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# Investigating Longitudinal Trajectories of COVID-19 Disruption: Methodological Challenges and Recommendations

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## Abstract

Relatively few studies have longitudinally investigated how COVID-19 has disrupted the lives and health of youth beyond the first year of the pandemic. This may be because longitudinal researchers face complex challenges in figuring out how to code time, account for changes in COVID-19 spread, and model longitudinal COVID-19-related trajectories across environmental contexts. This manuscript considers each of these three methodological issues by modeling trajectories of COVID-19 disruption in 1080 youth from 12 cultural groups in nine nations between March 2020-July 2022 using multilevel modeling. Our findings suggest that for studies that attempt to examine cross-cultural longitudinal trajectories during COVID-19, starting such trajectories on March 11, 2020, measuring disruption along 6-month time intervals, capturing COVID-19 spread using death rates and the COVID-19 Health and Containment Index scores, and using modeling methods that combine etic and emic approaches are each especially useful. In offering these suggestions, we hope to start methodological dialogues among longitudinal researchers that ultimately result in the proliferation of research on the longitudinal impacts of COVID-19 that the world so badly needs.

**Keywords** COVID-19 · Longitudinal · Multilevel modeling · Ecological disruption

## Introduction

COVID-19 has been confirmed to have spread to 771 million people and killed almost 7 million (Matheiu et al., 2023). These devastating impacts are worsened by fears that COVID-19 will disrupt numerous aspects of daily routine, work and school, and family life in the coming years for youth who have grown up during the COVID-19 pandemic (Kauhanen et al., 2023; Penninx et al., 2022). Evidence of these long-term trajectories of COVID-19 disruption are

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already emerging, including a global decline in human development back to 2016 levels (United Nations Development Program, 2022), global drop in life expectancy (Roser et al., 2023), and global learning loss (Betthäuser et al., 2023). Indeed, in cultures around the world, youth reports of greater COVID-19 disruption have been linked with numerous internalizing and externalizing mental health problems, and risky substance use (Rothenberg et al., 2023; Skinner et al., 2021). These dismaying findings make youth COVID-19 disruption a key variable of interest to developmental scientists and suggest that longitudinal investigations are urgently needed to track how COVID-19 has disrupted youths' lives over time.

Curiously, despite this need, relatively few studies have investigated how the COVID-19 pandemic has disrupted the lives of youth beyond the initial first year of the pandemic (Larsen et al., 2023). The absence of these studies is especially vexing given the enormous amount of cross-sectional research that was rapidly published at the beginning of the COVID-19 pandemic (Park et al., 2021). There are many possible explanations for this dearth of longitudinal research. However, one explanation may be that constructing and analyzing longitudinal trajectories of COVD-19 disruption is especially difficult because COVID-19 is a complex, dynamic developmental phenomena (Park et al., 2021; Wolkewitz & Puljak, 2020). We speak from firsthand experience. Despite being a team of over 20 developmental scientists from over a dozen institutions in nine countries, we were met with numerous methodological challenges as we attempted to construct trajectories of COVID-19 disruption in our longitudinal sample of 1080 young people from 12 cultural groups in nine nations followed from March 2020-July 2022. Specifically, we faced three major methodological challenges in constructing our trajectories: deciding how to code time when creating COVID-19 trajectories, accounting for changes in COVID-19 spread, and considering how to model trajectories of COVID-19 disruption across environmental contexts. The purpose of this paper is to consider each of these three methodological questions and describe how our research team attempted to answer these questions. Our intended audience for this manuscript is psychologists and developmental and prevention scientists interested in understanding how COVID-19 affected adolescents. We hope to make it easier to publish the longitudinal studies that are so sorely needed to understand the long-term effects of COVID-19 disruption in youth.

## Question 1: How Do You Code Time When You are Crafting COVID-19 Trajectories?

Coding time is the first step in constructing any developmental trajectory, because to understand a developmental phenomenon, you need to know its starting point and the intervals of time over which it changes (Bauer & Curran, 2013). For most developmental processes, coding time is somewhat intuitive. The starting point of the developmental process is birth, or the first timepoint of data collection in a study, and developmental change is measured over a period such as days, months, or years. However, studying COVID-19 is a unique developmental process because it upends both of these pillars of coding time. COVID-19 disruption did not "start" at the same time for people in different regions, nor did it change in similar intervals of time for most subjects (Matheiu et al., 2023). We elaborate upon both issues below.

First, it is unclear how one can determine the "starting point" of COVID-19 disruption when people in different cultures begin experiencing COVID-19 at relatively different times. This is especially true in a study like ours, which attempts to capture overall average trajectories of COVID-19 disruption across nine nations (China, Colombia, Italy, Jordan, Kenya, Philippines, Sweden, Thailand, and the United States). For instance, lockdowns and states of emergency were declared in these nations across a wide range of weeks (Hale et al., 2021). In China, school lockdowns began on January 27, 2020, whereas in Thailand, school lockdowns did not occur until March 23, 2020. In our other seven nations, school lockdowns occurred between March 4, 2020-March 18, 2020, but the extent of COVID-19 spread and conditions in these nations were vastly different across these dates (Hale et al., 2021; Matheiu et al., 2023). Even in longitudinal studies that focus on just a single cultural or environmental context, the question of COVID-19 start point can be vexing: Did COVID-19 "start" when the first case in the region where the sample was living was found? When lockdowns happened? When a World Health Organization Pandemic was declared? This is a difficult question to answer, with clear ramifications for the subsequent trajectories of COVID-19 that are estimated.

A similarly difficult time coding question emerges when one tries to ponder over what interval of developmental time one should study COVID-19. In developmental science, many processes have an established period of time over which studying a phenomenon might make intuitive sense. For instance, studying associations between adolescent emotion regulation and emotional responses is best studied within and across days in an adolescent's life, the emergence of developmental milestones is best studied over weeks or months early in an infant's life, and the impacts of early adversity on adult functioning are best studied over years.

However, choosing an interval of time over which to study COVID-19 is challenging, because depending on the point in the pandemic and the region of the world studied, youth COVID-19 disruption could occur on the timescale of days (e.g., one day youth are in school and the next day out; Hammerstein et al., 2021), weeks/months (e.g., during COVID-19 surges, especially stringent policies prevent anyone from travelling to connect with family or friends; Hale et al., 2021), or years (e.g., as several loved ones pass away due to COVID-19, symptoms of trauma, anxiety, and depression may build over time; Hillis et al., 2021). This is complicated even further because the same amount of time passing during the pandemic means vastly different things for youth in different environmental contexts. Experiences of COVID-19 disruption from March 2020-March 2021 may be different in Italy (where an initial and second surge of COVID-19 cases emerged over the course of the year), Jordan (where an initial surge of COVID-19 cases only emerged in late 2020), and Kenya (where comparatively few COVID-19 cases were reported over the entire time period) (Matheiu et al., 2023). It is relatively rare to examine a developmental phenomenon that is experienced so differently in different youth across different time intervals (depending on lockdowns, case surges, vaccine availability, etc.).

