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Mental health effects of social distancing in Switzerland

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ABSTRACT

This analysis examines the effect of COVID-19 on public mental health in Switzerland. Following an event-study framework, we compare helpline call volume and duration before and after the outbreak of the first and second wave. The use of administrative phone-level data allows us to i) decompose the total effects into an intensive and extensive margin and ii) calculate a measure of unmet need. For the first wave, our results show that callers with a history of helpline contacts increase calls substantially. We also identify capacity constraints leading to unmet need for psychological counseling. Finally, we find no effects in the second wave, which might be explained by a number of factors including the absence of a lockdown and less restrictive social distancing measures.

1. Introduction

The coronavirus disease (COVID-19) resulted in drastic measures to bring down infection rates. A significant part of public health policies revolved around social distancing and, more generally, reduction in mobility (Ayouni et al., 2021). Although important to stop the spread, these measures led to a historical decrease in economic activity and a pronounced increase in unemployment (Deb et al., 2022).

In addition to economic considerations, it is crucial to understand the broader consequences of the pandemic and related social distancing measures (Dal Santo et al., 2022; Berger et al., 2021; Nochaiwong et al., 2021). Since social relationships and loneliness are influential determinants of physical and mental health (Cacioppo and Cacioppo, 2014), the question of how public well-being is affected by the pandemic is of utmost importance. The state of population health is however inherently hard to measure. Using survey methods, a large body of research finds worse mental conditions after the outbreak (Mendez-Lopez et al., 2022; Richter et al., 2021; Ochnik et al., 2021; Banks and Xu, 2020; Holman et al., 2020; Holingue et al., 2020; Zajacova et al., 2020). However there might be a considerable measurement error associated with survey data (Bound et al., 2001), suggesting the use of alternative measures to capture public health effects. Online search behavior reveals a similar pattern, as searches related to anxiety and sadness are reported to increase during lockdowns (Fetzer et al., 2021; Silverio-Murillo et al., 2021; Brodeur et al., 2021). Fortunately, the strain that the pandemic put on mental health appears to have not passed through suicide rates, which are reported to have declined during the first wave of COVID-19 (Pirkis et al., 2021; Tanaka and Okamoto, 2021).

Another tool to measure mental health is helpline call data. These data are available at high frequency and can be used as a proxy for help-seeking and mental health in the general population. The suitability for assessing mental health has spurred research in this area since the outbreak (Monreal-Bartolomé et al., 2022; Batchelor et al., 2021; Zalsman et al., 2021; Turkington et al., 2020; Halford et al., 2020; Armbruster and Klotzbücher, 2020). Assembling helpline data from 19 countries, a recent study has shown that call volumes increased significantly during the first wave. Compared to before the pandemic, the number of calls is reported to have increased by 35% at the six-week peak (Brülhart et al., 2021).

In this paper, we use administrative data from the most prominent Swiss helpline, *Offering a Helping Hand*, to examine the mental health effects of the COVID-19 pandemic and associated policies. *Offering a Helping Hand* is a phone service that provides free counseling. The central aim of this paper is to find out if the number and duration of calls to the helpline increased after the outbreak of the pandemic. To achieve this goal, we follow an event study regression framework.

Being close to Italy – an early hotspot of the pandemic in Europe – Switzerland registered the first COVID-19 case on February 25, 2020. The first wave was characterized by an (in hindsight) relatively mild infection curve but a strong government response. A nationwide lockdown was put in place, with nonessential stores, schools, and

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recreational facilities forced to close and non-urgent medical procedures stopped. The second wave, starting at the beginning of October, featured an unprecedentedly large number of confirmed cases, while policy measures were relatively muted when compared to earlier in the year. In fact, the federal government abstained from introducing a second lockdown but restricted the number of people who could meet in private and closed nightlife activities. This differs from other parts of Europe where the government response was much stronger during the second wave.

For this study, we use the outbreak of the first and second wave in Switzerland to analyze the effects on public mental health. In particular, we test the reaction of both the intensive margin (people who needed counseling before the pandemic, hence a proxy for the population at risk) and the extensive margin (number of people looking for counsel and number of first time callers). This is possible due to a complete administrative record of phone-level data from the network provider, enabling us to also identify an unmet need for counseling services (Weathers and Stegman, 2012; Gibson et al., 2019).

