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Public Health Shock, Intervention Policies, and Health Behaviors: Evidence from COVID-19

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In response to the COVID-19 pandemic, many countries, including the U.S., adopted intervention policies aimed at averting the spread. However, these policies may have led to significant changes in public health behaviors. We use Google search queries to examine how state government actions are associated with people's internet searches (internet browsing habits) related to health behaviors. We employ the differences-in-differences method to determine the link between disease outbreak, associated intervention policies, and changes in health behavior related searches. Our findings show that school closures, restaurant restrictions, and stay-at-home orders lead to a significant rise in searches for *workout*, *physical activity*, *exercise*, *takeout*, *liquor*, and *wine*. Moreover, people's concerns regarding *weight loss*, *diet*, *nutrition*, *restaurant*, and *fast food* substantially decline following stay-at-home orders. Our event-study results indicate that changes in health behaviors began weeks before stay-at-home orders were implemented contemporaneously with emergency declarations and other partial closures. These findings suggest that people's health behaviors are notably affected by state government's intervention policies.

Keywords: Health shock, Health behaviors, COVID-19 policies, Physical activity, Dietary habits

JEL Classifications: I12, I18, I1

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

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governments' intervention policies such as stay-at-home orders were prioritized to avert the virus's spread and reduce the death toll, concerns regarding the contemporaneous and long-lasting effects of these policies on lifestyle and public health behaviors have broadly emerged.

Lifestyle choices and behavioral modification following changes in economic or health shocks are identified as the prominent determinants of the health outcomes in the health demand model (Grossman, 1972). In the U.S., unhealthy lifestyle behaviors have drawn much attention as one of the leading causes of morbidity and premature mortality over the recent decades (Mokdad et al., 2018; Ezzati and Riboli, 2013).

Previous studies show evidence of the long term changes in health behaviors and, in health outcomes following health shocks such as disease outbreak (Agüero and Beleche, 2017). In this sense, the link between health shocks, consequential policy interventions, and subsequent health behaviors has been of great concern for health authorities and policymakers from two aspects. First, lifestyle and health behaviors such as activity level and dietary habits lie at the root of many chronic diseases, including obesity, type II diabetes, cardiovascular disease, hypertension, and hypercholesterolemia (Warburton et al., 2006; Butterly et al., 2006; Naja and Hamadeh, 2020). Second, there is a reciprocal relationship between health behaviors and mental health (Arora and Grey, 2020; Parletta et al., 2016). Since the beginning of the COVID-19 outbreak in December 2019, a growing body of research has focused on investigating the mental health effects of intervention policies. These studies suggest that as a health shock, the COVID-19 pandemic and its attributed mitigation policies have contributed to increased mental health symptoms (Brodeur et al., 2021; Fayaz Farkhad and Albarracín, 2021; Hamermesh, 2020). Yet, less attention has been paid to the effects of such policies on lifestyle and population health behaviors. Existing research on changes in health behavior during the COVID-19 have exclusively focused on specific age groups, including adults or school-age children, using small-sample questionnaires (Knell et al., 2020; Flanagan et al., 2020; Zajacova et al., 2020). The present study aims to bridge this gap by examining the potential changes in population concerns regarding health behaviors that stem from confinement due to the pandemic. Such behavior modifications are likely to include physical inactivity, sedentary behaviors, and changes in dietary habits, including stress-related eating and increased eating due to more screen time.

A large number of studies that aim to identify lifestyle and health-related behaviors apply longitudinal analysis, allowing researchers to observe changes over time. However, carrying out longitudinal studies is expensive and requires enormous amounts of time. Furthermore, tracking the impact of intervention policies on related health behaviors following a health shock requires data from both before the shock and after the policy implementation, and this is not possible as these events are not expected ahead of time. Using search queries allows us to avoid this problem by providing a proxy for unobserved variables in the absence of official statistics. It also enables us to analyze the behaviors and concerns of society in real-time without carrying out costly surveys.

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.[1] Accordingly, the volume of queries submitted to Google reflects the majority of Americans' interests over time. As such, in this paper, we use daily Google Trends data from January 1st, 2019, to April 19th, 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 search queries to investigate the link between COVID-19 mitigation policies and public concerns about health behaviors.