## Question 2: How Do You Account for Changes in COVID-19 Spread?

Related to the question of coding time when estimating trajectories of COVID-19 disruption is how to account for rapid changes in COVID-19 spread and lethality when estimating these trajectories. In estimating trajectories in our own sample, we were confronted with two challenges related to this issue. The first is that COVID-19 disrupted life via both its spread and via the lockdowns and mitigation strategies it forced governments to take (Hale et al., 2021; Matheiu et al., 2023). COVID-19 spread and killed at vastly different rates during different times in the pandemic, and those rates only occasionally coincided with changes in lockdown and mitigation strategies. For instance, in the United States, death rates stayed stubbornly higher than those in other nations throughout late 2021–2022 as the Omicron variant took hold in unvaccinated individuals (Hale et al., 2021; Matheiu et al., 2023), even though relatively few COVID-19 related restrictions remained in place during this time. In the Philippines, death rates stayed low throughout much of the pandemic, but children were held out of school for the longest of all nations studied in our sample (only beginning classes again in mid-2022; Hale et al., 2021; Matheiu et al., 2023). In sum, estimating trajectories of COVID-19 disruption becomes challenging because both surges in COVID-19 cases/deaths, and changes in COVID-19 restrictions changed rapidly over time, but not necessarily in tandem with each other. Yet, any effort to estimate longitudinal trajectories of COVID-19 disruption must take into account both of these dynamically changing variables.

A second issue that needs to be accounted for when considering how changes in COVID-19 spread affect trajectories of COVID-19 disruption is what statistics should be used to account for COVID-19 spread. Primarily, COVID-19 spread has been captured by examination of COVID-19 case rates, death rates, total excess mortality rates during the COVID-19 pandemic, and changes in lockdowns and restrictions in response to COVID-19 (Hale et al., 2021; Matheiu et al., 2023). However, each of these measures has different advantages and drawbacks.

COVID-19 case rates are probably the broadest indicators of how COVID-19 spreads in different contexts. For instance, COVID-19 waves have been most popularly characterized by the spread of different COVID-19 variants (e.g., “Delta” and “Omicron”), and the surge in cases that accompany these variants (Matheiu et al., 2023). However, questions continue to persist about how well COVID-19 case rates actually capture COVID-19 spread, given the vast differences across towns, cities, and nations in how readily available COVID-19 testing was and how accurately COVID-19 case statistics were compiled throughout the pandemic (Matheiu et al., 2023). For instance, in the early stages of the pandemic, South Korea tested and traced COVID-19 cases more accurately than the United States (Matheiu et al., 2023).

COVID-19 death rates do not capture as broadly how many people have contracted COVID-19, but they are probably more accurate in capturing “true” COVID-19 spread than case rates. This is because whereas someone who contracted COVID-19 may or may not have tested for their symptoms and become a “confirmed” case, in many countries, hospitals were required to identify whether people who passed away during the COVID-19 pandemic died of COVID-19 (World Health Organization, 2020a, b). Consequently, especially early in the pandemic, COVID-19 cases were likely underreported compared to death rates (World Health Organization, 2020a, b). However, there are limitations to using COVID-19 death rates as a measure of COVID-19 spread as well, including infamous questions raised in the United Sates about whether COVID-19 was the primary cause of death when death certificates reported multiple causes (Armstrong, 2021). Some (probably inaccurately) asserted that COVID-19 death counts were overestimated because many individuals who died while positive for COVID-19 actually passed away or would have passed away from another underlying condition.

Measures of total excess mortality are yet another way to capture the spread of COVID-19 that overcome some of the arguments against using death rates. Excess mortality captures the number of deaths *from all causes* during a crisis above and beyond what would be expected under ‘normal’ conditions (Matheiu et al., 2023). Excess mortality is a more comprehensive measure of the *total* impact of the pandemic on deaths than the confirmed COVID-19 death rate alone (Matheiu et al., 2023). It captures not only the confirmed deaths, but also COVID-19 deaths that were not correctly diagnosed and reported as well as deaths from other causes that are attributable to the overall crisis conditions. Total excess mortality is a great way to counter claims made by many that death rates capture people who died of COVID-19 who would have otherwise passed away from another underlying condition.

However, there are also questions about whether total excess mortality is the best indicator of COVID-19 impact to use *when estimating COVID-19's disruption in individuals' lives*. This is perhaps best illustrated by two examples from the first author's own life. The first author had both a grandfather and a grandmother pass away during the COVID-19 pandemic. The death of the beloved grandmother occurred during the COVID-19 pandemic but was of primarily natural causes. The inability of the author's grandmother to receive routine healthcare visits during the COVID-19 pandemic *might* have contributed to her passing "earlier than expected" by a few years, and therefore count as "excess mortality" during the COVID-19 pandemic. However, the author did not attribute this death to COVID-19, and therefore would not think of this death as an example of COVID-19 life disruption. In contrast, the death of the author's beloved grandfather was a direct result of COVID-19 (the grandfather was a bus driver at a hospital serving COVID-19 patients and tested positive before passing away in the ICU). This death was grieved by the author as a direct result of COVID-19 and thought of as a prime example of COVID-19 disruption. Both deaths may be counted toward excess mortality due to COVID-19, yet only one was perceived as part of COVID-19- related disruption.

A final measure of the potential spread of COVID-19 is the extent to which lockdowns and mitigation strategies (e.g., masking, social distancing) were enacted in an area at any given point in the pandemic (Hale et al., 2021; Matheiu et al., 2023). However, it is difficult to imagine how the extent to which such lockdown and mitigation strategies were implemented in different contexts at different times could be measured empirically. In sum, it is especially difficult to estimate longitudinal trajectories of COVID-19 disruption because doing so requires taking into account how its spread differed across time and context using imperfect statistics.

### Question 3: How Do You Model Trajectories of COVID-19 Disruption Across Contexts?

Accurately modeling trajectories of COVID-19 disruption also requires figuring out ways to examine COVID-19 disruption across different cultural and environmental contexts. This is clearly an essential question to answer in our sample, where we are examining trajectories of COVID-19 disruption in nine countries. But this is also applicable to other samples, where COVID-19 disruption could differ drastically based on different environmental conditions such as geography (e.g., Northern versus Southern Italy; Matheiu et al., 2023) or racial/ethnic group (due to healthcare inequalities; Duong et al., 2023). One can adopt an etic or emic approach to incorporate these differences in COVID-19 experiences across environmental contexts into longitudinal models of COVID-19 disruption (Harris, 1976; Lansford et al., 2016). An etic approach (Lansford et al., 2016) may focus on universal trajectories of COVID-19 disruption (e.g., an average trajectory of COVID-19 disruption reported across all youth in all 12 cultural groups in our sample). It would eschew context-specific differences in COVID-19 experiences in favor of identifying trajectories of COVID-19 disruption that are applicable across cultural contexts. This approach offers the potential for wide generalizability. However, its drawback is that the universal trajectories identified within it may capture average changes in COVID-19 disruption across many environmental contexts that are not actually applicable in any single environmental context. In contrast, an emic approach (Lansford et al., 2016) may focus on identifying environmental context-specific COVID-19 trajectories of disruption (e.g., estimating 12 separate trajectories of COVID-19 disruption for youth in each cultural context). This approach may provide a rich understanding of how COVID-19 impacted youth in particular environmental contexts but may not be generalizable across contexts. That is the crux of this third methodological question: how can longitudinal examinations choose between emic and etic approaches to capture trajectories of COVID-19 disruption across contexts?

### Current Study

The current manuscript attempts to document how our international, longitudinal research team answered each of these three research questions. It provides answers for how time, changes in COVID-19 spread, and differences in COVID-19 experiences across environmental context can be accounted for in constructing longitudinal trajectories of COVID-19 disruption.

