Lifestyle and mental health disruptions during COVID-19

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Using a longitudinal dataset linking biometric and survey data from several cohorts of young adults before and during the COVID-19 pandemic ($N = 682$), we document large disruptions to physical activity, sleep, time use, and mental health. At the onset of the pandemic, average steps decline from 10,000 to 4,600 steps per day, sleep increases by 25 to 30 min per night, time spent socializing declines by over half to less than 30 min, and screen time more than doubles to over 5 h per day. Over the course of the pandemic from March to July 2020 the proportion of participants at risk for clinical depression ranges from 46% to 61%, up to a 90% increase in depression rates compared to the same population just prior to the pandemic. Our analyses suggest that disruption to physical activity is a leading risk factor for depression during the pandemic. However, restoration of those habits through a short-term intervention does not meaningfully improve mental well-being.

COVID-19 | mental health | lifestyle disruptions | physical activity

A mental health crisis has emerged during the COVID-19 pandemic. The US Centers for Disease Control and Prevention (CDC) estimates that as of June 2020 nearly one-third of US adults were suffering from anxiety or depression (1). The rates are almost two times higher for young adults, a population that has already seen a significant increase in the prevalence of mental health disorders over the past decade (2). Over 60% of individuals age 18 to 24 y were estimated to be at risk for depression or anxiety and a quarter reported considering suicide in the previous month. These estimates represent a large increase in depression rates compared to about 11% of all adults in 2019 (3) and about 25% of college students prior to the pandemic (4). The rise in depression has occurred at the same time that stay-at-home orders, campus closures, and social distancing measures have caused major disruptions to everyday life, altering the way people live, work, study, and interact.

In this paper we document disruptions in physical activity, sleep, and time use among young adults at the onset of the pandemic and examine the relationship between these disruptions and mental health. We take advantage of a wellness study that has enrolled multiple cohorts of US college students from February 2019 through July 2020. Participants received wearable devices (Fitbits) and answered repeated surveys about their well-being and time use over the course of a semester. Participants in the 2020 cohort began the study in February and continued participating after the university moved all classes online in March and encouraged students not to return to campus.

These data allow us to make two primary contributions. First, we can conduct longitudinal analysis examining how physical activity and mental health have evolved during the pandemic compared both to baseline prepandemic levels as well as to prior cohorts. The use of prepandemic data are critical as the studied behaviors exhibit significant seasonal patterns. Second, we can link biometric measures of physical activity and sleep to survey measures of mental well-being and social distancing. This approach allows us to identify risk factors for depression during COVID-19 and compare those factors to predictors of depression prior to the pandemic.

We first document large changes to physical activity and sleep. Over the course of the 3-mo semester, average steps decline by over half from 10,000 to 4,600 steps per day, overall physical activity declines by about a third from 4.4 h to 2.9 h per day, and sleep increases by about 25 to 30 min per night. We also find dramatic shifts in self-reported time use. Time spent socializing with others declines by over half to less than 30 min per day, while screen time more than doubles to over 5 h per day (excluding screen time for classes or work). These lifestyle disruptions stand alongside stark increases in depression during the pandemic. We estimate that at the end of the spring 2020 semester in April an estimated 61% of our participants were at risk for clinical depression. This represents about a 90% increase over rates of 32% in the same population just 2 mo earlier prior to the pandemic.

Using difference-in-differences and individual fixed-effects regressions, we show that the changes in physical activity, sleep, social interactions, screen time, and depression are all statistically significant compared to changes in prior cohorts ($P < 0.001$). The concurrent decline of both physical activity and mental health is particularly worrisome, as prior work suggests that the coexistence of mental health problems alongside poor physical activity worsens overall health outcomes (5). In line with this work, we find that large declines in physical activity during COVID-19 are associated with 15 to 18 percentage point higher rates of depression compared to small disruptions in baseline habits ($P = 0.012$).

To link lifestyle and mental health we exploit our rich longitudinal data and use tree-based classification methods to identify

Significance

COVID-19 has affected daily life in unprecedented ways. Drawing on a longitudinal dataset of college students before and during the pandemic, we document dramatic changes in physical activity, sleep, time use, and mental health. We show that biometric and time-use data are critical for understanding the mental health impacts of COVID-19, as the pandemic has tightened the link between lifestyle behaviors and depression. Our findings also suggest a puzzle: Disruptions to physical activity and mental health are strongly associated, but restoration of physical activity through a short-term intervention does not help improve mental health. These results highlight the large impact of COVID-19 on both lifestyle and well-being and offer directions for interventions aimed at restoring mental health.

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risk factors for depression during COVID-19. Taken together, the predictors of depression in the 2020 cohort differ significantly from prior cohorts ($P < 0.001$). When we examine specific risk factors we find that changes in lifestyle behaviors are more closely linked to depression during the pandemic than in prior cohorts. In particular, large disruptions in physical activity emerge as a leading risk factor for depression during COVID-19. In contrast to prepandemic cohorts in which there is little relationship between disruptions and mental health, those participants who sustain their baseline exercise habits during the pandemic are at significantly lower risk of depression.

Building on this analysis, after the spring 2020 semester ended in April we continued to track a subsample of our participants through July 2020. During this period, we find evidence of a partial "bounce back" in physical activity and mental health toward baseline levels. Average daily steps increase to about 6,400 steps per day in May and remain steady through July, closing about a third of the decline from the onset of the pandemic in March and April. There is also some decline in average measures of depression, with estimated rates of depression ranging from 46% to 50% in May through July. This represents an improvement compared to the end of the semester in April but remains flat over this period and is still about 50% higher than prepandemic rates.