Using Google Trends in academic studies dates back over a decade to when Ginsberg et al. (2009) successfully used this data to trace and predict the spread of influenza in the U.S. Recently, researchers have implemented search queries to measure economic activities (Hamid and Heiden, 2015; D'Amuri and Marcucci, 2017; Carrière-Swallow and Labbé, 2013), health care research, including infectious diseases (Desai et al., 2012; Jena et al., 2013), mental health (Yang et al., 2011; Tefft, 2011; Ayers et al., 2012), and health-related population behaviors (Wang and Chen, 2018; Glynn et al., 2011; Havelka et al., 2020), among many other applications. Along with utilizing internet data on population health behaviors, researchers attempted to assess the accuracy of search queries. For instance, White and Horvitz (2013) used a hospital utilization survey to compare behavioral patterns from both the survey and online health-seeking searches. Their results show that there is a strong correlation between online health-seeking behavior and healthcare utilization. Coogan et al. (2018) investigated the validity of search query data associated with obesity in a population's nutritional intake and dieting behaviors. They compared patterns in Australian Google Trends query data with data from the Australian National Nutrition and Physical Activity Survey. Their results confirm that search query data can be used to predict dietary behavior. In a recent study, Fayaz Farkhad and Albarracín (2021) verify the validity of Google Trends for more frequent data (i.e., daily or weekly) using Google mobility data and the Nielsen Retailer Scanner data. Their findings show a positive correlation between state-by-day mobility data and Google searches for park and pharmacy/grocery. Using the 2018 Nielsen Retailer Scanner data, they also show positive associations between weekly sales of over-the-counter pain killers, liquor, beer, and wine sold in a state with the 2018 weekly indexes of Google searches for headache, liquor, beer, and wine, respectively. Therefore, we can assume that Google searches are a valid representation of users' behavior or needs.

According to the WHO, health behaviors refer to actions and habits that improve health status, such as having a healthy diet and being physically active and actions that increase the risk of developing diseases, such as smoking, excessive drinking, and risky sexual behavior. The current study focuses on dietary habits, physical activity, tobacco, alcohol, and drug use. Using the National Health and Nutrition Examination Survey, we select 16 search queries: *workout*, *physical activity*, *exercise*, *weight loss*, *obese*, *overweight*, *diet*, *nutrition*, *restaurant*,

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

fast food, *takeout*, *liquor*, *Wine*, *Beer*, *Cigarette*, and *Cannabis*, which we consider to be in correlation with public health behaviors.

Our results rely on difference-in-differences analysis, suggesting a substantial increase in the search intensity for *workout*, *physical activity*, *exercise*, *takeout*, *liquor*, and *wine*. Despite the lower search for diet and nutrition-related information (i.e., *diet*, *weight loss*, *nutrition*, *restaurant*, and *fast food*), we find no impact on *obese* and *overweight* search intensities. The significant decrease in diet and nutrition-related searches may be the result of changes in priorities and lifestyle routines during the pandemic lockdown. We find no discernible effect on searches for *cigarette* and *cannabis*.

To trace the adaptation of health-related behaviors over time, we apply the event study method. Our findings show that changes in public concerns' regarding health behaviors 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 behaviors 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

To measure health-behavior concerns across U.S. states that imposed full lockdowns following the disease outbreak, we use Google Trends (Google Trends, 2020). Google Trends is a publicly available tool that provides researchers with real-time information in the form of time series query indices for specified geographical locations; these indices are 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.

We use 16 health-behavior-related search terms in Google Trends—*workout*, *physical activity*, *exercise*, *weight loss*, *obese*, *overweight*, *diet*, *nutrition*, *restaurant*, *fast food*, *takeout*, *liquor*, *Wine*, *Beer*, *Cigarette*, and *Cannabis*—and the search time frame is January 1st, 2019, to April 19th, 2020.[2] 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

[2]Stay-at-home orders in Alaska and Oklahoma expired on April 24th, 2020, and their governors allowed businesses to reopen on a rolling basis. These two are the first states in our dataset that lifted the stay-at-home orders. Therefore, we select April 19th as the end of our time period to exclude the possible effect of lifting policies.

