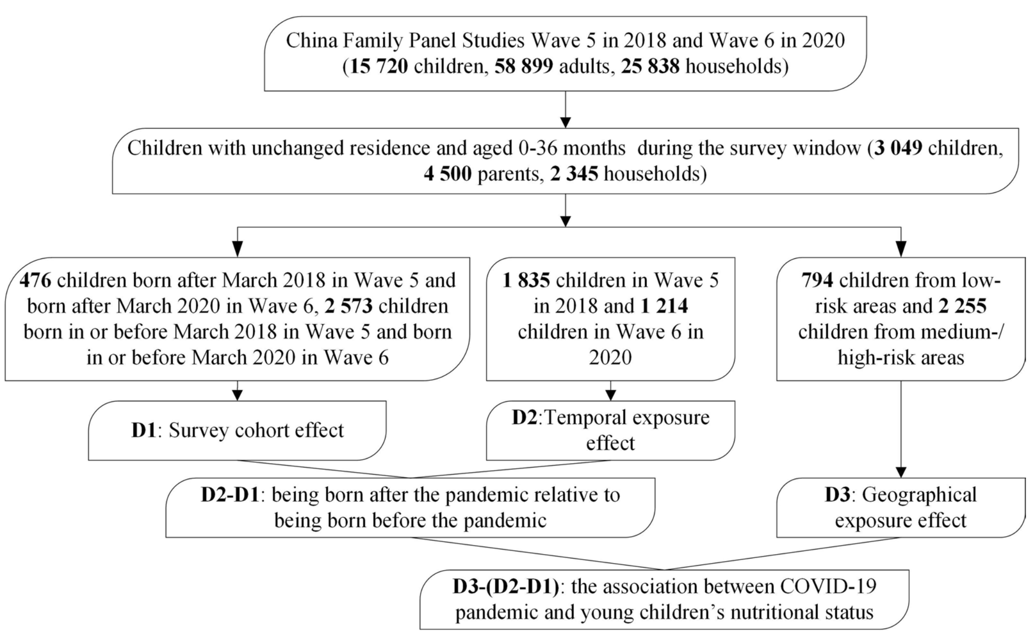

Fig. 2 Flowchart depicting the processing of analytical respondents

years. The average birth weight was 3.25 kg and the average gestational age was 9.47 months with no clear difference across years. It appears that the total months of breastfeeding gradually but slightly decreased from 9.59 months in 2016 to 8.89 months in 2020.

In terms of parental information, both parental and maternal age had significantly slightly increased. The mean paternal height was 1.72 m and the mean maternal height was 1.60 m with no significant difference across years. The increase in paternal mean BMI and ISEI was insignificant. However, there was a significant increase in maternal BMI and clear differences in maternal ISEI. Generally, the proportions of both fathers and mothers with no formal education, primary school education or middle school education reduced, and those with high school education or college or higher education increased. With regard to household information, the proportions of households residing in rural areas significantly decreased, the mean family size increased, and the proportions of households falling into the 3rd and 4th quartiles of average household income increased. The level of GDP per capita at the city level increased over time albeit with no significant difference, the level of city-level urbanization rate significantly increased and there was no significant difference in the proportion of cities being categorized as medium-/high-risk regions.

Figure 3 depicts the growth trajectories of WAZ, HAZ and BAZ over time. Compared to that of 2016, given the substantial overlap of shaded areas, there was no significant difference between 2018 and 2020 among children aged 0–24 months. Conversely, among children aged 24–36 months, WAZ was higher in 2018 and 2020 compared to that of 2016 with a small overlap of the shaded areas (Fig. 3a). Concerning HAZ, although there was considerable overlap of the shaded areas between 2018 and 2020, compared to that of 2016, the growth curve significantly went up for children aged 6–36 months, and it seems that the improvements increased by age (Fig. 3b). Concerning the growth trajectories of BAZ, there was no significant difference across years with substantial overlap of shaded areas (Fig. 3c).

The effects of the pandemic exposure on numerous nutritional indicators

Figure 4 depicts the DDD estimations of the effects of the pandemic on various nutritional indicators. With the inclusion of individual, parental, household and city-level covariates in Model 3, the COVID-19 exposure was (marginally) significantly linked to a higher WAZ, with the coefficients being respectively 0.92, 1.16 and 0.23 when 50, 15 and 10 accumulated confirmed cases were respectively used as the threshold for risk areas definition. Similarly, the pandemic was linked to a higher HAZ with the coefficients being 1.15 and 2.03 with 15 and 10 accumulated confirmed cases being used as the thresholds. Throughout the models, there was no significant association between COVID-19 exposure and BAZ (Fig. 4a).

Concerning the DDD estimations of categorical outcomes, with the consideration of covariates, COVID-19 exposure was linked to a lower likelihood of being underweight with 15 and 10 accumulated confirmed cases being used as the thresholds (Odds ratios being correspondingly 0.03 and 0.09 in Model 3). There was a lack of any significant impact of the pandemic on stunting, wasting, or overweight/obesity (Fig. 4b).