In order to examine whether a policy intervention could help counteract some of the adverse impacts of the pandemic, we implemented a randomized intervention halfway through this period. Building on our findings and on prior work on the link between physical activity and mental health (6), in June 2020 we randomized half of our participants to receive incentives for walking at least 10,000 steps per day for 2 wk. Our intervention significantly increased average steps by about 2,300 steps per day and physical activity by almost 40 min per day compared to the control group ($P < 0.001$), with the treatment group close to their baseline prepandemic levels. However, the impact on exercise did not translate into an improvement in mental health measured at the end of the intervention period.

In a postintervention follow-up we find that average steps in the treatment group declined to the same levels as in the control group about a week after the intervention ended. In July 2020, 1 mo after the intervention ended, we find no differences in average measures of depression between treatment participants who were randomized to the physical activity intervention and participants in the control group.

Our study contributes to the growing literature examining the impact of the coronavirus pandemic on physical activity and mental well-being. Lifestyle disruptions during COVID-19 have been documented in studies focusing on a single type of behavior, such as exercise (7), sleep (8), social distancing (9, 10), or mental health (11–21). While our sample is not nationally representative, our measures of mental health are in line with those from larger and nationally representative samples using various measures of mental health both prior to the pandemic (4) and during the pandemic (1, 22).[*]

Related work using cross-sectional data finds an association between self-reported changes in physical activity during the pandemic and measures of mental health (25). This paper also relates to the broader research on the determinants of mental health (26–30) as well as work on health behavior change. Prior studies demonstrate how changing circumstances or context can quickly disrupt healthy habits (31, 32). In addition to documenting such disruptions as a consequence of the pandemic, our work investigates the relationships between disruptions in lifestyle habits and well-being.

Taken together, our findings suggest a puzzle: Why are disruptions to physical activity and mental health strongly associated but restoration of physical activity through our intervention does not meaningfully improve mental health? First, the impact of physical activity may require a longer-term intervention. Second, physical activity may have important interactions with other lifestyle behaviors such as social interactions. It may also reflect correlation with other unobserved determinants of mental health. Finally, it could be the case that the relationship between physical activity and depression is driven more by mental health than it is by lifestyle habits. For example, the strong association between maintenance of healthy habits and depression during COVID-19 could partially reflect individuals' ability to adapt to adversity and sustain their lifestyle despite the pandemic. Such resilience in the face of large disruptions may be critical for well-being during COVID-19.

Data and Methods

Enrollment and Data Collection. We enrolled three cohorts of students from the University of Pittsburgh in the study: spring 2019, fall 2019, and spring 2020. The study was approved by the University of Pittsburgh Institutional Review Board and was preregistered in the American Economic Association Randomized Controlled Trials (AEA RCT) Registry (RCT ID AEARCTR-0003235). Data and materials can be accessed at Open Science Framework (https://osf.io/f85e3/) (33). A detailed description of the methods and measures can be found in *SI Appendix*.

At the beginning of each semester, we invited college students at the University of Pittsburgh to participate in a semester-long experiment on wellness. Eligible participants signed a consent form in the laboratory at the beginning of the study. They then filled out a baseline survey, received a wearable tracker (a Fitbit Alta HR device), and installed a custom-made smartphone application on their phone which allowed us to track their Fitbit data.

Throughout the semester we continuously collected daily Fitbit data, which measures steps, physical activity, and sleep based on heart rate and movement. We also collected weekly measures of time use through a diary survey following the structure of the American Time Use Survey (34).[†]

We measured mental health at the beginning, middle (spring 2020 only), and end of the semester. Our primary measure of mental health is depression, which we assessed using the Center for Epidemiologic Studies Depression Scale (CES-D) (35). The CES-D is a validated self-report instrument designed to assess the frequency of symptoms of depression, such as helplessness or loneliness, on a scale from 0 (rarely or none of the time) to 3 (most or all of the time) and has a total score between 0 and 60. Our primary benchmark for depression is a CES-D score of 16 or above, which is considered the cutoff for clinical concern, implying high levels of depressive symptoms (36). We additionally assessed anxiety, resilience, and life satisfaction.

In the spring 2020 cohort we continued to track a subsample of participants who agreed to continue their participation after the semester ended in April 2020. In June 2020 we randomized half of the participants to an intervention group to increase physical

[*]The Healthy Minds Network report (https://healthymindsnetwork.org/wp-content/uploads/2020/09/Healthy_Minds_NCHA_COVID_Survey_Report_FINAL.pdf) estimated that 40% of surveyed college students were at risk for depression based on the Patient Health Questionnaire-9 scale (23) in a self-selected sample that is not nationally representative from March to May 2020. The CDC estimated 52.3% of adults age 18 to 24 y were suffering from depression using the Patient Health Questionnaire scale-4 (24) in a nationally representative sample from 24 to 30 June 2020 (1). Further, using a representative sample of US adults, ref. 21 estimates that depression rates are threefold higher during the pandemic.

[†]For 4 wk during the middle of the semester we randomly assigned participants to interventions aimed at improving sleep habits (see *SI Appendix*, section 1 for details). We include controls for treatment assignment in our analysis and find no predictive power of treatment on our outcomes of interest.