## Methods

To begin this Methods section, we wanted to mention that some of the descriptions might "give away" answers to some of the questions posed above in the Introduction. Rest assured we will provide full details about how we answered each of our three questions in the Results section.

## Participants

Participants (Table 1) were drawn from a longitudinal study of parenting and child development and included 1,082 adolescents ($M = 19.98$ years, $SD = 1.23$, 52% girls) from 12 distinct ethnic/cultural groups across nine countries including: Chongqing, China ($n = 110$); Medellín, Colombia ($n = 80$); Naples ($n = 82$) and Rome ($n = 105$), Italy; Zarqa, Jordan ($n = 100$); Kisumu, Kenya ($n = 88$); Manila, Philippines ($n = 86$); Trollhättan/Vänersborg, Sweden ($n = 88$); Chiang Mai, Thailand ($n = 91$); and Durham, NC, United States ($n = 90$ White, $n = 86$ Black, $n = 76$ Latino). Participants were initially recruited into the original study through school letters and continued to participate during the COVID-19 pandemic. Sampling included adolescents from each country's majority ethnic group, except in Kenya where we sampled Luo (3rd largest ethnic group, 13% of population) and in the U.S. where we sampled equal proportions of White, Black, and Latino families. Socioeconomic status was sampled in proportions representative of each recruitment area. Specifically, participants were recruited from public and private schools serving neighborhoods of different socioeconomic strata in each recruitment area. This resulted in the socioeconomic makeup of families recruited from these schools approximating that of the recruitment area with regards to mother and father education and family income (Lansford et al., 2016; Skinner et al., 2021). Child age and gender did not vary across countries. Data for this study were drawn from interviews at five time periods during the first 2.5 years of the COVID pandemic between March 9, 2020-July 31, 2022.

## Procedures

All procedures were approved by ethics committees in each participating country. Interviews were conducted online, by mail, or by telephone because of COVID-19-restrictions, and typically lasted 5 min or less. Forward and backward translation of items ensured linguistic and conceptual equivalence of measures (Erkut, 2010).

Data collection spanned different amounts of time to collect each wave in each nation due to pandemic restrictions. Therefore, aligning with best practices in longitudinal literature (Bauer & Curran, 2013), we "turned" the data to examine trajectories of adolescent disruption over time, instead of by "wave." Specifically, we examined trajectories of adolescent disruption over five time periods, each coinciding with a half year of the pandemic: (1) March 2020-September 2020, (2) September 2020-March 2021, (3) March 2021-September 2021, (4) September 2021-March 2022, and (5) March 2022-July 2022. Supplemental Table 1 provides information about the exact months data were collected in each participating cultural group within each of those 5 time intervals. Because data collection time frames varied across sites, data were missing for some youth at some time points, but this did not substantively impact results (see Supplemental Missing Data Description).

## Measures

### Covariates

In all analyses that predicted trajectories of COVID-19 disruption, we controlled for adolescent age (in years), adolescent gender (0 = female, 1 = male), and number of years of parent education.

**Table 1** Descriptive statistics for demographics by cultural group

| Group | *N* | Youth gender (% girls) | Youth age | Parents' education (# of years of education completed by most educated parent) |
|---|---|---|---|---|
| Whole Sample | 1082 | 52% | 19.98 (1.23) | 14.43 (4.26) |
| Chongqing, China | 110 | 53% | 17.77 (0.39) | N/A |
| Medellín, Colombia | 80 | 51% | 19.75 (0.61) | 11.55 (5.56) |
| Naples, Italy | 82 | 59% | 20.94 (0.36) | 12.99 (4.58) |
| Rome, Italy | 105 | 48% | 20.74 (0.79) | 14.94 (4.34) |
| Zarqa, Jordan | 100 | 52% | 19.11 (0.31) | 14.97 (2.55) |
| Kisumu, Kenya | 88 | 60% | 21.04 (0.89) | 13.70 (3.61) |
| Manila, Philippines | 86 | 49% | 19.93 (0.45) | 15.10 (4.09) |
| Trollhättan, Sweden | 88 | 53% | 19.71 (0.61) | 15.48 (2.64) |
| Chiang Mai, Thailand | 91 | 53% | 18.80 (0.52) | 13.98 (4.22) |
| U.S. Black | 86 | 51% | 21.06 (0.64) | 14.66 (2.52) |
| U.S. Latino | 76 | 55% | 20.75 (0.73) | 11.97 (4.00) |
| U.S. White | 90 | 42% | 21.17 (0.54) | 18.64 (3.36) |

All numbers in parentheses are standard deviations. N/A means information was not available in that cultural group

### Adolescents' COVID-19-Related Life Disruption

Aligning with existing work (Skinner et al., 2021), youth rated the extent to which COVID-19 had disrupted their life during the five study time periods by rating this question: "Please rate how much the COVID-19 outbreak has been disruptive to you personally. Think about your daily routines, work, and family life" on a 1 = *Not at all disruptive* to 10 = *Extremely Disruptive* scale (see Supplemental COVID-19 Related Life Disruption Description).

### Culture Group Membership

Cultural group membership was captured via a categorical variable that identified each of the 12 cultural groups in the current study.

### COVID-19 Death Rates

We calculated average COVID-19 death rates per 100,000 people in each of the nine nations during each of the five time periods examined in the current study. Average death rates were calculated from data provided by Our World in Data (Matheiu et al., 2023).

### Stringency of COVID-19 Mitigation Strategies

How stringently a nation implemented COVID-19 mitigation strategies was measured in each of the nine nations during each of the five time periods examined in the current study via the COVID-19 Containment and Health Index (Hale et al., 2021). This index measures the strictness of government policies related to COVID-19 on a 0 to 100 scale (with 100 being the most strict) and is based on 13 areas of COVID-19 policy: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; international travel controls; testing policy; extent of contact tracing; face coverings; and vaccine policy (Matheiu et al., 2023). From the pandemic's onset until December 31, 2022, this measure was calculated in each country every day by researchers at Our World in Data, so we were able to calculate average scores on this Index in each country during each time period we examined.

## General Analytic Method

For simplicity, we describe our general analytic method here. Then, in the results, we elaborate upon this general analytic method by describing specific measurement and analytic decisions we made to overcome our three methodological challenges we explore in this study.

With regards to our general analytic method, following expert recommendations (Bauer & Curran, 2013), we estimated a series of multilevel models in SAS 9.4 using restricted maximum likelihood estimation to estimate a single overall trajectory of COVID-19 disruption across our entire sample. We identified the best-fitting trajectory using chi-square tests to compare alternative models (Bauer & Curran, 2013), and found the quadratic model fit the data best. More detail about the nature of this trajectory is provided in the Results. Moreover, specifics about how we estimated culture-specific trajectories of COVID-19 disruption based on this overall trajectory are also provided in the Results.

Additionally, to account for COVID-19 spread while estimating COVID-19 disruption trajectories, we turned to multilevel modeling. Specifically, measures of COVID-19 spread needed to account for how they affected *who* among adolescents experienced different levels of COVID-19 life disruption over the course of the pandemic (a between-person, time-invariant difference in trajectories; Bauer & Curran, 2013). To accomplish this, we used a multilevel modeling framework and grand-mean centered both measures of COVID-19 spread. In other words, we calculated each cultural group's deviations from the overall average death rate in the sample across all time points, and overall average stringency of COVID-19 mitigation score in the sample across all time points. Then, each person within that culture was assigned that deviation score. So, for instance, if the overall mean death rate across the entire sample was 50 people per 100,000 people across the entire March 2020-July 2022 time frame, and Sweden experienced a death rate of 70 people per 100,000 people in that same time frame, then Sweden's deviation score would be 20, and each Swedish person would be assigned that deviation score. We used these time-invariant grand-mean centered measures to predict changes in the trajectory of youth COVID-19 life disruption due to death rates and stringency measures.

