Body mass index in young men in Switzerland after the national shutdowns during the COVID-19 pandemic – Results from a cross-sectional monitoring study at population level since 2010

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Abstract

Background: Due to the COVID-19 pandemic, the Swiss Federal Council imposed a shutdown twice, which may have changed dietary and physical activity habits. On the question of weight change during the pandemic, there is little information based on measured weight data. In this study, we investigate whether the body mass index (BMI) of young Swiss men conscripted after the two shutdown periods in Spring and Fall 2020 differed from the conscripts examined before the shutdowns.

Methods: We are analysing body measurements of young Swiss men taken during mandatory recruitment for the Swiss Armed Forces on the cross-sectional (not individual longitudinal) monitoring level and across weeks of conscription between January 2010 and July 2021 (n=373,016). These cross-sectional data allow for continuous health monitoring of young men almost at the population level (coverage >90% of recruitment relevant age categories). For statistical modelling, we use GAM (Generalized Additive Model framework).

Results: We showed that the BMI of conscripts who were examined in the 15 weeks after the two shutdowns in Spring and Autumn 2020 was not or only weakly different from baseline. Sensitivity analyses showed that this conclusion also holds if assessing the BMI distribution or the prevalence of overweight and/or obesity. The GAM models further showed strong effects of individual and area-based SEP as well as age on BMI.

Conclusion: Our results suggest that any lifestyle changes during the pandemic in young men may have been too modest to be clearly reflected in body weight (suggesting small or none effect). However, longitudinal data and/or data on women, children, or the elderly may lead to different conclusions.

Keywords: BMI; Obesity; Monitoring; Lockdown; swiss Conscription; GAM

1. Introduction

In the wake of the COVID-19 pandemic in Spring 2020, the Federal Council decided on the first far-reaching shutdown on March 16, 2020, which was relaxed in several steps between April and June 2020.(1) Due to this first national shutdown, the lifestyle of the Swiss population changed markedly. On the one hand, physical activity behaviour was affected through staying home recommendations, home offices, suspension of schools, closed sports facilities and gyms, etc. On the other hand, eating habits, work environments, and mental well-being might also have changed, as has been documented for other countries.(2) These affected lifestyle factors are all well known to be associated with weight gain, overweight, and obesity. In autumn 2020, far-reaching measures were again taken by the Federal Council to limit the peak of the second COVID-19 wave. Nationwide mobility tracking in Switzerland has shown a striking reduction in the daily travelled distance during both periods.(3) Younger people were affected in particular, as they are the most mobile group of the population.(3) At present, it is unclear how these two shutdown periods have affected the health of the general population in Switzerland, especially concerning body weight. Based on the literature (4–7) nutritional status could have been influenced in two directions: increased outdoor activities combined with healthier nutrition (homemade, "slow food") may have led to less overweight. However, it is also conceivable that body weight was adversely influenced by increased immobility, unhealthier food, and psychological stress.

Since 2020, there has been a steady increase in the number of studies addressing this issue based on electronic surveys that capture the health and nutritional status of individuals based on self-reported information during home confinement. Two recent review articles summarize the evidence about weight gain during shutdowns in Spring 2020 based on surveys from various countries. The first systematic review and meta-analysis based on 59,000 people from 32 different countries documents weight gain regardless of age group.(8) The second review also highlights different clusters of weight change, with people with high baseline BMI and with low education level being particularly affected by weight gain.(9) For Switzerland, a recent survey based on self-reported weight information showed that between 2019 and 2021, the age group between 45-64 years gained more than four times as much weight as the younger age groups.(10)

In general, there is little information on this question of weight change during the pandemic based on measured weight data. Our study is intended to change this for Switzerland. We are analysing body measurements of young Swiss men taken during mandatory recruitment for the Swiss Armed Forces, which allow for continuous

health monitoring of young men almost at the population level (it is a unique feature of our study that it circumvents essentially all potential problems with sample selection by investigating almost all conscriptable individuals). On the cross-sectional (not individual longitudinal) monitoring level and across weeks of conscription between January 2010 and July 2021, we are investigating whether the body mass index (BMI) of the group of young Swiss men after the two shutdown periods in Spring and Fall 2020 differs from the group of conscripts examined before the shutdowns. To our knowledge, this is also the first of such study internationally based on measured routine weight monitoring data. Comparable data from other countries could follow our results.

2. Methods

Swiss Conscription

Conscription for the Swiss Armed Forces examines each year approximately 95% of a birth cohort of men with Swiss citizenship one time at age between 18 and 22 years.⁽¹¹⁾ A detailed description of the conscription process can be found elsewhere.⁽¹¹⁾ Together with other examinations, the medical examination during conscription serves to check the state of health and thus the physical fitness for military service of the individual conscript. These examinations enable the health status of young men to be monitored with unique broad coverage. The six centres where conscription is conducted based on identical protocols are Payerne, Mels, Monteceneri, Rüti, Sumiswald, and Aarau. All measurements are performed by trained army medical personnel or specifically trained soldiers serving in the conscription process. In addition to health data, current occupation and place of residence were recorded.

In the summer of 2018, the Swiss Armed Forces introduced a more flexible conscription system into the armed forces, in the course of which young men themselves determine the timing of their conscription based on the desired date of basic training occurring approximately 12 months later (we control our analyses for a change in this system change).