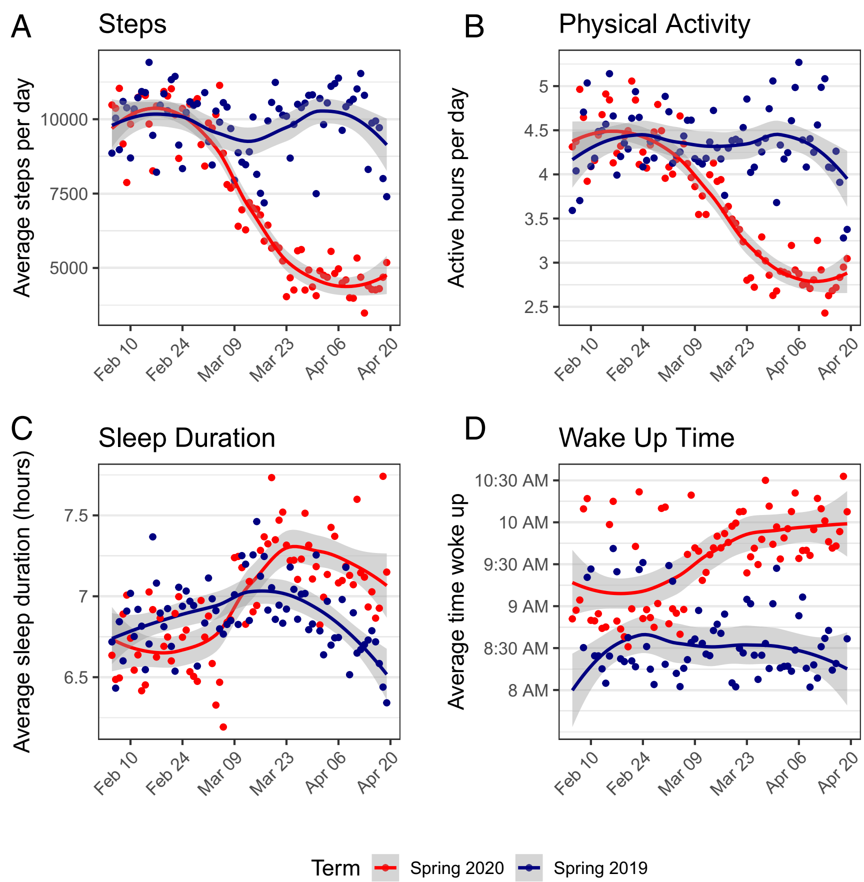

Fig. 1. (*A*–*D*) The figure plots the average outcomes by day for study participants in the spring of 2019 (red) and spring of 2020 (blue). Gray shading indicates 95% confidence intervals for the locally weighted smoothing curve.

activity and half to a control group for a 2-wk intervention period. This RCT was preregistered in the AEA RCT Registry (RCT ID AEARCTR-0005949). We measured mental health in May just before the intervention, mid-June at the end of the intervention, and mid-July a month after the intervention ended.

Sample and Analysis. Our sample includes all participants for whom we have a baseline survey, including baseline mental health measures: spring 2019 (n = 150), fall 2019 (n = 315), and spring 2020 (n = 316).[‡] The combined cohorts include $N = 682$ unique participants. In *SI Appendix*, Fig. S.1 we report the sample sizes at each stage of the study.

We present descriptive statistics for our sample in *SI Appendix*, Table S.1. While our sample is not nationally representative, as we noted above, our measures of baseline mental health are in line with estimates from representative surveys. We present estimates reweighted to match a nationally representative sample on gender, age, and race/ethnicity and the results do not change (*SI Appendix*, Table S.11).

The main analyses include all participants who have at least one observation for the relevant outcome. We examine attrition directly and also conduct several sensitivity checks to address attrition concerns (*SI Appendix*, section 4B). Unless noted otherwise below, our results are robust to these sensitivity analyses.

[‡]In the spring 2020 cohort, 99 of the participants first enrolled in the study in fall 2019 and continued their participation in spring 2020. The results are robust to excluding these participants from the spring 2020 analysis (*SI Appendix*, Table S.13).

Results

Lifestyle Disruptions. Our biometric and time use measures reveal that the pandemic led to major disruptions in daily behavior. Fig. 1 plots average daily physical activity and sleep across the semester for the spring 2019 and spring 2020 cohorts.

In the spring 2019 cohort, daily steps are fairly constant, with an average of about 10,300 to 10,400 steps throughout the term (Fig. 1*A*). At the beginning of the semester (February), the spring 2020 cohort is statistically indistinguishable from the spring 2019 cohort. In March, there is a sharp drop in the average number of steps from 10,000 to 4,600, a more than 50% decline ($P < 0.001$, from a regression of difference-in-differences across cohorts, *SI Appendix*, Table S.2, Panel B). We observe a similar pattern for physical activity (Fig. 1*B*), which is measured as minutes in which a person is nonsedentary for at least 10 continuous minutes, where nonsedentary minutes are defined as activity that raises heart rate enough to burn at least 1.5 times as many calories as at rest. Time spent in active (nonsedentary) activities dropped by about 1.5 h from 4.4 h to 2.9 h per day. The decline in active hours throughout the term is 10 times larger than in 2019 ($P < 0.001$; *SI Appendix*, Table S.2, Panel B). These results are robust to corrections for attrition and incomplete syncing (*SI Appendix*, section 4B).