However, measures of COVID-19 spread also needed to account for *when* during the pandemic experiencing especially high levels COVID-19 spread (compared to what youth normally face) leads to especially high levels of adolescent COVID-19 life disruption (a within-person, time-varying effect; Bauer & Curran, 2013). To accomplish this, we culture-mean centered both measures of COVID-19 spread. In other words, within every culture, we calculated the time-specific deviations from the culture's overall average death rate across all time points, and overall average stringency of COVID-19 mitigation score across all time points. We can build on the Sweden example started above to illustrate this. Let us say that Sweden experienced a death rate of 70 people per 100,000 people over the course of the entire March 2020-July 2022 time frame. However, let us suppose that this death rate was 68 per 100,000 people in the first of our 5 time frames (March, 2020-September, 2020), 69 in the 2nd time frame, 70 in the 3rd, 71 in the 4th, and 72 in the 5th. In that case, the corresponding time-specific deviation scores would be -2, -1, 0, 1, and 2 at each of the 5 time points. We then assigned each Swedish person that time-specific deviation at each time point. We then used these measures to predict deviations from the overall trajectory of adolescent life disruption due to COVID-19. Furthermore, we used interaction terms to examine how both the "who" and "when" associations of COVID-19 spread (i.e., death rates and stringency index ratings) with adolescent COVID-19 life disruption changed over the course of the pandemic (see Supplemental Details: Crafting Interaction Terms for further detail).

## Results

All study descriptive statistics can be found in Table 2, and correlations between all study variables can be found in Supplemental Table 2.

### Question 1: How Do You Code Time When You Are Crafting COVID-19 Trajectories?

In answering this question, we describe how we both chose a starting point and time interval for the trajectory of COVID-19 disruption we modeled.

#### Choosing a Starting Point

We decided to pick a single starting date from which we could estimate one overall average trajectory across all cultures in our sample. For this analysis, we decided the most logical starting date was March 11, 2020, because that was the day that the World Health Organization officially declared COVID-19 a pandemic (WHO, 2020a, b). With the exception of China, all school lockdowns in all cultural groups in our sample commenced either 1 week before (Italy; March 4, 2020) or by two weeks after this declaration. Given that we were interested in trajectories of culture groups that spanned the globe, this global pandemic declaration seemed especially justified as a starting point.

**Table 2** Descriptive statistics for main study variables

| Variable | M | SD |
|---|---|---|
| COVID-19 Death Rate Per 100,000 people | 36.58 | 34.62 |
| Stringency of COVID-19 Mitigation Strategies (Range: 0-100) | 56.16 | 14.89 |
| COVID-19 Related Life Disruption (Range: 1–10) | 6.26 | 2.47 |

#### Selecting Intervals of Time

We collected data every few months, so we did not have enough data to examine trajectories of daily, weekly, or monthly COVID-19 disruption. However, we debated whether to try to examine trajectories at 3-month, 6-month, or 1-year intervals. Estimating 3-month time intervals could allow our trajectories to be especially sensitive to changing COVID-19 conditions, but unfortunately our data were too sparse to be modeled across this time frame. Estimating yearly trajectories was easily possible with the amount of data we had but seemed too insensitive to rapidly changing COVID-19 conditions. Therefore, we decided to examine trajectories of COVID-19 disruption across five different 6-month time intervals from March 2020-July 2022. This 6-month time interval might be a bit of a "goldilocks" (i.e., not too much, not too little, but just right) time interval when estimating many different worldwide trajectories of COVID-19. This argument is best made by Fig. 1, which overlays the 5 time intervals we investigated over 7-day rolling average death rates throughout the pandemic. As seen in Fig. 1, our 6-month time intervals seem to capture the entirety of each of the waves within the pandemic. This allows for intuitive interpretations (e.g., Fig. 1 points 1–2 coincide with the initial surge, points 2–3 are the Delta Variant wave, etc.). Therefore, we constructed our trajectory on these 6-month intervals.

#### Estimating the Trajectory of COVID-19 Disruption

With our starting point and time interval decided upon, we estimated the trajectory of COVID-19 disruption in our sample. A quadratic trajectory best characterized how adolescents perceived that COVID-19 disrupted their life over the course of the pandemic (see Supplemental Details: Estimating Trajectory of COVID-19 Disruption for more). This quadratic trajectory revealed that in the first six months of COVID, adolescents reported an average score of 6.09 out of 10 on the COVID-19 life disruption scale, and this score increased linearly by 0.38 points for each additional half year (Table 3). However, this linear increase itself slowed over time at a rate of 0.10 points each half year (Table 3). This trajectory is depicted in Fig. 2, where average COVID-19 life disruption scores increased over time to approximately 6.5 from March 2021-September 2021, before subsequently decreasing over time back to a score of approximately 6 in March 2022-July 2022.

### Question 2: How Do You Account for Changes in COVID-19 Spread?

Accounting for changes in COVID-19 spread in estimating trajectories of COVID-19 disruption required decisions about what statistics to use.

