Temperature and Mental Health: Evidence from Helpline Calls*

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Abstract

This paper studies the short-term effects of ambient temperature on mental health using data on nearly half a million helpline calls in Germany. Leveraging location-based routing of helpline calls and random day-to-day weather fluctuations, I find a negative effect of temperature extremes on mental health as revealed by an increase in the demand for telephone counseling services. On days with an average temperature above 25°C (77°F) and below 0°C (32°F), call volume is 3.4 and 5.1 percent higher, respectively, than on mid-temperature days. Mechanism analysis reveals pronounced adverse effects of cold temperatures on social and psychological well-being and of hot temperatures on psychological well-being and violence. More broadly, the findings of this work contribute to our understanding of how changing climatic conditions will affect population mental health and associated social costs in the near future.

Keywords: Climate Change, Weather, Well-being

JEL Codes: I1, I31, Q5, Q54

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1 Introduction

Mental disorders affect nearly one billion people worldwide, accounting for five percent of the total global burden of disease (Ferrari et al., 2022). The World Health Organization (2012) expects that by the end of the decade mental illness will be the leading cause of disease burden worldwide, up from 13th in 1990. For those affected, mental illnesses such as depression are associated with high individual costs, as they reduce labor force participation and entail large earning penalties (Bütikofer et al., 2020; Biasi et al., 2021). Globally, the World Economic Forum estimates that the socioeconomic cost of mental disorders was \$2.5 trillion in 2010, and it is expected to more than double by 2030 (Bloom et al., 2011). Because of uncertainty in potential risk factors for human health, which include climate variability and trends (McMichael et al., 2006), and given an increase in global surface temperatures through at least mid-century (IPCC, 2021) projected costs are likely to be an underestimate.

Despite their large share of the global burden of disease and in the face of climate change, there is limited causal evidence on the impact of temperature extremes on mental health (Berry et al., 2018). Where existing work has explored the causal effects of temperature on mental distress, it has focused on suicidality (Burke et al., 2018; Carleton, 2017), health care utilization (Mullins & White, 2019), and self-reported mental health (Obradovich et al., 2018). However, these measures have limitations that ultimately make it difficult to infer the impact of temperature on mental health from them alone (Romanello et al., 2021; Obradovich & Minor, 2022) as they either focus on rare and extreme or clinical outcomes¹, or represent subjective measures of mental health that might suffer from systematic bias (e.g., Jahedi & Méndez, 2014).

This paper studies the short-term effects of ambient temperature on mental distress using administrative records from the largest general telephone counseling service in Germany, consisting of 485,274 individual calls received at 55 sites nationwide between November 2018 and March 2020. The data contains the timestamp, processing location, call topics, and caller characteristics for each call. Telephone helplines provide free, low-threshold, anonymous² counseling services for people with unmet mental health needs. Although not a direct measure of psychiatric disorders, the use of helpline data offers many advantages in-

¹Mental health stigma can discourage people from seeking professional help (Bharadwaj et al., 2017). In addition, access to evidence-based treatment remains inadequate even in high-income countries (Demyttenaere et al., 2004; World Health Organization, 2012).

²In Germany, anonymous and unobservable access to telephone counseling services is even guaranteed by federal law (§99 Abs. 2 Telecommunications Act (TKG)), which prohibits telecommunication service providers to list telephone counseling calls in call detail records.

cluding its high spatial and temporal resolution, its ability to capture subclinical mental health problems, and its potential to account for individuals who fail to seek professional treatment and are therefore not accounted for in clinical data. Compared to self-reported mental health, calls to counseling services can be seen as revealed rather than stated mental health problems, and compared to other high-resolution measures related to mental health, such as online searches, helpline calls are more likely to indicate help-seeking rather than information-seeking. Only recently, data from counseling centers were used during the COVID-19 pandemic as a real-time proxy for monitoring population mental health (Brülhart et al., 2021; Armbruster & Klotzbücher, 2020) and have been shown to be an appropriate tool for behavioral predictions of suicide rates (Choi et al., 2020).

I interpolate daily temperature, precipitation, sunshine duration, wind speed, relative humidity, and air pollution at each counseling center using monitor readings from the universe of German weather and air quality stations spread across the entire country. As callers are routed to the nearest crisis center based on location, I can exploit idiosyncratic day-to-day variations in ambient temperatures to determine their causal impact on mental health. I use these exogenous temperature variations to answer two main questions. First, I ask whether exposure to temperature extremes affects the incidence of mental health problems. In doing so, I assume that changes in population mental health are revealed by discrete changes in the number of calls to telephone counseling services. Second, I seek to answer why thermal stressors undermine mental health. In answering this question, I assume that the mechanism is partially revealed by the underlying concern of the call.

