COVID-19 Pounds: Quarantine and Weight Gain

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Abstract

In response to the COVID-19 pandemic, many countries, including the U.S., set a mandatory stay-at-home order in attempts to avert the spread. Although the primary goal of such a policy is to protect societies and save lives, it might result in other potential physical and psychological health threats. This paper examines the impact of stay-at-home policies on people's health behaviours towards weight gain and probable obesity attributable to imposing the order. Using Google Trends data, we investigate whether the lockdowns that were implemented in the U.S. led to changes in weight-gain-related online search behaviours. To probe the causal link between lockdown policies and changes in weight-gain-related topics, we employ the differences-in-differences method and regression discontinuity design and we find a significant increase in the search intensity for workout and weight loss, while the search intensity for fitness, nutrition and fast food appears to have declined. Our results from using event study regression suggest that changes in health behaviours began weeks before lockdown orders were implemented contemporaneously with emergency declarations and other partial closures about COVID-19. The findings suggest that people's health-related behaviours regarding weight gain were affected by the lockdowns.

JEL classification: I12, I18, H12

Key words: COVID-19, lockdown, health behaviours, weight gain, Obesity

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1. Introduction

The novel Coronavirus pandemic is recognized as the worldwide health threat that imposes a substantial burden on humans and leads to a significant disturbance in lifestyle globally. While mitigation measures were prioritized to avert the virus's spread and to flatten curves, concerns regarding the physical and psychological health impacts of these lockdowns and long-term induced effects have broadly emerged. Confinement due to the pandemic could be a potential factor that contributes to weight gain through unfavourable changes in lifestyle routines, including stress-related eating, fewer opportunities for physical activity, sedentary behaviours, and increased eating due to more screen time (Zachary et al., 2020; Pearl, 2020; Bhutani and Cooper, 2020). For instance, according to the 2020 U.S. WebMD reader poll, among the reasons cited for weight gain, 70% of respondents noted that stress eating and 72% noted that lack of exercise were more pronounced.[1]

Weight-gain-related health and socioeconomic consequences have attracted much attention. Some studies show that the likelihood of being at risk of mortality and various types of morbidities, such as stroke, diabetes, some types of cancer, poorer psychological health, life dissatisfaction, anxiety, depression, and wage disparity, is higher among the obese (CDC, 2020; Böckerman et al., 2019; Willage, 2018; Winter and Wuppermann, 2014; Chen, 2012). Further, higher medical expenses and greater productivity losses are among the economic burdens of obesity following weight gain (Cawley and Meyerhoefer, 2012; Konnopka et al., 2011).

There is a growing body of research on various COVID-19 related health aspects. Studies suggest that the pandemic and its attributed social distancing has shifted the population towards a lower mental health status (see,

[1] https://www.webmd.com/lung/news/20200518/webmd-poll-many-report-weight-gain-during-shutdown

e.g., Brodeur et al., 2020; Adams-Prassl et al., 2020; Proto and Quintana-Domeque, 2020), a reduction in happiness for singles (see, e.g., Hamermesh, 2020), and an increased related mortality (see, e.g., Katsoulis et al., 2020). However, studies concerning lifestyle behaviour issues, such as weight-gain-related behaviours due to the lockdown, are still in their infancy.

This paper contributes to the growing COVID-19 literature by analysing how stay-at-home orders affect health-related behaviours towards weight gain. We use daily Google Trends data from January 1st, 2019, to June 15th, 2020, across 42 U.S. states that imposed full lockdowns. To the best of our knowledge, this is the first study to use Google trends data to investigate the causal link between lockdown orders and individuals' current attitudes/behaviours towards weight-gain-related online searches.

Using Google Trends in academic studies dates back over a decade to when Ginsberg et al. (2009) successfully used this data to trace and edict the spread of influenza in the U.S. Over recent years, researchers have used search queries in measuring the change in public attention to the affordable care act repeal (Li and Stith, 2020), estimating investors attention to the stock market index (Hamid and Heiden, 2015), predicting the unemployment rate (D'Amuri and Marcucci, 2017), and analysing aggregate consumer behaviour in emerging markets (Carrière-Swallow and Labbé, 2013), among many other applications. Coogan et al. (2018) investigated the validity of search query data associated with obesity in a population's nutritional intake and dieting behaviour. They compared patterns in Australian Google Trends query data with data from the Australian National Nutrition and Physical Activity Survey. Their results showed that search query data can be used to predict dietary behavior. To examine the weight-gain-related behaviours, we use eight search queries: workout, fitness, diet, nutrition, fast food, weight loss, obesity, and stress, which we consider to be in correlation with weight gain during lockdowns and beyond.[2]

Our results rely on difference-in-differences analysis and regression discontinuity, suggesting a substantial increase in the search intensity for workout and weight loss. Despite the higher search for weight-loss-related information, we find no impact on obesity search intensity. On the contrary, searches for fitness and nutrition indicate a reduction possibly due to changes in priorities and lifestyle routines during the pandemic lockdown. In all of the estimated models, we also find large declines in searches for fast foods, while searches for stress are not significant.

To trace the adaptation of health-related behaviours over time, we apply the event study method. Findings show that changes in search intensity related weight gain began weeks before state-level lockdowns were imposed, suggesting the impact of emergency declarations or policies of partial closures early in the epidemic. Our analysis can inform policymakers in promoting policies that support health-related behaviours during and beyond lockdowns.

The rest of this paper is structured as follows. Section 2 describes the data applied to the analysis. Section 3 presents the identification strategy. Section 4 provides the main results, including our robustness checks. Section 5 concludes.