The above-mentioned impacts were generally robust. In our robustness check with multilevel frameworks, COVID-19 exposure was (marginally) significantly associated with a higher WAZ in Models 1 and 2 with 15 accumulated cases being used as the thresholds (coefficients: 0.87 and 0.86), and a higher WAZ in Model 3 with all definitions of the thresholds (coefficients: 0.92, 1.19 and 0.34). In Model 3 with all covariates being considered, COVID-19 exposure was significantly predictive

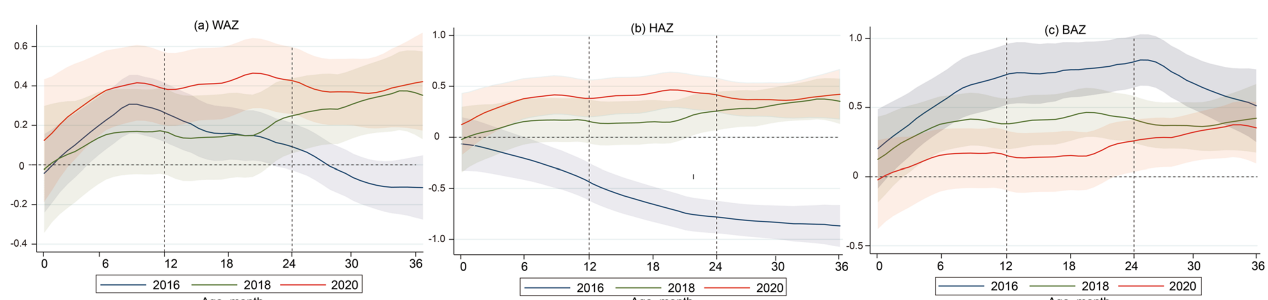

Fig. 3 The WAZ, HAZ and BAZ growth trajectories in 2016, 2018 and 2020 (*Note*: WAZ- weight-for-age z-score, HAZ- height/length-for-age z-score, BAZ- BMI-for-age z-score; shaded areas imply 95% CIs; the horizontal dashed lines represent the WHO standard median level, the vertical dashed line represent respectively the age of 12 and 24 months; the Epanechnikov kernel-density function was used in local polynomial regressions and the rule-of-thumb technique were used to select the bandwidth.)