Two-way linear fixed effects regression, in which I account for a wide range of concurrent environmental factors, shows a statistically significant adverse effect of exposure to suboptimal temperature levels on the incidence of mental health problems, with increasing effects toward the ends of the temperature distribution. I find that on days with an average temperature above 25°C and below 0°C, call volume is 3.4 and 5.1 percent higher, respectively, than on days with an average temperature in the middle range of the temperature spectrum. The estimates remain robust across alternative model specifications and survive in-space as well as in-time placebo tests. Effect sizes differ substantially both by age and gender. The results

³Helpline data also has certain limitations. For example, the observed number of calls may not reflect the actual demand for telephone counseling services because of capacity constraints of counseling centers or because of people who call more than once, artificially increasing the number of answered calls (so-called 'frequent callers'). See Liu & Tsai (2021) for an excellent discussion of the benefits and shortcomings of helpline call data for monitoring population-level mental distress. As argued by Brülhart et al. (2021), helpline data are a supplement to, rather than a replacement for, established indicators of population-level mental health.

indicate that only the number of calls from male help-seekers increases significantly on hot days, while there is no increase in female help-seekers. On cold days, however, the exact opposite is observed. For age-related effect heterogeneity, I document that the increase in call volume on cold days is mainly driven by older individuals and the increase in call volume on hot days is due to young individuals.

Based on the detailed call-level data, I estimate whether counseling topics change with temperature levels. Several interesting results emerge from this analysis. The findings suggest negative effects of hot temperatures on calls about psychological well-being (e.g., mood, stress, self-image) and violence (i.e., physical, mental, and sexual violence), as well as negative effects of cold temperatures on psychological and social well-being (i.e., relationships). For example, I document that the number of calls about social relations increases by 5.7 percent on extremely cold days, relative to mid-temperature days. I interpret this finding as evidence that cold temperatures have the potential to undermine mental health by decreasing social well-being, potentially as a consequence of isolation and limited mobility. At the other end of the temperature spectrum, results indicate that the number of calls about psychological well-being is 7.0 percent higher on extremely hot days than on days with average temperatures, suggesting a causal psychological link between hot temperatures and mental health.

When looking at the impact of past temperature exposure on mental health, the results provide evidence of the existence of an immediate adverse effect of hot temperatures on mental health, with no clear evidence of delayed effects. For extremely cold temperatures, my results suggest that the negative effect is caused by constant exposure over several days, further supporting the interpretation that cold temperatures primarily affect mental health through social isolation.

Additionally, I use the individual-level call data to estimate how temperature changes affect treatment resource utilization, as measured by the length of telephone counseling sessions. I find that temperature affects the intensity to which helplines are used and document that the duration of counseling monotonically decreases in temperature levels, even after controlling for compositional changes of callers. Results suggest that an increase in temperature by 1°C translates to a decrease in call length by 0.3 percent.

The main contribution of this work is to use a complementary and novel measure of mental health to overcome some of the limitations of conventional measures in assessing the effects of extreme temperatures at the population level, and to provide further causal evidence of the effects of suboptimal temperature levels on mental health. Most of the empirical literature to date has focused on single weather events, a very narrow geographic area, allows only for correlational evidence, or does not consider the full distribution of temperature (e.g., Hansen et al., 2008; Ajdacic-Gross et al., 2007; Nori-Sarma et al., 2022). This work builds on the small and recent body of economics literature that examines the causal impact of temperature on mental health (Burke et al., 2018; Carleton, 2017; Mullins & White, 2019; Obradovich et al., 2018). To the best of my knowledge, this the first work to use helpline data to study the link between temperature and mental health.

A second major contribution of this paper is to provide insights into some of the primary mechanisms underlying the negative effects of temperature extremes on mental health. The channels through which mental health might be impaired by thermal stressors are complex and not yet well understood. There are a number of mechanisms that have been proposed so far. Potential direct mechanisms include the disruption of thermoregulatory function and alterations in central neurophysiological signaling (Lõhmus, 2018). Short-term exposure to unusual temperature levels may also indirectly compromise mental health through worsening physical health (Deschenes, 2014), temperature-related sleep disturbances (Obradovich et al., 2017; Minor et al., 2022), temperature-intolerance of antipsychotic medications (Cusack et al., 2011), decreasing cognitive functions (Graff Zivin et al., 2018), anxiety and stress due to anticipation of climate change (i.e., climate anxiety) (Clayton, 2020), destructive behavior (Hsiang et al., 2013), or mood alterations (Baylis, 2020), all of which are strongly correlated with mental health (Prince et al., 2007; Fernandez-Mendoza & Vgontzas, 2013; Thompson et al., 2011). This is one of the first papers identifying the causal pathways behind this relationship, as few studies have empirically evaluated any of these claims (Massazza et al., 2022).