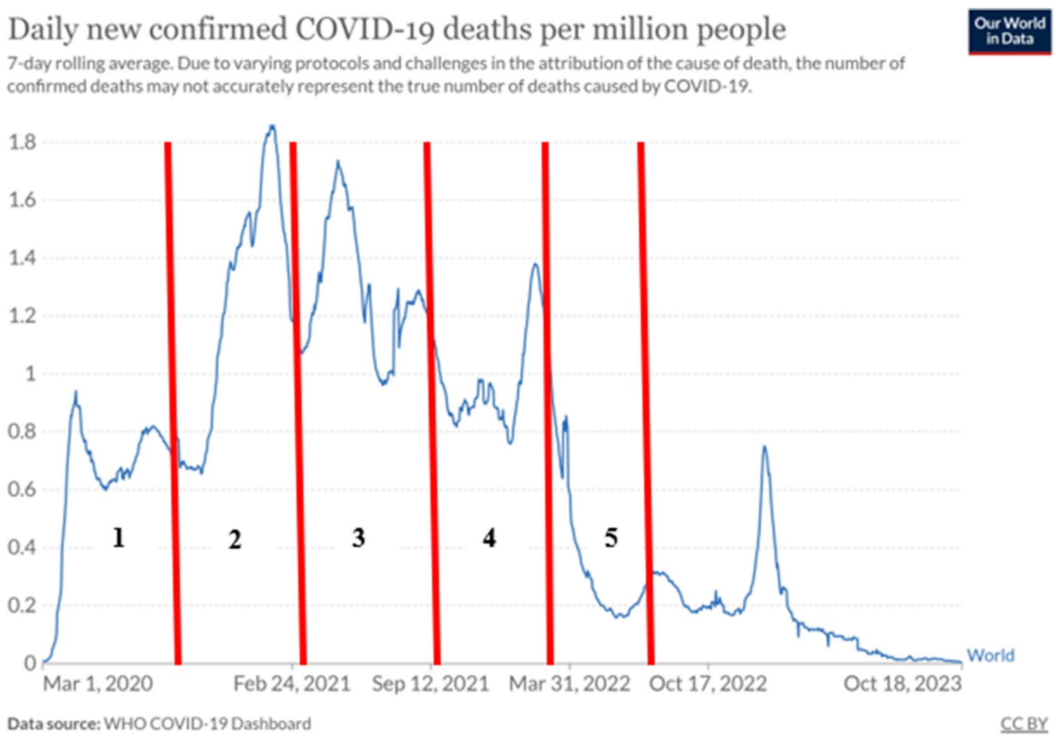


**Fig. 1** Demonstrating how investigation of COVID-19 pandemic at half year intervals coincides with COVID-19 surges. *Note.* Numbers 1-5 indicate half year time intervals used to code time to estimate trajectories of COVID-19 disruption.1 = March 1, 2020-September 1, 2020, 2 = September 2, 2020-March 1, 2021, 3 = March 2, 2021 – September 1, 2021, 4 = September 2, 2021 – March 1, 2022, 5 = March 2, 2022-July 31, 2022. Underlying graphic underneath the red lines generated directly from Our World in Data website on October 25, 2023 (https://ourworldindata.org/covid-deaths#what-is-the-cumulative-number-of-confirmed-deaths)

### Deciding What Statistics to Use

Ultimately, we decided to measure COVID-19 spread using two measures: COVID-19 death rates and the Containment and Health Index (Hale et al., 2021). We chose to use COVID-19 death rate as a measure of COVID-19 spread because we believed it to be more accurate than reports of case rates and more readily applicable to youths' actual experiences of COVID-19 disruption than total excess mortality rates. We used the Containment and Health Index to measure the extent to which mitigation strategies were implemented in different nations because it is the only comprehensive measure of the stringency of COVID-19 mitigation strategies across nations that we are aware of. These features make it a truly unique index (Hale et al., 2021).

### Modeling How COVID-19 Spread Impacts Trajectories of COVID-19 Disruption

Having decided upon statistics, we then modeled how COVID-19 spread impacted trajectories of COVID-19 disruption. This model built on our baseline, unconditional model that estimated the overall COVID-19 trajectory by adding national COVID-19 death rates and stringency of COVID-19 mitigation strategies as predictors.

**National COVID-19 Death Rates** National COVID-19 death rates were significant predictors of intercept, linear slope, and quadratic slope of adolescent-reported COVID-19 life disruption (Table 3). When probed, these combined effects indicated that youth *who* were from countries with higher overall death rates compared to other countries in the sample reported greater life disruption until September 2020 (Supplemental Fig. 1). Then, the pattern switched, and from September 2020-March 2022, youth *who* lived in countries with lower overall death rates compared to other countries in the sample reported greater life disruption due to the COVID-19 pandemic (Supplemental Fig. 1). Finally, from March 2022-July 2022, it appears that national COVID-19 death rates were not associated with *who* among youth experienced disruption due to COVID-19. National COVID-19-related death rates also predicted *when* during the pandemic adolescents experienced life disruption (Table 3). From March 2022-July 2022, *when* adolescents lived in nations that experienced death rates that were higher than typical for

**Table 3** Primary model predicting adolescent life disruption due to COVID-19 from risk factors

| | B | SE | p |
|---|---|---|---|
| Baseline Model | | | |
| Intercept | **6.09** | **0.11** | **< 0.01** |
| Linear Slope | **0.38** | **0.10** | **< 0.01** |
| Quadratic Slope | **-0.10** | **0.23** | **< 0.01** |
| "Who" Between-Person Effects on Adolescent Life Disruption Due to COVID-19 Intercept | | | |
| COVID-19 Death Rate Per 100,000 people | **0.02** | **0.01** | **0.02** |
| Stringency of COVID-19 Mitigation Strategies | **-0.03** | **0.01** | **0.05** |
| "Who" Between-Person Effects on Adolescent Life Disruption Due to COVID-19 Linear Slope | | | |
| COVID-19 Death Rate Per 100,000 people | **-0.03** | **0.01** | **< 0.01** |
| "Who" Between-Person Effects on Adolescent Life Disruption Due to COVID-19 Quadratic Slope | | | |
| COVID-19 Death Rate Per 100,000 people | **0.01** | **0.00** | **< 0.01** |
| "When" Within-Person Effects on Adolescent Life Disruption Due to COVID-19 | | | |
| COVID-19 Death Rate Per 100,000 people | -0.01 | 0.01 | 0.57 |
| COVID-19 Death Rate Per 100,000 people * Time | -0.01 | 0.01 | 0.40 |
| COVID-19 Death Rate Per 100,000 people * Time$^2$ | **0.01** | **0.00** | **0.03** |
| Stringency of COVID-19 Mitigation Strategies | **-0.07** | **0.03** | **0.03** |
| Stringency of COVID-19 Mitigation Strategies * Time | **0.10** | **0.03** | **< 0.01** |
| Stringency of COVID-19 Mitigation Strategies * Time$^2$ | **-0.02** | **0.01** | **< 0.01** |

"Baseline Model" values are intercept, slope, and quadratic slope scores for the average adolescent in the data set before accounting for any "who" or "when" effects or covariates. In other words, these are values derived from the unconditional model that estimates a universal trajectory of COVID-19 disruption across the entire sample. COVID-19 Death Rate and Stringency of COVID-19 Mitigation strategy estimates are derived from the conditional model where these predictors are added to the unconditional model to predict intercept, slope, quadratic slope, and within-person time-specific "when" effects. Stringency of COVID-19 Mitigation Strategies did not significantly interact with linear or quadratic effect of time (i.e., was not a significant predictor of linear or quadratic slope), so those effects were trimmed from the model to ensure effect at intercept was properly interpreted. Effect estimates presented controlled for effects of culture group membership, adolescent age, adolescent gender, and parent education. Bolded values are significant at $p < .05$

that nation, adolescents experienced greater COVID-19 life disruption (B = 0.05, $p < .01$).

**Stringency of COVID-19 Mitigation Strategies** Stringency of COVID-19 mitigation strategies was a significant predictor of the intercept, but not linear or quadratic slope, of adolescent-reported COVID-19 life disruption (Table 3). Therefore, youth *who* were from countries with less stringent COVID-19 reduction measures compared to other countries reported greater COVID-19 disruption at the beginning of the pandemic, and this association persisted throughout the time period studied (2022). Stringency of COVID-19 mitigation strategies was also a significant predictor of *when* during the pandemic adolescents experienced life disruption (Table 3). Specifically, for the initial wave of the COVID-19 pandemic (March 2020-September 2020; B = − 0.07, $p = .03$) and latest months of the COVID-19 pandemic in this study (March 2022-July 2022; B = − 0.07, $p = .03$) *when* youth lived in nations that enacted COVID mitigation measures that were less stringent than typical for that nation (i.e., lower than the mean stringency index in that nation for the whole 2020–2022 time period), youth reported greater COVID-19 disruption.

### Question 3: How Do You Model Trajectories of COVID-19 Disruption Across Contexts?

Ultimately, we decided upon an analytic strategy that combined both etic and emic approaches. Specifically, in line with an etic approach, we did estimate one universal trajectory of COVID-19 disruption across cultures (as depicted in Fig. 2). That way, we could get some sense of COVID-19 disruption across our entire sample. Next, in line with an emic approach, we built on this one universal trajectory by including cultural group membership as a predictor of the universal trajectory's intercept, slope, and quadratic slope, to see whether youth from specific cultures differed from this universal trajectory of COVID-19 disruption. Cultures did indeed differ from this universal trajectory in both starting point and rate of change over time (as depicted in Fig. 3).