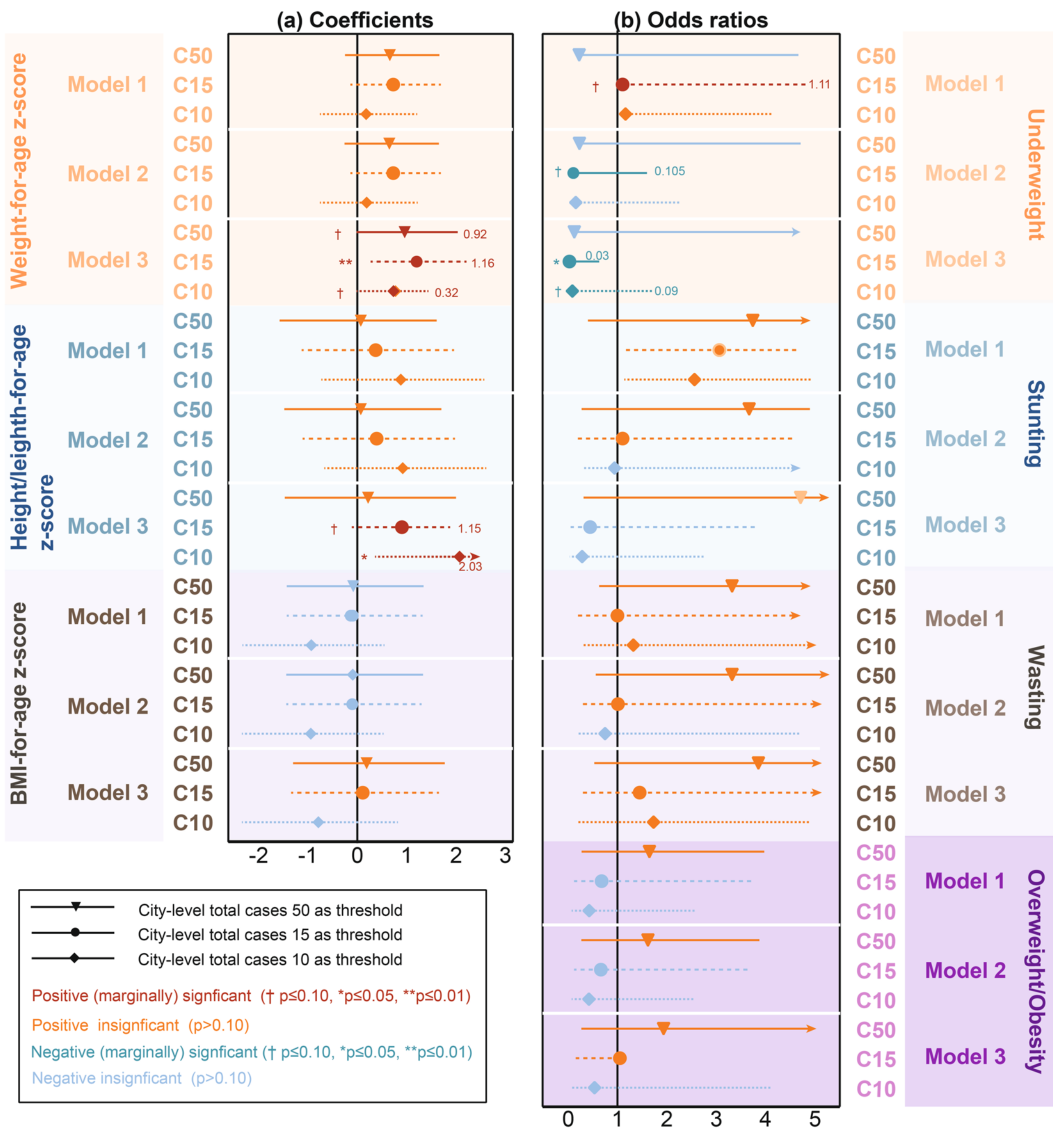

Fig. 4 The effect of the COVID-19 pandemic on various nutritional indicators of infants and toddlers (Note: C50, C15 and C10 imply respectively using 50, 15 and 10 accumulated confirmed cases as the thresholds of low-risk and medium-/high-risk areas.)

of a higher HAZ (coefficients: 2.10) with 10 accumulated confirmed cases being used as the threshold (Supplementary Table A1). In our multilevel DDD estimations of categorical indicators, the pandemic exposure was (marginally) significantly associated with a lower possibility of being underweight throughout all models with both 15 accumulated confirmed cases (odds ratios: 0.05, 0.06 and 0.03) and 10 accumulated confirmed cases (odds ratios: 0.09, 0.09 and 0.07) being used as the thresholds (Supplementary Table A2).

In our falsification tests with the 2016 and 2020 instead of the 2018 and 2020 data, the marginally positive effect of the pandemic exposure on WAZ persist with the coefficient being respectively 0.97, 0.68 and 0.21 in Models 3 with 50, 15 and 10 accumulated confirmed cases being used as the thresholds. Moreover, the marginally positive effect of COVID-19 exposure on HAZ persist in Model 3 with a coefficient of 1.73 with 10 accumulated confirmed cases being used as the thresholds (Supplementary Table B1). Similarly, the negative associations between pandemic exposure and underweight were significant in Models 1 and 2 with 50 accumulated confirmed cases being used as the thresholds (odds ratios: 0.08), the negative associations between COVID-19 exposure and underweight were significant in Models 3 with all definitions of the thresholds (odds ratios: 0.06, 0.20 and 0.54). Moreover, there were (marginally) significant associations between COVID-19 pandemic exposure and wasting in Models 1 (odds ratios: 0.19 and 0.17) and Models 2 (odds ratios: 0.19 and 0.17) with 15 and 10 accumulated confirmed cases being used as the thresholds (Supplementary Table B2).

In our falsification tests with the 2016 and 2018 instead of the 2018 and 2020 surveys, the positive impacts of the pandemic on WAZ and HAZ disappeared. Instead, there were (marginally) significant and positive associations for BAZ in Models 1 (coefficients: 0.99 and 1.52) and Models 2 (coefficients: 1.01 and 1.53) with 15 and 10 accumulated confirmed cases being used as thresholds. However, these associations no longer existed with the inclusion of more covariates (Supplementary Tables C1). The negative associations between the pandemic exposure and underweight mentioned earlier disappeared. Instead, a lower possibility of being wasted was found in Models 1 (odds ratios: 0.13, 0.20 and 0.13) and Models 2 (odds ratios: 0.13, 0.19 and 0.13) with all definitions of the thresholds (Supplementary Tables C2).

Socioeconomic and age heterogeneities

Our heterogeneity analyses indicated further the varied effects. With varying definitions of risk areas, the positive impacts on WAZ were significant or marginally significant merely among children with lower average family income (coefficients: 1.7, 1.76 and 0.49), from counties with lower GDP per capita (coefficients: 1.75, 2.20 and 0.94), and aged 0–12 months (coefficients: 1.16, 1.38 and 0.42). The positive effects of the pandemic exposure on HAZ were mainly among children from households with lower average family income when 15 accumulated confirmed cases (coefficients: 2.07) and 10 accumulated confirmed cases (coefficients: 2.52) were used as the thresholds. Moreover, although there was no significant association between COVID-19 exposure and BAZ in the main model, the heterogeneity analyses indicated that among children living in cities with higher GDP per capita, the pandemic was significantly associated with lower BAZ with 15 and 10 accumulated confirmed cases being used as the thresholds (coefficients: −3.32 and −3.11) (Fig. 5a).