up data from January 1st, 2019, to April 19th, 2020, Google Trends only provides weekly, and not daily, data. In order to obtain daily data, we are forced to download query answers in two calls (January 1st, 2019, to April 19th, 2019, and January 1st, 2020, to April 19th, 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 health-behavior-related queries during January–April 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 April 2020. To do this, we follow the re-scaling process proposed by Brodeur et al. (2021). First, we calculate the average weekly data using daily data that is downloaded in two calls (January 1– April 19, 2019 and January 1-April 19, 2020). The weight will be calculated by dividing the weekly data that is downloaded in one call (January 1, 2019– April 19, 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 normalize the re-scaled data in order to have values that are between 0 and 100.[3]

3 Identification Strategies

3.1 Difference-in-Differences Estimation

To estimate the effects of the health shock and intervention policies on people's health-behavior-related searches across states, we rely on common trend assumptions and conduct a difference-in-differences regression that accounts for both annual differences in search intensity and the expected changes in health-related behaviors immediately following the implementation of mitigation policies. The difference-in-differences strategy allows us to control for seasonal changes within states by comparing searches before and after mitigation policies were implemented in 2020 to searches on the same date in 2019. We estimate the following regression for each search query:

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

where $H_{i,t}$ denotes Google search index 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 health shock (2020) and 0 otherwise. Our main coefficient of interest, α, measures the effect of the stay-at-home orders on search query $H_{i,t}$ in state i on date t. The control variable $X_{i,t-1}$ denotes the lagged number of new deaths from COVID-19 per day per million.[4] We include state-level fixed effects (η_i) and time fixed effects (θ_t) to absorb

[3]For more detail about re-scaling Google Trends data, see Brodeur et al. (2021).

[4]The data on new deaths from COVID-19 come from The COVID Tracking Project (2020).

the effects of unobservable time-invariant state or time characteristics. Vector θ_t includes the fixed effects for the year, week, and day (Monday to Sunday). $\epsilon_{i,t}$ is the residual error term.

3.2 Event Study Estimation

To examine how people's search behaviors evolved during the period leading up to and following the stay-at-home orders, we implemented the following event study model for each search query:

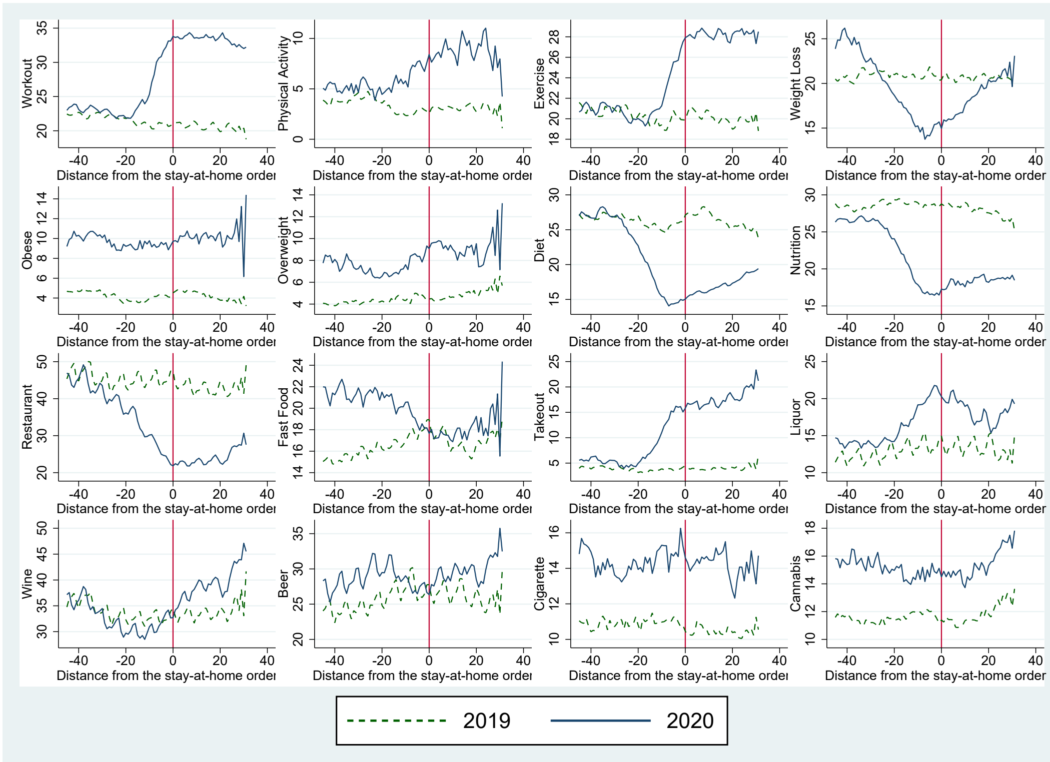
$$\begin{aligned} H_{i,t} = & \sum_{w=-3}^{3} \alpha''_w (D_{i,w} \times Year_t) + \sum_{w=-3}^{3} \beta''_w D_{i,w} \\ & + \gamma''_i X_{i,t-1} + \eta''_i + \theta''_t + \epsilon''_{i,t}, \end{aligned} \tag{2}$$