Variables

The delivered anonymized data included the age groups of the conscripts (18.00-18.99 years, 19.00-19.99 years, 20.00-20.99 years, 21.00-21.99 years, and older than 22.00 years). To measure body height (cm) and weight (kg) in underwear and without shoes, a stadiometer and a regular calibrated scale were used. Body mass index (BMI) ($\text{weight [kg]} / \text{height [m}^2\text{]}$) was calculated.

Self-reported occupation of the conscripts is the only variable that indicates the socioeconomic background at the individual level. Following established procedures,⁽¹²⁾ the occupations of conscripts were assigned to the Socio-Economic Index of Occupational Status (ISEI-08).⁽¹³⁾ The ISEI allows the comparison of occupations according to their socioeconomic status. The ISEI-08 distribution of the occupations was divided into three tertile groups (low, medium, high). Pupils and students together form a separate group, as do those conscripts with no or insufficient information about their occupation. The regional attributes (language region (3), larger

regions (Grossregionen, 7), MS region (microregional intermediate level for scientific and regional policy purposes, 106), urbanity) were linked to the data via residential postal code and place of residence before full anonymization and data delivery to the study team. The average Swiss neighbourhood index (Swiss-SEP 2.0) was also linked at the municipality level (14) Swiss-SEP 2.0 indicates the average socioeconomic situation in a postal code and was developed and made available by the Institute for Social and Preventive Medicine at the University of Bern. For this study, the Swiss-SEP of municipalities was divided into quintiles.

In the course of the COVID-19 pandemic and following national public health interventions, recruitment was suspended in Spring and Autumn 2020. During the first shutdown, conscription was stopped for a total of 13 weeks from calendar week 10 (Monday, March 09, 2020) to calendar week 20 (Friday, May 15, 2020). There was a second interruption of the conscription process for three weeks from calendar week 44 (Monday, October 26, 2020) until calendar week 46 (Friday, November 13, 2020). In both cases, we describe postshutdown effects as two 15-week stretches, starting in the week of resumption after the shutdowns. This time window was determined before the data analysis. On the one hand, these almost 4 months are short enough to track BMI changes at the level of groups, on the other hand, this window is also long enough to allow for a sufficiently large sample size as well as not only describe short-term rather random fluctuations.

Ethics

The fully anonymized dataset for this retrospective cross-sectional monitoring study was provided by the Armed Forces Medical Services (AFMS) on a contractual basis. The data were exported by the AFMS from the "Medizinisches Informationssystem der Armee" (MEDISA) and were made completely anonymous before being handed over to the study team. As described earlier (11), Swiss conscription is mandatory and the anthropometric measurements used in this study are non-clinical, governmental data. According to Swiss federal law ("Bundesgesetz über die militärischen Informationssysteme" MIG, BG 510.91, Art. 2, 9, 24–29), the Swiss Army is authorized to make the data accessible for academic research in anonymous form. When dealing with fully anonymized and non-clinical data, no additional ethical approval is needed for analyses based on such governmental data (Swiss data privacy act, SR 235.1; 19.6.1992).

Statistical analysis

Our analysis is based on a model of the GAM (generalized additive model (15,16)) class, using penalized splines for smooth terms to achieve sufficient flexibility and t-distribution (with degree of freedom estimated from data) for the error term to achieve robustness to occasional data coding errors. The structure of the model for BMI of the i -th individual of residence municipality s at time t (coded in weeks since the beginning of the study) is correcting for spatial, temporal and individual heterogeneity nuisance effects to extract post-shutdown effects as follows:

$$\begin{aligned}
& BMI_{ist} \\
&= \beta_0 + \beta_{urban} \cdot I(\text{municipality } s \text{ is of urban type}) + \sum_k \alpha_k \cdot I(\text{individual } i \text{ is of age class } k) \\
&+ \sum_l \gamma_l \cdot I(\text{individual } i \text{ is of ISEI group } l) \\
&+ \beta_{scheme} \cdot I(\text{time } t \text{ is before the change in conscription scheme}) + s_{year}(\text{year of } t) \\
&+ s_{seasonality}(\text{week of } t) + s_{SEP}(\text{mean SEP value of municipality } s) \\
&+ s_{region}(\text{MS region of municipality } s) \\
&+ s_{postshutdown1}(\text{week after end of first shutdown}) \cdot I(t \text{ is within 15 weeks after the end of first shutdown}) \\
&+ s_{postshutdown2}(\text{week after end of second shutdown}) \cdot I(t \text{ is within 15 weeks after the end of second shutdown}) \\
&+ \varepsilon_{ist}
\end{aligned}$$

where

- $I(.)$ is an indicator function (assumes a value of 1 if its argument is true and a value of 0 otherwise)
- $\beta_0, \beta_{urban}, \beta_{scheme}$ are unknown coefficients
- α_k 's and γ_l 's are unknown coefficients corresponding to the ANOVA-like submodels in age and ISEI factors (with usual baseline identifiability restrictions)
- s_{year}, s_{SEP} are smooth terms implemented as cubic splines
- $s_{seasonality}$ has to satisfy (as any proper seasonal profile) periodic conditions so that it is implemented as a cyclic cubic spline
- s_{region} is the spatial random effect modelled as GMRF (Gaussian Markov random field)