2. Data

We use Google Trends data for 42 U.S. states that imposed full lockdowns following the COVID-19 breakout. Google Trends is a publicly available tool that provides researchers with near-real-time information in the form of time series query indices for specified geographical locations; these indices are

[2]The three search terms: weight loss, diet, and fitness were used Coogan et al. (2018). The rest of the keywords were selected based on previous studies on weight gain and obesity.

constructed from queries users enter into a Google search. The index for the search intensity of any particular topic is obtained from dividing the total search volume for a specific time by the maximum number of times that term was searched throughout the selected time period and geographical location. The resulting associated volumes are then scaled from zero to 100. A score of 100 applies to the day with the peak number of searches for a given topic and a value of 0 is attributed to days with insufficient search volumes for a selected search term.

For our study, we extract Google Trends data on lockdown-attributed weight-gain-related searches. This data provide us with the variations in search interest on weekly and daily bases across the U.S. With over eighty percent of the browser market share in the U.S., in 2020, Google is indeed the U.S.'s most popular search engine.[3] Accordingly, the volume of queries submitted to Google reflects the majority of Americans' interests over time. Accordingly, the volume of queries submitted to Google reflects the majority of Americans' interests over time. This, along with providing a proxy for unobserved variables in the absence of official statistics, is the main reason for using online search queries in our study.

We use eight weight-gain-related search terms in Google Trends—workout, fitness, diet, nutrition, fast food, weight loss, obesity, and stress—and the search time frame is January 1st, 2019, to June 15th, 2020.[4] One of the limitations of Google Trends is that it does not provide daily data for a query period that is longer than nine months. This means if we use one query to call up data from January 1st, 2019, to June 15th, 2020, Google Trends only provides weekly, and not daily, data. In order to obtain daily data, we are forced to

[3] https://gs.statcounter.com/search-engine-market-share

[4] New Hampshire's stay-at-home order expired on June 15th, 2020, and the governor allowed businesses to reopen on a rolling basis. New Hampshire is the last state in our dataset that lifted the stay-at-home order; this is the reason for selecting June 15th as the end of our time period.

download query answers in two calls (January 1st, 2019, to June 15th, 2019, and January 1st, 2020, to June 15th, 2020). This creates a problem as we cannot compare data for two different query periods. This is because Google Trends provides a search intensity index rather than raw data. To compare internet searches for weight-gain-related queries during January–June 2020 and the same period in 2019, we need to re-scale our daily data according to search intensity weights that are calculated using weekly data obtained from calling up queries from January 2019 to June 2020. To do this, we follow the re-scaling process proposed by Brodeur et al. (2020). First, we calculate the average weekly data using daily data that is downloaded in two calls (January 1-June 30, 2019 and January 1-June 30, 2020). The weight will be calculated by dividing the weekly data that is downloaded in one call (January 1, 2019-June 15, 2020) to the calculated average weekly data that uses daily data. In the next step, we calculate the re-scaled data by multiplying the initial daily data by the calculated weight. Finally, we normalise the re-scaled data in order to have values that are between 0 and 100.[5]

3. Identification Strategies

To study the effects of stay-at-home orders on health behaviours, we conduct three broad empirical analyses. First, we estimate a difference-in-differences regression that accounts for both annual differences in search intensity and the expected changes in health-related behaviours immediately following the U.S. lockdowns. Second, we use the combined regression discontinuity design and differences-in-differences to examine the immediate structural break that occurred before and after these lockdowns. Third, we examine the relationship between the initial health-related behaviours and

[5]For more detail about re-scaling Google Trends data, see Brodeur et al. (2020).

states' lockdowns, using an event study model at the week-by-state level. These three sets of analyses allow us to assess the pre-trends and to anticipate the effects in considerable detail.

3.1 Difference-in-Differences Estimation

To measure the effects of policy interventions on health behaviours, we estimate the following generalised difference-in-differences model for each search query:

$$H_{i,t} = \alpha(Post_{i,t} \times Year_t) + \beta Post_{i,t} + \gamma X_{i,t-1} + \eta_i + \theta_t + \epsilon_{i,t} \qquad (1)$$

where $H_{i,t}$ denotes healthy behaviours (search queries) in state i on date t. $Post_{i,t}$ is a binary variable that is equal to one after the stay-at-home order was implemented and zero otherwise. The binary variable $Year_t$ is 1 for the year of the lockdown (2020) and 0 otherwise. Our main coefficient of interest, α, measures the difference in health behaviours found in Google searches between 2019 and 2020, before versus after imposing lockdowns. The control variable $X_{i,t-1}$ denotes the lagged number of new deaths from COVID-19 per day per million.[6] We include state-level fixed effects (η_i) and time fixed effects (θ_t) to absorb the effects of unobservable time-invariant state or time characteristics. Vector θ_t includes the fixed effects for the year, week, and days (Monday to Sunday). $\epsilon_{i,t}$ is the residual error term.

[6] The data on new deaths from COVID-19 come from The COVID Tracking Project: https://covidtracking.com/data/download .