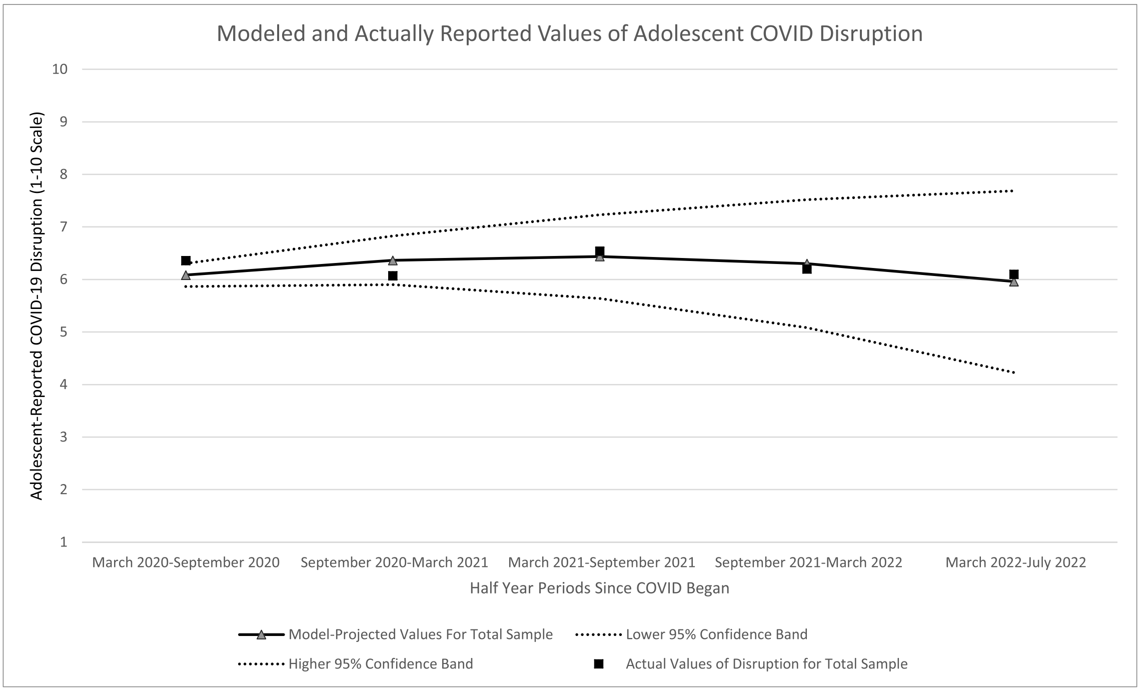


**Fig. 2** Modeled trajectory of adolescent-reported COVID-19 life disruption compared to actual mean levels of adolescent-reported COVID-19 life disruption in current sample. *Note.* Trajectory is a quadratic growth curve trajectory modeled in a multilevel modeling framework (see results for further details)

### Differences in Trajectories of COVID-19 Disruption by Environmental Context

Findings reported in Table 4; Fig. 3 indicate significant heterogeneity in youth COVID-19 life disruption starting points and rates of change by culture (see "Supplemental Results: Differences in Trajectories of COVID-19 Disruption by Environmental Context" for more specific detailed findings by culture). Youth from most cultures at most time points reported their life had been disrupted by COVID-19 between a "6" and a "7" on a 1–10 scale across the first 2.5 years of the pandemic, with peak levels of disruption occurring between March 2021-March 2022. However, some cultural groups demonstrated different patterns of COVID-19 disruption. The COVID-19 pandemic was most disruptive to the lives of US White and US Latino youth at its onset (with reported disruption scores over 7), before steadily decreasing over time. Youth from Rome, Italy and Chongqing, China reported low levels of disruption throughout the pandemic (as their scores remained below "6"). The pandemic was most disruptive to the lives of youth from Thailand and the Philippines from September 2021-July 2022, during which youth from both cultures reported disruption scores well above "7." Finally, the disruptive effects of the pandemic for Colombian youth seemed to decrease dramatically from March 2022-July 2022, as these youths' disruption scores fell below "4."

## Discussion

This study answered three methodological questions about how to investigate trajectories of COVID-19 disruption over time: how to code time, how to account for changes in COVID-19 spread, and how to model trajectories of COVID-19 disruption in different environmental contexts. Below we offer our recommendations for answering each of these questions, as well as potential alternative strategies one could use to answer these questions.

### How to Code Time: Consider the WHO Declaration Date and 6-Month Time Intervals

We used the date that the WHO officially declared COVID-19 a pandemic (March 11, 2020) as the starting point of our trajectories in this analysis, because it represented a uniform start point across our different cultural contexts (WHO, 2020a, b). For researchers investigating COVID-19 in cross-cultural studies, using this date may be sensible because it marks global experts' consensus evaluation of when the pandemic started worldwide (WHO, 2020a, b). Therefore, it seems to be a good starting point for the initiation of responses to the pandemic across most cultures. Indeed, within days of the WHO declaration, every nation in our sample had locked down schools and instituted nationwide mitigation strategies (Skinner et al., 2021).