where $D_{i,w}$ represents the weekly dummy variables for the three weeks before and the three weeks after the lockdowns were imposed. The parameter α''_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. η''_i and θ''_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 1 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 terms *workout*, *physical activity*, and *exercise* starting three weeks before the official lockdowns. Searches for *workout* and *exercise* surged to the highest level in the first week of the lockdown. Searches for *weight loss*, *diet*, and *nutrition* show stable trends in 2019, while in 2020, they show a sudden drop from weeks before the lockdowns were imposed and an upward trend afterward. There was also a sharp drop in Google searches for *restaurant* and *fast food* starting weeks before the lockdowns were implemented, compared to the mostly unchanged pattern that was observed in 2019 for the same period. Searches for *takeout*, *liquor*, and *wine* experienced a remarkable rise starting three weeks before lockdowns. In all search queries except those that follow the same trend as 2019 (i.e., *obese*, *cigarette*, and *cannabis*), we observe a sudden change in the search intensities 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 might have affected health-related behavior. These early changes in search intensities may also be the effect of states' emergency declarations issued 8–25 days before imposing stay-at-home orders, influencing the public's expectation about possible future lockdowns.

Figure 1: 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.

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 indicate that Google searches for *workout*, *physical activity*, and *exercise* spiked after the implementation of state-at-home orders. The estimated effects are statistically significant at the 1% level and are more pronounced for the terms *workout* and *exercise*, respectively. We find no noticeable effects on *obese* and *overweight*. It could be argued that overweight and obesity are the results of weight accumulation over the long term, while the current study only focuses on short-term changes due to alternations in physical activity and diet.

In contrast, search intensity for *restaurant*, *fast food*, *nutrition*, *weight loss*, and *diet* appeared to be negatively influenced by the stay-at-home orders. These statistically significant drops may be due to people's priority for self-care, fear of virus transmission through food or food packaging, and changing their eating habits during the early stage of the lockdowns. The decrease in searches for *restaurant*, *fast food*, and *nutrition* accords with Flanagan et al. (2020)'s results that show significant changes in eating behavior during the pandemic. This study also found that consuming fast foods and eating meals at restaurants decreased, indicating overall healthier eating among survey participants.

We also find a discernible and statistically significant increase in searches for *takeout*, *liquor*, and *wine*. This could result from restaurant/bar limits that led to a shift from having meals at restaurants to having takeout and purchasing alcohol at bars and restaurants to purchasing drinks at stores. Finally, we find no significant effect on searches for *cigarette* and *cannabis*.

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

	Panel A: Dependent Variable							
	Workout	Physical Activity	Exercise	Obese	Overweight	Weight Loss	Diet	Nutrition
$\text{Post}_{i,t} \times \text{Year}_t$	15.873***	2.555**	9.169***	0.559	0.758	−2.046**	−5.600***	−6.136***
	(0.891)	(0.965)	(0.565)	(0.707)	(0.981)	(0.885)	(1.082)	(1.177)
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		
No. of Observations	9,198	5,935	9,181	7,571	7,405	9,184	9,198	9,198

	Panel B: Dependent Variable							
	Restaurant	Fast Food	Takeout	Liquor	Wine	Beer	Cigarette	Cannabis
$\text{Post}_{i,t} \times \text{Year}_t$	−13.441***	−4.905***	14.205***	2.781**	4.188***	−1.621	−0.604	0.661
	(1.130)	(1.056)	(1.173)	(0.762)	(0.399)	(1.301)	(0.920)	(0.513)
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	9,198	9,016	7,367	9,188	9,198	9,198	8,729	9,075

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.