3.2 Regression Discontinuity-Difference-in-Differences Estimation

Following the model by Brodeur et al. (2020), we use a quasi-experimental regression discontinuity design to test how the health behaviours related to weight gain discretely changed following the stay-at-home orders. Since we need to compare the estimated breaks in 2020 presented in Figure 1 with the ones in 2019 in Figure 2, we use an regression discontinuity-difference-in-differences regression as follows:

$$
\begin{aligned}
H_{i,t} = {} & \alpha'(Post_{i,t} \times Year_t) + \lambda(f(Distance_{i,t}) \times Post_{i,t} \times Year_t) \\
& + \phi(f(Distance_{i,t}) \times (1 - Post_{i,t}) \times Year_t) \\
& + \mu f(Distance_{i,t}) \times Post_{i,t} + \psi f(Distance_{i,t}) \times (1 - Post_{i,t}) \\
& + \beta' Post_{i,t} + \gamma_i' X_{i,t-1} + \eta_i' + \theta_t' + \epsilon_{i,t}'
\end{aligned} \tag{2}
$$

where α' captures the effect of the stay-at-home orders on search query $H_{i,t}$ in state i on date t. Similar to the difference-in-differences model, $Post_{i,t}$ is a dummy variable that is equal to one after the stay-at-home order was implemented and zero otherwise. The binary variable $Year_t$ is 1 for the year of the lockdown (2020) and 0 otherwise. $Distance$ measures the elapsed time between period t and the official dates of the lockdowns. Since we are using daily data in the analysis of health behaviours, the elapsed time is measured in the number of days. We use the same control variable, the lagged number of new deaths per day from COVID-19 ($X_{i,t-1}$), as in the previous model. η_i' is a set of state fixed effects, and θ_t' is a set of time fixed effects. $\epsilon_{i,t}'$ is the residual error term.

3.3 Event Study Estimation

We use an event study analysis to examine how measures of state-level health-related behaviours evolved during the period leading up to and following the stay-at-home orders. We estimate the following regression equations for each search query:

$$\begin{aligned} H_{i,t} = &\sum_{w=-3}^{6} \alpha_w^{''}(D_{i,w} \times Year_t) + \sum_{w=-3}^{6} \beta_w^{''} D_{i,w} \\ &+ \gamma_i^{''} X_{i,t-1} + \eta_i^{''} + \theta_t^{''} + \epsilon_{i,t}^{''}, \end{aligned} \tag{3}$$

where $D_{i,w}$ represents the weekly dummy variables for the three weeks before and the six weeks after the lockdowns were imposed. The parameter $\alpha_w^{''}$ represents the event study coefficients that trace any deviations from the common trends states experienced in the weeks leading up to and following the lockdowns. $\eta_i^{''}$ and $\theta_t^{''}$ are the sets of state fixed effects and time fixed effects, respectively. $\epsilon_{i,t}^{''}$ denotes the error term.

4. Estimation Results

Before conducting our formal analysis, we provide informal evidence on how stay-at-home orders affected daily searches on selected search queries. Figure 3 presents the raw daily search activity for our topics, weighted by the population of each state. As the figure shows, there was a noticeable increase in searches using the term workout, starting three weeks before the official lockdowns. Searches for workout surged to the highest level in the first week of the lockdown. Searches for fitness shows a stable trend in 2019, while in 2020, it shows a sudden drop from a week before the lockdowns were imposed, a constant trend for six weeks after the lockdowns and an upward trend afterward. There was also a sharp drop in Google searches for diet, nutrition, fast food, and weight loss starting three weeks before the lockdowns were implemented, compared to the mostly unchanged pattern that was observed in 2019 for the same period. In all search queries except for workout, we notice a drop in the search intensity starting before the lockdown. As Table A1 shows, policies for partial closures were implemented before the full lockdowns were imposed. These policies that were introduced early in the pandemic, led to a substantial increase in time spent at home and consequently influenced health-related behaviours that may cause weight gain.

4.1 Difference-in-Differences Results

Table 1 shows the results obtained from the difference-in-differences framework described in Section 3.1. Our findings reveal that there is a statistically significant association between the U.S. lockdowns and increased search intensity for workout and weight loss. The effect is more pronounced for the term workout. One plausible reason may be the increased number of media programs that make it easier to exercise at home.[7]

Weight-gain-related concerns in the present circumstances could be in line with the results from prior evidence on small annual weight gains (0.4-1 kg) (Schoeller, 2014) and faster gains during holidays (Helander et al., 2016). With some cautious similarities drawn between prolonged stay-at-home restrictions and evidence from the literature on holidays, it could be argued that while the short-term weight changes due to alterations in physical activity and diet can appear to be relatively small at first glance, weight accumulation over the long term (between 5 and 10 kg over a 10-year period) could be sufficient for explaining the emerging obesity epidemic (Mason et al., 2018; Schoeller, 2014; Bhutani and Cooper, 2020).

[7] https://www.nytimes.com/2020/08/08/at-home/coronavirus-weight-gain.html

In contrast, fitness, nutrition, and fast food search intensity appeared to be negatively influenced and this was likely owing to people's priority for self-care, fear of virus transmission through food or food packaging, changing eating habits towards home cooking and eating less fast food take-out at the early stage of the initiation of the lockdowns.

4.2 Regression Discontinuity-Difference-in-Differences Results

Table 2 presents the findings from the regression discontinuity-difference-in-differences regression that was used to investigate the immediate lockdown-related impacts. Our results indicate a significant and positive short-run impact of lockdowns on workout and weight loss. The lockdowns do not appear to have had any statistically significant immediate impact on diet, nutrition, obesity, and stress. However, the findings indicate that the search intensity for fitness and fast food decreased a few days after the lockdowns were imposed. Further, the positive lockdown-related search intensity for stress can demonstrate the pressure that was imposed on society at the beginning of the lockdowns, however, it is insignificant.