More broadly, this work joins two larger strands of literature. First, it adds to the rapidly growing climate economics literature which documents a range of negative consequences of human exposure to temperature extremes, including adverse effects on decision making (Heyes & Saberian, 2019), sentiment (Baylis, 2020), violence and destructive behavior (Hsiang et al., 2013; Almås et al., 2019; Mukherjee & Sanders, 2021), cognitive attainment (Graff Zivin et al., 2018; Park, 2020), physical performance (Sexton et al., 2021), pregnancy outcomes (Deschênes et al., 2009; Fishman et al., 2019), and more general health outcomes, such as mortality (Deschênes & Greenstone, 2011; Barreca et al., 2016) and morbidity (White, 2017; Karlsson & Ziebarth, 2018). Second, this work contributes to the broad economics liter-

ature identifying causal determinants of mental health, including income (Gardner & Oswald, 2007), indebtedness (Gathergood, 2012), residential environment (Katz et al., 2001), career and family choices (Bertrand, 2013), school environment (Butikofer et al., 2020; Kiessling & Norris, 2022), police violence (Ang, 2021), prenatal stress (Persson & Rossin-Slater, 2018), paid maternity leave (Bütikofer et al., 2021), early life stressors (Adhvaryu et al., 2019), social media usage (Braghieri et al., 2022), and air quality (Zhang et al., 2017; Chen et al., 2018).

The remainder of this paper is organized as follows. Section 2 introduces the data. Section 3 presents the empirical approach. Section 4 reports and discusses the results. Section 5 concludes.

2 Data and Summary Statistics

The analysis relies primarily on three data sources. The first data source is high-resolution administrative data from a major European nonprofit telephone counseling service. The other two consist of the universe of measurements from German weather and air quality stations, which I use to interpolate daily environmental conditions at each site.

Helpline Data - Individual contact-level data are provided by *TelefonSeelsorge*, Germany's largest general telephone counseling service with more than 100 counseling centers, 300 employees, and nearly 7,700 volunteer counselors. The crisis service, founded in 1956, is well known⁴ and can be reached around the clock at one of two nationwide toll-free numbers, both from German landlines and mobile phones. Callers to the telephone counseling service are directed to the nearest crisis center, based on their location. The catchment area of each counseling center is defined by telephone area codes, with each crisis center serving surrounding phone codes in its vicinity. Figure A.2 in the Appendix shows the extent of the catchment area of a representative counseling center operated by the helpline service.⁵ Toward the end of 2018, the telephone counseling service introduced a new comprehensive data collection system, in which more than half of the crisis centers participate.⁶ The data I receive was collected from November 2018 through the end of 2020. To obtain the final

⁴Panel A of Figure A.1 in the Appendix shows the result of a representative online search for mental health concerns. Information about telephone counseling services is prominently placed on top of the landing page so that people seeking help for mental health problems can easily find out about the possible treatment option of telephone counseling. Panel B shows an example of an information poster.

⁵Telephone area codes do not follow administrative boundaries and can sometimes even cross state lines.

⁶Each counseling center is operated independently, which is why at the time this study was conducted some sites in East Germany were using their own recording systems.

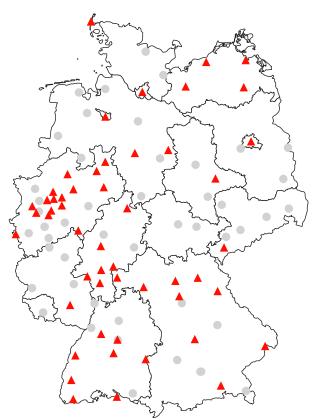


Figure 1: Map of helpline counseling centers in Germany

Notes: This figure shows the geographical distribution of *TelefonSeelsorge*'s counseling centers in Germany. In total there are 105 counseling centers. Sampled locations are represented by a red triangle, non-sampled locations are represented by a grey dot.

data set, I apply some sample selection criteria. First, because telephone counseling centers experienced a large increase in contact volume due to the COVID-19 pandemic (Brülhart et al., 2021), I limit the observation period to before March 2020 to avoid bias. Second, apart from telephone counseling, *TelefonSeelsorge* offers counseling services via mail and chat. Since these contacts are routed nationwide, I focus on telephone counseling service only. 6.3 and 4.4 percent of all contacts recorded during the observation period were mail and chat contacts, respectively. Third, as some sites only began using the main data collection system during the observation period, I exclude all locations that did not provide data on calls received on at least 100 days. Based on this exclusion criteria, I exclude 20 counseling centers from the analysis that recorded a total of 27,175 calls, representing less than five percent of the total call volume before March 2020. Figure 1 shows the geographical distribution of all counseling centers in Germany. The sampled sites are distributed throughout the country,

⁷The first containment measures in Germany were introduced on March 8, 2020.