Our paper contributes to the rapidly growing literature on the effects of the pandemic on mental health. Using mental health surveys, Costa-Font et al. (2022), Mendez-Lopez et al. (2022), Muresan et al. (2022), Serrano-Alarcón et al. (2022), Burdett et al. (2021), Richter et al. (2021), and Banks and Xu (2020) find worse mental conditions after the outbreak.[3]

On the other hand, our study differs from this literature in two important dimensions. First, all the papers except Batchelor et al. (2021) and Bullinger et al. (2021) rely on manually recorded data entries. In our paper, we make use of administrative data from the network provider. Apart from being a comprehensive data source, it also allows us to identify repeat callers, as we have a unique hashed caller identifier in our data set. Moreover, we can identify the unmet need for help-seeking as our data also contain calls that were not answered. This is important since unmet need is found to be a determinant of future health status (Weathers and Stegman 2012, Gibson et al. 2019).

Second, our data allow us to analyze both the first COVID-19 wave in February 2020 and the second wave in the late fall of 2020. It is interesting to analyze the second wave for Switzerland because the social distancing policies were much less restrictive during the second wave (both compared to the first wave in Switzerland and compared to the second wave in other countries in western Europe). This allows us to compare (i) the mental health effects at the beginning of the pandemic combined with strict social distancing measures with (ii) the mental health effects in the second wave with less restrictive policies. Our results show increased frequency and duration of calls during the first wave. On the other hand, we do not find significant effects for the second wave.

2. Study data and methods

2.1. Data sources

We obtained detailed call-level data from the Swiss phone network provider for calls to the helpline *Offering a Helping Hand* ("Dargebotene Hand" in German). The helpline is a well-known nationwide service that is available 24–7 and provides free counseling by trained volunteers, adhering to the standards of the International Federation of Telephone Emergency Services (IFOTES). The helpline is organized as an association of twelve regional call centers spread throughout Switzerland. Callers are automatically connected to a helpline center based on their location, taking into account their respective language regions. Our administrative call data covers the population of calls and includes a unique hashed calling number. In order to be able to compare pandemic events to pre-pandemic trends, the sample ranges from January 2017 to the end of March 2021. There are a total of 69,212 unique phone numbers making 1,632,925 calls. Each call entry has records on the exact time, the helpline center, the duration spent on the phone, and whether the call was answered by the helpline or not. Appendix Fig. A.1 shows scatter plots for weekly call counts and duration.

Moreover, we obtained data on the stringency index (Ritchie et al., 2020). In particular, Fig. 1 shows the evolution of new infections as a seven-day moving average along with the stringency index of the Oxford COVID-19 government response tracker for Switzerland. The figure shows that the first wave was mild in terms of infections compared with the second wave, while the stringency index shows a stronger reaction from the government during the first wave.

2.2. Methods

Our empirical approach uses event-study and pre-post methods to analyze the influence of the pandemic on public mental health in Switzerland. The models explain the daily number and duration of calls by regional center through a linear combination of several variables. Using our panel of daily call information for 12 regional centers, we estimate the following baseline model with ordinary least squares:

$$\ln(\text{Calls}_{r,t}) = \beta \text{Post}_t + \delta_d + \eta_r + \mu_w + \epsilon_{r,t} \tag{1}$$

where the dependent variable is the natural logarithm of the number or duration of calls to regional center r recorded on day t. The indicator variable Post_t is set equal to 1 for all days after which the stringency index (a) increases for the first wave (February 25, also the first confirmed case), and (b) increases again in fall 2020 for the second wave (October 19). The coefficient β therefore allows us to assess whether there has been a significant difference between before and after the outbreak of the first and second waves. Since the dependent variable is log-transformed, it can be interpreted as the percentage deviation in daily calls. To prevent these coefficients from picking up the time trend present in the data, we include a weekly linear time trend μ_w to capture the long-term increase in the number and duration of calls. The model also includes day-of-week fixed effects δ_d. To control for constant characteristics related to regional centers, we also add call center fixed effects η_r.

To capture the effect of the pandemic with more granularity we also estimate the following specification:

$$\ln(\text{Calls}_{r,t}) = \sum_{\tau=-16}^{-1} \beta^\tau \text{Week}_t^\tau + \sum_{\tau=1}^{22} \beta^\tau \text{Week}_t^\tau + \delta_d + \eta_r + \mu_w + \epsilon_{r,t} \tag{2}$$

where the base period ($\tau = 0$) for the two waves is again defined as the week the stringency index (a) turns positive and (b) increases in the fall of 2020. The indicator variable Week^τ is set 1 for all days of event week τ. Its coefficient β^τ thus allows us to assess the significance of call dynamics in week τ relative to the base week.

The third model we estimate is a difference-in-differences (DiD) model with 2019 as control and 2020 as treatment group. In other words, we compare the daily evolution of calls after the outbreak of the pandemic to the same days in the previous (pre-COVID) year:

$$\ln(\text{Calls}_{r,l,y}) = \beta(\text{Post}_l \times 2020_y) + \delta_d + \eta_r + 2020_y + \text{Post}_l + \epsilon_{r,l,y} \tag{3}$$

where the explained variable is the logarithm of the number or duration of calls to regional center r in year y on the day of the year l. The coefficient of interest is again β, which links the interaction of variable 2020_y (treatment indicator, which is one for 2020) and Post_l (day indicator) to the number of calls. While the trend is controlled for in models (1) and (2) by including a weekly linear time trend, this approach automatically controls for trends as 2020 is compared to 2019.

