Did Our Trousers Fit After the Quarantine?

Effects of COVID-19 Lockdowns and Digital Social Support on Personal Health Choices

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Abstract

Background: In this paper, we investigate the impact of COVID-19 lock-downs on individual health choices, especially weight management.

Method: Exploiting rich consumer-level data, we find that introducing the shelter-in-place (SIP) order leads to a significant increase in calorie consumption, an increase in the weekly number of calories burned via physical exercise (by 39.845 units), and a one percentage point reduction in the probability of being obese.

Results: Result suggests that individuals with active text-based coach messaging are more likely to achieve their health investment goals compared with their inactive counterparts. Concretely, more digitally active people increase their inputs in managing calorie consumption by setting a more restrictive calorie budget than those receiving less text-based coach messaging.

Conclusion: These results indicate that reducing obesity via these SIP orders and digital social support during the pandemic saved the U.S. health care system $1.47 billion.

Key words: COVID-19, text-based coach messaging, health behavior, weight management.

JEL codes: I12, I18, I31

1. Background

Obesity is a global health problem. Individuals with obesity suffer greater mortality compared with individuals without obesity. This is a socioeconomic problem and needs better management strategies both at the individual and governmental levels. Previous research has investigated several intervention strategies including exercise and fiscal interventions. Though these interventions have been shown some degree of success in mitigating obesity, it is important to note the financial implications, extensive governmental planning and time-consuming implementation strategies associated with these intervention processes.

Behavioral and self-imposed health management strategies to control obesity have increased over time. With the increase in the number of smartphone users in recent periods, smartphone apps have become a health management tool for many users and researchers (Allen, et al. 2013). Later, smartphone apps have shown limited effectiveness in promoting weight reduction strategies and health management. Though we observe some results related to the role of smartphone apps and weight management, all the studies so far used limited data from small-scale studies, with a short period of study. This gives us a large discrepancy in the literature. Flores Mateo et al. (2015) concluded a systematic relationship between smartphone app users and weight loss. On the other hand, Semper et al. (2016) found no difference in weight between app users and non-app users. The objective of this study is twofold. We investigate the effect of text-based coach messaging on app users' health and weight change. We estimate the change in weight at the county level to analyze the effect of the shelter-in-place (SIP) orders and the behavior change between pre-and post-COVID periods. We further look at the welfare effect of weight management under a pandemic.

To empirically examine this causal relationship in the first place, we leverage the staggered adoption of the SIP orders across counties and states throughout the COVID-19 crisis. We then employ a generalized difference-in-differences (DID) design and use rich consumer-level data to measure personal health behaviors and outcomes. Overall, we find that introducing the SIP order leads to a significant decline in the difference between one's weekly calorie budget and the actual calories consumed per week (76.729 units), an increase in the weekly number of calories burned by physical exercise by 39.845 units, and a one percentage point reduction in the probability of being obese. Meanwhile, we also provide evidence that individuals with active text-based coach messaging are more likely to achieve their health investment goals. Specifically, more digitally active people increase their inputs in managing calorie consumption by setting a more restrictive calorie budget than those receiving less text-based coach messaging.

To assess the causal interpretation and robustness of identification, we conduct several exercises including implementing an event-study specification, employing alternative robust difference-in-differences estimators, and addressing the concern of selection bias.

These results suggest that the SIP orders triggered by the COVID-19 crisis may raise people's expected costs of obesity and being overweight and thereby incentivize individuals to take actions to reduce the obesity risk. To probe the validity of this hypothesis, we collect Google Trends data and leverage the search queries for topics related to weight management as a proxy for such expected costs. Along this line, we empirically provide some tentative evidence: Following the enactment of a SIP order, there is an increase in the daily search intensity for topics including anti-obesity medication, overweight, and weight management, reflecting rising public concerns about being obese and overweight.

Meanwhile, our estimated results in weight management and obesity could shed new light on social welfare of the SIP orders. To gauge the social benefits in terms of health, we benchmark the magnitude of reductions in obesity prevalence: the estimated state-level decline associated with a SIP order is equivalent to a decrease of one percentage point in the national obesity prevalence. In turn, such reductions suggest that increased weight management/reducing obesity during the COVID-19 pandemic saved the U.S. health care system $1.47 billion (in 2008 dollars) a year.

Our paper contributes to an emerging strand of literature investigating the impact of the COVID-19 pandemic (as well as relevant policies) on personal health behaviors and health outcomes. Most studies, to the best of our knowledge, have focused on mental health and the level of well-being (e.g., Adams-Prassl et al. (2020), Armbruster and Klotzbücher (2020), Brodeur et al. (2021), Davillas and Jones (2020), de Pedraza et al. (2020), Hamermesh (2020), Tubadji et al. (2020), etc.). Although some literature has provided suggestive evidence concerning the association between COVID-19 and lifestyle health behaviors, there is relatively sparse research establishing the casual relationship.[1] The closest economic literature to ours is Alishahi and Hasanzadeh (2022), in which the authors find that school closures, restaurant restrictions, and stay-at-home orders lead to a significant increase in searches for workout, physical activity, and exercise, but a decline in concerns for weight loss, diet, nutrition, etc. In contrast to this paper purely focusing on search behaviors regarding weight management, we take one step forward and directly explore the impacts on physical exercise, dietary intake adherence, and the probability of being obese. In other words, our paper provides the very first study investigating the effect of COVID-19 related policies on personal weight management and the prevalence of obesity.

[1] For example, Mitchell et al. (2021) found that food preferences and consumption behaviors are modified in populations during the COVID-19 pandemic.

This paper also adds value to the public health literature exploring the role of digital interventions in health behaviors and outcomes, especially personal weight management (see for example, Allen et al. (2013), Banerjee et al. (2020), Beratarrechea et al. (2014), Carter et al. (2013), Czernichow et al. (2021), de Jongh et al. (2012), Ferraro (2003), Grave et al. (2011), Hebden et al. (2014), Kim et al. (2015), Klasnja and Pratt. (2012), Laing et al. (2014), Spring et al. (2013), and Xu et al. (2018)). Compared with prior research utilizing relatively small-scale randomized controlled trails (RCTs), our paper leverages a large-scale, unexpected public health shock, the COVID-19 pandemic, as a quasi-experiment to provide plausibly causal evidence. Furthermore, we advance this strand of research by shedding new light on the welfare implications associated with both the SIP orders and digital health interventions.

The rest of the paper proceeds as follows. Section 2 describes the key data sources we utilized in our empirical analysis. Section 3 provides the features and characteristics of the sample. Section 4 shows the baseline empirical strategies we rely on, and Section 5 presents the main results on personal management of calorie consumption, calorie expenditure via physical exercise, and the probability of being obese. Section 6 assesses the role of text-based coach messaging in weight management, and Section 7 probes the validity of our estimates by conducting several robustness checks. Section 8 explores one potential channel through which personal health behaviors are altered: by raising the expected costs of obesity, the SIP order incentivizes people to self-invest in weight management and reduce the risk of obesity. Section 9 examines the welfare implications of these SIP orders, and eventually, Section 10 concludes.

2. Data

To conduct the empirical analysis, we collect data on (1) the timing of adopting the shelter-in-place orders at the county level, (2) measures of personal health behaviors and outcomes related to weight management, (3) measures of digital social support using text-based coach messaging, and (4) measures of concerns for personal weight management. In this section, we describe the corresponding data sources and how we construct the key variables.