⁸To be included in the sample, counseling centers must have begun using the main data system consecutively from November 11, 2019 onward. However, as shown in Table A.1, the majority of counseling centers already started collecting data in early 2019. The last site covered began collecting data in September 2019.

with most of the crisis centers studied located in West and South Germany. Individual call-level data include the purpose and duration of the call, sociodemographic information about the caller (i.e., gender, age group, employment status, and living situation)⁹, topics of the conversation (i.e., physical and psychological well-being, violence, social well-being, livelihood, and other)¹⁰, and the counseling center where the call was answered. Finally, based on the recorded purpose of the call, I exclude all silent calls, prank calls, and sexually motivated calls which leads me to drop about one-fifth of the answered calls because they do not constitute help-seeking behavior for mental health problems.

After applying the above exclusion criteria, I am left with 485,274 calls, that were answered at 55 counseling centers across Germany between November 3, 2018 and February 29, 2020. To obtain the number of calls answered at each location I collapse the individual calls to the daily level resulting in 21,138 counseling-center-day observations. Tables A.1 and A.3 in the Appendix provide a more detailed overview of the sampled crisis centers and the individual calls that were received by *TelefonSeelsorge*. Figure A.3 and Figure A.4 in the Appendix show the distribution of the daily number of calls answered and average helpline call duration, respectively. A crisis center answers an average of 22.96 calls per day, that last on average 1457.71 seconds (24 minutes, 18 seconds). The largest crisis center receives an average of 35.94 calls per day, while the smallest facility receives an average of 8.41 calls.

Weather Data - Station-level weather measurements are drawn from the Climate Data Center, which is a climate database operated by *Deutscher Wetterdienst (DWD)*, the German Meteorological Service. I extract daily information on temperature, precipitation, sunshine duration, surface wind speed, and relative humidity. Since the telephone counseling service does not have information about the exact location of the caller, I take advantage of the fact that callers are routed to the nearest counseling center and use the weather conditions of the site that answered the call. To aggregate daily station-level weather realizations to the counseling-center-level, I take an inverse-distance weighted average of all observations provided by weather stations that are located within a predefined range to each counseling centers' location¹², so that measured values closest to the counseling center have more influ-

⁹ TelefonSeelsorge offers anonymous telephone counseling, which is why the information about the callers is based on the counselor's assessment. Some information is known from the contact (e.g., if the caller explicitly states her age), others are assumed from the context.

¹⁰Operators categorize calls by the topics they discuss with callers, allowing them to select up to three topics from a list of 34 in total. To avoid a too extensive disaggregation, I aggregate the topics in six main groups. Table A.2 in the Appendix shows the classification of the call topics.

¹¹In practice, I omit weather stations above 1,500 m since they are unlikely to represent the weather experienced by most of the population.

¹² TelefonSeelsorge only discloses the zip code of the area where the site is located. Therefore, I use the

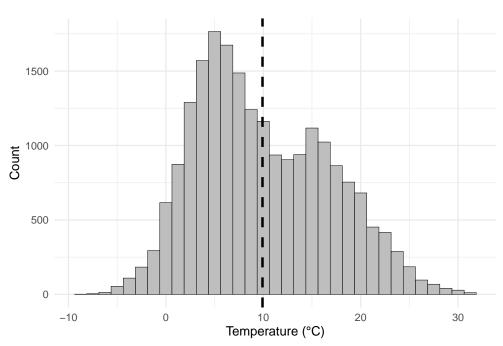


Figure 2: Temperature distribution

Notes: This figure illustrates the distribution of all daily mean temperatures at any given counseling-center-day in the study sample. The horizontal dashed line represents the sample mean (9.93°C).

ence on the predicted value than those farther away.¹³ Figure 2 illustrates the temperature distribution. The observation period provides a large temperature range to study the impact of temperature on mental health concerns, with the minimum average daily temperature of -8.3°C recorded on January 23, 2019 in Auerbach (Saxonia) and the maximum daily average of 31.6°C recorded on July 25, 2019 in Essen (North Rhine-Westphalia). Panel A - D of Figure A.5 in the Appendix provide an overview of the distribution of other contemporaneous weather conditions realized within the study sample.