With regards to categorical indicators, the pandemic was associated with a lower likelihood of being underweight among children with lower family income when 15 and 10 confirmed cases were used as the thresholds (0.01 and 0.08), and those aged 0–12 months when 50 and 15 confirmed cases were used as the thresholds (0.91 and 0.04). Although no significant association between the pandemic and other categorical nutritional indicators had been detected in the main model, the heterogeneity analyses detected a positive effect of the pandemic on the possibility of overweight/obesity among children aged 13–24 months when 50 and 15 confirmed cases were used as the thresholds (odds ratios: 2.48 and 2.34) (Fig. 5b).

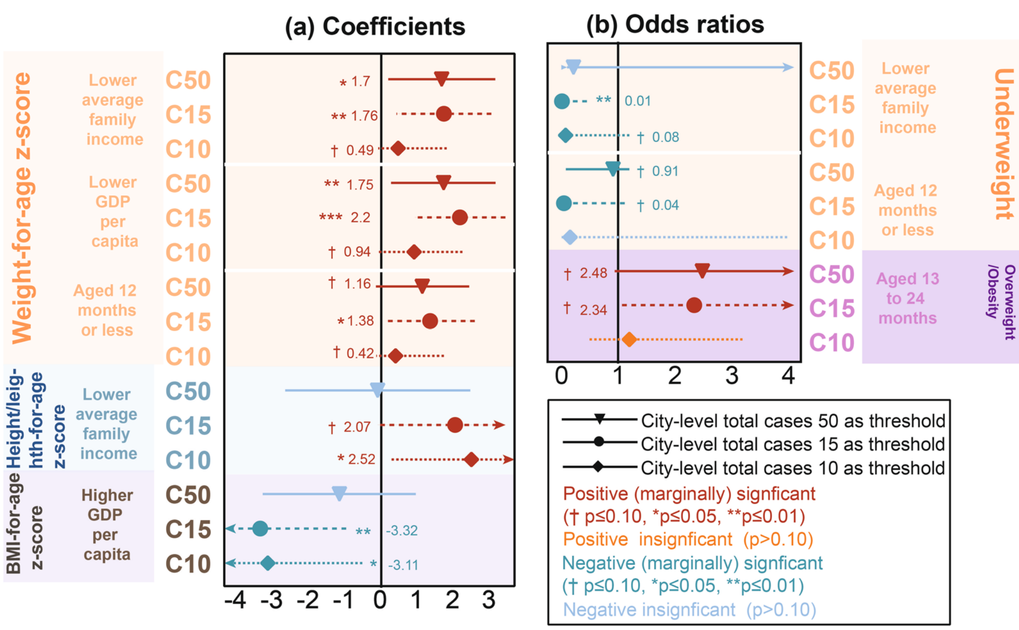

Fig. 5 The effect of the COVID-19 pandemic on various nutritional indicators stratified by socioeconomic backgrounds and age groups (Note: Only estimations of Model 3 s with all covariates being included and with significant or marginally significant associations are shown. C50, C15 and C10 imply respectively using 50, 15 and 10 accumulated confirmed cases as the thresholds of low-risk and medium-/high-risk areas.)

Discussion

The COVID-19 pandemic may heighten the risk of all forms of early-life malnutrition [3]. To develop effective adaptive strategies ensuring children's nutrition security, it is imperative to evaluate the pandemic's impacts on diverse nutritional indicators. Previous studies have mainly conducted comparative analyses to scrutinize changes in pre- and post-pandemic weight status among individuals aged 3–25 years. Yet, there is a pressing need for more empirical research examining a broader spectrum of nutritional indicators besides weight, with a specific focus on younger children under 3 years. Moreover, a more stringent modeling technique is necessary to disentangle the pandemic's impact from the influence of normal growth processes. Leveraging the outbreak that originated in Wuhan as the case, utilizing epidemic data, multi-wave national survey data and statistical yearbook data, considering simultaneously geographical exposure, temporal exposure and survey cohort effects, this study conducted a preliminary natural experimental analysis to assess the causal effect of the pandemic on various nutritional indicators of infants and toddlers aged 0–3 years. We found that the pandemic exposure was predictive of a higher WAZ and HAZ, and a lower likelihood of being underweight. These effects were generally robust to our sensitivity analyses, robustness checks and falsification tests. Moreover, our heterogeneity analyses revealed that the effects of the pandemic in increasing WAZ and reducing underweight were mainly among children from disadvantaged economic backgrounds or those aged 0–12 months, and the positive association between the pandemic and HAZ was predominantly among children with lower family income. The pandemic negatively affected the BAZ of children from cities with higher GDP per capita, and children aged 13–24 months exhibited an increased likelihood of being overweight/obese.