2.1 Adoption of Shelter-in-Place Orders

This study aims to capture the differential effect of the "shelter-in-place" (SIP) orders related to COVID-19 on the health management behavior of the Noom Weight users. Shelter-in-place orders require residents to stay at home, except for essential work, essential shopping, and other permitted duties. We obtained the shelter-in-place orders from the New York Times 2020 data page titled: See Which States and Cities Have Told Residents to Stay at Home.[2] The shelter-in-place orders consist of both state and local government-imposed COVID-19 related social distancing policies executed, between February 1, 2020, and April 5, 2020.

In addition, we collect data on state and local emergency lockdown orders, the orders lifting original SIP, and the closure and reopening orders for gyms and restaurants. We also obtain county-level monthly unemployment rates from the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics (LAUS) program. To merge all data, we first use the crosswalk files from the U.S. Department of Housing and Urban Development (HUD) to map each zip code to the corresponding county in the Noom sample.[3] We then merge all control variables to the Noom data using the county FIPS code.

2.2 Measuring Health Behaviors and Health Outcomes Related to Weight Management

Throughout the analysis, we rely on detailed consumer-level data provided by Noom, Inc. to measure individuals' health behaviors and health outcomes. Noom Weight saves daily activity, exercise (frequency and calories burned), food intake, weight trends (initial weight and weight change), calorie intake by meals (breakfast, lunch, and dinner), and nutritional summaries of the app users. The app then records how users adhered to the recommended calorie budget and ratios of low to high calorie density foods (eg dietary intake adherence). Therefore, the data covers self-monitored observance data, including body weight, target body weight, daily food intake, steps, and an activity check built into the app.

The database provides information on instructional text-based coach messaging (coach messages received) and internal messages exchanged between app users. Our data is weekly for app users between January 2019 and April 2021, including the pre and post COVID-19 periods mentioned above. The data also provides information on the gender, age, and height (BMI) of each user. We have 287,447 unique Noom Weight users in the database. The benefit of the Noom Weight data over other similar databases is the nature of the detailed information available per individual app users. Compared to the initial and targeted weights, weekly weight change allows us to evaluate the most effective strategies.

Our first measure of personal health behaviors is dietary intake adherence, which is the difference between the weekly calorie budget and the actual calories consumed per week (i.e., calorie budget minus calories consumed through food intake). Specifically, we utilize the rich information on individuals' daily consumption of calories via breakfasts, lunches, dinners, and snacks and derive the weekly calorie

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[2] See https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html, last accessed on 3/9/2022.

[3] The HUD-USPS ZIP Code Crosswalk data are downloaded from https://www.huduser.gov/portal/datasets/usps_crosswalk.html, last accessed on 3/10/2022.

consumption by aggregating the amounts of calories for each consumer.[4] The target calorie consumption, which is proxied by calorie budget, is set and updated by the Noom Weight based on personal information and recorded data.[5] We also aggregated these amounts of calories at the individual-week level to mirror the construction of the actual caloric intake. Along this line, we argue this measure records how users adhered to the recommended calorie budget and ratios of low to high calorie density. Put it differently, the more the value of dietary intake adherence approaches zero, the better one performs in following the recommendation.

Besides calorie consumption, regular physical activity and exercise are especially important as well if one is trying to lose weight or to maintain a healthy weight. To examine the effects of the SIP orders on energy expenditure, we employ a second measure as the actual number of calories burned via physical exercise per week. All variables are assembled from the Noom sample.

Finally, we also utilize the probability of being obese, the probability of being overweight, and weekly BMI to measure the key health outcome: weight loss. Following the definition provided by the World Health Organization (WHO), we define the probability of being obese as one if one's weekly BMI is at least 30 and zero otherwise. The probability of being overweight is constructed as one if the weekly BMI is between 25 and 30 and zero if the weekly BMI is below 25. Again, the variables are all constructed with the Noom sample on a weekly basis.

2.3 Measuring Text-based Coach Messaging

To investigate one channel associated with weight management, text-based coach messaging, we rely on consumer information provided by Noom. The data provides the number of coach messages received by users via the Noom Weight and we aggregate this information at the week level for each Noom user. We consider messages exchanged between users and the coaches. To avoid the potential that the message is sent automatically by the system, we define an individual as "social active" if the number of messages received by users per week is at least two and zero otherwise.67 In the empirical analysis, we first test

[4] In the final sample of analysis, we include all observations regardless of one's weekly number of logged meals, in order to capture the aggregate level of calorie intake per week. In another robustness check, we restrict our sample to those users with three full meals per day and find similar results. Specifically, among those who logged 3 full meals per day throughout the entire week (N = 3,737,908), the estimated decline in dietary intake adherence is 66.687 units following the enactment of a SIP order.

[5] Noom uses the Harris-Benedict equation to establish consumers' daily caloric intake. Using this principle, Noom first determines one's BMI (basic metabolic rate) based on personal information (e.g., gender, age, height, starting weight) and then applies this index to the Harris-Benedict equation to determine the daily calorie number. The App assumes a sedentary amount for each user (meaning no exercise) and any logged exercises are credited by adding to one's total calorie allowance for that day. See https://web.noom.com/support/faqs/question-topics/food-logging/2016/08/noom-determine-daily-calorie-budget/, last access on 3/9/2022.

[6] When first signing up for Noom Weight, the system would automatically send one message to new users.

whether one's status of getting text-based coach messaging changes following the adoption of SIP orders, and then directly explore the differential effects of the SIP order by the status of text-based coach messaging.

2.4 Measuring Public Concerns for Weight Management

In order to explore potential mechanisms driving the observed reduction in weight, we also collected Google Trends data to construct measures for public concerns related to weight management. Google Trends data provides an index for search intensity by topics over the sample period in each area. Such an index is the raw number of daily searches for a target topic divided by the maximum number of daily searches for this topic over the sample period. And the index is scaled from 0 (there is not sufficient information regarding the search for a specific term/topic) to 100 (this is the day with the maximum volume of searches over a specific period). In particular, we select several topics related to weight management: *overweight, obesity, anti-obesity medication* and *weight loss.* We choose to submit the topic queries including all related search-terms in any language, which are better proxies for public concerns.

One limitation of the Google Trends data is that daily data on search intensity is only offered for a query period shorter than 9 months (Brodeur et al., 2021). Therefore, the scaling factors used to calculate the search intensity over different periods are not identical to each other. To obtain comparable daily data from January 1st 2019 to June 30th 2020, we followed the rescaling approach described in Brodeur et al. (2021): assembling the raw daily search intensity data via submitting two queries (1/1/2019-6/30/2019 and 1/1/2020-6/30/2020), collecting the raw weekly search intensity data and calculate the weekly search interest weights, and finally rescaling the daily data for each period with the weights.[8]

3. Summary Statistics

In this section, we first provide the summary statistics of the data described in Section 2, and then compare the patterns of these variables between the treatment and control groups.

To begin with, Table 1 presents the summary statistics of the full sample, which includes 8,852,308 observations from January 1st, 2019, to April 30th, 2021. Throughout the empirical analysis, we measure personal health choices and weight management from three dimensions: dietary intake adherence, calorie expenditure via physical exercise, and the probability of being obese and overweight. Specifically, the difference between the weekly calorie budget and the actual calories consumed per week is approximately

[7] In other words, we only consider those messages sent by coaches.