Air Pollution Data - Daily station-level concentration measurements of fine particulate matter with a diameter of less than 2.5 micrometers ($PM_{2.5}$) are obtained from the *Umwelt-bundesamt (UBA)*, the German Federal Environmental Agency. I proceed in the same way as with the weather data and assign air quality information to each crisis center by taking

centroid of the respective zip code area to calculate the distance to the weather stations.

¹³In total there are 1,924 precipitation monitoring stations, 502 temperature monitoring stations, 505 humidity monitoring stations, 287 surface wind speed monitoring stations, and 304 monitoring stations that provide information on sunshine duration. The choice of range is informed by the density of the respective monitoring network. I choose 15 km for precipitation, 25 km for temperature and humidity, and 35 km for wind speed and sunshine duration. An average counseling center is surrounded by 3.6 precipitation, 2.6 temperature, 2.5 humidity, 2.5 surface wind speed, as well as 2.9 sunshine duration stations in the specified radii.

an inverse-distance weighted average of observations of surrounding monitoring stations.¹⁴ Panel E of Figure A.5 in the Appendix shows the distribution of measured air pollution over the course of the study period.

3 Empirical Approach

To estimate the causal impact of ambient temperature on mental health I use a panel fixed effects model, as is standard in the climate economics literature (Dell et al., 2014; Hsiang, 2016). I consider two different margins along which the use of telephone counseling service might be affected by exposure to abnormal temperature levels. In a first step I analyze if the incidence of helpline calls changes with temperature (i.e, the extensive margin). The model reads as follows:

$$y_{ct} = f(\text{TEMP}_{ct}) + \gamma W_{ct} + \alpha_c + \lambda_t + \epsilon_{ct}, \tag{1}$$

where the dependent variable, y_{ct} , is the logarithm of the number of helpline calls answered in counseling center c on day t. To avoid specifications of the relationship between average daily temperature levels and helpline call volumes, most of the time temperature enters the regression with a flexible functional form. More specifically, I let $f(\text{TEMP}_{ct}) = \sum_{\substack{j=1 \ j \neq 4}}^{j} \beta^j \text{TEMP}_{ct}^j$ by dividing the temperature spectrum in seven five-degree intervals, ranging from less than 0°C to more than 25°C. The main variables of interest, TEMP_{ct}^j , indicate whether the average temperature on a given day at a given counseling center falls within the jth of the above mentioned temperature bands. I omit the temperature bin which is equal to unity if the average daily temperature is between 10°C and 15°C (i.e., $j \neq 4$). As relative differences between conditional means are preserved, the choice of the omitted temperature range does not change the shape of the estimated response function. The coefficients β^j show the relative change in helpline call volumes on a day in one of the temperature bins relative to a day in the omitted category.

To account for the possibility that other weather dimensions besides temperature affect mental health, I include a vector of control variables, W_{ct} , that contains additional contemporaneous meteorological conditions, such as the sum of daily precipitation, daily sunshine duration, average daily wind speed, and average daily relative humidity. As mental health

 $^{^{14}}$ There is a total of 203 PM_{2.5} monitoring stations that I use for the interpolation of counseling-center-level observations. As the monitoring network for PM_{2.5} is not as dense as the weather monitoring network and is mainly located in urban areas, I have to choose a radius of 85 km so that all crisis centers are assigned at least one monitoring station. However, most of the counseling centers have a measurement station close to them, which has a larger impact on the predicted value due to the inverse distance weighting. The median distance to the nearest station is 7.9 km.

is potentially impaired by air quality (Zhang et al., 2017) the vector of control variables also includes daily average concentrations of a key air pollutant (i.e., $PM_{2.5}$). α_c is a vector of location-specific fixed effects to capture permanent unobserved factors at the counseling center level, such as differences in recognition of mental health problems in the population served. λ_t are day-of-week (including public holidays) and year-month fixed effects to control for trends within weeks, on holidays, and systematic seasonality. Assuming that the temperature-variation, conditional on the covariates and fixed effects, is exogenous to the unobserved determinants of the number of calls to counseling centers, the β_j coefficients can be interpreted as the causal impact of temperature on mental health concerns as reflected in the demand for telephone counseling services. To allow for correlation of error terms standard errors are two-way clustered at the counseling center and year-month level. I further stratify the sample by demographic information of the caller and main topics of the conversation and re-estimate the regression for each group separately.¹⁵