- $\varepsilon_{ist} \sim t(0, \nu, \sigma^2)$ is a t-distributed error term with scale and degrees of freedom parameters estimated from the data. Use of t-distributed error term with rather low degrees of freedom (estimated from data), instead of traditional Gaussian errors makes the model highly robust – resistant to potential outliers that might occur in big-data that we model.
- $s_{postlockdown1}$ and $s_{postlockdown2}$ are smooth effects of main interest. They are implemented as cubic splines with the restrictions $s_{postlockdown1}(0) = s_{postlockdown2}(0) = 0$

All unknown coefficients and smooth terms are estimated from data via optimization of penalized likelihood, with penalty coefficients estimated by REML. The calculations were performed in R (17) with the help of the mgcv library (15). It is important to note that our GAM-based, semiparametric approach is a substantial generalization as compared to the linear or other pre-defined functional shape analysis promoted in traditional approaches like e.g., interrupted time series regression (18). In fact, the approach we use allows for non-linear and non-constant effects, as salient effects are important in our analysis of post-shutdown transient effects of a priori unknown functional shape.

As a sensitivity check, we employed also an ordinal regression model with WHO BMI categories and similar structure of the explanatory variables in order to check the results in an alternative and even more robust (or outlier-resistant) way.

3. Results

The dataset used for this analysis included 373,016 conscripts examined between January 1, 2010, and July 31, 2021. There were no extreme and unreliable values in height or weight we had to exclude. The relative frequency of age groups, greater regions, and occupational groups did not markedly change over time (Table 1). In 2020 (the most recent full calendar year included in the dataset), the mean BMI was 22.30 kg/m² (SD 4.0), 19.6% of the conscripts were overweight, and 5.9% were obese. For the first six months of 2021, for which data were already available, the BMI of young men did not change significantly compared to 2020. Overall, the mean BMI and the prevalence of overweight and obesity stabilized at a high level since 2010 (Table 1).

Our best fitting GAM model (7.7% deviance explained) included two separate postshutdown effects of 15 weeks each, starting at the end of the shutdowns, and included smoothed terms (full model results see appendix Chapter 1. Figure 1 shows that after the first shutdown in Spring 2020, the BMI of the conscripts entering conscription 15 weeks after the temporary suspension of conscription during the shutdown was not significantly different from that of the conscripts before the shutdown (Figure 1A). However, there was a significant effect ($p=0.011$) after the second, shorter shutdown in Fall 2020 (Figure 1B), with a slight increase in BMI in the first 2 weeks, followed by a decrease in BMI until week 15 of the post-shutdown effect. In both cases in Figure 1, the confidence intervals are relatively wide, indicating a rather weaker effect.

Our main model also revealed significant differences in BMI for the other included covariables (detailed results can be found in the Supplementary Appendix): Compared to the reference group of the 19-year-old conscripts, older conscripts had a significantly higher BMI, and conscripts with a higher ISEI group and students had a significantly lower BMI. We also found that conscripts living in urban and lower Swiss-SEP areas of Switzerland had a higher BMI (the smoothed effect was almost linear, see Appendix 1.1, Figure B). There was also a significant spatial effect across the 106 MS regions in Switzerland, with the northwestern part of Switzerland having higher BMI values. We also found weak but significant effects for seasonality (lowest BMI values in the summer months) and across years, when the average BMI of Swiss conscripts slightly decreased since 2010.

The same conclusion (only weak effects of shutdown periods on BMI) can be drawn when the model was stratified by larger regions or when we used the heteroskedastic GAMLSS model as an alternative (taking into account the nature of the BMI distribution). The conclusion also did not change when using ordinal regression models to assess WHO categories for BMI.

4. Discussion

In this paper, we analysed whether shutdowns during the COVID-19 pandemic affected the measured body weight of young men in Switzerland. We showed that the BMI of conscripts who were examined in the 15 weeks after the two shutdowns in Spring and Autumn 2020 was not or only weakly different from baseline. Sensitivity analyses showed that this conclusion also holds if assessing the BMI distribution or the prevalence

of overweight and/or obesity. The models further showed strong effects of individual and area-based SEP as well as age on BMI.

Because the number of similar studies based on measured monitoring data is still very small, contextualization with the literature is difficult at the moment. The comparison with the many survey studies based on self-reported before-after weight data is challenging in many aspects. Many of these survey studies show weight gain during the pandemic, especially for women, previously overweight people, and older people.⁽¹⁹⁾ This was also recently shown by the only Swiss study on this topic.⁽¹⁰⁾ The reasons for the young men in our data not gaining weight may be multifactorial. One possible explanation could be that the shutdowns in Switzerland were relatively unrestrictive. Despite the recommendation to stay at home, the Swiss population was allowed to go outside at any time. Even with visible shutdown effects in national mobility tracking,⁽³⁾ the more local movement patterns of young people might not have been restricted. Another possibility is that changes in the balance between diet and exercise level over several weeks are less likely to translate into additional body weight in younger people than in older people. One possible explanation could be that lipid turnover in fat tissue decreases during ageing.⁽²⁰⁾ In future events such as shutdowns, health monitoring of young men should include not only anthropometric parameters but also body composition and metabolic parameters, which are particularly relevant in terms of later health risk.