[3] This is in line with worse mental health in the aftermath of the financial crisis as documented by McInerney et al. (2013) and Phillips and Nugent (2014). On the contrary, Baird et al. (2013) finds an increase in mental health after a positive income shock.

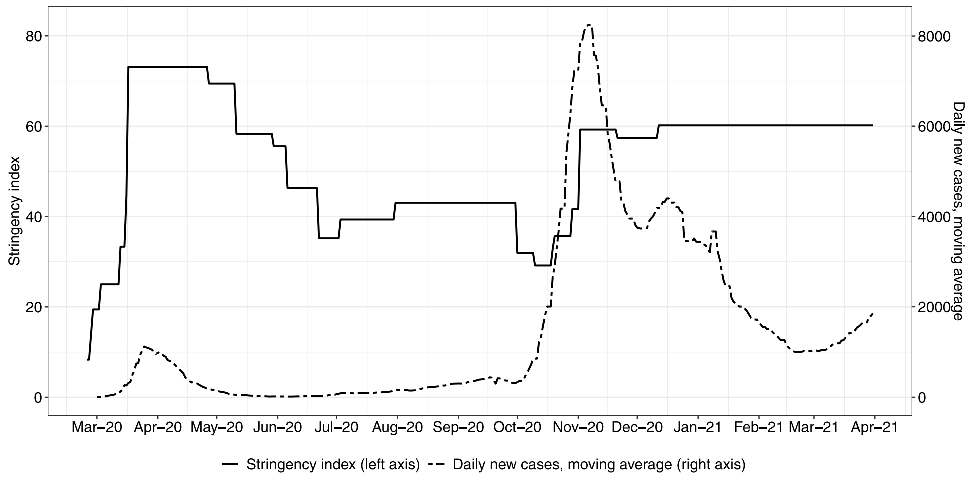

Fig. 1. COVID-19 infections and stringency index.
This figure shows daily COVID-19 infections and the stringency index for Switzerland. Infections are plotted as seven-day moving averages (right axis, dotted line) in order to reduce variability. The stringency index (left axis, straight line) is taken from the Oxford COVID-19 government response tracker and ranges from 0 to 100 with the latter indicating the most restrictive policy regime.
Source: Ritchie et al. (2020).

So far, all models have been estimated on the regional level. Next, we look at the individual level. The panel is constructed so that each number has weekly observations from the first to the last call, and if a caller is not calling in a given week the entry is equal to zero. A count model is thus sensible as most help-seekers call only sporadically, i.e. the weekly panel often contains zero entries that cannot be log-transformed. Using the information on calling numbers, we estimate the following individual fixed-effects Poisson model:

$$\ln\left[\mathbb{E}\left(\text{Calls}_{i,w}|\mathbf{X}\right)\right] = \beta\text{Post}_t + \mu_w + \gamma_i \qquad (4)$$

where the dependent variable is the number or duration of calls from phone number i during week w. We again include a linear time trend μ_w and add individual fixed-effects γ_i. In order to estimate fixed-effects for a large amount of numbers, we do so only for the entire sample spanning from January 2017 to 20 July 2020. For this period of time, the data set consists of calls from 69,212 unique phone numbers.[4]

3. Study results

Fig. 2 shows the evolution of the daily number and duration of helpline contacts for the first and second wave in Switzerland. We compare the evolution in the pandemic year (in red) with the corresponding values on the same dates in 2019 (in blue). To facilitate comparison, solid trend lines are fitted using a local polynomial regression. We define the start of the first wave to be on February 25, 2020, when Switzerland had its first confirmed case. The outbreak of the second wave is defined as the day the stringency index from the Oxford COVID-19 government response tracker increases greatly (October 19, 2020), see Fig. 1. After the outbreak of the first wave, we observe a sharp increase in total calls and total duration in 2020, whereas the previous year does not see such behavior. In the second COVID-19 wave, total daily call counts are parallel in both years, with total duration exhibiting a minor positive reaction after one month.

Fig. 3 presents our main results. The coefficient plot on the left shows evidence from our event-study model for total attempted calls, while the total call duration is shown on the right. The weekly dots represent the estimated percentage deviation to the week of the outbreak of the first wave (week zero). We also plot 95% confidence intervals to measure the degree of statistical uncertainty.