Our findings of the increased WAZ because of the pandemic align with previous viewpoints and research [1, 8, 15, 30]. However, the reasons behind this phenomenon may vary across regions, households and individuals. On one hand, it could be caused by the increased food intake and decreased outdoor activities prompted by government-mandated measures. The dramatic disruptions to daily routine, altered dietary habits, limited access to sports facilities, and heightened anxiety during quarantine may lead to unhealthy food choices, increased food intake, and reduced physical activity [31], which subsequently may cause weight gain [9]. It is reasonable to speculate a similar behavioral and weight trend among both adults and their young children. On the other hand, it could be due to the improved nutrition quality and increased family time due to the pandemic. It has been previously argued that COVID-19 did not threaten food security in China; instead, to strengthen their resistance against the virus, residents enhanced their dietary quality by consuming more vegetables, legumes and aquatic products [32] and fewer fats, sugars and salts due to decreased dining out [16], which is beneficial to the growth of children. Moreover, before the pandemic, because of the restrictions of China's hukou policy, numerous people from falling-behind regions seek jobs in better-off areas, leaving their children at home of origin with surrogate caregivers [33]. Because of the pandemic, the increased family time during quarantine [34] may have facilitated bonding activities between parents and their young children, fostering heightened parental care and emotional security, which in turn could contribute to overall well-being and nutritional growth. Given that underweight is calculated based on WAZ, the increase in WAZ may explain our finding of the decreased likelihood of underweight.

Unlike previous arguments suggesting impaired height growth because of the pandemic [1, 35], we found a positive link between the pandemic and HAZ. Given the multifaceted effects of the pandemic on health-related factors as discussed earlier, this finding appears plausible. Aside from the previously mentioned enhanced dietary quality and gained family time that could happen during the pandemic, the increase in HAZ may also stem from young children's reduced exposure to illness and increased sleep duration. There were observed lower incidences of various infectious diseases such as influenza, enterovirus, pneumococcus, and respiratory syncytial virus among children because of the stringent measures during the pandemic [36, 37], which could lead to enhanced height growth. The longer duration of sleep time and daytime sleepiness during confinement [38] could also contribute to greater body length by stimulating the body's production of growth hormone, a key factor in height growth [39].

Our heterogeneity analyses revealed significant improvements in WAZ and HAZ among mainly children from households with lower average family incomes, children from cities with lower GDP per capita, and infants aged 0–12 months. In China, among young children aged 0–5 years, those from lower-income households or impoverished areas are more prone to experiencing inadequate weight and height growth [40]. Moreover, according to previous research [33], this group of children is more likely to be left behind by parents seeking job opportunities in other regions and may suffer more from infectious diseases. During home confinement and amidst stringent anti-virus measures, compared to children from more affluent backgrounds, these children were more likely to enjoy increased family time and reduced illness compared to their usual circumstances. Moreover, it was previously found that rural households engaged in food-related agricultural production, which typically have lower household incomes, experienced both decreased dietary diversity and increased dietary quality during the pandemic [32]. Since heightened parental care, reduced illness and improved dietary quality can all add to better weight and height growth, the increased WAZ and HAZ among children with inferior household and regional economic backgrounds are logical. In light of the intense bursts of weight growth during the first year of life with most babies tripling their birth weight [41], the increased WAZ among children aged 0–12 months during this pandemic wave, which lasted approximately 2 months, is plausible. Considering the increased WAZ among children with lower family income and children aged 0–12 months, our finding of their decreased likelihood of being underweight is understandable.

Our finding of lower BMI among children from cities with higher GDP per capita contradicts previous studies that reported increased BMI in developed contexts [8, 15]. Previous research has mainly ascribed the increased BMI to unhealthy food choices, increased energy intake and decreased physical activity because of the pandemic. However, as indicated before, the pandemic might generate multifaceted effects by making people more health-conscious and more ready to embrace lifestyle changes to stay well [42], although true wellness may remain elusive for people from disadvantaged backgrounds [43]. Given China's rising overweight/obesity prevalence in recent years, people's intensified awareness of health maintenance because of the pandemic, and the greater capability of individuals from more developed regions to pursue true wellness, our finding of decreased BMI among children from regions with higher GDP per capita is justifiable.

The finding that the likelihood of being overweight/obese increased among children aged 13–24 months generally conforms to previous viewpoints. An increase in childhood overweight/obesity could happen due to several factors mentioned earlier. However, there have been limited previous studies investigating the impacts of the pandemic on the nutritional indicators of children aged 3 years or younger. Among the few studies that have included children of this age group [15, 35], there is a lack of investigation into potential differential effects across varying age groups. Searching literature, toddlerhood, spanning from 12 to 36 months of age, is a critical stage for establishing healthy dietary and lifestyle behaviors [44]. Probably because of the gradual slowdown of growth velocity at this period compared to the first year of life and the transition of consumption patterns, children aged 1–3 years are more likely to be overweight/obese [45, 46]. Moreover, transitioning from a diet consisting mainly of breast milk or formula to an adult-like diet, compared to that of older toddlers, the diet pattern of children aged 13–24 months may include fewer vegetables and fruit and be higher in high-calorie foods such as sugar and fat [47]. In this circumstance, we speculate that the transition of dietary patterns and the introduction of adult-like food have made children of the 13–24 months age range particularly susceptible to the negative influence of the pandemic, thus increasing their likelihood of being overweight/obese. To validate this finding, more studies considering the differential impacts of the pandemic on childhood growth across varying age groups are required.