[8] For details regarding this scaling procedure, please refer to the description in Brodeur et al. (2021).

1631.056 units; on average, the weekly calories used through physical exercise is 1,164.539. The portion of users who have received at least two messages from coaches via Noom Weight per week is 34% and the average number of messages received from personal coaches is approximately 1.3 per week. In terms of the sample characteristics, the average age is 50.2 and the portion of male consumers is 19%. The BMI (weekly) among all consumers, on average, is 31.562, and both the prevalence of obesity and the prevalence of overweight are relatively high (54.2% and 70.9%, respectively).

Table 1. Summary Statistic (full sample)

	Mean	Std. Dev.	N
dietary intake adherence	1,631.056	2,185.817	8,852,308
calories burned via physical exercise	1,164.539	1,907.474	8,852,308
log(calories burned via physical exercise)	3.810	3.675	8,852,308
# of messages with coaches	1.327	1.893	8,852,308
log(# of messages with coaches)	0.609	0.653	8,852,308
$\mathbb{1}_{messages>1}$	0.339	0.473	8,852,308
Age	50.229	13.361	8,852,308
Male	0.189	0.392	8,852,308
BMI (weekly)	31.562	6.508	8,852,308
Obesity	0.542	0.498	8,852,308
Overweight	0.709	0.454	4,054,842

Notes: All data are collected from the Noom sample (from 1/1/2019 to 4/30/2021). See text for details of how variables are constructed.

To provide some motivating evidence that the SIP orders related to the COVID-19 pandemic indeed affect personal health behaviors in weight management, we compare the summary statistics of key variables for the treatment and control groups in Table 2. On average, the difference between calories budget and calories consumed, and the number of calories burned via physical exercise are both slightly higher after introducing an SIP order. Meanwhile, one can tell that compared with consumers in the control group (i.e., counties without the adoption of a SIP order), those in the treatment group (i.e., counties with a SIP order in place) are less active digitally: they tend to communicate less with coaches by receiving fewer messages and being less likely to interact with their coaches. Furthermore, when it comes to the features of personal weight, one can observe a decline in all three dimensions following a SIP order: the weekly BMI, the probability of being obese, and the probability of being overweight.

Table 2. Summary Statistics (by the status of treatment)

	Treatment Group			*Control Group*		
	Mean	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**

dietary intake adherence	1,660.719	2,195.490	7,210,701	1,500.762	2137.943	1,641,607
calories burned via physical exercise	1,198.472	1,935.075	7,210,701	1,015.493	1,773.510	1,641,607
log(calorie burned via physical exercise)	3.867	3.683	7,210,701	3.562	3.629	1,641,607
# of messages sent with coaches	1.220	1.805	7,210,701	1.797	2.179	1,641,607
log(# of messages sent with coaches)	0.568	0.639	7,210,701	0.786	0.684	1,641,607
$\mathbb{1}_{messages>1}$	0.315	0.464	7,210,701	0.445	0.497	1,641,607
age	50.010	13.438	7,210,701	51.194	12.973	1,641,607
male	0.194	0.395	7,210,701	0.170	0.375	1,641,607
BMI (weekly)	31.482	6.548	7,210,701	31.912	6.318	1,641,607
obesity	0.534	0.499	7,210,701	0.577	0.494	1,641,607
overweight	0.702	0.457	3,360,224	0.739	0.439	694,618

Notes: All data are collected from the Noom sample (from 1/1/2019 to 4/30/2021). See text for details of how variables are constructed.

4. Method

The main goal of this paper is to empirically test whether and how the SIP orders induced by COVID-19 would affect people's health behaviors related to weight management and the corresponding health outcome (i.e., weight loss). To this end, we leverage the staggered adoption of SIP orders across counties and employ a generalized difference-in-differences (DID) specification as follows:

$$y_{igt} = \alpha + \beta SIP_{gt} + X_{igt}\gamma + \tau_{gt} + \rho_g + week_t + year_t + \epsilon_{igt} \quad (1)$$

where i denotes individual, g represents the county and t refers to time. y_{igt} is the key outcome of interest (i.e., calories consumption management, calories burned via physical exercise, and whether an individual is overweight or obese). The key explanatory variable, SIP_{gt}, is the indicator equaling to one if there is a "*shelter-in-place"* order in effect in county g at time t. ρ_g represents the county fixed effect, which captures the within-period variation across counties; $week_t$ and $year_t$ are the week-of-year and year fixed effects, respectively. We include these two dimensions of time fixed effects to capture the within-county variations over time. Therefore, the main parameter of interest, β represents the change in our outcomes related to weight management due to the introduction of SIP orders.

In addition, we include individual- and county-level controls in some specifications. X_{igt} refers to a vector of individual-level characteristics, including age, gender, and the number of weeks since one's sign-up of the Noom Weight. And τ_{gt} is a vector of county-level controls (the unemployment rate, an indicator that a county has adopted emergency orders due to COVID-19, the order of closure of restaurants and gyms, and the reopening order of gyms and restaurants. Standard errors are clustered at the county level in all regressions to allow for heteroskedasticity and correlation of the error terms within a county.

Alternatively, we consider the potential heterogeneity across counties during the COVID-19 pandemic and propose another specification.[9] In this model, we interact the week fixed effect and year fixed with a full set of county dummies, respectively. These are the $week_{gt}$ and $year_{gt}$ variables included in equation 2 below, respectively. These account for any weekly or annually changing county level heterogeneities, including changing patterns in weather, political attitudes, and other unobservable variances such as demographics and the county populations health related differences, including health infrastructural differences varying within the counties over the time frame of our study. These variables also control migration of individuals from one county to another, or the number of people trave ling in and out of the county, carrying information and potentially spreading the virus. Therefore, this specification controls for heterogeneities across counties' economic, political, health demographics and health services infrastructure, social conditions, etc. in a more comprehensive way.

$$y_{igt} = \alpha + \beta SIP_{gt} + X_{igt}\gamma + \tau_{gt} + \rho_g + week_{gt} + year_{gt} + \epsilon_{igt} \qquad (2)$$

where $week_{gt}$ and $year_{gt}$ are the corresponding fixed effects mentioned above. All others remain the same as those listed in equation (1). Standard errors are still clustered at the county level.

We also estimate the additional effects of 'coach-interactions' in Noom Weight. We call this effect "text-based coach messaging" as this involves exchanges of messages using the internet (like text messages) related to health behavior. We include those users who are present both in the pre and post pandemic periods.

5. Results

The baseline results for the effects of SIP orders on personal health behaviors are presented in Section 5.1 (calories consumption management) and Section 5.2 (calories burned via physical exercises). In Section 5.3, we further assess its impact on personal health outcomes, which is proxied by the probability of being obese.

5.1 Effects of Shelter-in-Place Orders on Dietary Intake Adherence

[9] For example, besides the county-level controls we have considered in the main specification, there are multiple sets of policies being introduced during the sample periods. Omitting such controls might bias our results.