In Fig. 3, we find no difference in calling behavior from help-seekers before the outbreak of the pandemic compared with the base week. However, weekly contact volumes begin to increase strongly after the first confirmed case and peak three months after the outbreak (+22.5%), before gradually decreasing to pre-pandemic levels. Interestingly, the duration that callers spent on the phone follows the same dynamics, however much more muted in terms of effect size. A possible explanation is the occurrence of capacity constraints, potentially causing an unmet need for psychological counseling.

Our estimation results for the second wave (Fig. A.2) confirm the suggestive graphical findings in Fig. 2, i.e., demand for psychological counsel does not increase during the second wave.

In the Appendix, we reproduce the findings for the first wave using two alternative models (Table A.1). One replaces the weekly indicator with a post-outbreak indicator spanning twenty weeks, while the other is a standard difference-in-differences model, comparing call dynamics in 2020 to 2019. The latter design rules out seasonality as an explanation for our findings. Our results were robust to these checks.

The increase in total call volumes after the outbreak of the pandemic can be driven by both more people in need of psychological counseling and people that have called before requiring more support. Fig. 4 compares the 20 weeks following the outbreak with pre-pandemic times. The extensive margin is measured as the number of unique phone numbers calling the helpline and the number of first-time callers. Both measures indicate whether more people make use of the service. The intensive margin measures the reaction of help-seekers who have called at least once before and after the outbreak of the pandemic (13,438 phone numbers). As such, the intensive margin is also a measure of how people who had already been vulnerable were affected by the events surrounding COVID-19. Our results show a strong reaction from this group. Total call counts increase by 19%, translating into a 16% increase in total call duration. Compared with the average increase after the outbreak (+8% calls, +5% duration, see Appendix Table A.1), this population suffers from significantly higher distress caused by the pandemic. Although more muted, we also find an expansion of the total caller base by 9% as shown in the right panel of Fig. 4. A major driver of this expansion is first-time callers (+28%), thus underlining the importance of helplines as broadly accessible mental health care providers.

Our final figure builds on the two previous results. First, call duration performs consistently lower in terms of effect size compared

[4] From this set of numbers, roughly half (34,888) have called more than once, and 13,438 have called before and after the pandemic. The latter are responsible for 75% of all calls between January 2017 and 20 July 2020.

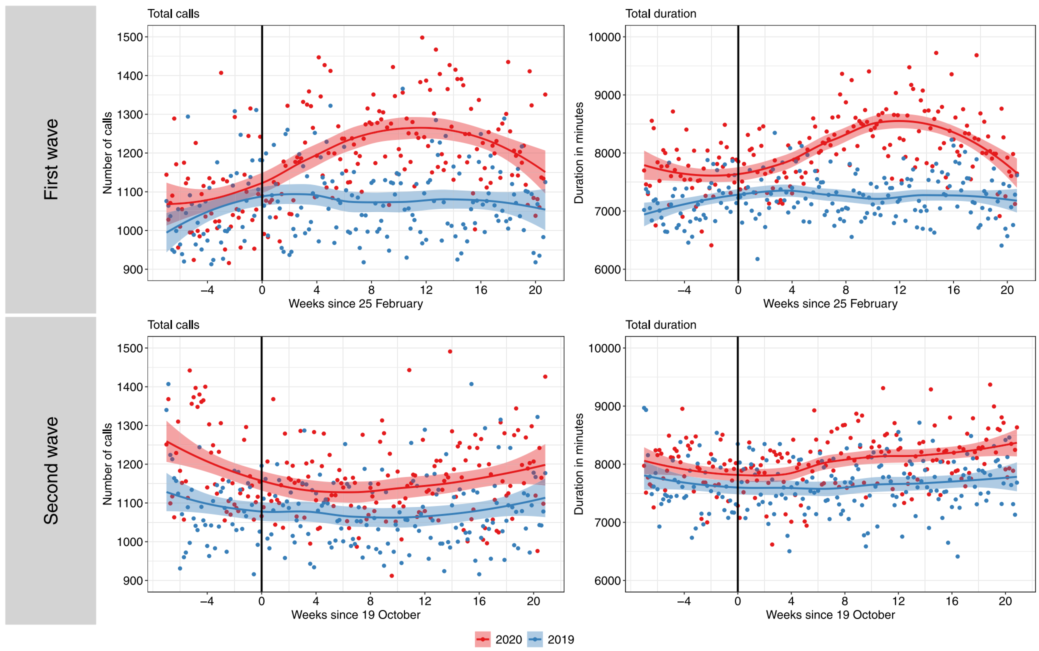

Fig. 2. Daily call counts and duration.
For the first wave (upper row) and the second wave (bottom row), the scatter plot shows daily helpline calls and duration before and after the reference day for the years 2019 and 2020. The vertical black line depicts the reference day for the first (February 25, 2020) and the second (October 19, 2020) wave. The colored solid lines are fitted using local polynomial regression, while the surrounding area represents the 95% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Network provider.