Previous understanding of the potential impacts of the COVID-19 pandemic on the nutritional indicators of young children aged 0–3 years is inadequate. To address this, using the outbreak that originated in Wuhan as a natural experimental case, this study primarily used the Difference-in-Difference-in-Differences (DDD) technique to evaluate the potential causal effect of the pandemic on the nutritional status of infants and toddlers, differentiating between varying socioeconomic and age groups. The originality of this study lies in applying a rigorous modeling technique to examine the impacts of the pandemic on numerous childhood nutritional indicators within an under-investigated age group. By applying a natural experimental analysis, an inference of the potentially causal relationships between the COVID-19 pandemic and childhood nutrition is enabled. Our findings provide valuable insights for developing efficient mitigation strategies that consider social justice to safeguard children's right to optimal growth from exogenous shocks. Furthermore, these insights are crucial for aligning efforts with the children-related SDGs for 2030.

The limitation of this study lies in three aspects. First, because of our limited access to epidemic data at finer scales, we relied on city-level data to define epidemic risk areas. Although the central government had provided general guidelines concerning countermeasures that should be taken during the transmission process, it is unavoidable that varying specific strategies existed across cities, counties, or even communities. Given that some counties with zero confirmed cases within a high-risk city might take flexible countermeasures, our study may therefore underestimate the true impact of pandemic exposure on childhood nutrition. Second, limited by the survey data, our consideration of the survey cohort effect was confined to infants aged 0–7 months, our D2-D1 estimator therefore may not fully control for the survey cohort effect between the treated and control groups. However, it has been previously suggested that the survey cohort differentials caused by macro-environments of any age group could be similar, and be measured by the differentials between exposure areas [48, 49], which may partially mitigate this limitation. Third, our interpretations of how the pandemic may affect childhood nutrition were mainly based on literature, future investigation into particular mechanisms is warranted to validate our inferences and to understand further the underlying pathways.

Conclusions

Using China's first and largest outbreak of the COVID-19 pandemic, which originated in Wuhan in Dec 2019, as a case, as well as national-wide survey data and statistical yearbook data, this study conducted a natural experimental analysis with the consideration of geographical exposure effect, temporal exposure effect and survey cohort effect to investigate the pandemic's impacts on the nutritional status of infants and toddlers aged 0–36 months. Moreover, the potential heterogeneities of these impacts across varying socioeconomic and age groups were examined. We found that the pandemic exposure was predictive of a higher weight-for-age z-score (WAZ) and length/height-for-age z-score (HAZ), and a lower likelihood of being underweight. The effects of the pandemic in increasing WAZ and reducing underweight were mainly among children from economically disadvantaged backgrounds and infants aged 0–12 months. The improved HAZ was mainly among children from lower income households. Conversely, the pandemic was negatively linked to the BMI-for-age z-score (BAZ) of children from higher GDP per capita cities, and children aged 13–24 months were more likely to be overweight/obese. This study adds to a more comprehensive understanding of the pandemic's effect on childhood nutrition. Given that weight gain due to the pandemic disproportionately affected vulnerable children from disadvantaged backgrounds and younger children, who were already at a higher risk of overweight/obesity prior to the pandemic, our findings imply the necessity of greater caution to the widened gap in child nutrition post-pandemic. In the long run, our findings can inform the development of adaptable strategies that prioritize social justice to safeguard all children's right to optimal growth from exogenous shocks and support the achievement of child-related SDGs by 2030.

Abbreviations

BMI	Body mass index (weight in kg divided by height in metres squared)
WAZ	Weight-for-age z-score
HAZ	Length/height-for-age z-score
BAZ	BMI-for-age z-score
SDGs	Sustainable Development Goals
CFPS	China Family Panel Studies
ISEI	International Standard Classification of Occupation
DDD	Difference-in-Difference-in-Differences estimator

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12963-024-00353-x.

Supplementary material 1.

Acknowledgements

We thank the Institute of Social Science Survey (ISSS) of Peking University for providing the survey data.

Author contributions

LG and LY led the conception and design of the study. LG and HL cleaned and analyzed the data. LG, LY and HL prepared tables and figures. LG and LY drafted the manuscript, HL revised the manuscript. All authors read and approved the final manuscript.

Funding

The research was supported by funding from the Second Tibetan Plateau Scientific Expedition and Research (2021QZKK0103) and the Youth Program of the National Natural Science Foundation of China (41901179).

Availability of data and materials

The data that support the findings of this study are available from the Institute of Social Science Survey of Peking University but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the corresponding author upon reasonable request and with permission of the Institute of Social Science Survey of Peking University.