To begin, we examine whether the SIP order affects the intake of calories through food consumption. Table 3 shows the estimates for dietary intake adherence based on our main specifications (equation (1) and (2)). We start with estimating a version of equation (1) that excludes all individual-level and county-level controls. As reported in column (1) of Table 3, we find that following the introduction of a SIP order, the difference between one's weekly calorie budget and the actual calories consumed per week reduces by 125.72 units. After including both individual- and county-level controls described in Section 4, such an average effect declines in magnitude (76.729 units, shown in column (2)) but remains statistically significant. Allowing the coefficients on $week_{gt}$ and $year_{gt}$ to vary by county, one can observe that a SIP order still significantly reduces the difference between calorie budget and calorie consumption. That is, after the enactment of the SIP orders, individuals who are in the treatment group, exceeded their calorie consumption past their budgeted calories. Such estimates (-72.859 in column (3) and -69.465 in column (4)) are not substantially different from the baseline point estimate in column (2) and thereby alleviates the concern that omitted variables are likely to play a meaningful role in the estimation. This set of our main results emphasized the direct effect of SIP orders on health behaviors that are directly related to personal weight management. In the following analysis, we will present some evidence that SIP orders also affect other key margins of health behaviors substantially and therefore have the potential to change the key outcome of interest --- the prevalence of obesity.

ble 3. Effects of SIP Orders on Dietary Intake Adherence

	(1)	(2)	(3)	(4)
SIP order$_{gt}$	-125.720***	-76.729***	-72.859***	-69.465***
	(16.470)	(16.054)	(17.374)	(16.871)
emergency order$_{gt}$	-	-42.175***	-46.116***	-46.818***
	-	(9.537)	(9.409)	(9.682)
unemployment rate$_{gt}$	-	0.077	1.206	0.829
	-	(1.058)	(1.054)	(1.045)
age$_{gt}$	-	3.860***	3.860***	3.860***
	-	(0.281)	(0.281)	(0.281)
male$_{gt}$	-	783.691***	783.621***	783.733***
	-	(11.479)	(11.475)	(11.470)
county fixed effects	Yes	Yes	Yes	Yes
week-of-year fixed effects	Yes	Yes	No	No
year fixed effects	Yes	Yes	No	No
week×division fixed effects	No	No	Yes	No
year×division fixed effects	No	No	Yes	No
week×region fixed effects	No	No	No	Yes
year×region fixed effects	No	No	No	Yes
week-since-sign-up fixed effects	No	Yes	Yes	Yes
# of observations	8,852,308	8,852,308	8,852,308	8,852,308

Standard errors in parentheses. * *$p < 0.1$*, ** *$p < 0.05$*, *** *$p < 0.01$*

Notes: This table presents the results from regression on dietary intake adherence based on equation (1) and equation (2). To measure one's dietary intake adherence, these models use the weekly calorie budget minus the actual calories consumed (via breakfasts, lunches, dinners, and snacks) as a proxy. The first two models rely on the specification listed in equation (1) and the next two models estimate the regression specification listed in equation (2). Standard errors, adjusted for clustering at the county level, are reported in parentheses.

5.2 Effects of Shelter-in-Place Orders on Calories Burned via Physical Exercise

Turning to another key margin related to weight management, the calories used through physical activities, we present the corresponding results in Table 4. As shown in column (1) of Table 4, the adoption of SIP orders leads to an increase of 35.476 calories burned by taking physical exercise. Even after including a full set of individual and county controls, the result is still statistically significant and almost identical in terms of the magnitude (39.845, shown in column (2)). In our preferred, more flexible specifications, which take into account the unobserved geographic heterogeneity across counties (column (3) and column (4)), one can tell that introducing a SIP order, on average, is associated with an increase in weekly calories burned via exercise by 54.363/46.147 units.

Collectively, these results in Section 5.1 and 5.2 imply that following the SIP orders related to COVID-19, individuals who utilize the Noom Weight consume more calorie per week but simultaneously perform more physical exercises. These two findings thus shed new light on a key margin of weight management: balancing one's calorie consumption and expenditure . One potential mechanism is that the enactment of COVID-19 lockdowns might increase calorie consumption, but it also increases calories burned. COVID-19 lockdowns increase one's expected costs associated with obesity (e.g., reduced life expectancy and increased healthcare expenditure) by delaying the delivery of medical treatment. As a result, a priori, individuals with a high risk of being obese or overweight are likely to make more efforts to manage one's weight and maintain a healthier status under the developing COVID-19 threats. This set of results thus emphasizes the importance of incentivizing/encouraging people's *self-investment* in health, especially in light of the shortage of formal medical resources during the public health crisis.

Table 4. Effects of SIP Orders on Calories Burned via Physical Exercise

	(1)	(2)	(3)	(4)
SIP order$_{gt}$	35.476***	39.845***	54.363***	46.147***
	(13.315)	(14.710)	(14.407)	(14.576)
emergency order$_{gt}$	-	-5.746	-21.078**	-15.481*
	-	(8.602)	(8.290)	(8.416)
unemployment rate$_{gt}$	-	-1.979**	-0.106	-0.607
	-	(0.821)	(0.821)	(0.804)
age$_{gt}$	-	-16.750***	-16.749***	-16.749***
	-	(0.286)	(0.287)	(0.287)
male$_{gt}$	-	565.299***	565.542***	565.490***
	-	(11.512)	(11.506)	(11.504)
county fixed effects	Yes	Yes	Yes	Yes
week-of-year fixed effects	Yes	Yes	No	No
year fixed effects	Yes	Yes	No	No
week×division fixed effects	No	No	Yes	No
year×division fixed effects	No	No	Yes	No
week×region fixed effects	No	No	No	Yes
year×region fixed effects	No	No	No	Yes
week-since-sign-up fixed effects	No	Yes	Yes	Yes
# of observations	8,852,308	8,852,308	8,852,308	8,852,308

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the results from regression on dietary intake adherence based on equation (1) and equation (2). The first two models rely on the specification listed in equation (1) and the next two models estimate the regression specification listed in equation (2). Standard errors, adjusted for clustering at the county level, are reported in parentheses.

5.3 Effects of Shelter-in-Place Orders on the Prevalence of Obesity

Thus far, we have examined the impacts of SIP orders on personal health behaviors related to weight management. While both dietary intake adherence and the expenditure of calories by exercise are good measures of weight management, more relevant to welfare purposes is whether SIP orders lead to changes in actual health outcomes.

These results are presented in Table 5, which provides the baseline estimates for the impact of the SIP orders on the probability of being obese. After including all control variables, the introduction of the SIP orders results in a statistically significant decrease in the probability of getting obese by one percentage point (column (2)). According to the results shown in column (3) (-0.011) and column (4) (-0.01), other variations at the county level are not likely to explain such an effect.

Taking together, we have assessed the plausibly causal effect of these COVID-19-induced SIP orders on the key outcome of interest: the prevalence of obesity. The results derived above are not only crucial to weigh the costs and benefits of such public policies during a public health crisis, but also enable us to further explore the potential mechanisms driving such causal effects.

Table 5. Effects of SIP Orders on the Incidence of Obesity

	(1)	(2)	(3)	(4)
SIP order$_{gt}$	-0.007*	-0.010**	-0.011**	-0.010**
	(0.004)	(0.004)	(0.004)	(0.005)
emergency order$_{gt}$	-	-0.008***	-0.006**	-0.006**
	-	(0.002)	(0.002)	(0.002)
unemployment rate$_{gt}$	-	0.001***	0.001***	0.001***
	-	(0.000)	(0.000)	(0.000)
age$_{gt}$	-	-0.001***	-0.001***	-0.001***
	-	(0.000)	(0.000)	(0.000)
male$_{gt}$	-	0.100***	0.100***	0.100***
	-	(0.003)	(0.003)	(0.003)
county fixed effects	Yes	Yes	Yes	Yes
week-of-year fixed effects	Yes	Yes	No	No
year fixed effects	Yes	Yes	No	No
week×division fixed effects	No	No	Yes	No
year×division fixed effects	No	No	Yes	No
week×region fixed effects	No	No	No	Yes
year×region fixed effects	No	No	No	Yes
week-since-sign-up fixed effects	No	Yes	Yes	Yes
# of observations	8,852,308	8,852,308	8,852,308	8,852,308

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the results from regression on dietary intake adherence based on equation (1) and equation (2). The first two models rely on the specification listed in equation (1) and the next two models estimate the regression specification listed in equation (2). Standard errors, adjusted for clustering at the county level, are reported in parentheses.