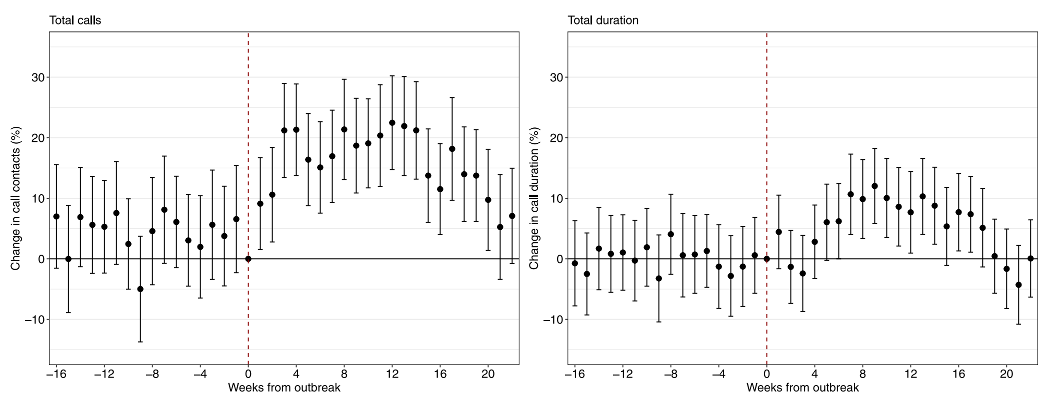

Fig. 3. Main findings for the first COVID-19 wave.
The graph shows point estimates together with 95% confidence intervals from the event study regression model (2) for the first COVID-19 wave. Week zero serves as base week and lasts from 25 February 2020 to 02 March 2020. All coefficients are estimated relative to the base week. The sample used in this regression ranges from 01 January 2017 to 20 July 2020, thus containing 15,564 observations (12 centers × 1297 days). Robust standard errors are used for calculating uncertainty measures.
Source: Network provider.

to attempted call numbers. A possible reason is supply-side capacity constraints. Second, people with a history of mental health problems are strongly affected. Thus, we analyze whether capacity constraints occur and, if so, imply an unmet need for mental health services. In a first step, we decompose total call volumes into unanswered (e.g., left ringing, busy line) and answered calls. Unanswered calls are a good estimate for capacity constraints, but not for unmet need, as the same person might try to call several times before potentially receiving an answer. Thus, our measure for unmet need only counts unanswered calls that are not followed by an answered call within 24 h. To prevent inflated counts from close succession of multiple call attempts, we additionally discard unanswered calls that are closer than one hour to each other.

Fig. 5 presents evidence that the Swiss helpline faced pronounced capacity constraints. Twelve weeks into the pandemic, the number of unanswered calls is 75% higher than in the base week (middle panel). Subtracting unanswered calls from total call counts yields only a muted increase for answered call counts (left panel), more in line with the earlier estimates of total duration. We also find capacity constraints to cause an increase of unmet need (right panel), almost doubling after seven weeks. Coefficients for capacity constraints and unmet need follow a distinctive hump-shaped pattern, thus reverting to initial levels. Appendix Table A.2 presents robustness checks using a pre-post regression model and different base periods. The results clearly support our findings.

Before coming to the general discussion, an analysis of the effect size might be helpful to understand the magnitude of the estimated effects. The increase of total call volume centers around 20% for post-outbreak weeks 3 to 14 (Fig. 3). Since the helpline received 7,414 calls per week in the base week (summing all calls in the country), this amounts to