4.3 Event Study Results

Table 3 and Figure 4 present estimates from the event study specification. The results show that there was a continuous rise in Google searches for workout starting two weeks prior to the implementation of the lockdowns until the orders were put in place. The gradual drop that followed the spike's week continued until the end of our time frame (June 15, 2020). A plausible reason for the larger increase in the search intensity for this term could be the positive effects that regular physical activity would have in improvements to the immune system and on stress management. [8]

The reduction in the number of searches for fitness continued throughout the lockdown period and this might be the result of fitness center closures during this period. Google searches for diet and nutrition continued to fall, starting from three weeks before the lockdowns until the end of the lockdowns. Although the negative impact of the lockdowns on fast food searches resumed during the period of the lockdowns, the magnitude of the impact gradually diminished. The drop in the number of weight-loss searches starting three weeks before the lockdowns occurred simultaneously with the declarations of emergencies across U.S. states. The negative impact on GR weight-loss searches continued until the end of the second week. Such an effect might be the result of changes in people's priorities following major changes in their lifestyle. By continuing the lockdown period, people to some degree have learned how to adjust to their new routines and this could be the reason behind the soaring weight-loss searches starting in the fourth week of the lockdowns.

4.4 Robustness Check

To verify the robustness of the main specification results—applying the lockdown implementation date as the benchmark—we carry out different robustness checks, using alternative mitigation policies: school closure dates and restaurant restrictions dates. We also include three states with partial lockdowns (Oklahoma, Utah, and Wyoming) to see how the results are affected. Tables A2–A4 in the appendix show the results of the robustness exercises. Our findings confirm the consistency of the current coefficients with the results from our main regression for the search queries: workout, fitness, nutrition, fast food, and stress. The findings from our robustness exercises

[8] https://www.health.harvard.edu/staying-healthy/how-to-boost-your-immune-system

suggest that the policies for the partial closures that occurred before the full lockdowns were implemented had a negative impact on the search intensity for diet. However, the results from using stay-at-home orders as a policy intervention and including states with partial lockdowns are similar to our main results. Our findings do not show any significant effects of intervention policies on obesity and stress.

5. Conclusions

There appears to be a great deal of uncertainty associated with lifestyles and human health, globally, during the COVID-19 pandemic, particularly in relation to the lockdowns that took place across the U.S. This has led to widespread research efforts. We contribute to the emerging literature on the health impacts of COVID-19 by providing the first study to use Google Trends data across U.S. states to investigate a plausible causal link between the lockdowns and weight gain . Although Google Trends does not provide us with detailed information on each individual, it enables us to exploit variations in peoples' behaviours towards obesity and weight gain disorders on a day-to-day basis and it can offer insights into how societies' attitudes towards health-related behaviours would differ during a pandemic and the resulting health shocks.

Applying the difference-in-differences approach along with regression discontinuity-difference-in-differences analyses, we find a significant increase in the search intensity for workout and weight loss. Our results highlight more concerns over the short-run (weight gain/loss) than the long-run effects (obesity). These findings also present a substantial drop in fitness and fast food searches, while searches for stress do not reveal significant results.

In summary, our findings suggest that the impact of a health shock on search behaviours related to weight gain diminished over time, during the pandemic. That is, to some degree, people adapt to the new lifestyle routines following the outbreak of this disease.

Even though in most places the lockdown orders are currently lifted, people's lives have not returned to normal. Many companies have announced that employees can/must work remotely, meaning "from home". Many schools will not offer in-person classes for the coming semester, and many people do not use fitness centres for fear of transmission of the virus. Under current circumstances, public health planners need to consider lockdown-related health behaviours regarding weight gain and promote supportive programs and policies accordingly to avoid the associated consequent long-term impacts of these types of lockdowns.