We also find disruptions to sleep habits (Fig. 1*C*), as students started to sleep about 25 to 30 min more per night throughout the pandemic ($P < 0.001$; *SI Appendix*, Table S.2). As shown in Fig. 1*D*, the increase in sleep is driven by later wake-up times: Average wake times shift by 30 to 40 min from about a quarter after 9 AM to a little before 10 AM ($P < 0.001$; *SI Appendix*, Table S.2). There is little change in bedtimes (*SI Appendix*,

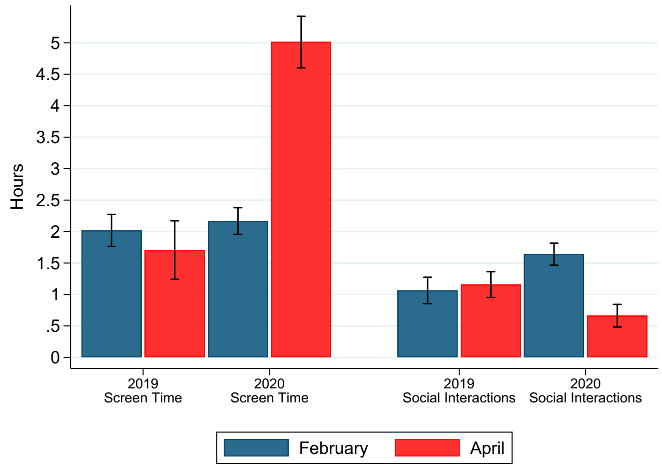

Fig. 2. Screen time and social interactions. The figures show the average time spent with friends (social time) and the average screen time at the beginning (February) and end (April) of the semester during the spring 2019 and spring 2020 terms. Screen time includes time spent playing games, watching television, or surfing the Internet and does not include time spent working or studying on a device. Bars indicate 95% confidence intervals.

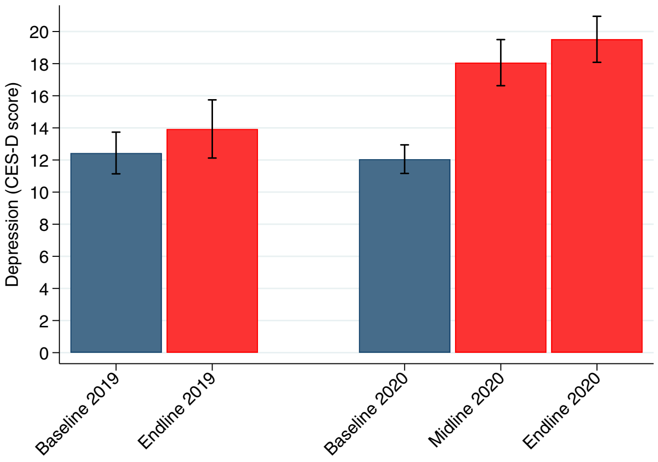

Fig. 3. Depression. The figures show the average CES-D score at the beginning (February), middle (March 2020 only), and end (April) of the semester during the spring 2019 and spring 2020 terms. Bars indicate 95% confidence intervals.

Fig. S.5). Previous studies document that misalignment of sleep timing with respect to the natural dark–light cycle may have detrimental effects on sleep quality, health, and depression (37–40). Thus, the later timing of sleep during the pandemic may have contributed to mood disorders or exacerbated depression symptoms in individuals predisposed for mental health disorders. We note, however, that the estimated impacts of the pandemic on sleep are less robust than those for active hours and steps. There are baseline differences in the sleep habits of our cohorts and so they may not be as comparable, and the estimates are sensitive to corrections for attrition (*SI Appendix*, Table S.7). The imbalance on sleep across cohorts may also bias our estimates of the impact of the pandemic on physical activity.

We next examine shifts in self-reported time use. Fig. 2 shows average daily social interactions and screen time in February compared to April for the spring 2019 and spring 2020 cohorts. In the 2020 cohort, screen time—time spent watching TV, playing video games, or surfing the internet outside of work or studying—more than doubled after the announcement that classes would be moved remotely, reaching an average of 5 h per day at the end of the term. By contrast, screen time averaged around 2 h per day throughout the semester in 2019 with only a moderate decrease at the end of the term ($P < 0.001$; *SI Appendix*, Table S.2, Panel C). We also observe a substantial drop in the number of hours spent interacting with friends, from approximately 1.5 h per day at the beginning of 2020 to less than 30 min per day at the end of April, a more than 50% decline ($P < 0.001$; *SI Appendix*, Table S.2, Panel C). This drop is consistent with self-reported declines in face-to-face interactions (*SI Appendix*, Fig. S.6). In *SI Appendix* we also document a drop in the number of work hours—driven by a subset of our participants who lost their jobs as a result of the campus closure—and a significant drop in the number of hours spent studying in the second half of the semester (Table S.2, Panel C).

Mental Health. Our primary measures of mental health are assessments of depression using the CES-D scale. Fig. 3 shows average CES-D scores for the spring 2019 and spring 2020 cohorts. We present the baseline measures taken at the beginning of the semester (February), the midsemester measures taken in March (spring 2020 cohort only), and the end-of-semester measures taken in April.

Our results show large increases in depression during the pandemic. In the spring 2019 cohort, we estimate a 1.5-point increase in average CES-D scores over the term from 12.4 at the beginning of the semester to 13.9 at the end of the semester. The spring 2020 cohort has very similar scores at baseline, averaging 12.1 at the beginning of the semester. However, the estimated increase in scores across the term is over four times larger than in spring 2019. We estimate that average CES-D scores increase from 12.1 to 19.5, a more than 60% increase ($P < 0.001$ from a difference-in-differences regression across cohorts; *SI Appendix*, Table S.2, Panel A).[§].

As shown in *SI Appendix*, we find directionally similar results when we look at anxiety using the Generalized Anxiety Disorder (GAD-7) scale (*SI Appendix*, Table S.2 and Table S.3, Panel A).