4.2 Event Study Results

Table 2 and Figure 2 present estimates from the event study specification. The results show that there was a continuous rise in Google searches for *workout* starting three 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 (April 19, 2020). Our

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

	Panel A: Dependent Variable							
	Workout	Physical Activity	Exercise	Weight Loss	Obese	Overweight	Diet	Nutrition
3 weeks before× Year	2.804**	0.098	0.752	−14.067***	0.758	−1.632	−9.328***	−8.699***
	(0.830)	(1.895)	(1.361)	(1.306)	(0.575)	(2.197)	(1.083)	(2.287)
2 weeks before× Year	9.562***	3.037	3.007*	−14.615***	−2.183	−1.292	−15.429***	−16.762***
	(1.847)	(1.590)	(1.327)	(1.057)	(1.485)	(1.742)	(2.168)	(1.257)
1 week before× Year	15.926***	2.423**	11.223***	−14.197***	−1.770	−0.858	−18.189***	−15.536***
	(1.817)	(0.979)	(0.749)	(1.413)	(1.392)	(2.849)	(1.504)	(0.929)
The week of lockdown × Year	22.025***	2.607*	11.206***	−10.444***	0.679	1.506	−13.733***	−14.666***
	(2.028)	(1.139)	(1.515)	(2.303)	(2.445)	(1.257)	(1.265)	(1.691)
1 week after× Year	17.879***	4.473**	10.109***	−7.623***	1.699	−0.790	−11.185***	−10.009***
	(1.465)	(1.724)	(1.075)	(1.618)	(1.846)	(2.046)	(1.829)	(1.788)
2 weeks after× Year	19.103***	3.038	12.739***	−2.876	−0.311	1.544	−7.632**	−9.797***
	(1.257)	(2.229)	(1.258)	(2.220)	(0.959)	(1.630)	(2.255)	(1.762)
3 weeks after× Year	18.315***	2.471	13.228***	−0.402	2.532	−3.060	−5.059**	−3.864
	(2.062)	(2.074)	(2.368)	(1.855)	(1.903)	(2.437)	(1.979)	(2.573)
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	9,198	5,936	9,181	9,184	7,571	7,405	9,198	9,198