As an additional empirical exercise, I investigate whether temperature affects the intensity of use of counseling services (i.e., the intensive margin). To do so, I use the logarithm of the duration of call i answered at counseling center c at time t, z_{ict} , as the dependent variable. I also include a vector of sociodemographic covariates, X_{ict} , to control for a set of individual-level caller characteristics that might correlate with the length of the counseling, including gender, age cohort, employment status and living situation. In this way, I can control for possible temperature-related changes in caller composition. To additionally control for trends within days, I include a full set of hour-of-day fixed effects. The rest of the model is similar to the one described in equation (1). Standard errors are clustered at the counseling-center-day level. In particular, I estimate the following regression equation using the full sample of individual call-level data:

$$z_{ict} = f(\text{TEMP}_{ct}) + \gamma W_{ct} + \delta X_{ict} + \alpha_c + \lambda_t + \epsilon_{ict}.$$
 (2)

There are some potential concerns related to the empirical strategy that I will discuss in more detail below. First, *TelefonSeelsorge* does not have information on the exact location of the caller, so I leverage the fact that the caller is routed to the nearest counseling center and interpolate the weather data at that location. This introduces a potential measurement

 $^{^{15}}$ Since there are days when no calls are answered from a particular subgroup or on a particular topic, I sometimes use a log(helpline calls + 1) transformation. For the full sample there are no zero valued observations. Results obtained using alternative transformations of the dependent variable (e.g., inverse hyperbolic since (IHS)) and Poisson regression lead to the same conclusion (Table A.4).

error in the explanatory variables, as the daily average temperature at a given counseling center is unlikely to be exactly the same as the temperature at the caller's site. However, since the telephone counseling service operates a fairly dense network of counseling centers¹⁶, the extent of the catchment areas is relatively small and daily average temperatures are likely to be comparable in this area since temperature is rather uniform in space. In addition, the choice of wide temperature ranges provides a potential safeguard against the introduction of significant measurement error, as this increases the likelihood that the temperature at the caller's location and at the counseling center are at least within the same temperature interval.

Second, the relatively short observation period could be a cause for concern. However, the data I receive are of high spatial and temporal resolution. In addition, the year 2019, from which most of the observations come, was marked by high regional weather variability and extreme temperatures.¹⁷ The high resolution of the helpline data in combination with the large weather fluctuations during the observation period provide a great variation for the model to be identified. As a falsification test, I conduct several placebo exercises. I replace the interpolated daily ambient weather realizations and air pollution measurement for each counseling center with the interpolated observations of the same day for the most distant counseling center. For example, for the crisis center in Berlin (Berlin), the placebo temperature is taken from Wehr (Baden-Wurttemberg), which is about 670 km away. Then I replace the measurements for each location with the observations for the same location, but recorded one quarter (90 days) before that day. For example, for the crisis center in Berlin, the placebo temperature for June 1, 2019 is taken from March 3, 2019. Finally, I do both, which means that the placebo temperature for the crisis center in Berlin on June 1, 2019 is taken from the crisis center in Wehr on March 3, 2019.

Third, there is potential measurement error in the dependent variable. This does not bias the estimates but does affect their precision. While all calls made from a landline can be easily routed to the nearest counseling center based on the area code, the location-based routing of calls made from a cell phone is more difficult and is based on the location of the cell tower. As a result a small fraction of these calls is distributed randomly across Germany.¹⁸ Additionally, the individual counseling centers are organized into organizational

¹⁶By comparison, while the largest telephone helpline in the United States (i.e., *National Suicide Prevention Lifeline*) operates about 180 crisis centers across the country, *TelefonSeelsorge* has a network of about 100 crisis centers. Yet Germany is approximately 28 times smaller in size than the United States.

¹⁷The year 2019 was the second warmest year since records began in 1881. Also, for the first time, a maximum temperature of 40°C was measured for three consecutive days (DWD, 2020).

¹⁸In August 2016, 78.4 percent of calls were routed according to the caller's location (Telefonseelsorge,

units consisting of three to seven sites that are geographically close to each other. While priority is given to routing a call to the nearest crisis center, if the call cannot be answered due to lack of available capacity, it is routed to another counseling center in the organizational unit. However, I cannot directly test if this affects the results, as the data does not provide any information on whether a call was diverted or not.¹⁹

Fourth, counseling centers might self-select for data collection. This does not pose a threat to identification, however, if participation in data collection is unrelated to the climatic conditions at the site, an assumption which is likely to hold.

Finally, data from counseling centers may be an inaccurate indicator of mental health service demand and significantly underestimate the real need. However, if actual demand is even higher than it is reflected in the number of calls to counseling centers, the coefficients presented in this study represent a conservative estimate of the true effect of temperature on helpline call volumes and mental health concerns.