6. Assessing the Role of Text Based Coach Messaging

The above results described in Section 5 reveal that SIP orders have improved one's performance in weight management. This section outlines and examines one channel that could create substantially differential effects: the app users who subscribe to digital guidance are more motivated and educated in managing weight and maintaining personal health scientifically. To empirically test it, we leverage the information regarding consumers' status of digital social interaction with personal coaches and check if a SIP order creates more significant effects on people remaining active in receiving text-based coach messaging.

6.1 Did the SIP Order Change the Status of Receiving Text Based Coach Messaging?

If the adoption of SIP orders raises individuals' expected costs of obesity and encourages people to take more effort in weight management, then one might expect an increase in the frequency of exchanging messages and seeking guidance from coaches after the lockdowns. We test for such compositional changes in Table 6 and find no evidence to support such a shift in the composition of people engaged in getting support from coaches via Noom. These point estimates are imprecise and inconsistent across specifications, and most of them are statistically insignificant. It confirms that shifts and changes in consumer composition do not meaningfully influence our estimation and there are no significant selection effects for app users who exchange more digital guidance and messages. Hence a two-step Heckit selection effect control is not called for.

Table 6. Effects of SIP Orders on Text-based Coach Messaging

	(1)	(2)	(3)	(4)
SIP order$_{gt}$	0.013***	-0.001	-0.002	-0.001
	(0.004)	(0.002)	(0.002)	(0.002)
emergency order$_{gt}$	-	0.003**	0.005***	0.005***
	-	(0.002)	(0.002)	(0.002)
unemployment rate$_{gt}$	-	-0.000	-0.000*	-0.000*
	-	(0.000)	(0.000)	(0.000)
age$_{gt}$	-	-0.000***	-0.000***	-0.000***
	-	(0.000)	(0.000)	(0.000)
male$_{gt}$	-	-0.083***	-0.083***	-0.083***
	-	(0.001)	(0.001)	(0.001)
county fixed effects	Yes	Yes	Yes	Yes
week-of-year fixed effects	Yes	Yes	No	No
year fixed effects	Yes	Yes	No	No
week×division fixed effects	No	No	Yes	No
year×division fixed effects	No	No	Yes	No
week×region fixed effects	No	No	No	Yes
year×region fixed effects	No	No	No	Yes
week-since-sign-up fixed effects	No	Yes	Yes	Yes
# of observations	8,852,308	8,852,308	8,852,308	8,852,308

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the results from regression on dietary intake adherence based on equation (1) and equation (2). The first two models rely on the specification listed in equation (1) and the next two models estimate the regression specification listed in equation (2). Standard errors, adjusted for clustering at the county level, are reported in parentheses.

6.2 Differential Effects of SIP Orders by the Status of Receiving Text-based Coach Messaging

As mentioned above, we argue that the introduction of SIP orders would incentivize individuals to increase their inputs into weight management and health maintenance. However, the extent to which such SIPs would raise individuals' inputs is likely to be unevenly distributed and might hinge on several determinants. For example, a change in adopting the SIP orders will lead to a more considerable impact when individuals face lower barriers to seeking help and guidance. We implement an additional test to check such heterogeneous effects by focusing on text-based coach messaging with their coaches via the Noom Weight. In this case, text-based coach messaging might enhance one's awareness of keeping fit, scientifically offering more weight management information and consistent motivation. For all these reasons, it is plausible to observe a more significant effect on the management of calories and the health outcomes among digitally active individuals than other Noom users who are not digitally active.

We present this set of results in Table 7. Row 1-5 record the corresponding estimates for dietary intake adherence, the level of actual calorie consumption, the level of calorie budget, calorie expenditure via exercise, and the probability of obesity, based on the model listed in equation (2). Column (1) shows the result for the full sample, and the differential effects by the status of text-based coach messaging via the Noom Weight are provided for non- users in column (2) and in column (3) for text-based coach messaging users.

Consistent with our hypothesis, the impact on the probability of obesity is more prominent among people communicating more frequently with their coaches. We also separately check the effects on the level of actual calorie consumption and the target calorie budget: among the text-based coach messaging active sample, the SIP order has insignificant impacts on their actual calorie consumption but would reduce the target budget by 1.1%. In contrast, it leads to an increase in both the actual number of calories intake (by 3%) and the weekly budget (by 1.1%) for the relatively inactive sample. The effects on calorie expenditure between text-based coach messaging active and non-active individuals are almost identical. Results from this exercise imply that compared with those receiving less text-based coach messaging support, more text-based coach messaging active people increase their inputs in managing calorie consumption by setting a more restrictive calorie budget.

While the SIP orders can incentivize all users of the Noom Weight to increase efforts into health maintenance and weight management, it would be most efficient only if it makes people more inclined to take actions. Text-based coach messaging provided by Noom Weight undoubtedly can lead consumers to achieve their health investment goals. Our suggestive evidence in this section has supported this premise.

Table 7. Differential Effects of SIP Orders by the Status of Text-based Coach Messaging

	(1) *Full Sample*	(2) *Digital Active*	(3) *Digital Inactive*
Dietary Intake Adherence	-72.859***	-59.371***	-63.581***
	(17.374)	(21.536)	(18.123)
Actual Calorie Consumption (%)	0.014**	0.003	0.030***
	(0.006)	(0.005)	(0.007)
Calorie Budget (%)	-0.003	-0.011***	0.011**
	(0.004)	(0.003)	(0.004)
Calorie Expenditure	54.363***	52.377***	55.615***
	(14.407)	(17.537)	(16.873)
Obesity Prevalence	-0.011**	-0.011**	-0.009*

	(1)	(2)	(3)
	(0.004)	(0.005)	(0.005)
county fixed effects	Yes	Yes	Yes
week×division fixed effects	Yes	Yes	Yes
year×division fixed effects	Yes	Yes	Yes
week-since-sign-up fixed effects	Yes	Yes	Yes

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The key independent variable in all regression of Table 7 is the indicator for adopting a SIP order. Results are from linear regressions based on equation (2) with the week-division fixed effect and the year-division fixed effect. Column (1) presents results based on the full sample. Results for the sample with text-based coach messaging and the sample without text-based coach messaging are shown in column (2) and column (3), respectively. Standard errors, adjusted for clustering at the county level, are reported in parentheses.

7. Assessing the Causal Interpretation and Robustness

In this section, we implement several tests to assess the causal interpretation of our estimates and probe the robustness of these results.