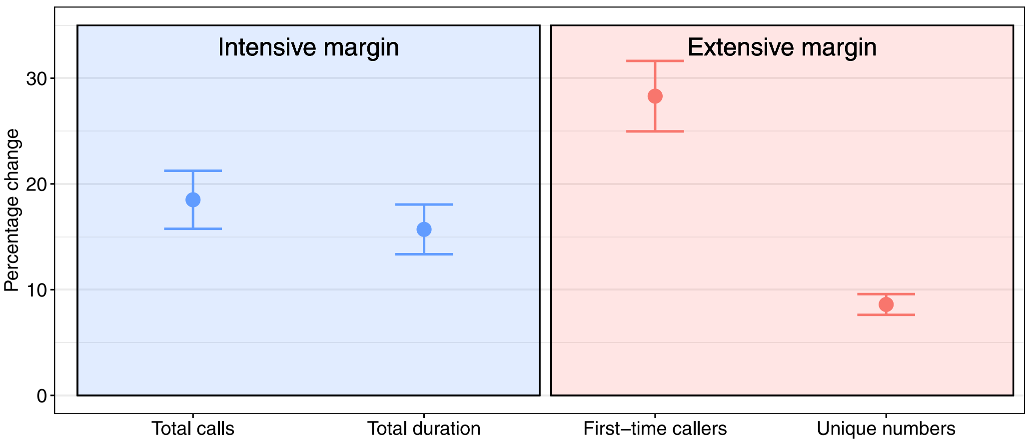

Fig. 4. Intensive and extensive margin.
The graph shows point estimates together with 95% confidence intervals from pre-post regression models for the first COVID-19 wave. The estimated coefficient is from an indicator variable, which is set to zero before 25 February 2020 and one afterward. All models are estimated using data from 01 January 2017 to 20 July 2020 (i.e. ending 20 weeks after the reference day). Results for the intensive margin are computed using model (4) and data at the phone level (calls: 2,4 m observations, duration: 2.3 m observations), while the estimates for the extensive margin come from model (1) and data at the regional center level (first-time callers and unique numbers: 12 centers × 1297 days = 15,564 observations). Robust standard errors are used for calculating uncertainty measures.
Source: Network provider.

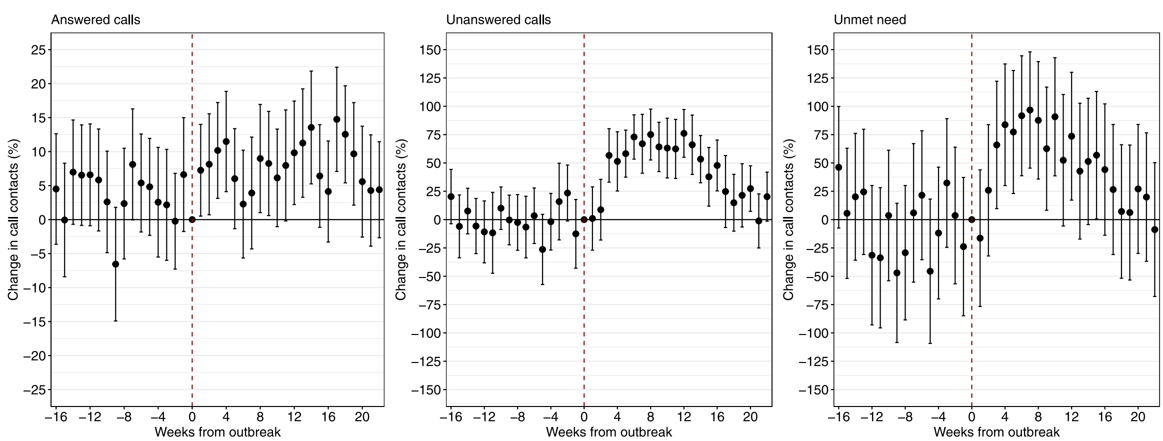

Fig. 5. Capacity constraints during the first COVID-19 wave.
The graph shows point estimates together with 95% confidence intervals from the event study regression model (2) for the first COVID-19 wave for the number of answered (left), unanswered (middle) and never answered (right) calls. Week zero serves as base week and lasts from 25 February 2020 to 02 March 2020. All coefficients are estimated relative to the base week. Note that the panel for answered calls (left) has a different scaling for better visibility. The sample used in this regression ranges from 01 January 2017 to 20 July 2020, thus containing 15,564 observations (12 centers × 1297 days). Robust standard errors are used for calculating uncertainty measures.
Source: Network provider.

an absolute weekly increase of around 1,480 calls. In the same period, weekly total call duration increased on average by 7.5%. With 905 h of counseling in the base week, this translates into an increase of around 68 h per week. In terms of population, that is 1.7 additional calls and 63 additional minutes per 10,000 inhabitants.

4. Discussion

The COVID-19 pandemic clearly poses a threat to physical health. However, fear of infection, social isolation, and economic hardship are likely to also have consequences for mental well-being. Our study uses event-study and pre-post methods to analyze public mental health in Switzerland during the first two infection waves. We find significant increases in the total number and duration of calls during the first wave. Notably, call dynamics after the outbreak of the second wave are not significantly different from shortly before. This is surprising given that Switzerland suffered from more than 8,000 daily new cases during the peak of the second wave (Fig. 1), compared with 1,000 in the first wave. A possible explanation is the differential government response, as no lockdown was imposed in the second wave. The stringency index thus fares significantly lower despite higher infection rates. This reasoning is in line with studies that assess the association between policy restrictions and public mental health (Aknin et al., 2022; Brülhart et al., 2021).