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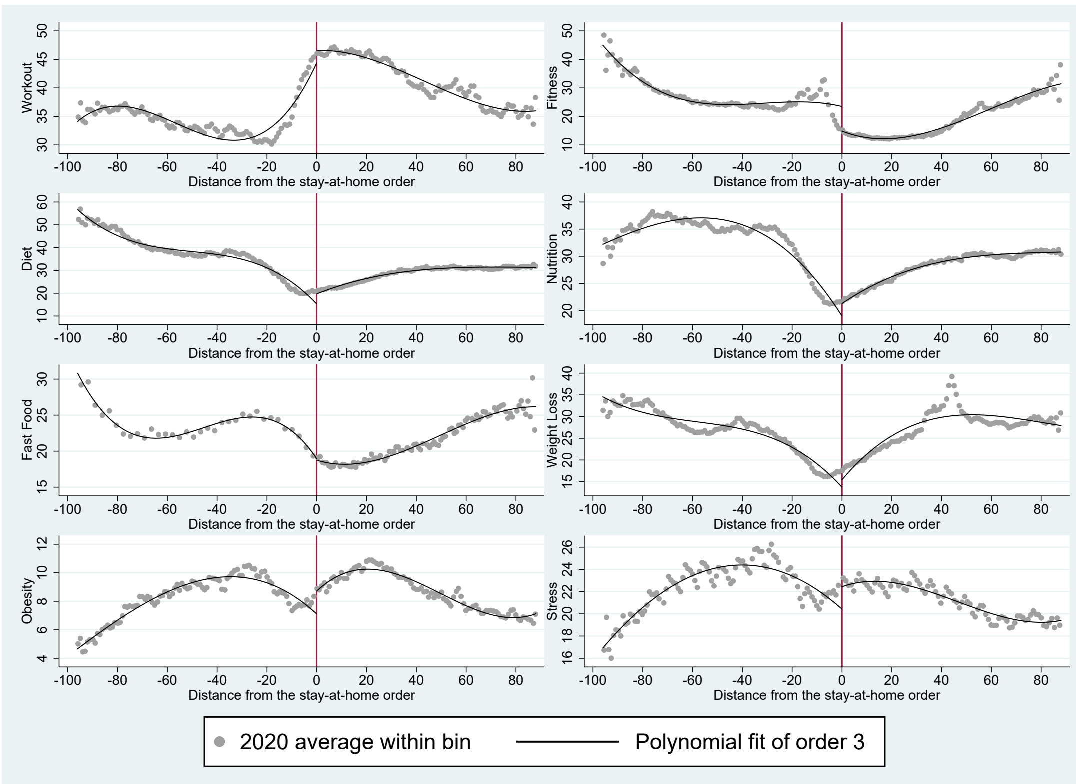
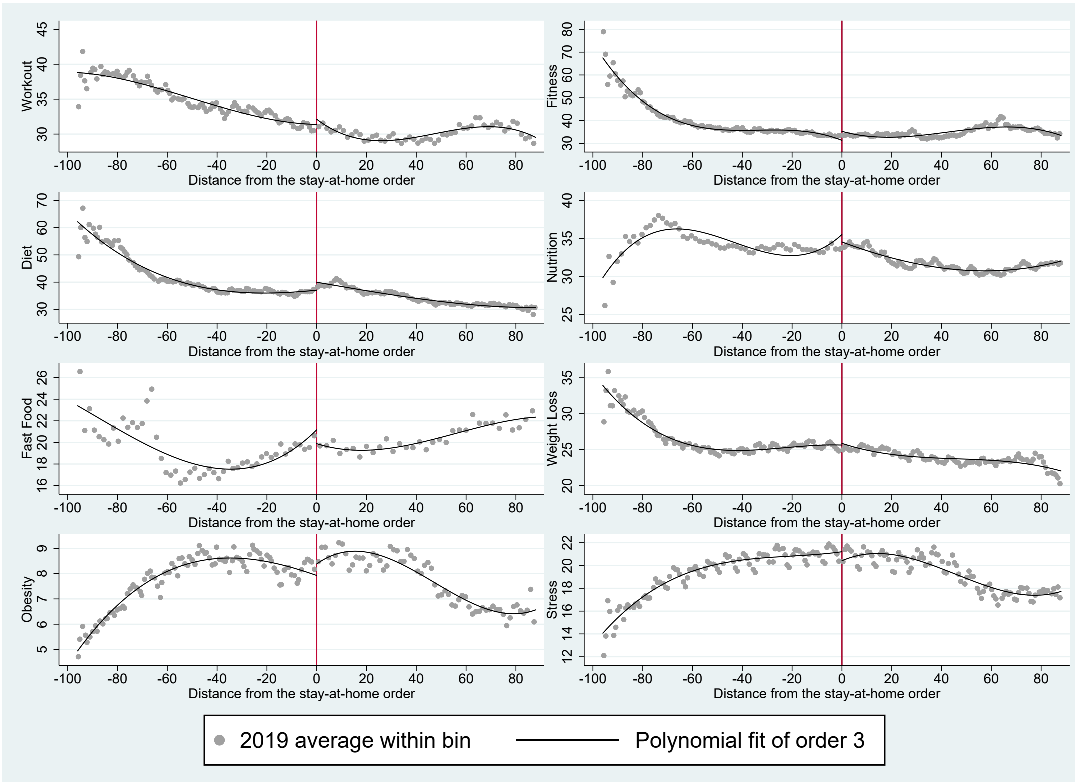
Figure 1: Google Search Trends Pre- and Post-lockdowns across 42 U.S States in 2020 (Regression Discontinuity)



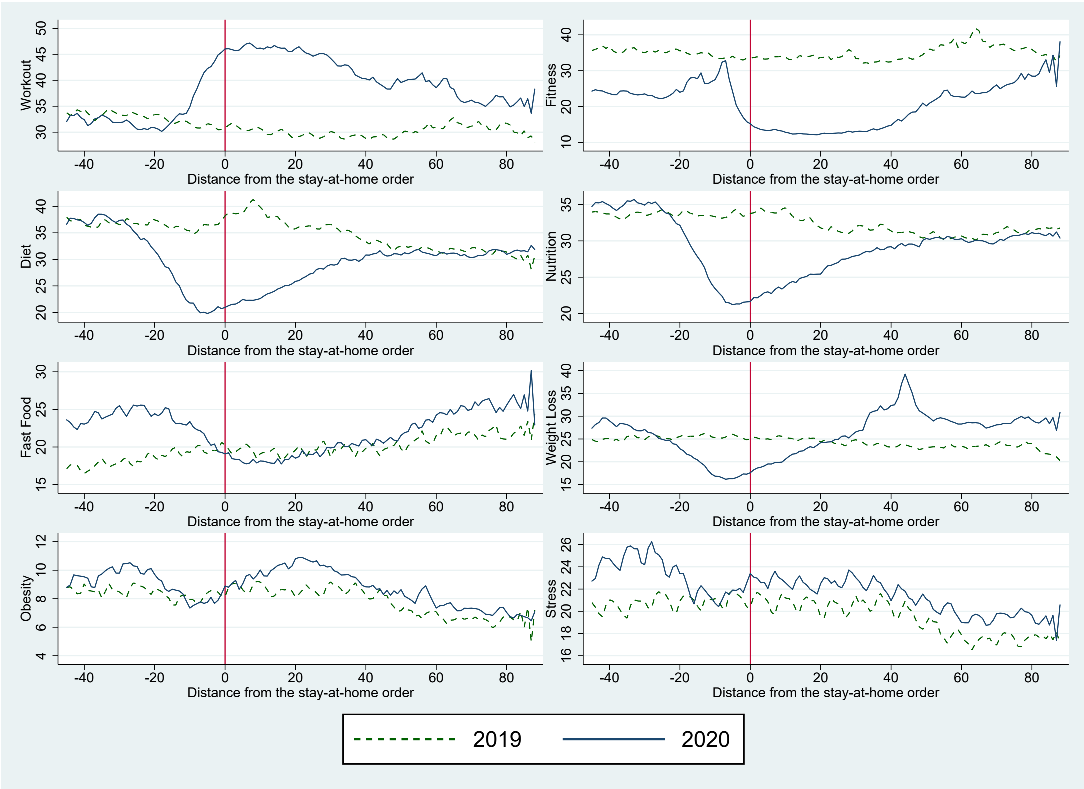
Note: The vertical axis shows the weighted average of raw searches (on a scale from 0 to 100) in the days before (negative values) and after (positive values) the lockdown implementation. We use states' populations as of 2019 as the weights. Solid lines are fitted using a third-degree polynomial regression.