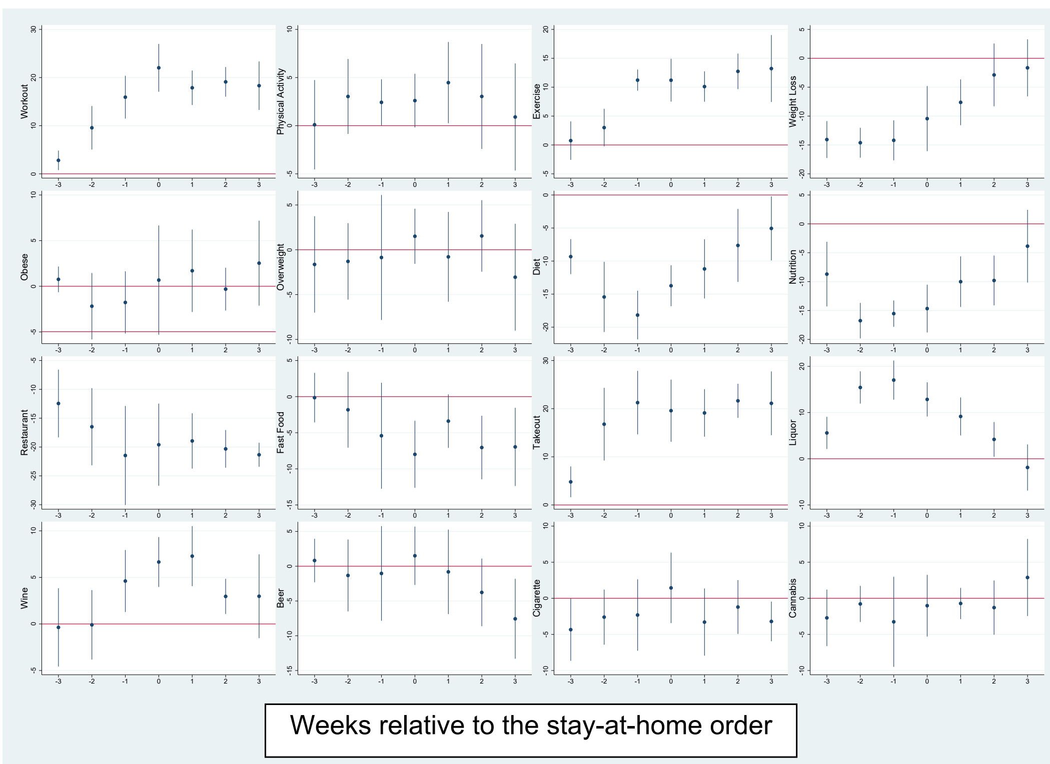
	Panel B: Dependent Variable							
	Restaurant	Fast Food	Takeout	Liquor	Wine	Beer	Cigarette	Cannabis
3 weeks before× Year	−12.450***	−0.142	4.803**	5.592***	−0.367	0.821	−4.337**	0.821
	(2.402)	(1.403)	(1.307)	(1.422)	(1.719)	(1.278)	(1.765)	(1.278)
2 weeks before× Year	−16.485***	−1.820	16.780***	15.436***	−0.094	−1.325	−2.603	−1.325
	(2.731)	(2.144)	(3.082)	(1.424)	(1.523)	(2.113)	(1.559)	(2.113)
1 week before× Year	−21.467***	−5.415	21.261**	17.032***	4.612**	−1.035	−2.314	−1.035
	(3.506)	(2.998)	(2.694)	(1.729)	(1.360)	(2.782)	(2.021)	(2.782)
The week of lockdown × Year	−19.596***	−7.988***	19.584***	12.845***	6.653***	1.506	1.439	1.506
	(2.912)	(1.896)	(2.639)	(1.512)	(1.095)	(1.713)	(1.992)	(1.713)
1 week after× Year	−18.944***	−3.392*	19.115***	9.160***	7.286***	−0.808	−3.293	−0.808
	(1.960)	(1.515)	(2.014)	(1.680)	(1.318)	(2.483)	(1.901)	(2.483)
2 weeks after× Year	−20.318***	−7.047***	21.634***	4.193**	2.961***	−3.763	−1.209	−3.763
	(1.335)	(1.799)	(1.451)	(1.535)	(0.771)	(1.988)	(1.524)	(1.988)
3 weeks after× Year	−21.341***	−6.959***	21.112***	−1.885	2.976	−7.559	−3.204**	−7.559**
	(0.850)	(2.213)	(2.705)	(2.038)	(1.839)	(2.350)	(1.124)	(2.350)
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	9,198	9.016	7,367	9,188	9,198	9,198	8,729	9,075

Notes: The table presents event study coefficients corresponding to Figure 2. 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.

findings indicate that the increase in the number of searches for *exercise* continued throughout the lockdown period. This may be the result of restricted access or full closure of fitness facilities during this period. It may also reflect that during the pandemic people managed to engage in alternative forms of physical activity, such as participating in online classes, or purchasing personal exercise equipment for home use (Knell et al., 2020).

Google searches for *weight loss*, *diet*, *nutrition*, *restaurant*, and *fast food* continued to fall, starting from three weeks before the lockdowns until the end of the lockdowns. Although the negative impact of the lockdowns on *weight loss*, *diet*, and *nutrition* searches resumed during the period of the lockdowns, the magnitude of the impact gradually diminished. The event study results show that the lockdown effects on *restaurant* and *fast food* have not decreased over time. The increase in the number of *takeout*, *liquor*, and *wine* searches started from three weeks before the lockdowns occurred simultaneously with the declarations of emergencies across U.S. states.

Figure 2: Estimated Effects of Stay-at-Home Orders 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 2. 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.

4.3 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. In terms of the effect magnitude, partial closure policies that occurred before the implementation of full lockdowns had the most effect on the health behavior measures. The estimated coefficients using stay-at-home orders as a policy intervention and including states with partial lockdowns are similar to our main results.

5 Conclusion and Discussion

We contribute to the emerging literature on the health impacts of COVID-19 by providing the first study to use Google Trends data to investigate a plausible link between the health shock, state government's intervention policies, and people's health behaviors. Although Google Trends does not provide us with detailed information on each individual, it enables us to exploit variations in peoples' concerns about their health behavior on a day-to-day basis and it can offer insights into how societies' attitudes towards health-related behaviors would differ during a health shock and the resulting policy intervention.