7.1 Does the SIP Order Affect the Probability of Signing up?

Another potential threat to identification is that the COVID-19 pandemic and related policies could substantially change the composition of Noom users and thereby introduce selection bias on the margin of entry. Put it differently, people with higher risks of obesity and overweight are more likely to sign up for the Noom Weight. To alleviate this concern, we focus on the sample of newly signed users and implement the following regression analyses:

$$log\ log\ (\#of\ newly\ signed\ users_{st})\ =\ \alpha + \beta SIP_{st} + \tau_{st} + \rho_s + week_t + year_t + \epsilon_{st} \quad (3)$$

$$log\ log\ (\#of\ newly\ signed\ users_{st})\ =\ \alpha + \beta SIP_{st} + \tau_{st} + \rho_s + week \times year_t + \epsilon_{st} \quad (4)$$

where $log\ log\ (\#of\ newly\ signed\ users_{st})$ if the logarithm of the number of consumers newly signed up the Noom Weight in state s at time t. SIP_{st} is an indicator whether there is a SIP order in place in state s at time t. τ_{st} is the state-level controls, including the enactment of a state emergency order and the introduction of lifting a SIP order. We also incorporate the state fixed effect to control time-invariant heterogeneities across states. And the key difference between equation (3) and (4) is that the latter one allows us to within-state variants with a full set of $week \times year$ fixed effects in a flexible way.

Table 8 provides the results: without controlling for other state-level, COVID-19 relevant policies and more flexible time fixed effects, the number of newly signed consumers has increased by 11.44% following the SIP order at the 10% significance level. However, in column (2), we present the evidence that in our preferred, more conservative specification (i.e., eq (4)), the impact of an SIP order on the prevalence of signing up for the Noom Weight is statistically insignificant. Thus, we prefer to claim that there is little supportive evidence for a compositional effect on the entry margin.

Table 8. Effects of SIP Orders on Signing-up

	(1)	(2)
SIP_{gt}	0.1144*	0.0438
	(0.0581)	(0.0780)
$SIP\ lift_{gt}$	-	0.0839*
	-	(0.0456)
$emergency\ order_{gt}$	-	0.0331
	-	(0.0650)
state fixed effect	Yes	Yes
week-of-year fixed effect	Yes	No
year fixed effect	Yes	No
week×year fixed effect	No	Yes
# of observations	19,680	19,680

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The key independent variable Table 8 is log(# of newly signed consumers). Column (1) presents results based on the specification with year fixed effect and week fixed effect. Results based on a specification with a full set of *week×year* fixed effects are shown in column (2). Standard errors, adjusted for clustering at the county level, are reported in parentheses.

7.2 Does the SIP Order Affect Recommended Calorie Budget?

Additionally, we perform another exercise to test whether introducing the SIP order would affect the target calorie budget recommended by Noom Weight.[10] Table 9 presents the result: Overall, we find little evidence that the SIP order per se would meaningfully change this index (column (1), (2), and (3)). Yet, when separately exploring the effects by users' status of receiving text-based coach messaging, it suggests that compared with text-based coach messaging users who experienced a 1.2% decline in this target budget following the SIP order (column (4) – (6)), the population communicating less frequently with coaches are more likely to have a higher level of calorie budget per week (an increase of approximately 1.3%, column (7) – (9)). According to Noom Weight, the calorie budget remains unchanged from week to week, but it can change when users request the coach to lower their calorie budget. Our results thus suggest that text-based coach messaging users are requesting lower budget following the SIP order and thereby imply compared with their less-active counterparts receiving digital social support, users frequently communicating with coaches are setting more ambitious goals in managing personal weight.

In terms of relevant policy implications, our results in this exercise highlight the potential role of digital platforms in altering individual health behaviors. Specifically, encouraging the adoption of the digital

[10] We appreciate the helpful suggestions provided by Noom to guide us in interpreting how to adjust the weekly target calorie budget in Noom Weight. Generally speaking, only personal coaches have the autonomy to lower a user's budget throughout a week, once the index is set at the very beginning.

social support system during the pandemic might leave room for additional positive health externalities. In the meantime, expanding this digital social networking feature in relevant products can improve the quality and thereby add value to consumer wellbeing, especially to personal health outcomes.

7.3 Event-Study Specification

One key assumption for our difference-in-differences design is that treatment and control groups would follow common trends in the absence of a SIP change in the treated states. In the context of the COVID-19 pandemic, the validity of this assumption might be violated if changes in COVID-19 cases led to both the implementation of various policies and concerns of infection that lead to care avoidance that would have occurred even in the absence of any formal policy changes (Cantor et al., 2020).

To formally address this concern, we employ an event study specification to test for pre- and post-treatment trends. Allowing for a 13-weeks pre-treatment window and a 10-weeks post-treatment window, we implement the analysis with the following regression model:

$$y_{igt} = \alpha + \sum_{k=-10}^{13} \beta_k SIP_{gt-k} + X_{igt}\gamma + \tau_{gt} + \rho_g + week_t + year_t + \epsilon_{igt} \quad (5)$$

In equation (5), a series of coefficients β_k would capture the impacts of the SIP orders in the weeks before and after the formal implementation.

In Figure 1.A – 1.C, we plot the coefficients on the leads and lags of adopting a SIP order. We normalize the coefficient on SIP_{gt-1} to be zero. Overall, there is little evidence suggesting that prior to introducing the SIP orders, the trends in treatment and control groups are substantially different. Meanwhile, our results based on those lag coefficients indicate the impacts of such SIP orders can persist for at least 10 weeks.

Table 9. Differential Effects of SIP Orders on Calorie Budget by Text-based Coach Messaging

	Full Sample			*Digital Active*			*Digital Inactive*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SIP order$_{gt}$	-0.001	0.002	0.003	-0.012***	-0.009***	-0.007***	0.013***	0.017***	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
SIP lift$_{gt}$	-0.004	-0.010***	-0.006**	-0.001	-0.005*	-0.003	-0.005*	-0.012***	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
emergency order$_{gt}$	0.001	0.005**	0.002	-0.012***	-0.011***	-0.012***	0.004	0.008***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
unemployment rate$_{gt}$	0.001***	0.001***	0.001**	0.001***	0.001***	0.001***	0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age$_{igt}$	0.002***	0.002***	0.002***	0.000***	0.000***	0.000***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
male$_{igt}$	0.298***	0.298***	0.298***	0.298***	0.298***	0.298***	0.321***	0.321***	0.321***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
county fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
week-of-year fixed effects	Yes	No	No	Yes	No	No	Yes	No	No
year fixed effects	Yes	No	No	Yes	No	No	Yes	No	No
week×division fixed effects	No	Yes	No	No	Yes	No	No	Yes	No
year×division fixed effects	No	Yes	No	No	Yes	No	No	Yes	No
week×region fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
year×region fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
week-since-sign-up fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of observations	8,850,967	8,850,967	8,850,967	2,997,396	2,997,396	2,997,396	5,853,571	5,853,571	5,853,571