Figure 2: Google Search Trends Pre- and Post-lockdowns across 42 U.S States in 2019 (Regression Discontinuity)



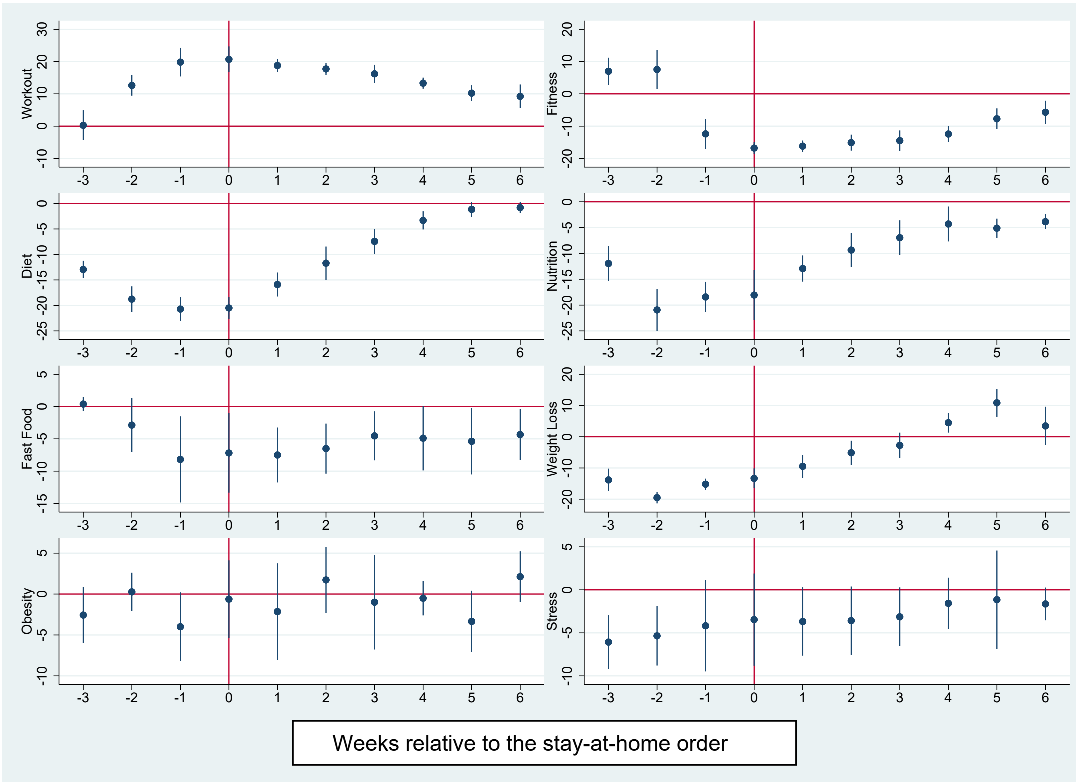
Note: The vertical axis shows the weighted average of raw searches (on a scale from 0 to 100) in the days before (negative values) and after (positive values) the lockdown implementation. We use states' populations as of 2019 as the weights. Solid lines are fitted using a third-degree polynomial regression.

Figure 3: Google Search Trends Pre- and Post-lockdowns across 42 U.S. States



Note: The vertical axis shows the weighted average of raw searches (on a scale from 0 to 100) in the days before (negative values) and after (positive values) the lockdown implementation. We use states' populations as of 2019 as the weights. Horizontal axis represents the time distance from the lockdown implementation. Zero represents the day of implementation in 2020.

Figure 4: Estimated Effects using Event Study Model



Note: The vertical axis shows the estimated coefficients for weekly dummy variables interacted with the year of the lockdown presented in Table 3. Horizontal axis represents the weeks elapsed from the lockdown implementation. Zero represents the week of the implementation in 2020. Observations from 2019 used as reference.

Table 1: Difference-in-Differences Estimates using the Lockdowns Implementation Dates

	DEPENDENT VARIABLE							
	Workout	Fitness	Diet	Nutrition	Fast Food	Weight Loss	Obesity	Stress
$\text{Post}_{i,t} \times \text{Year}_t$	13.974^{***}	-8.286^{***}	-1.129	-2.135^{**}	-4.234^{**}	3.268^{***}	0.771	-0.896
	(0.604)	(1.339)	(0.744)	(0.717)	(1.357)	(0 .819)	(0.738)	(0.790)
Death	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, Week, and Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of States	42	42	42	42	42	42	42	42
No. of Observations	13,986	13,986	13,986	13,984	13,930	13,978	13,366	13,984

Notes: The models include the binary variable $Post_{i,t}$ that is equal to 1 in the days after the stay-at-home order was implemented. All regressions contain state, year, week, and day fixed effects. The control variable Death denotes the lagged number of new deaths from COVID-19 per day per million. *, ** and *** indicate significance at 10%, 5% and 1%. Robust standard errors are in parentheses. Standard errors are clustered at the day level.