The pandemic shifted the distribution of CES-D scores with a substantial increase in the share of subjects with a CES-D score above 15, the threshold commonly used to identify clinical depression (*SI Appendix*, Fig. S.4). By the end of the semester in April 2020 we estimate that 61% of our participants were at risk for depression, about a 90% increase over the baseline rate of 32% just 2 mo earlier prior to COVID-19 ($P < 0.001$). By comparison, these same rates increase by only 6 percentage points over the course of the spring 2019 semester from 31% to 37% ($P = 0.30$). Using Lee bounds (41), we estimate a difference-in-difference increase in depression rates of 15 to 24 percentage points in spring 2020 compared to spring 2019 ($P < 0.001$; *SI Appendix*, Table S.7).[¶]

About 80% of the increase in CES-D scores occurs by the time of the midline survey in March 2020 (20 March). This pattern aligns with the timing of lifestyle disruptions shown in Fig. 1, in which, for example, average daily steps largely decline within a 2-wk period in the middle of March and then plateau.

Lifestyle Changes and Depression. Building on the analysis above, we examine the link between the large disruptions to behaviors

[§]We restrict the baseline sample to participants who also answered the endline survey. Average baseline CES-D scores are similar if we include all participants, 12.6 and 12.8 in 2019 and 2020, respectively.

[¶]We note that the increase in the proportion of the population at risk for depression may overstate the true increase given that there are false positives using the CES-D scale.

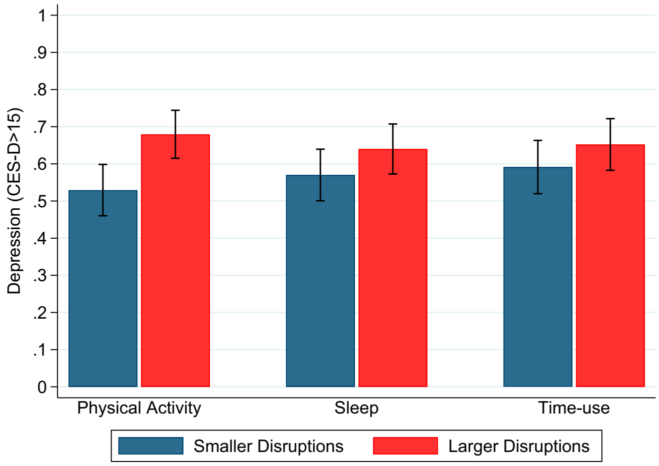

Fig. 4. Habit disruptions and depression. The figure reports the proportion of individuals reporting clinical depression (CES-D>15) below (smaller disruptions) and above (larger disruptions) median change in physical activity (steps and active minutes), sleep (duration and wake-up time), and time use (screen time and social interactions). Bars indicate 95% confidence intervals.

during the pandemic and endline depression in 2020. We measure lifestyle changes as the difference between average behavior during the onset of the pandemic in March and April minus average baseline behavior in February. Fig. 4 compares rates of depression among participants with smaller and larger disruptions using below-vs. above-median changes in physical activity, sleep, and time use.[#]

Larger declines in physical activity are associated with significantly higher rates of depression. There is a 15 to 18 percentage point gap in depression rates between participants who experience large disruptions and those who maintain their baseline habits ($P = 0.012$; *SI Appendix,* Table S.17). These results are robust to Anderson (2008) corrections (42) for multiple hypothesis testing ($P = 0.036$). We additionally examine the relationship between students' location during lockdown and endline depression (by the end of the term approximately 79% of students were not in Pittsburgh). We find no evidence of an association between depression and locations with higher COVID-19 cases or deaths (*SI Appendix,* Table S.19).

Risk Factors for Depression. To better understand the dramatic rise in depression during COVID-19, we combine our rich data to identify risk factors for depression in the spring 2020 cohort. We then compare those predictors to prior cohorts (pooling the spring 2019 and fall 2019 cohorts). We focus on risk factors for having an end of semester CES-D score that meets or exceeds 16, the threshold for clinical depression (36).

Building on the above results suggesting the importance of lifestyle disruptions, we focus on a "differences" model that uses changes in lifestyle measures (physical activity, sleep, and time use) along with baseline measures of mental health and demographics. We feed these variables as potential features into the XGBoost machine-learning algorithm (43), a flexible and robust decision tree-based classification method. The pooled 2019 and spring 2020 models achieve 89% and 91% predictive accuracy, respectively (i.e., the overall percentage of observations that are correctly predicted by the model). See *SI Appendix,* section 5 for the full list of variables and a detailed description of the prediction exercise.

Before pooling the 2019 cohorts we first estimated the model for each cohort: spring 2019, fall 2019, and spring 2020. We then examined the accuracy of the spring 2019 model for predicting endline depression in fall 2019 compared to predicting endline depression in spring 2020. We find that the spring 2019 model is significantly more accurate for fall 2019 than for spring 2020 ($P < 0.001$). These results suggest an overall shift in risk factors for depression during the pandemic compared to prior cohorts.

We find further support for this hypothesis when comparing the specific risk factors for depression across cohorts. Fig. 5*A* reports the cumulative importance—adding up to 1—of the different features for the pooled 2019 and spring 2020 cohorts, grouped by category. Below the figure we list the three most important features for each model along with their relative importance, which approximates the average gain in predictive accuracy from using that feature in the model.