Declarations

Ethics approval and consent to participate

CFPS was conducted in accordance with the relevant guidelines of the Declaration of Helsinki, and approved and monitored by the Biomedical Research Ethics Review Committee of Peking University (protocol code IRB00001052-14010, Beijing, China; dates of approval were updated in each survey wave). Informed written consent was obtained from every participant.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Author details

[1]Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11 A Datun Road, Beijing 100101, People's Republic of China. [2]College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100101, People's Republic of China.

Received: 25 April 2024 Accepted: 6 November 2024
Published online: 12 November 2024

References

1. Fore H, Dongyu Q, Beasley D, Ghebreyesus T. Child malnutrition and COVID-19: the time to act is now. Lancet. 2020;396:517–8.
2. Dunn C, Kenney R, Leischhacker S, Bleich S. Feeding low-income children during the CoviD-19 pandemic. N Engl J Med [Internet]. 2020;382:E40.
3. Headey D, Heidkamp R, Osendarp S, Ruel M, Scott N, Black R, et al. Impacts of COVID-19 on childhood malnutrition and nutrition-related mortality. Lancet. 2020;396:519–21.
4. Laborde D, Martin W, Vos R. Poverty and food insecurity could grow dramatically as COVID-19 spreads. Int Food Policy Res Inst blog. 2020.
5. Krupa-Kotara K, Wojtas G, Grajek M, Grot M, Rozmiarek M, Wypych-Ślusarska A, et al. Impact of the COVID-19 pandemic on nutrition, sleep,