Standard errors in parentheses. * *$p < 0.1$*, ** *$p < 0.05$*, *** *$p < 0.01$*

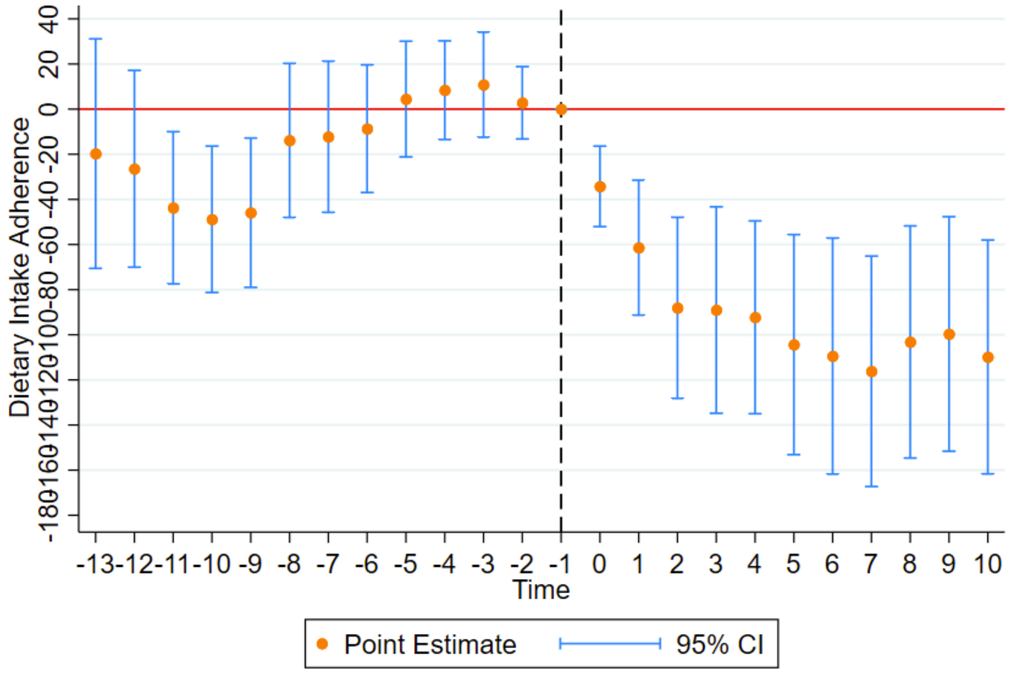

Figure 1.A. Event Study (Dietary Intake Adherence)

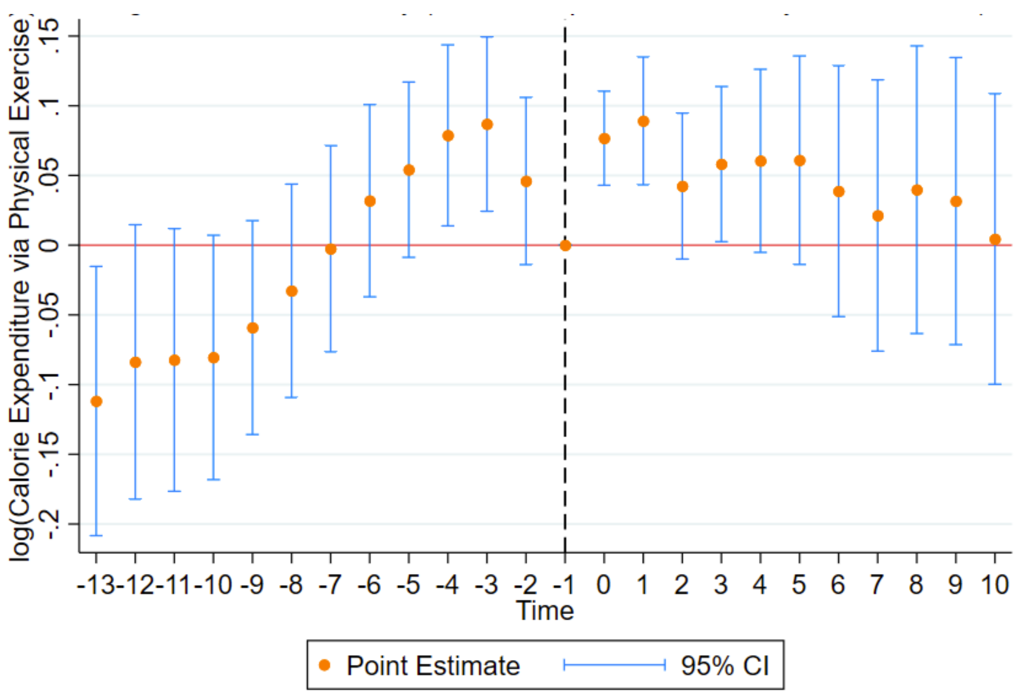

Figure 1.B. Event Study (Calorie Expenditure via Physical Exercise)

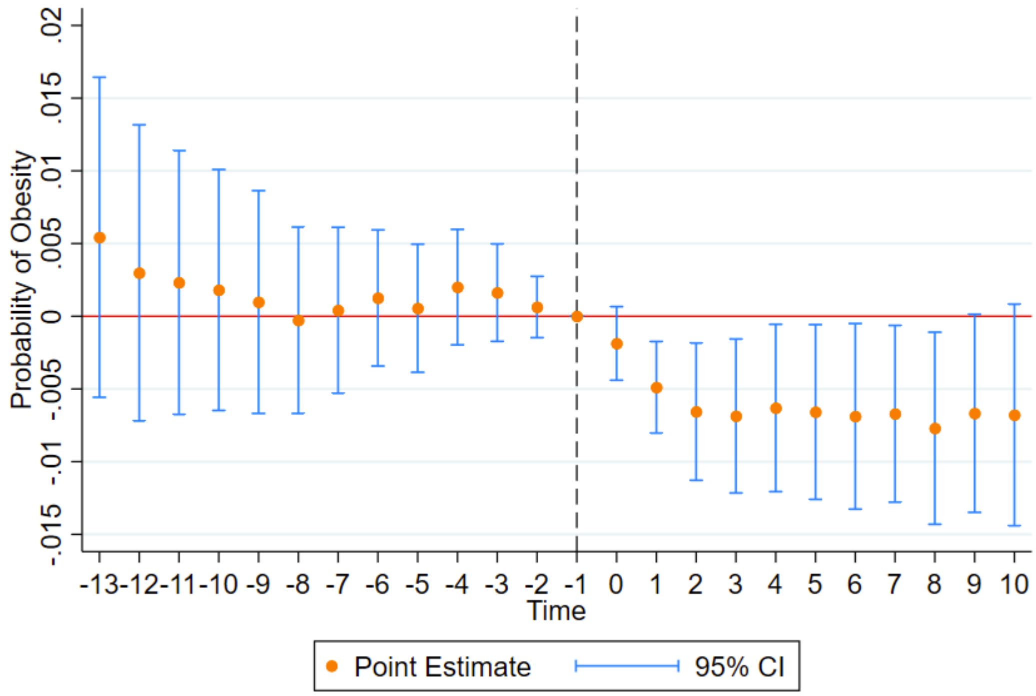

Figure 1.C. Event Study (Probability of Obesity)

7.3 Alternative Choices of Specification

In the appendix, we also probe the robustness of our results by checking if the baseline estimates are sensitive to changes along the following dimensions: the choice of the reference date, including other relevant state policies, and addressing the role of county urbanicity. We report these results in Table A1 – A5. Our main estimates hold up against alternative specifications and thereby suggest that the impacts on personal health behaviors and outcomes driven by COVID-19 SIP orders are plausibly causal and convincing.

8. Why Do SIP Orders Affect Obesity?

The above results reveal that the SIP order related to the COVID-19 pandemic substantially affected individuals' health behaviors and outcomes in weight management. In Section 5, we have discussed one mechanism that can drive such effects: by delaying the medical service, the COVID-19 pandemic can raise individuals' expected costs of being obese and overweight. Consequently, people with high risks of being obese are more likely to self-invest in weight management in advance, leading to economically significant improvements in health outcomes.