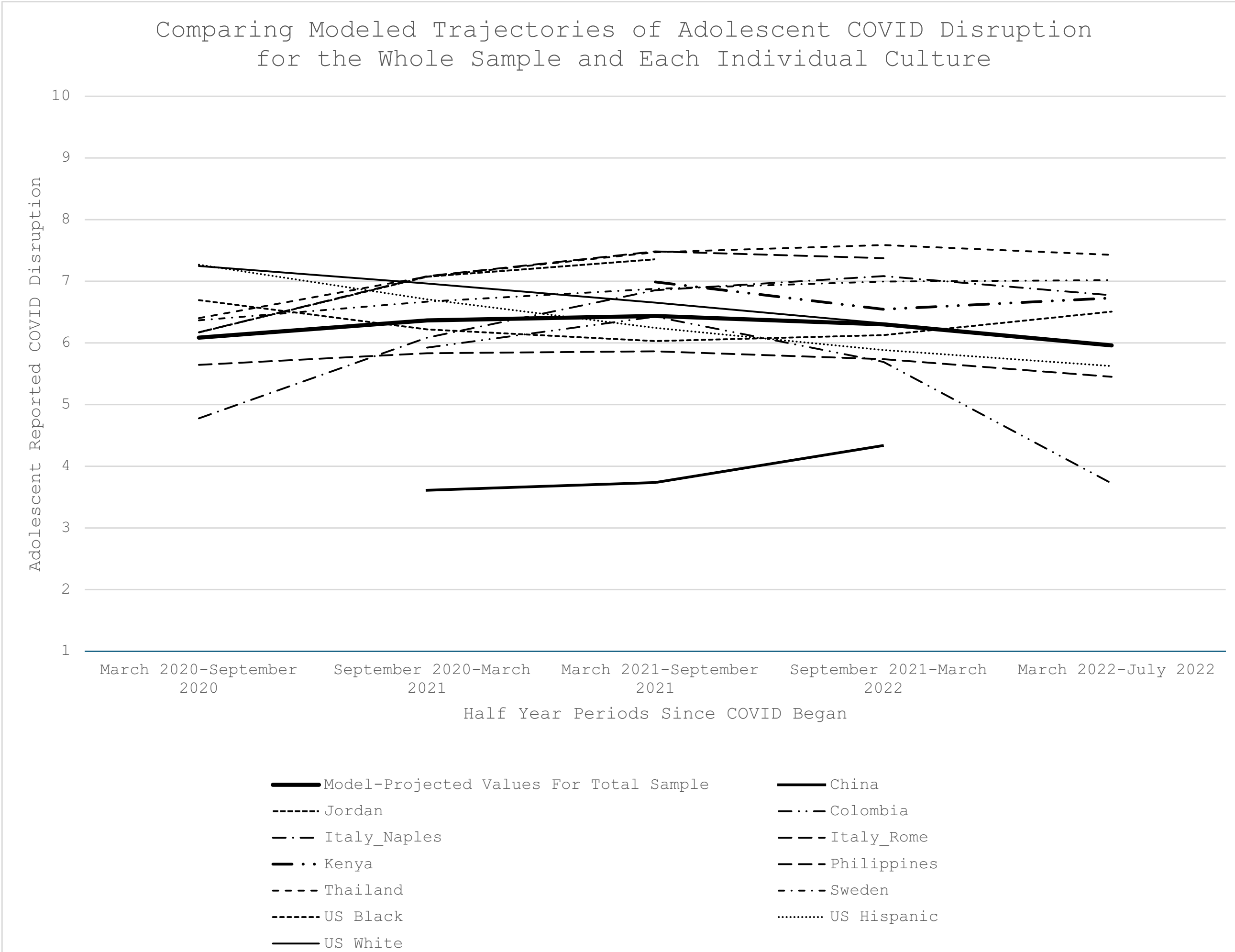


**Fig. 3** Differences in modeled trajectories of adolescent-reported COVID-19 life disruption across cultures. *Note.* Trajectories in each culture are only modeled at time points where the adolescents in that culture reported on their life disruption due to COVID-19. So for instance, the trajectory for the Chinese sample consists of only 3 time points because Chinese adolescents only reported on their COVID-19-related disruption between September 2020 and November 2021

However, for researchers investigating longitudinal trajectories of COVID-19 (or other pandemics/ecological disruptions) in specific cultural contexts, it alternatively might make sense to declare the first day that cases appeared in a specific context, or the first day the government in a specific context instituted mitigation strategies, or the first day of school closures in a specific context, as the official start of the pandemic. Given that researchers strongly suspect that the spread of COVID-19 itself and the institution of mitigation strategies because of COVID-19 are the two major causes of long-term COVID-19 disruption (Kauhanen et al., 2023; Pennix et al., 2022), identifying the first time either case rates or mitigation strategies emerged in a local context might be especially effective in marking the beginning of systematic effects of COVID-19 disruption in that context.

Alongside other longitudinal researchers (e.g., Larsen et al., 2023), we also had to grapple with the time intervals along which we should measure COVID-19 disruption. We ultimately found that 6-month time intervals optimally balanced model complexity and accuracy in measuring COVID-19 trajectories in our sample. However, in so doing, we also discovered a bit of a “quirk” in COVID-19 modeling: if a research team starts modeling COVID-19 trajectories around March 1, 2020 and measures along 6-month time intervals, each time interval will pretty accurately capture each worldwide “wave” of the pandemic (e.g., Fig. 1). That is why, all else being equal, we might suggest measuring trajectories of COVID-19 disruption every 6 months. Doing so allows for an understanding of how COVID-19 disruption changed during successive pandemic waves. But it also has another benefit: any time-varying covariates that one uses to predict

**Table 4** Overall trajectory of adolescent life disruption due to COVID-19 and differences by culture

| Cultural group | B | SE | *p* |
|---|---|---|---|
| Overall Sample Trajectory | | | |
| Intercept | **6.09** | **0.11** | **< 0.01** |
| Linear Slope | **0.38** | **0.10** | **< 0.01** |
| Quadratic Slope | **-0.10** | **0.23** | **< 0.01** |
| Culture-Specific Effects on Intercept | | | |
| Chongqing, China | **-2.30** | **1.00** | **0.02** |
| Medellín, Colombia | **-1.98** | **0.63** | **< 0.01** |
| Naples, Italy | **-1.34** | **0.55** | **0.01** |
| Rome, Italy | **-0.52** | **0.27** | **0.05** |
| Zarqa, Jordan | 0.14 | 0.65 | 0.83 |
| Kisumu, Kenya | **3.70** | **1.93** | **0.05** |
| Manila, Philippines | 0.07 | 0.36 | 0.84 |
| Trollhättan, Sweden | 0.30 | 0.35 | 0.39 |
| Chiang Mai, Thailand | 0.32 | 0.31 | 0.31 |
| U.S. Black | 0.64 | 0.52 | 0.21 |
| U.S. Latino | **1.28** | **0.44** | **< 0.01** |
| U.S. White | **1.30** | **0.35** | **< 0.01** |
| Culture-Specific Effects on Linear Slope | | | |
| Chongqing, China | -1.13 | 1.06 | 0.29 |
| Medellín, Colombia | **2.13** | **0.54** | **< 0.01** |
| Naples, Italy | **1.22** | **0.49** | **0.01** |
| Rome, Italy | -0.10 | 0.26 | 0.69 |
| Zarqa, Jordan | 0.89 | 0.61 | 0.15 |
| Kisumu, Kenya | -2.41 | 1.35 | 0.07 |
| Manila, Philippines | **0.88** | **0.45** | **0.05** |
| Trollhättan, Sweden | -0.04 | 0.44 | 0.93 |
| Chiang Mai, Thailand | 0.50 | 0.29 | 0.08 |
| U.S. Black | **-1.06** | **0.47** | **0.02** |
| U.S. Latino | **-1.07** | **0.41** | **< 0.01** |
| U.S. White | **-0.75** | **0.35** | **0.03** |
| Culture-Specific Effects on Quadratic Slope | | | |
| Chongqing, China | 0.38 | 0.25 | 0.13 |
| Medellín, Colombia | **-0.57** | **0.10** | **< 0.01** |
| Naples, Italy | -0.16 | 0.10 | 0.09 |
| Rome, Italy | 0.02 | 0.06 | 0.72 |
| Zarqa, Jordan | -0.22 | 0.12 | 0.06 |
| Kisumu, Kenya | 0.42 | 0.22 | 0.06 |
| Manila, Philippines | -0.17 | 0.14 | 0.21 |
| Trollhättan, Sweden | 0.06 | 0.11 | 0.57 |
| Chiang Mai, Thailand | -0.04 | 0.07 | 0.52 |
| U.S. Black | **0.26** | **0.10** | **< 0.01** |
| U.S. Latino | 0.17 | 0.09 | 0.07 |
| U.S. White | 0.10 | 0.08 | 0.19 |

First, we estimated the overall sample trajectory. Next, in line with an emic approach, we built on this one overall sample trajectory by including cultural group membership as a predictor of the universal trajectory's intercept, slope, and quadratic slope, to see whether youth from specific cultures differed from this universal trajectory of COVID-19 disruption. Each culture-specific effect estimate can be interpreted as the difference in the culture's intercept/linear slope/quadratic slope from the overall sample trajectories' intercept/linear slope/quadratic slope. Bolded values are significant at $p < .05$

individuals' perturbations off average trajectories of COVID-19 are made even more interpretable. For example, in our study, increased stringency of COVID-19 mitigation strategies seemed especially protective against COVID-19 disruption in the initial pandemic wave (Table 3). Of course, we also readily admit that many longitudinal investigations might investigate COVID-19 changes over different time scales (e.g., days, weeks, or years) and would be justified in choosing different time intervals, depending on the research question of interest.