However, there are also alternative explanations for the difference in the findings across the two waves. Importantly the first wave of the pandemic was much more of a surprise and the severity of the pandemic was relatively unclear. Relatedly, individuals in Switzerland and elsewhere were arguably much better able to cope with the pandemic. Finally, it is unclear what the counterfactual of stricter measures would have looked like in terms of mental health effects for the population. Therefore we want to reemphasize that given the low spatial variation within Switzerland (Pleninger et al., 2022), we are unable to give a definitive answer to the exact mechanism underlying the different responses to the two waves.

Sensible policy measures account for vulnerable members of society, also in terms of mental health. Using the complete record of phone-level data from the network provider, we are able to decompose the total effects into an extensive and intensive margin. In the 20 weeks following the outbreak, we find people with a history of helpline

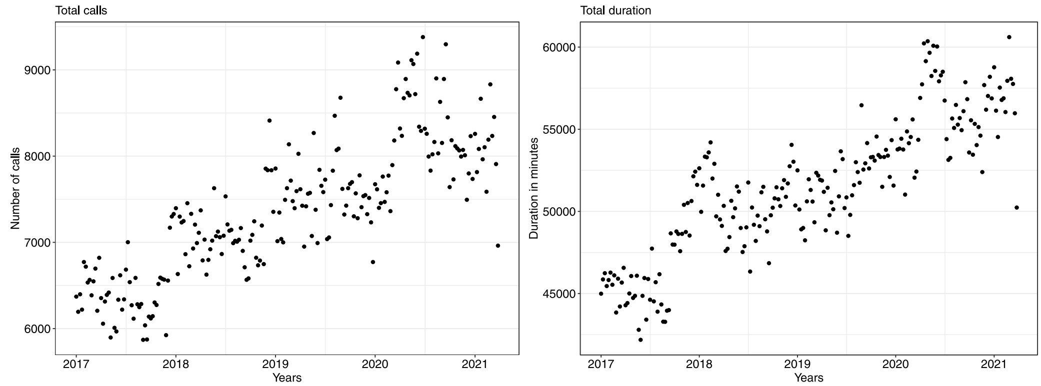

Fig. A.1. Nationwide call number and duration.
For the entire observation period, this figure shows scatter plots for total call number (left) and total duration (right). To gain a better overview, each dot represents the weekly sum instead of daily values.
Source: Network provider.

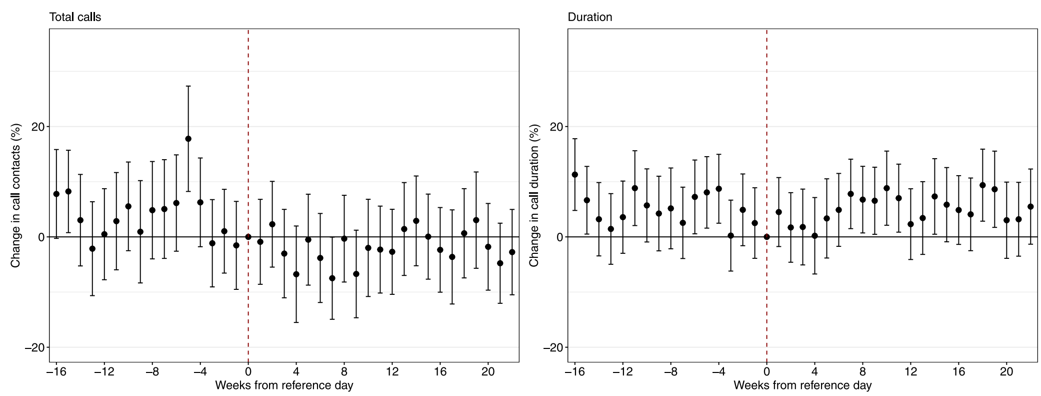

Fig. A.2. Event study: main findings for the second Covid-19 wave.
The graph shows point estimates together with 95% confidence intervals from the weekly event study regression model (2) for the second Covid-19 wave. Week zero serves as base week and lasts from 19 October 2020 to 25 October 2020. All coefficients are estimated relative to the base week. The sample used in this regression ranges from 01 June 2020 to 14 March 2021, thus containing 3444 observations (12 centers × 287 days). Robust standard errors are used for calculating uncertainty measures.
Source: Network provider.

contacts to increase call volumes and duration substantially more than the average population. This is accompanied by an expansion also of the weekly caller base, measured by the count of unique phone numbers calling the helpline.

Our study shows that the increase in demand from help-seekers exceeds the supply-side capacities since the number of unanswered calls increases substantially after the outbreak. However, if a caller has to call multiple times to eventually reach the helpline, then this is arguably less of an issue compared to not reaching a call agent at all. For this reason, we calculated a measure of unmet need, which only counts calls that did not find an answer within 24 h while adjusting for multiple call attempts. This is important since the unmet need is found to be a determinant of future health status (Weathers and Stegman, 2012; Gibson et al., 2019). We find that our measure of unmet need almost doubles in the weeks following the outbreak of the pandemic. This is especially troubling given the previous finding that vulnerable people drive the response of total call volumes and duration. These results suggest that a policy to increase helpline capacity in times of need is likely to lead to beneficial outcomes.