Our findings indicate that intervention policies (stay-at-home orders, school closures, and restaurant/other restrictions) are positively associated with the search intensity for *workout*, *physical activity*, *exercise*, *takeout*, *liquor*, and *wine*. Furthermore, people's search behaviors show that they did not have any significant concerns regarding weight gain during the early stages of the pandemic following the partial closures. Our results highlight a noticeable drop in searches for *weight loss* and *diet*, and no significant change in searches for *overweight* and *obese*. Since excess weight and obesity are the long-term outcomes of excessive body fat accumulation, it could take time to observe the effects of the pandemic and intervention policies on this major health concern in the U.S. The estimated coefficients also present a substantial drop in *nutrition*, *restaurant* and *fast food* searches, while searches related to smoking do not reveal significant results.

In summary, our findings suggest that the pandemic and lockdowns significantly impacted people's dietary habits, physical activity, and alcohol intake. We also show that the effects of the pandemic and lockdowns on a number of measures of health behaviors (i.e., *physical activity*, *diet*, *nutrition*, *liquor*, and *wine*) diminished over time. 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 the current circumstances, public health planners need to consider changes in public health behaviors and promote supportive programs and policies targeting public physical well-being to avoid the long-term health consequences of restrictions during a pandemic.

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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 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. (2021).

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

Panel A: Dependent Variable

	Workout	Physical Activity	Exercise	Obese	Overweight	Weight Loss	Diet	Nutrition
$Post_{i,t} \times Year_t$	16.691***	2.576**	10.218***	0.267	0.318	−5.934***	−10.019***	−9.642***
	(1.150)	(0.794)	(0.717)	(0.920)	(1.061)	(1.291)	(1.228)	(1.032)
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	9,198	5,935	9,181	7,571	7,405	9,184	9,198	9,198

Panel B: Dependent Variable

	Restaurant	Fast Food	Takeout	Liquor	Wine	Beer	Cigarette	Cannabis
$Post_{i,t} \times Year_t$	−18.349***	−5.540**	17.896***	8.058***	4.895***	−0.617	−0.273	−0.254
	(2.075)	(1.787)	(1.934)	(1.013)	(0.719)	(1.759)	(0.994)	(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	9,198	9,016	7,367	9,188	9,198	9,198	8,729	9,075

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

PANEL A: DEPENDENT VARIABLE

	Workout	Physical Activity	Exercise	Obese	Overweight	Weight Loss	Diet	Nutrition
$Post_{i,t} \times Year_t$	17.385***	2.278**	10.570***	−0.158	0.161	−6.165***	−10.354***	−10.255***
	(1.028)	(0.680)	(0.922)	(1.093)	(0.969)	(1.360)	(1.347)	(1.081)
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	8,979	5,823	8,962	7,420	7,242	8,965	8,979	8,979

PANEL B: DEPENDENT VARIABLE

	Restaurant	Fast Food	Takeout	Liquor	Wine	Beer	Cigarette	Cannabis
$Post_{i,t} \times Year_t$	−18.756***	−5.630**	19.176***	8.814***	4.523***	−0.889	−0.796	−0.046
	(2.135)	(1.720)	(1.786)	(1.157)	(0.723)	(1.839)	(1.031)	(0.691)
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	8,979	8,797	7,241	8,969	8,979	8,979	8,510	8,856

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

	Panel A: Dependent Variable							
	Workout	Physical Activity	Exercise	Obese	Overweight	Weight Loss	Diet	Nutrition
$Post_{i,t} \times Year_t$	15.193***	2.880**	8.879***	0.817	0.707	−2.235**	−5.707***	−6.141***
	(0.717)	(0.868)	(0.585)	(0.644)	(1.136)	(0.878)	(1.059)	(1.258)
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	9,855	6,197	9,817	8,003	7,834	9,820	9,855	9,855

	Panel B: Dependent Variable							
	Restaurant	Fast Food	Takeout	Liquor	Wine	Beer	Cigarette	Cannabis
$Post_{i,t} \times Year_t$	−13.378***	−4.768***	14.187***	3.156***	4.062***	−1.644	−0.699	0.828
	(1.112)	(0.955)	(1.218)	(0.752)	(0.421)	(1.362)	(0.829)	(0.507)
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	9,855	9,654	7,644	9,840	9,855	9,855	9,269	9,629

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.