In this section, we explicitly test whether this mechanism holds. Formally, we consider a measure of public concerns for weight management: search queries for weight-related terms and topics via Google. As described in Section 2.4, we collect Google Trends data and construct the number of Google daily searches for the following topics: *obesity, overweight, anti-obesity medication,* and *weight loss.*

$$y_{st} = \alpha + \beta SIP_{st} + \tau_{st} + \rho_s + day_t + week_t + year_t + \epsilon_{st} \qquad (6)$$

where y_{st} is the aggregate number of daily searches for topic y in state s at time t. SIP_{st} is an indicator if a SIP order is in place in state s at time t. τ_{st} is a set of state-level controls, including the enactment of state emergency declaration and the introduction of lifting a SIP order. We include state fixed effect, day-of-week (i.e., Monday to Sunday) fixed effect, week-of-year fixed effect and year fixed effect.

In Table 10, our results indicate that enacting the SIP order is associated with a rise in search intensity for *anti-obesity medication, overweight,* and *weight loss.* Such estimates are both statistically and economically significant, reflecting a shift in public concerns/interests for these health topics during the pandemic. We thus assert that this exercise provides some suggestive evidence that the SIP orders triggered by the COVID-19 pandemic are altering people's health behaviors through the psychological channel.

In the meantime, the implications of our findings can shed some new light on policymaking as well. For example, the burden of a public health crisis might be far-reaching and go beyond one single dimension. In the case of the COVID-19 pandemic, due to the crowd-out of medical resources and healthcare capacity, people with other chronic diseases (e.g., obesity) would suffer from unexpected negative externalities both physically and psychologically. As a result, it emphasizes the necessity to take into account these extra costs when designing relevant policies aiming to mitigate the adverse effects during these pandemics.

Table 10. Effects of SIP Orders on Search Queries

	(1) *Anti-obesity Med*	(2) *Obesity*	(3) *Overweight*	(4) *Weight Loss*
SIP_{gt}	4.7970***	0.6743	3.1246*	2.8505***
	(1.1871)	(1.1196)	(1.5693)	(0.9370)
$SIP\ lift_{gt}$	1.0981	-1.8825	-0.8028	0.5327
	(0.8871)	(1.1326)	(1.1020)	(0.7117)
$emergency\ order_{gt}$	-2.9794**	1.6048	-0.9171	-2.8695***
	(1.2949)	(1.1076)	(1.4610)	(0.9132)
state fixed effect	Yes	Yes	Yes	Yes
day-of-week fixed effect	Yes	Yes	Yes	Yes
week-of-year fixed effect	Yes	Yes	Yes	Yes
year fixed effect	Yes	Yes	Yes	Yes
# of observations	15,113	15,714	15,927	16,638

Notes: This table presents the results from linear regressions on the search queries for anti-obesity medication, overweight, and weight loss based on equation (6). Standard errors, adjusted for clustering at the county level, are reported in parentheses.

9. Welfare Implications

Obesity, as a notorious public health epidemic, has long been receiving intensive concerns. Public debates regarding this issue have centered on how to provide efficient interventions in medical treatment, legal framework, and social safety net programs. In this paper, we have provided empirical evidence that one target policy related to the COVID-19 crisis can create unexpected, substantial spillover effects on the prevention of obesity. By reducing the obesity risk among the population, it thus leaves the potential to raise social welfare.

In the empirical portion of this paper, we have documented that adopting a SIP order leads to substantial improvements in preventing obesity: on average, one adoption would result in a one percentage point decline in the probability of getting obese. Though the COVID-19 SIP orders were a curse for all societies and economies alike but analyzing this measurable positive impact of these SIP orders on welfare-improvement might suggest further policy for controlling obesity. To put this magnitude in perspective, one helpful benchmark is to rescale the result at the national level.

According to the Behavioral Risk Factor Surveillance System (BRFSS), the U.S. obesity prevalence was 27.8% in 2011 and 30.9% in 2018, with the average as 29.54%.[11] Among the states with a SIP order during the COVID-19 pandemic, the average prevalence of obesity was 29.4% from 2011 through 2018. Our estimate (a decrease of 1 percentage point shown in Table 5) is thus equivalent to a decline of 3.40% (= 1/29.423*100%) throughout the sample period. After applying this percentage response to the national level, adopting the SIP order also implies a decrease of 1 percentage point in the national obesity

[11] These statistics are drawn from https://nccd.cdc.gov/BRFSSPrevalence/rdPage.aspx?rdReport=DPH_BRFSS.ExploreByLocation&irbLocationType=States&islClass=&islLocation=&islTopic=&islYear=&rdRnd=52148, last accessed on 3/10/2022.

prevalence. Therefore, such a decline induced by the SIP orders is comparable to preventing the aggregate growth of obesity prevalence by 2.26 years.[12] Meanwhile, as pointed out by the Center of Disease Control and Prevention (CDC), the medical costs of obesity are $147 billion per year (in 2008 dollars).[13] The estimated reduction in the U.S. aggregate obesity prevalence thus implies that increased weight management/ reducing obesity during the pandemic saved the U.S. health care system $1.47 billion (= $147 billion*1%, in 2008 dollars) a year.

10. Conclusion and discussion

After the pandemic, users active via 'digital social support' achieved more beneficial effects of Noom Weight *vis-à-vis* their health choices and outcomes. Social networking on the app helped users better achieve their calorie consumption goals, comparing to their pre pandemic goals. 'Text-based coach messaging' in the weight loss App also helped users exercise more comparing to their pre pandemic goals. 'Text-based coach messaging'. 'Coach message system' users enjoyed significantly more calories burn and weight loss. Non-coach system users do not enjoy significant calorie burn or clear weight loss.

Overall Noom has had a positive effect on users' health management during the pandemic but not without the digital messaging feature of it.

Declarations

Ethics approval and consent to participate: This research followed all research protocols approved by Auburn University. Informed consent from participants was waived by the IRB/ Ethics committee of Auburn University. The authors did not have access to participants or did not have access to any participant identifiable information, this research did not perform any experiment and did not use human subjects or human identified information. Research is performed in accordance with the Declaration of Helsinki. An exemption from the Auburn University office of institutional research was obtained. The reason for the exemption is that the data received and used in the research was completely de-identified or anonymous.

Consent for publication: No consent was obtained from any subject because human subject was not used directly. No experiment was conducted in this study. The data used is secondary data with no identified human information. Consent of publication was obtained from Noom Inc., the owner of the data.

Availability of data and materials: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. The data is available from Noom Inc. on request but not publicly available.

Competing interests: Authors have no competing interests to declare.

Funding: No funding was obtained.

Authors' contributions: All authors contributed equally for the preparation of the manuscript. Dr. Banerjee and Dr. Nayak collected and prepared the data.

Acknowledgements: We thank Noom Inc. for providing the data.

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[12] Such a statistic is derived as follows: 1/0.443 = 2.26, where 0.443 is the annual growth rate of obesity during the period of 2011-2018.

[13] See https://www.healthaffairs.org/doi/pdf/10.1377/hlthaff.28.5.w822?casa_token=NM_Zpd94b-MAAAAA:ygU-g0ECe9tx4V8keAuELABP_1KxWDYxSwOVgOVc2tt7ixM-BYTVapL9MQuhcrnwEmRNQxfSKQ, last accessed on 3/10/2022.

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