Table 2: Regression Discontinuity-Difference-in-Differences Estimates using the Lockdowns Implementation Dates

	Dependent Variable							
	Workout	Fitness	Diet	Nutrition	Fast Food	Weight Loss	Obesity	Stress
$\text{Post}_{i,t} \times \text{Year}_t$	11.709^{***}	-14.048^{***}	-0.129	1.414	-6.699^{***}	7.986^{***}	1.076	0.005
	(0.961)	(1.837)	(1.136)	(0.775)	(0.952)	(1.151)	(0.987)	(0.764)
Death	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, Week, and Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of States	42	42	42	42	42	42	42	42
No. of Observations	13,986	13,986	13,986	13,984	13,930	13,978	13,366	13,984

Notes: The models include the binary variable $Post_{i,t}$ that is equal to 1 in the days after the stay-at-home order was implemented. All regressions contain state, year, week, and day fixed effects. The control variable Death denotes the lagged number of new deaths from COVID-19 per day per million. *, ** and *** indicate significance at 10%, 5% and 1%. Robust standard errors are in parentheses. Standard errors are clustered at the day level.

Table 3: Event Study Coefficients

	DEPENDENT VARIABLE							
	Workout	Fitness	Diet	Nutrition	Fast Food	Weight Loss	Obesity	Stress
3 weeks before× Year	0.269	7.007***	−12.943***	−11.940***	0.392	−13.824***	−2.565	−6.070***
	(1.898)	(1.722)	(0.700)	(1.388)	(0.451)	(1.480)	(1.388)	(1.272)
2 weeks before× Year	12.630***	7.567**	−18.7626***	−20.930***	−2.870	−19.508***	0.270	−5.346***
	(1.302)	(2.466)	(1.024)	(1.654)	(1.719)	(0.751)	(0.957)	(1.410)
1 week before× Year	19.846***	−12.387***	−20.711***	−18.421***	−8.186**	−15.190***	−3.992*	−4.175
	(1.818)	(1.887)	(0.944)	(1.202)	(2.727)	(0.731)	(1.718)	(2.169)
The week of lockdown × Year	20.715***	−16.790***	−20.493***	−18.056***	−7.181**	−13.318***	−0.623	−3.461
	(1.628)	(0.781)	(0.894)	(1.963)	(2.514)	(1.299)	(1.937)	(2.189)
1 week after× Year	18.795***	−16.196***	−15.897***	−12.917***	−7.499***	−9.466***	−2.138	−3.678*
	(0.812)	(0.718)	(0.963)	(1.037)	(1.740)	(1.505)	(2.408)	(1.623)
2 weeks after× Year	17.731***	−15.107***	−11.708***	−9.338***	−6.513***	−5.121**	1.728	−3.580*
	(0.768)	(1.013)	(1.332)	(1.333)	(1.584)	(1.580)	(1.653)	(1.620)
3 weeks after× Year	16.219***	−14.497***	−7.441***	−6.949***	−4.533**	−2.748	−0.997	−3.136*
	(1.149)	(1.297)	(0.996)	(1.376)	(1.552)	(1.662)	(2.362)	(1.396)
4 weeks after× Year	13.320***	−12.430***	−3.318***	−4.291**	−4.891*	4.504**	−0.508	−1.568
	(0.699)	(1.040)	(0.728)	(1.384)	(2.045)	(1.298)	(0.859)	(1.218)
5 weeks after× Year	10.228***	−7.715***	−1.152***	−5.107***	−5.383**	10.879***	−3.340*	−1.146
	(0.994)	(1.317)	(0.603)	(0.758)	(2.097)	(1.828)	(1.533)	(2.334)
6 weeks after× Year	9.237***	−5.685***	−0.807***	−3.841***	−4.334**	3.467	2.120	−1.638*
	(1.503)	(1.461)	(0.441)	(0.599)	(1.613)	(2.521)	(1.267)	(0.779)
Death	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, Week, and Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of States	42	42	42	42	42	42	42	42
No. of Observations	13,986	13,986	13,986	13,984	13,930	13,978	13,366	13,984

Notes: The table presents event study coefficients corresponding to Figure 4. The models include the weekly dummy variables for the three weeks before and the six weeks after the lockdowns were imposed. All regressions contain state, year, week, and day fixed effects. *, ** and *** indicate significance at 10%, 5% and 1%. Robust standard errors are in parentheses. Standard errors are clustered at the day level.