4 Results

4.1 Baseline Results

In Table 1, Panel A I present the results of different specifications of the model described in equation (1). I exclude specific fixed effects step by step to test for sensitivity of the results. Column (1) in Panel A of Table 1 presents the results for the main specification, where temperature enters the model with a flexible functional form. Although there are relatively few days in the upper and lower ranges of the daily temperature distribution, differences between call volumes on extreme-temperature days and days in the base category are statistically significant at conventional levels. The number of helpline calls answered in counseling centers is 5.1 percent higher on extremely cold days with an average temperature below 0°C than on days with average temperatures between 10°C and 15°C. On the other end of the temperature distribution the demand for telephone counseling is 3.4 percent higher on extremely hot days with average temperatures above 25°C, relative to days in the excluded temperature

^{2017).} For comparison, unlike *TelefonSeelsorge*, the *National Suicide Prevention Lifeline* routes calls based on area code only, as all telephone numbers, whether landline or cell phone, have an area code. Due to the high mobility of cell phones, the area code of a mobile number may not reflect the actual location of the caller.

¹⁹Another option would be to aggregate the call data at the organizational unit level and interpolate the environmental factors for the geographic center of gravity of each unit. However, I observe only four complete organizational units out of a total of 23.

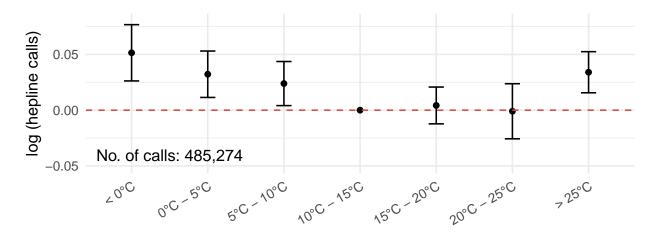
Table 1: Effect of average daily temperature on helpline call volume

		Dependen	t variable:	
		helplir	ne calls	
	(1)	(2)	(3)	(4)
Panel A. Nonlinear				
$< 0^{\circ} C$	0.051***	0.053***	0.054***	0.054***
	(0.013)	(0.014)	(0.014)	(0.015)
0°C - 5°C	0.032***	0.035***	0.033***	0.036***
	(0.011)	(0.011)	(0.011)	(0.011)
5°C - 10°C	0.024**	0.026**	0.024**	0.026***
	(0.010)	(0.010)	(0.010)	(0.010)
10°C - 15°C	Ref.	Ref.	Ref.	Ref.
15°C - 20°C	0.004	-0.0004	0.003	-0.001
	(0.008)	(0.009)	(0.008)	(0.009)
20°C - 25°C	-0.001	-0.004	-0.001	-0.004
20 0 20 0	(0.013)	(0.013)	(0.013)	(0.013)
> 25°C	0.034***	0.033***	0.035***	0.034***
,	(0.009)	(0.007)	(0.009)	(0.007)
Observations	21,138	21,138	21,138	21,138
Adjusted R^2	0.455	0.454	0.455	0.454
Panel B. Linear				
Temperature (°C)	-0.001	-0.001	-0.001	-0.002
Temperature (e)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	21,138	21,138	21,138	21,138
Adjusted R ²	0.455	0.454	0.455	0.454
Counseling-center fixed effects	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes
Environmental controls	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	No	Yes	No
Holiday fixed effects	Yes	Yes	No	No

Notes: The dependent variable is the natural logarithm of the daily number of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in parentheses are two-way clustered at the counseling center and year-month level. *p<0.1; **p<0.05; ***p<0.01.

range. For comparison, on a day with an average temperature in the mid-temperature range a counseling center answers 22.8 calls, on average. Therefore, on extremely cold or hot days a crisis center answers an additional 1.2 or 0.8 calls, respectively. The coefficients increase toward the ends of the temperature distribution, indicating a U-shaped relationship between temperature and mental health problems. The number of calls answered on days with an average temperature in the middle range is not statistically different from the number of calls on a day in the excluded category. The magnitude of the point estimates is close to zero and statistically insignificant for days with average temperatures greater than 15°C but less than 25°C. The pattern still holds when day-of-week fixed effects and holiday fixed effects are further excluded in columns (2) - (4). As the focus of this paper lies on the effects of exposure to temperature on mental health, I do not report results for other weather dimensions or air pollution in the interest of space. In addition, other environmental factors are spatiotemporally highly heterogeneous compared to temperature, so the coefficients should be interpreted with caution as the exact location of the caller is not known. It is worth noting, however, that in the preferred specification (Table 1, Panel A column (1)), I do not