Given the ongoing debate surrounding mental health during the pandemic, the study findings have relevant implications. The strong upward trend in daily call volumes over the last years shows that helpline services are an important tool for mental health protection. It can offer immediate, cheap, and anonymous help to suffering people, especially in times when face-to-face contact should be avoided. In the case of Switzerland, the helpline has voiced problems recruiting sufficient volunteers to meet the growing demand. It might thus be sensible to provide financial incentives to the pool of call agents, requiring either an expansion of private funding or providing (sporadic) public funding, especially in times of crisis. Higher access barriers could exacerbate existing healthcare inequalities, as it is likely that the lower-income population is overrepresented in terms of the use of helplines. Since we do not know the composition of the caller population, future research is needed to analyze socio-demographic differences in calling activity. In any case, the provision of mental health services to the general public should be guaranteed.

Our study has several limitations. First, our results are limited to the adult population, since there is a different helpline for children and juveniles. Second, the composition of callers in terms of sociodemographic characteristics, health, and other factors is unknown. Third, we are unable to isolate the underlying mechanism of how the pandemic affects public mental health (e.g., policy measures, fear of virus, economic concerns). In Switzerland, policy measures were relatively homogeneous across the administrative units. It is thus infeasible to test whether stricter measures would have led to an increase in helpline calls.

Table A.1
Robustness tests for the first COVID-19 wave.
Source: Network provider.

Dependent variable:	ln(Calls)			ln(Duration)		
Estimated equation:	(1)	(1)	(3)	(1)	(1)	(3)
Coefficient						
$\hat{\beta}$	0.079***	0.106***	0.107***	0.054***	0.048***	0.048***
	(0.008)	(0.019)	(0.018)	(0.006)	(0.014)	(0.014)
Analysis period						
01 January 2017–20 July 2020	✓			✓		
08 October 2019–20 July 2020		✓			✓	
01 January–20 July 2020/2019			✓			✓
Pretreatment mean	83.9	89	89.4	591.8	635.8	620.4
Observations	15,564	3444	4824	15,564	3444	4824
R^2	0.62	0.66	0.66	0.76	0.78	0.78

The table shows estimates from pre-post regression model (1) and difference-in-differences model (3) for the first COVID-19 wave. $\hat{\beta}$ is the coefficient from an indicator variable, which is set to zero before 25 February 2020 and one afterward. Model (1) is estimated using data from (a) 01 January 2017 to 20 July 2020 (i.e. ending 20 weeks after the reference day) as well as (b) a symmetric time window of 20 weeks around the reference day as a robustness check. Model (3) uses data from 01 January to 20 July in the years 2020 and 2019. The first three rows show results for call count as the dependent variable, while subsequent rows do so for call duration. Robust standard errors are given in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.2
Robustness tests for capacity constraints during the first COVID-19 wave.
Source: Network provider.

Dependent variable:	ln(Answered)		ln(Unanswered)		ln(Unmet need)	
Coefficient						
$\hat{\beta}$	0.011	0.029*	0.299***	0.462***	0.411***	0.760***
	(0.008)	(0.017)	(0.029)	(0.070)	(0.055)	(0.131)
Analysis period						
01 January 2017–20 July 2020	✓		✓		✓	
08 October 2019–20 July 2020		✓		✓		✓
Pretreatment mean	69.5	77.8	14.3	11.1	2.7	2.4
Observations	15,564	3444	15,564	3444	15,564	3444
R^2	0.70	0.72	0.29	0.37	0.15	0.20

The table shows estimates from pre-post regression model (1) for the first COVID-19 wave for answered and unanswered calls. $\hat{\beta}$ is the coefficient from an indicator variable, which is set to zero before 25 February 2020 and one afterward. The model is estimated using data from (a) 01 January 2017 to 20 July 2020 (i.e. ending 20 weeks after the reference day) as well as (b) a symmetric time window of 20 weeks around the reference day as a robustness check. The first two rows show results for the answered call count as the dependent variable, while the subsequent two rows do so for unanswered calls. The final two rows show estimates for unmet need, which is an adjusted version of unanswered calls. Robust standard errors are given in parentheses. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Data availability

The data that support the findings of this study are available from *Offering a Helping Hand* ("Dargebotene Hand" in German) but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of *Offering a Helping Hand*. In order to request the data, please contact Stefan Pichler.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Figs. A.1 and A.2.
See Tables A.1 and A.2.

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