Appendix

Table A1: U.S. State Policy Enactment Dates During COVID-19

State	School Close	Restaurant/Other Restrict	Stay At Home
Alaska	16-Mar-20	17-Mar-20	28-Mar-20
Alabama	19-Mar-20	20-Mar-20	4-Apr-20
Arizona	16-Mar-20	20-Mar-20	31-Mar-20
California	19-Mar-20	15-Mar-20	19-Mar-20
Colorado	23-Mar-20	17-Mar-20	26-Mar-20
Connecticut	17-Mar-20	16-Mar-20	23-Mar-20
Delaware	16-Mar-20	16-Mar-20	24-Mar-20
Florida	16-Mar-20	17-Mar-20	3-Apr-20
Georgia	18-Mar-20	24-Mar-20	3-Apr-20
Hawaii	23-Mar-20	17-Mar-20	25-Mar-20
Idaho	23-Mar-20	25-Mar-20	25-Mar-20
Illinois	17-Mar-20	16-Mar-20	21-Mar-20
Indiana	19-Mar-20	16-Mar-20	24-Mar-20
Kansas	18-Mar-20		30-Mar-20
Kentucky	16-Mar-20	16-Mar-20	26-Mar-20
Louisiana	16-Mar-20	17-Mar-20	23-Mar-20
Massachusetts	17-Mar-20	17-Mar-20	24-Mar-20
Maryland	16-Mar-20	16-Mar-20	30-Mar-20
Maine	16-Mar-20	18-Mar-20	2-Apr-20
Michigan	16-Mar-20	16-Mar-20	24-Mar-20
Minnesota	18-Mar-20	17-Mar-20	27-Mar-20
Missouri	23-Mar-20	17-Mar-20	6-Apr-20
Mississippi	20-Mar-20	24-Mar-20	3-Apr-20
Montana	16-Mar-20	20-Mar-20	28-Mar-20
North Carolina	16-Mar-20	17-Mar-20	30-Mar-20
New Hampshire	16-Mar-20	16-Mar-20	27-Mar-20
New Jersey	18-Mar-20	16-Mar-20	21-Mar-20
New Mexico	16-Mar-20	16-Mar-20	24-Mar-20
Nevada	16-Mar-20	17-Mar-20	1-Apr-20
New York	18-Mar-20	16-Mar-20	22-Mar-20
Ohio	17-Mar-20	15-Mar-20	23-Mar-20
Oklahoma	17-Mar-20	25-Mar-20	25-Mar-20
Oregon	16-Mar-20	17-Mar-20	23-Mar-20
Pennsylvania	16-Mar-20	17-Mar-20	1-Apr-20
Rhode Island	16-Mar-20	16-Mar-20	28-Mar-20
South Carolina	16-Mar-20	18-Mar-20	7-Apr-20
Tennessee	20-Mar-20	23-Mar-20	31-Mar-20
Texas	23-Mar-20	20-Mar-20	2-Apr-20
Utah	16-Mar-20	18-Mar-20	27-Mar-20
Virginia	16-Mar-20	17-Mar-20	30-Mar-20
Vermont	18-Mar-20	17-Mar-20	25-Mar-20
Washington	17-Mar-20	16-Mar-20	23-Mar-20
Wisconsin	18-Mar-20	17-Mar-20	25-Mar-20
West Virginia	16-Mar-20	17-Mar-20	24-Mar-20
Wyoming	16-Mar-20	19-Mar-20	28-Mar-20

Source: Data on stay-at-home orders are from The New York Times (last updated April 20, 2020) available at https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html. Data on school closure, and restaurant restrictions are obtained from Gupta et al. (2020).

Table A2: Difference-in-Differences Estimates using School Closure Dates

	DEPENDENT VARIABLE							
	Workout	Fitness	Diet	Nutrition	Fast Food	Weight Loss	Obesity	Stress
$\text{Post}_{i,t} \times \text{Year}_t$	17.456^{***}	-12.525^{***}	-6.748^{***}	-7.068^{***}	-5.831^{**}	-1.216	-0.063	-1.573
	(0.764)	(1.202)	(0.953)	(0.978)	(1.709)	(1.196)	(0.716)	(1.186)
Death	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, Week and Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of States	42	42	42	42	42	42	42	42
No. of Observations	13,986	13,986	13,986	13,984	13,930	13,978	13,366	13,984

Notes: The models include the binary variable $Post_{i,t}$ that is equal to 1 in the days after the school closure order was implemented. All regressions contain state, year, week, and day fixed effects. The control variable Death denotes the lagged number of new deaths from COVID-19 per day per million. *, ** and *** indicate significance at 10%, 5% and 1%. Robust standard errors are in parentheses. Standard errors are clustered at the day level.

Table A3: Difference-in-Differences Estimates using Restaurant/Other Restrict Dates

	Dependent Variable							
	Workout	Fitness	Diet	Nutrition	Fast Food	Weight Loss	Obesity	Stress
$\text{Post}_{i,t} \times \text{Year}_t$	18.022^{***}	-11.976^{***}	-6.858^{***}	-7.133^{***}	-5.751^{**}	-1.257	-0.692	-1.773
	(0.847)	(1.186)	(1.034)	(1.048)	(1.699)	(1.297)	(0.577)	()
Death	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, Week and Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of States	41	41	41	41	41	41	41	41
No. of Observations	13,653	13,653	13,653	13,651	13,597	13,645	13,052	13,651

Notes: The models include the binary variable $Post_{i,t}$ that is equal to 1 in the days after the restaurant/other restrict order was implemented. All regressions contain state, year, week, and day fixed effects. The control variable Death denotes the lagged number of new deaths from COVID-19 per day per million. *, ** and *** indicate significance at 10%, 5% and 1%. Robust standard errors are in parentheses. Standard errors are clustered at the day level.

Table A4: Difference-in-Differences Estimates for States with Full and Partial Lockdowns

	DEPENDENT VARIABLE							
	Workout	Fitness	Diet	Nutrition	Fast Food	Weight Loss	Obesity	Stress
$\text{Post}_{i,t} \times \text{Year}_t$	13.870^{***}	-8.040^{***}	-1.215	-1.976^{**}	-4.121^{**}	3.024^{***}	0.748	-1.102
	(0.649)	(1.160)	(0.806)	(0.727)	(1.277)	(0.795)	(0.695)	(0.758)
Death	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, Week and Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of States	45	45	45	45	45	45	45	45
No. of Observations	14,985	14,985	14,985	14,982	14,928	14,977	14,248	14,982

Notes: The regressions include 42 states with full lockdowns and three states with partial lockdowns (Oklahoma, Utah, and Wyoming). The binary variable $Post_{i,t}$ is equal to 1 in the days after the lockdowns were implemented. All regressions contain state, year, week, and day fixed effects. The control variable Death denotes the lagged number of new deaths from COVID-19 per day per million. *, ** and *** indicate significance at 10%, 5% and 1%. Robust standard errors are in parentheses. Standard errors are clustered at the day level.