physical activity, and mood disorders of polish children. Nutrients. 2023;15:1928.
6. de Pee S, Taren D, Bloem MW. Nutrition and health in a developing world. Cham: Humana Press; 2017.
7. Pérez-Escamilla R, Cunningham K, Moran VH. COVID-19 and maternal and child food and nutrition insecurity: a complex syndemic. Matern Child Nutr. 2020;16:e13036.
8. Fäldt A, Nejat S, Durbeej N, Holmgren A. Childhood overweight and obesity during and after the COVID-19 pandemic. JAMA Pediatr. 2024;178(5):498.
9. Anderson LN, Yoshida-Montezuma Y, Dewart N, Jalil E, Khattar J, De Rubeis V, et al. Obesity and weight change during the COVID-19 pandemic in children and adults: a systematic review and meta-analysis. Obes Rev. 2023. https://doi.org/10.1111/obr.13550.
10. Beynon C, Davies L. The impact of the COVID-19 pandemic on childhood obesity rates, by Health Board area, in Wales, UK. J Public Health (Bangkok). 2024;46:223.
11. Cena H, Fiechtner L, Vincenti A, Magenes V, Giuseppe R, Manuelli M, et al. COVID-19 pandemic as risk factors for excessive weight gain in pediatrics: the role of changes in nutrition behavior. Narrat Rev Nutr. 2021;13:4255.
12. Masonbrink AR, Hurley E. Advocating for children during the COVID-19 school closures. Pediatrics. 2020;146.
13. Cai P, Liu Y, Yang Z, Luo Y, Zhang Y, Ye P, et al. Impact of lockdown on the growth of children in China aged 3–6 years during the COVID-19 pandemic. Front Endocrinol (Lausanne). 2023. https://doi.org/10.3389/fendo.2023.1301889.
14. Dong WH, Gu TM, Zhu BQ, Shen Y, He XY, Bai GN, et al. Comparison of anthropometric parameters and laboratory test results before and after the COVID-19 outbreak among Chinese children aged 3–18 years. Front Public Heal. 2023. https://doi.org/10.3389/fpubh.2023.1048087.
15. Hummel S, Rosenberger S, von dem Berge T, Besser REJ, Casteels K, Hommel A, et al. Early-childhood body mass index and its association with the COVID-19 pandemic, containment measures and islet autoimmunity in children with increased risk for type 1 diabetes. Diabetologia. 2024;67:670–8.
16. Wen J, Zhu L, Ji C. Changes in weight and height among Chinese preschool children during COVID-19 school closures. Int J Obes. 2021;45:2269–73.
17. Seth P, Gupta S, Pingali P. Did the COVID-19 lockdown reverse the nutritional gains in children? Evidence from rural India. Econ Polit Wkly. 2024;59:48–58.
18. Gu L, Yang L, Wang L, Guo Y, Wei B, Li H. Understanding the spatial diffusion dynamics of the COVID-19 pandemic in the city system in China. Soc Sci Med. 2022;302:114988.
19. Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan. China Lancet. 2020;395:497–506.
20. The State Council. Guiding opinions on scienfic prevention and control and implementing precise strategies to curb the pandemic. 2020.
21. Institute of Social Science Survey. China Family Panel Studies (CFPS). 2015.
22. Dong E, Du H, Gardner L. An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect Dis. 2020;20:533.
23. Department of Rural Surveys. China Statistical Yearbook (County-level). Beijing, China: China Statistics Press; 2019.
24. Department of Urban Surveys. China City Statistical Yearbook (2019). Beijing, China: China Statistics Press; 2019.
25. World Health Organization. WHO Child Growth Standards: Length/height-for-age, weight-for-age, weight-for-length, weight-for-height and body mass index-for-age: Methods and development. Geneva; 2006.
26. People's daily online. Analyzing the situation of the pandemic and reinforcing prevention and control work. 2020;
27. Olden A, Moen J. The triple difference estimator. Econom J. 2022;25:531–53.
28. Rubin DB. Multiple imputation for nonresponse in surveys. Hoboken: John Wiley & Sons; 2004.
29. Statacorp. Stata statistical software: release 17. Coll. Stn. Statacorp IP. 2021.
30. Stavridou A, Kapsali E, Panagouli E, Thirios A, Polychronis K, Bacopoulou F, et al. Obesity in children and adolescents during covid-19 pandemic. Children. 2021;8:135.
31. Miranda D, Athanasio B, Oliveira AC, Simoes-e-Silva AC. How is COVID-19 pandemic impacting mental health of children and adolescents? Int J Disaster Risk Reduct. 2020;51:101845.
32. Tian X, Zhou Y, Wang H. The impact of COVID-19 on food consumption and dietary quality of rural households in China. Foods. 2022;11:510.
33. Gu L, Yang L, Li H. Does social capital aid in leveling the income gradient in child mental health? A structural analysis of the left-behind and not-left-behind Chinese children. BMC Public Health. 2023. https://doi.org/10.1186/s12889-023-16264-9.
34. Toran M, Sak R, Xu Y, Şahin-Sak İT, Yu Y. Parents and children during the COVID-19 quarantine process: experiences from Turkey and China. J Early Child Res. 2021;19:21–39.
35. Rahman A, Othman N, Kuddus MA, Hasan MZ. Impact of the COVID-19 pandemic on child malnutrition in Selangor, Malaysia: a pilot study. J Infect Public Health. 2024;17:833.
36. Yang MC, Su YT, Chen PH, Tsai CC, Lin TI, Wu JR. Changing patterns of infectious diseases in children during the COVID-19 pandemic. Front Cell Infect Microbiol. 2023. https://doi.org/10.3389/fcimb.2023.1200617.
37. Kadambari S, Goldacre R, Morris E, Goldacre MJ, Pollard AJ. Indirect effects of the covid-19 pandemic on childhood infection in England: population based observational study. BMJ. 2022;376.
38. Camacho-Montaño LR, Iranzo A, Martínez-Piédrola RM, Camacho-Montaño LM, Huertas-Hoyas E, Serrada-Tejeda S, et al. Effects of COVID-19 home confinement on sleep in children: a systematic review. Sleep Med Rev. 2022;62:101596.
39. Zhou Y, Aris IM, Tan SS, Cai S, Tint MT, Krishnaswamy G, et al. Sleep duration and growth outcomes across the first two years of life in the GUSTO study. Sleep Med. 2015;16:1281–6.
40. Liu J, Sun J, Huang J, Huo J. Prevalence of malnutrition and associated factors of stunting among 6–23-month-old infants in central rural China in 2019. Int J Environ Res Public Health. 2021;18:8165.
41. Waseem M, Thakore K, Campbell N, Lominy M-M, Shariff MA, Rosario D. Are infants doubling their birth weight sooner? Pediatrics. 2021;147:32–3.
42. Anyanwu OA, Naumova EN, Chomitz VR, Zhang FF, Chui K, Kartasurya MI, et al. The effects of the COVID-19 pandemic on nutrition, health and environment in Indonesia: a qualitative investigation of perspectives from multi-disciplinary experts. Int J Environ Res Public Health. 2022;19:11575.
43. World Economic Forum. 6 trends that define the future of health and wellness. 2022. Available from: https://www.weforum.org/agenda/2022/02/megatrends-future-health-wellness-covid19/
44. Pesch MH, Lumeng JC. Early childhood obesity: a developmental perspective. Annu Rev Dev Psychol. 2021;3:207–28.
45. Sserwanja Q, Mutisya LM, Olal E, Musaba MW, Mukunya D. Factors associated with childhood overweight and obesity in Uganda: a national survey. BMC Public Health. 2021. https://doi.org/10.1186/s12889-021-11567-1.
46. Tchoubi S, Sobngwi-Tambekou J, Noubiap JJN, Asangbeh SL, Nkoum BA, Sobngwi E. Prevalence and risk factors of overweight and obesity among children aged 6–59 months in Cameroon: a multistage, stratified cluster sampling nationwide survey. PLoS ONE. 2015;10:e0143215.
47. Welker EB, Jacquier EF, Catellier DJ, Anater AS, Story MT. Room for improvement remains in food consumption patterns of young children aged 2–4 years. J Nutr. 2018;148:1536S-1546S.
48. Chen Q. Advanced econometrics and stata applications. Beijing: Higher Education Press; 2014.
49. Guo C, Hu X, Xu C, Zheng X. Association between olympic games and children's growth: evidence from China. Br J Sports Med. 2022;56:1110–4.

Publisher's Note