Our study had several limitations. First, we only considered young Swiss men in our study. Women were not considered, even though they are particularly at risk of gaining weight according to a French study.⁽²¹⁾ A second limitation is that we only have cross-sectional data. To make a statement about the weight profile of an individual, it would be necessary to collect longitudinal, individual measurements before and after the pandemic. At the moment, such data only exist in the form of self-reported weight information. Furthermore, we have no information on how the lifestyle of young men has changed during shutdowns, especially regarding diet, physical activity, psychological condition and well-being. However, this information would be crucial to put the observed effect in a broader context. Last but not least, it is a limitation of BMI that it only reflects the relation between weight and height and cannot say anything about body composition. Therefore, changes in body composition and/or metabolic parameters could also have occurred in young men during and after the shutdowns, which, however, were not reflected in additional body weight.

Prevention is the most effective therapy.(20,22) It is important to understand how the behaviour and health of a population adapt and change in response to a crisis on a larger scale. Surveillance and monitoring of the population and public health are the basic prerequisites for possible targeted intervention and are therefore of paramount importance. This especially applies to young men because being obese in adolescence increases the risk of being obese as an adult, and the disease risks associated with excess weight in men in particular increase with age.(20) Certainly, it would be wrong to say that no prevention against weight gain is needed in the event of another shutdown event among young men based on our study results. For successful prevention, not only should risk factors be addressed, but underlying risk-reducing resources should be identified and strengthened. For this purpose, our study population could also be helpful for further studies for other population groups (women, children, elderly people), not only in Switzerland but also in other countries.

Author statements

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Conflict of Interest Statement

The authors do not declare a conflict of interest.

Data Availability Statement

This article used fully anonymized individual data as provided by the Swiss Armed Forces upon signing a data contract. By this contract, the authors of the article are not authorized to make individual datasets publicly available. However, other researchers may request the very same data set from the Swiss Armed Forces via submission of a study protocol. The R-code for the analysis of the datasets can be obtained from the corresponding author.

Key-points

- We were able to show, based on measured monitoring data, that the weight of young men was only slightly influenced by environmental changes such as mobility restrictions or home office due to the corona-related shutdowns.
- Over the last 10 years, the BMI of young Swiss people has stabilised at a high level, with those living in urban areas having a significantly higher BMI than those living in rural areas.
- In the case of a negative study outcome regarding BMI increase due to shutdowns, our study population can be used to identify and strengthen underlying risk-reducing resources that could be useful for other more vulnerable populations.