There are substantial shifts in the importance of each category across cohorts. For the 2019 cohorts, who participated prior to the pandemic, baseline measures of mental health at the beginning of the semester largely explain depression rates at the end of the semester, with baseline depression by far the leading factor, accounting for an estimated 36% of the predictive accuracy of the model. The cumulative importance of the baseline mental health measures declines during the pandemic from 0.57 in 2019 to 0.31 in 2020, though not all of the measures move in the same direction. Baseline measures of depression and life satisfaction decline in relative importance in 2020, while baseline measures of anxiety and resilience increase in relative importance compared to prepandemic cohorts.[‖] Our results suggest that those most resilient to stress and least susceptible to anxiety may be especially protected against depression during the pandemic (*SI Appendix,* Fig. S.15). This is in line with work suggesting that resilience protects individuals against stressful events (27) and helps them preserve their health despite adversity (44).

Differences between endline and baseline lifestyle behaviors (physical activity, sleep, and time use) become more important in 2020: Their cumulative importance increases from 0.34 in 2019 to 0.58 in 2020. The increased importance of these measures suggests that the pandemic has tightened the link between between lifestyle behaviors and mental health. In particular, disruptions in physical activity emerge as a critical predictor of depression during COVID-19, increasing in estimated relative importance from 0.026 to 0.114.

The importance to well-being of maintaining physical activity is illustrated in Fig. 5*B*. The figure displays estimated Shapley Additive Explanations (SHAP) values by differences in physical activity. A SHAP value approximates the marginal contribution of a feature to a particular observation's predicted risk, where a higher SHAP value indicates a higher risk of endline depression. In the 2020 cohort, depression risk increases substantially with larger declines in daily active hours, while in 2019 the relationship is largely flat. The high-risk group in 2020 experiences a decline of about one to three fewer daily active hours (around the 2020 average of 1.5 h), with disruptions of such magnitude largely absent in the 2019 cohort. Importantly for the 2020 cohort, those participants who maintain daily active hours similar to baseline (i.e., differences near zero) demonstrate strikingly lower risk of endline depression. These results suggest that sustaining healthy physical habits is strongly associated with well-being during the pandemic.

[#] We measure changes by averaging the z-scores for each outcome within a category: physical activity (steps and active minutes), sleep (duration and wake-up time), and time use (screen time and social interactions). In *SI Appendix*, Fig. S.14 and Table S.18 we report each measure separately and the results are similar.

[‖] Baseline resilience is the fourth most important factor in both 2019 and 2020, increasing in relative importance from 0.049 to 0.076.

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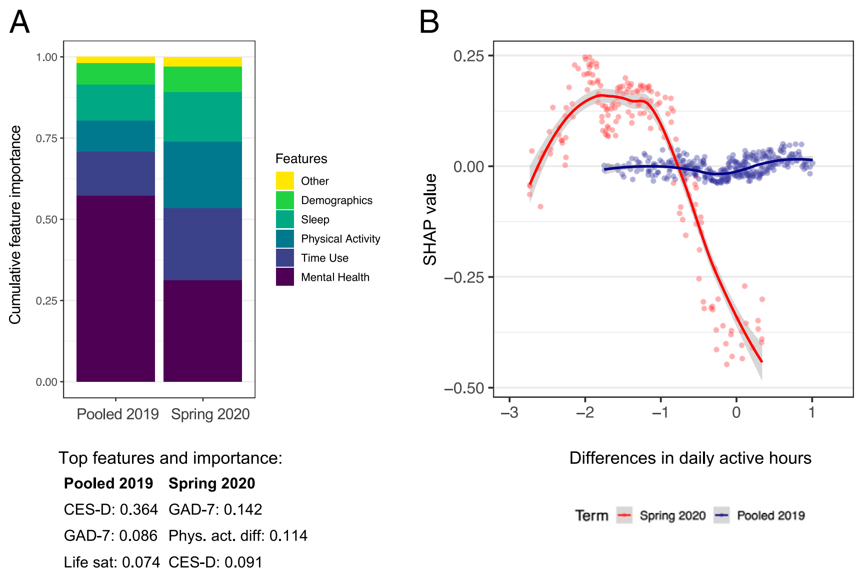

Fig. 5. Risk factors for depression. (*A*) The relative importance (out of 1) in the 2019 pooled cohorts and 2020 cohort of variables grouped by baseline mental health; differences between endline and baseline levels of physical activity, sleep, and time use; demographics; and other (baseline self-reported health and treatment assignment in our sleep intervention). We report the top three most important features and their relative importance in the pooled 2019 and spring 2020 cohorts: CES-D measures baseline depression, GAD-7 measures baseline anxiety, Life sat. measures baseline life satisfaction, and Phys. act. diff. measures differences in average daily active minutes between endline and baseline. (*B*) Estimated SHAP values by physical activity differences for the pooled 2019 and spring 2020 cohorts, where higher SHAP values indicate higher risk of depression. Gray shading indicates 95% confidence intervals for the locally weighted smoothing curve.