## How to Account for Changes in COVID-19 Spread: Use Death Rates and the Containment and Health Index to Distinguish Who Was Impacted by COVID-19 Spread When

When capturing COVID-19 spread, it is especially difficult to determine which of many different statistics can be accurately used. Aligning with other developmental scientists (Kauhanen et al., 2023; Pennix et al., 2022), we believed capturing measures of both COVID-19 virus spread, and COVID-19 mitigation strategy spread are essential in evaluating COVID-19 disruption trajectories, because long-term difficulties due to COVID-19 emerge from both sources, and because spread and mitigation strategies often did not align across time and culture. We chose to capture COVID-19 spread using COVID-19 death rates because death rates appear more accurate than case rates across cultural contexts, but also more readily perceived and, therefore, impactful for developmental trajectories, than total excess mortality rates (i.e., youth were aware of the death rates being publicized daily via media outlets, whereas excess mortality rates were never given such attention). However, we could also see arguments for evaluating COVID-19 viral spread using case rates (e.g., especially when investigating the effects of COVID-19 sickness on daily functioning) or total excess mortality rates (e.g., especially when investigating the effects of COVID-19 policies on population outcomes) as well.

Regarding measuring stringency of COVID-19 mitigation strategies over time, we can think of no better index than the Containment and Health Index (Hale et al., 2021). It is a freely-available, daily compilation of the 13 mitigation strategies most experienced by people around the world throughout the COVID-19 pandemic on a country-by-country basis. Regardless of whether one is measuring case rates, death rates, total excess mortality rates, the Containment and Health Index, or any combination thereof, we highly recommend using Our World in Data's COVID-19 dashboard (Matheiu et al., 2023; https://ourworldindata.org/coronavirus). It is a free-to-use compilation of numerous COVID-19 statistics that is still updated frequently and includes visualizations and datasets for most nations on earth. It is an invaluable resource for longitudinal COVID-19 researchers.

Finally, given that the COVID-19 virus and COVID-19 mitigation strategies spread at different rates in different cultural contexts, and often not in tandem, we recommend group- and person-mean centering predictors of COVID-19 spread to determine *who* among study participants had their COVID-19 related trajectories most disrupted by these measures of spread, and *when* in the pandemic these measures of spread were especially salient for specific participants (Bauer & Curran, 2013). The fact that in our sample, both COVID-19 death rates and stringency of mitigation strategies predicted who among adolescents experienced the greatest COVID-19 disruptions and when such disruptions were highest speaks to the utility and validity of this group- and person-mean centering disaggregation strategy (Bauer & Curran, 2013). Notably, we centered these measures in a multilevel modeling framework, but this same process can also be accomplished in a latent growth curve modeling framework if longitudinal researchers so desire (Curran & Bauer, 2013).

### How to Model COVID-19 Trajectories in Different Environmental Contexts: Combine Etic and Emic Approaches

In studying COVID-19 and other ecological disruptions that span multiple contexts, longitudinal investigators have to constantly balance etic approaches (which examine universal developmental trajectories and processes) and emic approaches (which examine culture-specific developmental trajectories and processes; Harris, 1976, Lansford et al., 2016). We recommend selecting analytic methods that balance both perspectives. We did so by using multilevel modeling techniques to identify one overall average trajectory of COVID-19 disruption in youth across cultural contexts (an etic approach) and then investigating how cultures significantly differed from this overall trajectory in starting point and rate of change (an emic approach). However, certain analytic decision points differently balance etic and emic perspectives. For instance, by estimating one universal trajectory that best fit all the youth in our sample (Fig. 2) and then estimating culture-specific effects (Fig. 3), we are making a statistical assumption: That culture-specific trajectories differ in starting point and rate of change, *but not shape* from our overall trajectory. In other words, our modeling approach assumes that youth from different cultures in our sample all follow the same quadratic-growth curve shaped trajectory. This is an analytic choice that slightly favors an etic approach, because it only allows culture-specific deviations from one universally-shaped trajectory.

In contrast, other analytic approaches (like multiple group latent growth-curve modeling), lean towards a slightly more emic perspective. For instance, in multiple group latent growth curve modeling, the first empirical evaluation of trajectories from different contexts is if they significantly differ in shape (e.g., linear, quadratic, etc.), and not just starting point and rate of change (Curran & Bauer, 2013). This test increases validity in an emic sense (by allowing each culture to have its own trajectory shape) but decreases generalizability in an etic sense (by making comparisons between cultures much more difficult). We do not think either of these analytic methods is more "correct" than the other: they both just weigh etic and emic perspectives differently. We do think both of these types of quantitative methods are valuable, because they attempt to combine etic and emic approaches to different degrees. It is only through such combined modeling strategies that both the global and local conditions that determine COVID-19 disruption can be identified (Park et al., 2021).

## Strengths and Limitations

The current study has several strengths, including its longitudinal, cross-cultural nature, use of administrative data about death rates and COVID-19 mitigation strategies, and ability to balance emic and etic approaches to examine COVID-19 disruption trajectories. However, it also has several limitations. COVID-19 disruption is measured by a single item reported on by a single reporter. Future work could examine more "objective" measures of COVID-19 life disruption, such as scholastic performance on standardized tests or early career earnings. Additionally, although the current study samples are representative of the local geographic areas from which they are drawn, they are not nationally representative. Therefore, study inferences cannot be generalized to national populations, and future work estimating trajectories in nationally representative samples is needed. Finally, although longitudinal in nature, the current study is observational. Therefore, true causal effects of death rates and COVID-19 mitigation strategies on youth COVID-19 life disruption cannot be inferred.

## Conclusion

Despite these limitations, we hope that the current study can serve as a baseline with which future longitudinal investigations of COVID-19 and other ecological disruptions can compare their methods. In the context of cross-cultural longitudinal investigations of COVID-19 like ours, we recommend starting the modeling of trajectories on March 11, 2020, measuring disruption along 6 month time intervals, capturing COVID-19 spread using death rates and the COVID-19 Health and Containment Index, and using methods that combine etic and emic approaches to model trajectories. In offering these suggestions, we hope to start methodological conversations among longitudinal researchers that ultimately result in the proliferation of research on the longitudinal impacts of COVID-19 in youth that the world so badly needs.

**Supplementary Information** The online version contains supplementary material available at https://doi.org/10.1007/s11121-024-01726-2.

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## Declarations

**Ethics Approval** This study was approved by the appropriate institutional review boards at universities in each of the participating countries, including the institutional review boards at Duke University, USA, University of Macau, China, Università di Roma "La Sapienza," Italy, University West, Sweden, Chiang Mai University, Thailand, Chonqing Medical University and Duke Kunshan University, China, Masen University, Kenya, Universidad de San Buenaventura, Colombia, Ateneo de Manila University, Philippines, Hashemite University, Jordan, and University of Naples "Federico II," Italy. The study was performed in accordance with the ethical standards as laid down in the 1964 Declaration of Helsinki and its later amendments.

**Consent to Participate** All study participants provided written consent to participate in this research investigation in accordance with applicable ethical standards.

**Conflict of Interest** The authors declare no competing interests.

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