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Table 1: Data overview

Year	2010		2011		2012		2013		2014		2015		2016		2017		2018		2019		2020		2021	
Conscripts	n		n		n		n		n		n		n		n		n		n		n		n	
Total	36792		37251		36272		35673		34914		34724		33785		32201		38188		24517		18869		9830	
Agegroups	n %		n %		n %		n %		n %		n %		n %		n %		n %		n %		n %		n %	
<19.00	8534	23.2	8849	23.8	8890	24.5	8902	25.0	10819	31.0	10832	31.2	10818	32.0	11514	35.8	13327	34.9	8831	36.0	4467	23.7	2306	23.5
19.00-19.99	16751	45.5	17234	46.3	16702	46.0	16413	46.0	15702	45.0	15726	45.3	15479	45.8	13785	42.8	15666	41.0	10208	41.6	8048	42.7	3744	38.1
20.00-20.99	8489	23.1	8298	22.3	7784	21.5	7575	21.2	6170	17.7	6058	17.4	5419	16.0	5212	16.2	6913	18.1	4309	17.6	4609	24.4	2614	26.6
21.00-21.99	3018	8.2	2870	7.7	2896	8.0	2783	7.8	2223	6.4	2108	6.1	2069	6.1	1690	5.2	2282	6.0	1169	4.8	1745	9.2	1166	11.9
Grossregionen	n %		n %		n %		n %		n %		n %		n %		n %		n %		n %		n %		n %	
Central Switzerland	4103	11.2	4038	10.8	4072	11.2	3901	10.9	3844	11.0	3792	10.9	3740	11.1	3625	11.3	2917	7.6	2735	11.2	2311	12.2	1064	10.8
Eastern Switzerland	6128	16.7	6218	16.7	5859	16.2	5293	14.8	5293	15.2	5598	16.1	5176	15.3	5073	15.8	4519	11.8	3926	16.0	2963	15.7	1311	13.3
Espace Mittelland	9191	25.0	8867	23.8	8282	22.8	8767	24.6	8524	24.4	8131	23.4	7388	21.9	7269	22.6	12515	32.8	6122	25.0	4550	24.1	2441	24.8
Lake Geneva Region	5362	14.6	5539	14.9	6116	16.9	6359	17.8	5986	17.1	5805	16.7	5795	17.2	5258	16.3	8839	23.1	3393	13.8	2602	13.8	1354	13.8
Northwestern Switzerland	4971	13.5	4972	13.3	4939	13.6	4884	13.7	4936	14.1	4756	13.7	4420	13.1	4463	13.9	3240	8.5	3284	13.4	2480	13.1	1410	14.3
Ticino	1421	3.9	1372	3.7	1377	3.8	1349	3.8	1308	3.7	1323	3.8	1402	4.1	1325	4.1	1344	3.5	1045	4.3	813	4.3	453	4.6
Zurich	5615	15.3	6244	16.8	5627	15.5	5112	14.3	5018	14.4	5304	15.3	5863	17.4	5187	16.1	4811	12.6	4010	16.4	3148	16.7	1796	18.3
ISEI-Groups	n %		n %		n %		n %		n %		n %		n %		n %		n %		n %		n %		n %	
Tertile 1 (low)	8428	22.9	8317	22.3	7504	20.7	7321	20.5	7119	20.4	6952	20.0	6591	19.5	6141	19.1	6719	17.6	4942	20.2	3835	20.3	1681	17.1
Tertile 2 (medium)	7998	21.7	7916	21.3	7904	21.8	7745	21.7	6919	19.8	6758	19.5	8963	26.5	8428	26.2	9058	23.7	6439	26.3	5235	27.7	2366	24.1
Tertile 3 (high)	7321	19.9	7658	20.6	7584	20.9	7516	21.1	7341	21.0	7365	21.2	5176	15.3	4905	15.2	5487	14.4	4026	16.4	3260	17.3	1503	15.3
Students	9964	27.1	9740	26.1	9626	26.5	9195	25.8	9508	27.2	9830	28.3	8704	25.8	7438	23.1	8822	23.1	5590	22.8	3565	18.9	2429	24.7
Imprecise	3080	8.4	3620	9.7	3654	10.1	3896	10.9	4027	11.5	3819	11.0	4351	12.9	5289	16.4	8099	21.2	3520	14.4	2974	15.8	1851	18.8
Mean values	m sd		m sd		m sd		m sd		m sd		m sd		m sd		m sd		m sd		m sd		m sd		m sd	
Height [cm]	178.2	6.5	178.2	6.5	178.3	6.6	178.2	6.6	178.3	6.6	178.4	6.6	178.4	6.6	178.5	6.6	178.5	6.6	178.8	6.6	178.7	6.6	178.7	6.6
Weight [kg]	74.5	13.1	74.5	13.0	74.5	13.1	74.4	13.2	74.3	13.2	74.2	13.3	74.4	13.5	74.3	13.9	74.3	13.8	74.4	13.4	74.6	13.7	74.5	14.0
BMI [kg/m ²]	23.4	3.8	23.4	3.8	23.4	3.8	23.4	3.8	23.3	3.8	23.3	3.9	23.4	3.9	23.3	4.0	23.3	4.0	23.3	3.9	23.3	4.0	23.3	4.1
BMI [kg/m ²] (WHO categories)	n %		n %		n %		n %		n %		n %		n %		n %		n %		n %		n %		n %	
<18.5	1290	3.5	1374	3.7	1402	3.9	1421	4.0	1535	4.4	1640	4.7	1655	4.9	1738	5.4	2060	3.5	1328	3.5	1019	3.5	575	3.5
18.5-24.9	26125	71.0	26409	70.9	25671	70.8	25300	70.9	24805	71.0	24531	70.6	23438	69.4	22313	69.3	25018	71.0	16934	71.0	12944	71.0	6718	71.0
25.0-29.9	7220	19.6	7257	19.5	7077	19.5	6835	19.2	6529	18.7	6445	18.6	6584	19.5	6039	18.8	6687	19.6	4658	19.6	3579	19.6	1828	19.6
≥ 30.0	2157	5.9	2211	5.9	2122	5.9	2117	5.9	2045	5.9	2108	6.1	2106	6.2	2111	6.6	2324	5.9	1524	5.9	1255	5.9	652	5.9

Figure legend

Figure 1: Population-level changes in young men's BMI after the first (A, Spring 2020) and second (B, autumn 2020) shutdown ($s_{postshutdown1}$ and $s_{postshutdown2}$ model terms). The y-axis indicates the effect (partial changes in BMI). The x-axis indicates the time in weeks after the end of the shutdown. Upper and lower limits of the grey area correspond to the (pointwise constructed) 95% asymptotic intervals.

Appendix Material to:

Body mass index in young men in Switzerland after the national shutdowns during the COVID-19 pandemic – Results from a cross-sectional monitoring study at population level since 2010.

Samuel Meili, Marek Brabec, Frank Rühli, Thomas W. Buehrer, Nejla Gültekin, Zeno Stanga, Nicole Bender, Kaspar Staub, Emilie Reber

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1 Statistical methods

Our analysis is based on a model of the (slightly generalized) GAM (generalized additive model (15,16)) class, using penalized splines for smooth terms to achieve sufficient flexibility and t-distribution (with degree of freedom estimated from data) for the error term to achieve robustness to occasional data coding errors. The structure of the model for BMI of the i -th individual of residence municipality s at time t (coded in weeks since the beginning of the study) is correcting for spatial, temporal and individual heterogeneity nuisance effects to extract post-shutdown effects as follows:

$$\begin{aligned}
 BMI_{ist} &= \beta_0 + \beta_{urban} \cdot I(\text{municipality } s \text{ is of urban type}) + \sum_k \alpha_k \cdot I(\text{individual } i \text{ is of age class } k) \\
 &+ \sum_l \gamma_l \cdot I(\text{individual } i \text{ is of ISEI group } l) \\
 &+ \beta_{scheme} \cdot I(\text{time } t \text{ is before the change in conscription scheme}) + s_{year}(\text{year of } t) \\
 &+ s_{seasonality}(\text{week of } t) + s_{SEP}(\text{mean SEP value of municipality } s) \\
 &+ s_{region}(\text{MS region of municipality } s) \\
 &+ s_{postshutdown1}(\text{week after end of first shutdown}) \cdot I(t \text{ is within 15 weeks after the end of fist shutdown}) \\
 &+ s_{postshutdown2}(\text{week after end of second shutdown}) \cdot I(t \text{ is within 15 weeks after the end of second shutdown}) \\
 &+ \varepsilon_{ist}
 \end{aligned}$$

where

- $I(\cdot)$ is an indicator function (assumes a value of 1 if its argument is true and a value of 0 otherwise)
- $\beta_0, \beta_{urban}, \beta_{scheme}$ are unknown coefficients
- α_k 's and γ_l 's are unknown coefficients corresponding to the ANOVA-like submodels in age and ISEI factors (with usual baseline identifiability restrictions)
- s_{year}, s_{SEP} are smooth terms implemented as cubic splines

- $s_{seasonality}$ has to satisfy (as any proper seasonal profile) periodic conditions so that it is implemented as a cyclic cubic spline
- s_{region} is the spatial random effect modelled as GMRF (Gaussian Markov random field)
- $\varepsilon_{ist} \sim t(0, \nu, \sigma^2)$ is a t-distributed error term with scale and degrees of freedom parameters estimated from the data.
- $s_{postlockdown1}$ and $s_{postlockdown2}$ are smooth effects of main interest. They are implemented as cubic splines with the restrictions $s_{postlockdown1}(0) = s_{postlockdown2}(0) = 0$

All unknown coefficients and smooth terms are estimated from data via optimization of penalized likelihood, with penalty coefficients estimated by REML.

2 Full results of the main model

Family: Scaled t(3.735,2.679)

Link function: identity

Formula:

```
BMI ~ s(Year, bs = "cr") + fUrbanNon. Urban + fAgegroup +  
fscheme + fISEIGroups + s(Mean_SSEP, bs = "cr") + s(Week_Mon,  
bs = "cc") + s(fMSRegion, bs = "mrf", xt = x. MSRegion) +  
s(postlockdown1, by = zero, bs = "cr", pc = 0) + s(postlockdown2,  
by = zero, bs = "cr", pc = 0)
```

Parametric Terms:

	df	F	p-value
fUrbanNon.Urban	1	24.327	8.13e-07
fAgegroup	3	756.106	< 2e-16
fscheme	1	0.003	0.957
fISEIGroups	4	434.268	< 2e-16

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Year)	5.127	6.228	30.740	< 2e-16
s(Mean_SSEP)	3.966	4.913	133.142	< 2e-16
s(Week_Mon)	6.093	8.000	9.554	2.51e-16
s(fMSRegion)	91.078	101.507	21.928	< 2e-16
s(postlockdown1):zero	1.750	2.136	0.744	0.4679
s(postlockdown2):zero	3.240	3.948	3.459	0.0108

```
> summary(a.cs.2)
```

Family: Scaled t(3.735,2.679)

Link function: identity

Formula:

```
BMI ~ s(Year, bs = "cr") + fUrbanNon. Urban + fAgegroup +
fscheme + fISEIGroups + s(Mean_SSEP, bs = "cr") + s(Week_Mon,
bs = "cc") + s(fMSRegion, bs = "mrf", xt = x. MSRegion) +
s(postlockdown1, by = zero, bs = "cr", pc = 0) + s(postlockdown2,
by = zero, bs = "cr", pc = 0)
```

Parametric coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	22.914251	0.030166	759.601	< 2e-16 ***
fUrbanNon.UrbanUrban	0.069570	0.014105	4.932	8.13e-07 ***
fAgegroup20.00-20.99	0.318353	0.015070	21.124	< 2e-16 ***
fAgegroup21.00-21.99	0.686759	0.022935	29.944	< 2e-16 ***
fAgegroup<19.00	-0.291254	0.013667	-21.310	< 2e-16 ***
fschemeold	0.001864	0.034516	0.054	0.957
fISEIGroupswithout occupation	-0.426096	0.039082	-10.903	< 2e-16 ***
fISEIGroupsTertile 1 (low)	0.109151	0.016116	6.773	1.27e-11 ***
fISEIGroupsTertile 3 (high)	-0.145160	0.016511	-8.792	< 2e-16 ***
fISEIGroupsStudents	-0.549195	0.016464	-33.358	< 2e-16 ***

signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Year)	5.127	6.228	30.740	< 2e-16 ***
s(Mean_SSEP)	3.966	4.913	133.142	< 2e-16 ***
s(Week_Mon)	6.093	8.000	9.554	2.51e-16 ***
s(fMSRegion)	91.078	101.507	21.928	< 2e-16 ***
s(postlockdown1):zero	1.750	2.136	0.744	0.4679
s(postlockdown2):zero	3.240	3.948	3.459	0.0108 *

signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.0218 Deviance explained = 7.74%

```
fREML = 4.7316e+05  scale est. = 1          n = 332320
> AIC(a.cs.2)
[1] 1785788
```

2.1 Visualization of the smoothed terms and MS region effect on BMI

Figure A: Smoothed BMI effect across years

Figure B: Smoothed BMI effect across SSEP

Figure C: Smoothed BMI effect across Weeks

Figure D: Smoothed BMI effect across MS regions

3 Results from alternative models

3.1 Ordinal regression

Here, we use ordinal regression formulated as a GAM model with smooth effects similar to those used previously for BMI modelling. The main motivation is to utilize an alternative model (less influenced by potential outliers or other data problems) as a form of sensitivity check.