We find similar results if we exclude baseline mental health measures as potential risk factors: The importance of lifestyle behaviors increases in 2020 and disruption to physical activity is the leading predictor of endline depression during COVID-19 (*SI Appendix*, Fig. S.18). We also report the results of "baseline" models that use baseline measures of lifestyle habits rather than differences (*SI Appendix*, section 5C). In line with our main results, the importance of baseline lifestyle behaviors increases in 2020 compared to 2019. Also, some of the typical relationships between baseline habits and endline depression diverge during the pandemic. For example, whereas walking the recommended 10,000 steps per day minimizes depression risk in prepandemic cohorts, these same baseline activity levels are associated with increased risk of depression during the pandemic.[**]

Improving Physical Activity and Mental Health. In the 2020 cohort we continued to track a subsample of our participants after the semester ended in April. These participants (n = 205) filled out a consent form, agreed to continue wearing the Fitbit, and completed weekly time-use surveys as well as mental health surveys in May, June, and July. We find that in May lifestyle behaviors—and physical activity in particular—demonstrate a "bounce-back" moving toward baseline levels. As shown in Fig. 6*A*, we find that daily steps increase from 4,600 in April to 6,400 in May, which closes a third of the decline from baseline ($P < 0.001$; *SI Appendix*, Table S.25). We also observe small decreases in sleep duration of about 10 min ($P < 0.05$) and a small increase in social interactions of about 10 min ($P = 0.10$), while screen time continues to increase ($P < 0.01$; *SI Appendix*, Table S.25).

In June 2020 we implemented a randomized intervention to further stimulate physical activity among our participants. We randomly assigned participants to receive incentives for walking a minimum of 10,000 steps a day. Participants in the treatment group received a monetary transfer of $5 every day they reached the minimum number of steps. The control group received a similar distribution of payments (see *SI Appendix* for experimental procedures). The intervention began on 1 June and lasted 14 consecutive days. After the end of the intervention, on 16 June, we measured mental health again. Then, we continued to track the subjects through July and measured mental health on 17 July.

As shown in Fig. 6*A*, the intervention had a large impact on physical activity, increasing average steps by about 2,300 steps ($P < 0.001$) and active minutes by almost 40 min ($P < 0.001$; *SI Appendix*, Table S.26 and Fig. S.19). As a result, daily steps in the treatment group approached baseline prepandemic levels, averaging approximately 9,000 steps per day. On average, participants in the treatment group met the step goal on 50% of days vs. 16% of days in the control group ($P < 0.001$; see *SI Appendix*, Fig. S.20 for the distribution).

However, as shown in Fig. 6*B*, we find no effect on CES-D scores measured at the end of the intervention period in mid-June. We estimate a difference between treatment and control of -0.30 points ($P = 0.85$; *SI Appendix*, Table S.27, column 1). Our 95% confidence intervals exclude that treatment caused more than a 3.4-point change in the CES-D score, which is about 45% of the increase in average CES-D scores observed at the onset of the pandemic.[††]

[**] As shown in Fig. 5, demographic features account for only a small share of the predictive accuracy for depression. In *SI Appendix* we report regression analysis for demographic characteristics including gender, race/ethnicity, whether a student receives financial aid, and whether a student is a first-generation college student (*SI Appendix*, Table S.23). Consistent with recent work (11), we find evidence that women experience larger increases in depression during the pandemic. We also explore the relationship between demographics and disruptions to physical activity and find that minority and first-generation college students demonstrate the largest declines in average daily steps (*SI Appendix*, Table S.24).

[††] *SI Appendix*, Table S.27 provides regression estimates. As a robustness check, we also examine interactions of our exercise intervention with the randomized interventions aimed at improving sleep habits that we implemented over 2 mo earlier in February and March. We find no evidence of interaction effects (*SI Appendix*, Table S.30).

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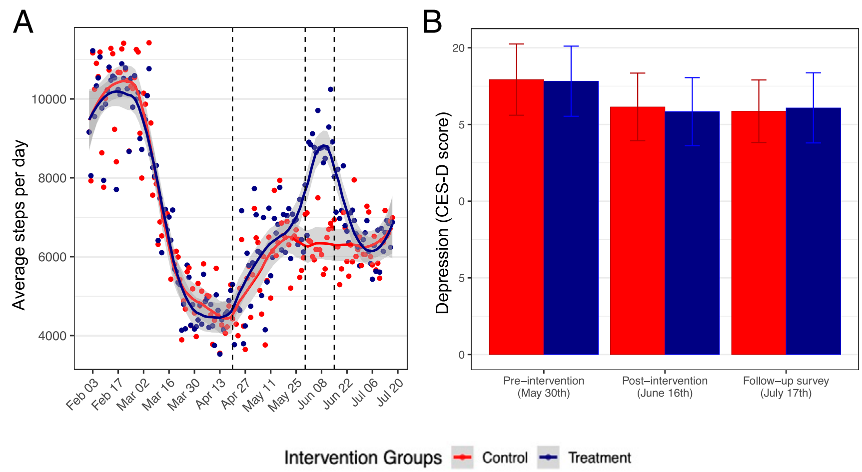

Fig. 6. Improved physical activity and depression. (*A*) Steps over time in the treatment and control groups for the subset of participants who elected to participate in the second phase of the study. The dashed vertical lines indicate the end of the first phase of the study (20 April), the beginning of the intervention (1 June), and the end of the intervention (14 June). (*B*) Average CES-D scores before the intervention (30 May) and after the intervention (16 June and 17 July) for the treatment and control groups.

We continued to track participants for a month after the intervention ended. As shown in Fig. 6*A*, after the intervention ended physical activity in the treatment group declined within about a week to the control group's levels. In the week after the intervention, we estimate a difference of about 1,200 steps between the treatment and control group ($P < 0.001$). When we examine the month-long postintervention period as a whole we do not find a significant difference in steps between the treatment and control groups ($P = 0.32$; *SI Appendix*, Table S.28, column 1). In the follow-up survey of mental health a month after the intervention ended we estimate a difference between the treatment and control group of 0.60 points ($P = 0.70$; *SI Appendix*, Table S.29, column 1). Our 95% confidence intervals exclude that treatment caused more than a 2.4-point decline in the CES-D score in July, less than a third of the increase in average CES-D scores observed at the onset of the pandemic.

In preregistered heterogeneity analysis we examine treatment effects within the following subgroups: preintervention depression (CES-D score above 15 vs. 15 or below) and preintervention recovery in physical activity, where we split participants by above/below median improvement in physical activity during the "bounce-back" period in May.

We find suggestive evidence that the impact on physical activity is larger and more persistent for participants who experienced smaller improvements in physical activity prior to the intervention. We estimate that during the intervention period, treatment increased their physical activity by almost an hour a day compared to about 30 min for participants who experienced larger bounce-backs in May ($P < 0.001$ compared to control, $P = 0.012$ comparing effects across subgroups; *SI Appendix*, Table S.26, column 8).

In the postintervention period, those with limited recovery prior to the intervention continue to experience treatment impacts, with an estimated average increase of about 30 min per day over the month ($P = 0.044$ compared to control, $P < 0.001$ comparing effects across subgroups; *SI Appendix*, Table S.28, column 8). Point estimates for the impact on steps in both the intervention and postintervention periods are consistent with the results for physical activity but are less precisely estimated.

Despite the sustained impact of the intervention on the behavior of these participants, we do not find evidence of short or longer run effects on their mental health (*SI Appendix*, Tables S.27 and S.29, columns 3 and 8). In our second subgroup analysis split by preintervention depression status we find no evidence of differential treatment effects on either physical activity or mental health (*SI Appendix*, Tables S.26–S.29, columns 4 and 9).

We note that in both the control and treatment groups, average CES-D scores improved in the period from May to July compared to April. Estimated depression rates in May, June, and July were 50%, 46%, and 48%, respectively. While this represents a significant improvement from rates of 61% in April, depression scores plateau in July and remain about 50% higher than prepandemic levels. The improvement and then plateauing in CES-D scores coincides with the bounce-back and then plateauing of physical activity from May through July 2020. Our short-term intervention successfully counteracts the plateauing of physical activity during the intervention period but has no meaningful effect on mental health.

Discussion

The COVID-19 pandemic has upended much of society in unprecedented ways. The measures adopted to mitigate the public health emergency, such as border closures, travel restrictions, and lockdowns, have affected labor markets, consumption patterns, and economic activities all over the world (11, 15, 45–48). The impact of such disruptions on mental health is of critical policy concern. Over the last two decades mental health disorders have imposed a growing burden on society, with estimated costs of over $200 billion per year in the United States alone (49). These costs may substantially increase as a result of the pandemic.

The consequences of COVID-19 for mental health have been dire, as highlighted in a May 2020 United Nations policy brief urging the international community to protect vulnerable populations (50). Among those identified as a specific population of concern were adolescents and young adults, who have faced large disruptions to their education and living situations and may suffer lifelong economic impacts from the pandemic. Our findings provide evidence of these disruptions and highlight the heavy toll of the pandemic on the well-being of college students.

We document several findings linking lifestyle disruptions to mental health. First, we show large disruptions to physical activity, sleep, and time use, particularly at the onset of the pandemic in March and April. Second, we document substantial declines in mental health with dramatic increases in depression. Third, we find that risk factors for depression diverge substantially during the pandemic compared to prior cohorts, with evidence that the pandemic tightened the relationship between the maintenance of lifestyle habits and mental health. Finally, while disruption of physical habits is a leading predictor of depression during COVID-19, the restoration of habits through our short-term intervention does not help restore well-being during the pandemic.

Why is this? First, the impact of physical activity may require a more intensive intervention. Prior work on physical activity and mental health has focused on interventions that encourage exercising two or three times per week over an extended period, generally 8 to 12 wk (6). In contrast, our intervention offered incentives based on steps and occurred every day, and for a shorter period. Future interventions could test incentives for more intensive physical activity or could extend our incentives for steps over a longer period. In our context, the concurrent decline in physical activity and mental health occurred over a short time period (largely in mid-March). We therefore were interested in testing whether restoring physical activity in a similarly short time span could have an impact on well-being. We also note that, even among the subgroup of participants who experienced sustained increases in physical activity over the 6 wk spanning the intervention and postintervention periods, there is little impact on mental health.

Second, physical activity may have important interactions with other lifestyle behaviors such as social interactions, for example because it is often undertaken in a social context (50). Future work could attempt to restore physical activity in conjunction with other important lifestyle habits.

Third, there may be important drivers of mental health during the pandemic that we do not measure, for example related to the move to remote education. While we explore some of these, such as the role of where students are located when classes move online, there may be omitted variables driving the effects of on well-being that we document in this paper.

Another possibility is that the relationship between physical activity and well-being is driven primarily by mental health rather than lifestyle. That is, changes in lifestyle habits may be (early) symptoms of depression. Relatedly, physical activity and mental health disruptions could both be driven by participants' underlying response to the pandemic. For example, our results may reflect that the kinds of people who are able to maintain their lifestyle during the pandemic are the kinds of people who are also better able to maintain their mental health in the face of major disruptions. We find evidence that these people may be those who, prior to the pandemic, were most resilient to stress and least prone to anxiety. Prior work has shown that it is possible to foster resilience (51). Future work could explore whether doing so can help mitigate the large impact of the COVID-19 pandemic on physical activity and mental well-being.

Data Availability. Anonymized data have been deposited in Open Science Framework (https://osf.io/f85e3/) (33).

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