Family: Ordered Categorical(-1,3.19,4.86,84)

Link function: identity

Formula:

```
oBMI ~ s(Year, bs = "cr") + fUrbanNon. Urban + fAgegroup +  
fscheme + fISEIGroups + s(Mean_SSEP, bs = "cr") + s(Week_Mon,  
bs = "cc") + s(fMSRegion, bs = "mrf", xt = x. MSRegion) +  
s(postlockdown1, by = zero, bs = "cr", pc = 0) + s(postlockdown2,  
by = zero, bs = "cr", pc = 0)
```

Parametric Terms:

	df	F	p-value
fUrbanNon.Urban	1	27.631	1.47e-07
fAgegroup	3	508.905	< 2e-16
fscheme	1	2.201	0.138
fISEIGroups	4	495.313	< 2e-16

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Year)	5.174	6.295	13.051	< 2e-16
s(Mean_SSEP)	4.144	5.117	124.832	< 2e-16
s(Week_Mon)	5.278	8.000	7.267	< 2e-16
s(fMSRegion)	87.587	99.966	16.613	< 2e-16
s(postlockdown1):zero	2.839	3.470	2.658	0.05172
s(postlockdown2):zero	1.005	1.017	8.182	0.00406

```
> AIC(o2)
[1] 575938.1
```

```
> summary(o2)
```

Family: Ordered Categorical(-1,3.19,4.86,84)

Link function: identity

Formula:

```
oBMI ~ s(Year, bs = "cr") + fUrbanNon. Urban + fAgegroup +
fscheme + fISEIGroups + s(Mean_SSEP, bs = "cr") + s(Week_Mon,
bs = "cc") + s(fMSRegion, bs = "mrf", xt = x. MSRegion) +
s(postlockdown1, by = zero, bs = "cr", pc = 0) + s(postlockdown2,
by = zero, bs = "cr", pc = 0)
```

Parametric coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.164111	0.020490	105.619	< 2e-16 ***
fUrbanNon.UrbanUrban	0.050210	0.009552	5.257	1.47e-07 ***
fAgegroup20.00-20.99	0.166459	0.010043	16.575	< 2e-16 ***
fAgegroup21.00-21.99	0.362823	0.014948	24.272	< 2e-16 ***
fAgegroup<19.00	-0.172659	0.009382	-18.404	< 2e-16 ***
fschemeold	0.034897	0.023520	1.484	0.138
fISEIGroupswithout occupation	-0.267770	0.026995	-9.919	< 2e-16 ***
fISEIGroupsTertile 1 (low)	0.077609	0.010648	7.289	3.13e-13 ***
fISEIGroupsTertile 3 (high)	-0.117048	0.011061	-10.582	< 2e-16 ***
fISEIGroupsStudents	-0.404172	0.011235	-35.975	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

edf	Ref.df	F	p-value
-----	--------	---	---------

```

s(Year)          5.174  6.295  13.051 < 2e-16 ***
s(Mean_SSEP)     4.144  5.117 124.832 < 2e-16 ***
s(Week_Mon)      5.278  8.000   7.267 < 2e-16 ***
s(fMSRegion)     87.587 99.966  16.613 < 2e-16 ***
s(postlockdown1):zero 2.839  3.470   2.658 0.05172 .
s(postlockdown2):zero 1.005  1.017   8.182 0.00406 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Deviance explained = 1.11%

fREML = 7.03e+05 Scale est. = 1 n = 332320

3.2 Heteroscedastic normal regression

Family: gaulss

Link function: identity logb

Formula:

```

BMI ~ s(Year, bs = "cr") + fUrbanNon.Urban + fAgegroup +
fscheme + fISEIGroups + s(Mean_SSEP, bs = "cr") + s(Week_Mon,
bs = "cc") + s(fMSRegion, bs = "mrf", xt = x.MSRegion) +
s(postlockdown1, by = zero, bs = "cr", pc = 0) + s(postlockdown2,
by = zero, bs = "cr", pc = 0)
~s(Year, bs = "cr") + fUrbanNon.Urban + fAgegroup + fscheme +
fISEIGroups + s(Mean_SSEP, bs = "cr") + s(Week_Mon,
bs = "cc") + s(fMSRegion, bs = "mrf", xt = x.MSRegion) +
s(postlockdown1, by = zero, bs = "cr", pc = 0) + s(postlockdown2,
by = zero, bs = "cr", pc = 0)

```

Parametric Terms:

```

df    Chi.sq  p-value

```

fUrbanNon.Urban	1	42.884	5.81e-11
fAgegroup	3	2084.781	< 2e-16
fscheme	1	1.523	0.217
fISEIGroups	4	2653.398	< 2e-16
fUrbanNon.Urban.1	1	139.207	< 2e-16
fAgegroup.1	3	1055.304	< 2e-16
fscheme.1	1	2.471	0.116
fISEIGroups.1	4	2532.459	< 2e-16

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value
s(Year)	6.299	7.427	117.003	< 2e-16
s(Mean_SSEP)	4.546	5.522	806.765	< 2e-16
s(Week_Mon)	5.717	8.000	56.932	< 2e-16
s(fMSRegion)	90.552	101.290	2129.421	< 2e-16
s(postlockdown1):zero	2.322	2.820	5.588	0.11021
s(postlockdown2):zero	3.952	4.793	15.897	0.00592
s.1(Year)	8.609	8.950	144.468	< 2e-16
s.1(Mean_SSEP)	5.011	6.017	882.793	< 2e-16
s.1(Week_Mon)	4.686	8.000	17.579	0.00115
s.1(fMSRegion)	89.891	100.930	1703.167	< 2e-16
s.1(postlockdown1):zero	3.676	4.482	11.458	0.02479
s.1(postlockdown2):zero	3.754	4.563	12.514	0.02156

> summary(h2)

Family: gaussian

Link function: identity logb

Formula:

BMI ~ s(Year, bs = "cr") + fUrbanNon.Urban + fAgegroup +
 fscheme + fISEIGroups + s(Mean_SSEP, bs = "cr") + s(Week_Mon,
 bs = "cc") + s(fMSRegion, bs = "mrf", xt = x.MSRegion) +
 s(postlockdown1, by = zero, bs = "cr", pc = 0) + s(postlockdown2,

```
by = zero, bs = "cr", pc = 0)
~s(Year, bs = "cr") + fUrbanNon.Urban + fAgegroup + fscheme +
fISEIGroups + s(Mean_SSEP, bs = "cr") + s(Week_Mon,
bs = "cc") + s(fMSRegion, bs = "mrf", xt = x.MSRegion) +
s(postlockdown1, by = zero, bs = "cr", pc = 0) + s(postlockdown2,
by = zero, bs = "cr", pc = 0)
```

Parametric coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	23.489049	0.038207	614.776	< 2e-16	**
*					
fUrbanNon.UrbanUrban	0.108642	0.016590	6.549	5.81e-11	**
*					
fAgegroup20.00-20.99	0.350243	0.018178	19.267	< 2e-16	**
*					
fAgegroup21.00-21.99	0.753080	0.028849	26.104	< 2e-16	**
*					
fAgegroup<19.00	-0.355315	0.015528	-22.883	< 2e-16	**
*					
fschemeold	0.054605	0.044244	1.234	0.217	
fISEIGroupswithout occupation	-0.497002	0.046899	-10.597	< 2e-16	**
*					
fISEIGroupsTertile 1 (low)	0.200299	0.019995	10.017	< 2e-16	**
*					
fISEIGroupsTertile 3 (high)	-0.203014	0.019788	-10.259	< 2e-16	**
*					
fISEIGroupsStudents	-0.741893	0.018841	-39.377	< 2e-16	**
*					
(Intercept).1	1.340836	0.007522	178.246	< 2e-16	**
*					
fUrbanNon.UrbanUrban.1	0.037137	0.003148	11.799	< 2e-16	**
*					

fAgegroup20.00-20.99.1	0.040068	0.003349	11.963	< 2e-16	**
*					
fAgegroup21.00-21.99.1	0.091549	0.005098	17.958	< 2e-16	**
*					
fAgegroup<19.00.1	-0.054712	0.003027	-18.073	< 2e-16	**
*					
fschemeold.1	0.013815	0.008789	1.572	0.116	
fISEIGroupswithout occupation.1	-0.061976	0.008594	-7.211	5.54e-13	**
*					
fISEIGroupsTertile 1 (low).1	0.041921	0.003581	11.706	< 2e-16	**
*					
fISEIGroupsTertile 3 (high).1	-0.025292	0.003661	-6.908	4.90e-12	**
*					
fISEIGroupsStudents.1	-0.139698	0.003654	-38.232	< 2e-16	**
*					

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value
s(Year)	6.299	7.427	117.003	< 2e-16 ***
s(Mean_SSEP)	4.546	5.522	806.765	< 2e-16 ***
s(Week_Mon)	5.717	8.000	56.932	< 2e-16 ***
s(fMSRegion)	90.552	101.290	2129.421	< 2e-16 ***
s(postlockdown1):zero	2.322	2.820	5.588	0.11021
s(postlockdown2):zero	3.952	4.793	15.897	0.00592 **
s.1(Year)	8.609	8.950	144.468	< 2e-16 ***
s.1(Mean_SSEP)	5.011	6.017	882.793	< 2e-16 ***
s.1(Week_Mon)	4.686	8.000	17.579	0.00115 **
s.1(fMSRegion)	89.891	100.930	1703.167	< 2e-16 ***
s.1(postlockdown1):zero	3.676	4.482	11.458	0.02479 *
s.1(postlockdown2):zero	3.754	4.563	12.514	0.02156 *

signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Deviance explained = 2.67%

-REML = 9.1307e+05 scale est. = 1 n = 332320

> AIC(h2)

[1] 1825621