Figure 3: Estimated relationship between daily helpline call volume and average daily temperature



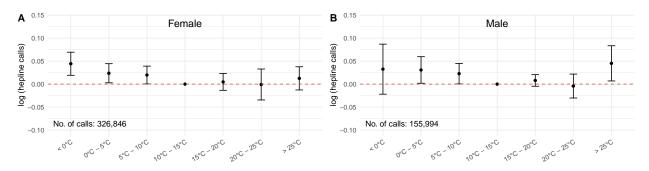
Notes: This figure illustrates the response function between the natural logarithm of daily helpline call volumes and average daily temperatures (Table 1 Panel A column (1)). The response function is normalized with the 10° C - 15° C category set equal to zero. Each coefficient can be interpreted as the percentage change in the number of helpline calls on a day in bin j relative to a day with an average temperature in the base category. Whiskers denote the obtained 95% confidence intervals.

document statistically significant effects for weather realizations other than temperature. For ease of interpretation, Figure 3 illustrates the response function between daily helpline call volumes and average daily ambient temperature.

Even though the results indicate a nonlinear relationship, I estimate a simpler version of the model where temperature enters the regression continuously. Results of that alternative continuous specification are provided in Panel B of Table 1. The temperature coefficients are close to zero and insignificant across all specifications, an outcome that underscores the importance of considering more flexible responses of the outcome variable to temperature.

The baseline estimates presented are consistent with previous work in that exposure to hot temperatures has adverse effects on mental health. However, the nonlinear shape of the estimated response function between the incidence of helpline calls and temperature is different from the previously studied relationship between temperature and more serious mental health outcomes, such as suicidality (Burke et al., 2018) and health care utilization (Mullins & White, 2019), as most studies employing traditional measures of mental health suggest a linear relationship. Instead, the U-shaped relationship mirrors that of temperature and general health outcomes (e.g., Deschênes & Greenstone, 2011). Previous work looking at self-reported mental health also suggests nonlinear relationships between temperatures and mental health (Obradovich et al., 2018), with no clear evidence of temperature-related

Figure 4: Estimated relationship between daily helpline call volume and average daily temperature by gender



Notes: This figure illustrates the response function between the natural logarithm of daily helpline call volumes and average daily temperatures by gender. Female (A); male (B), as estimated by applying the full model in equation (1) to the respective subsample. The response function is normalized with the 10° C - 15° C category set equal to zero. Each coefficient can be interpreted as the percentage change in the number of helpline calls on a day in bin j relative to a day with an average temperature in the base category. Whiskers denote the obtained 95% confidence intervals.

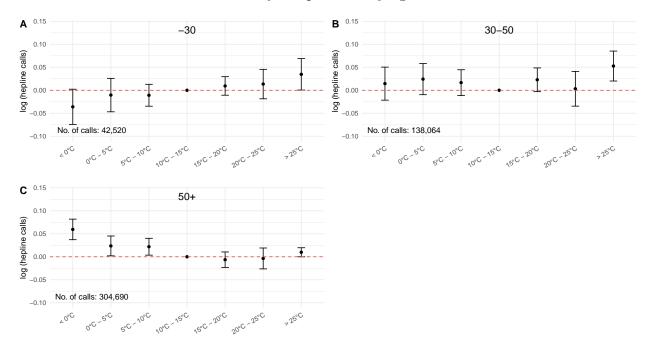
changes in mental health due to extreme cold. For comparison, Obradovich et al. (2018) report a 1.3 percent increase in the probability of self-reported mental health issues on days with an average maximum temperature above 30°C relative to days with temperature maxima between 10°C and 15°C. Burke et al. (2018) document a 0.7 percent increase in suicide rates for a 1°C increase in monthly average temperatures.

4.2 Heterogeneity

Heterogeneity by Gender - To examine the heterogeneous responses to temperature for mental health problems, I first stratify daily calls to helplines by gender. Figure 4 plots the results when the sample is split by gender of the caller. While the estimates suggest an increase in call volumes on hot days for male callers relative to mild days by 4.5 percent, the number of calls to telephone counseling centers from female help-seekers on hot days does not differ from the number of calls on mid-temperature days. The magnitudes of the point estimates are closer to zero and statistically insignificant. However, on days with an ambient temperature in the lower end of the temperature spectrum the number of calls from women to helplines increases significantly relative to call volumes on days in the middle of the temperature range. Call volume for women is up by 4.4 percent on extremely cold days with average temperatures below 0°C. Call volumes for male help-seekers also increase on colder days, but the magnitude of the effect for the outermost bin is smaller in size and the coefficient is imprecisely estimated, being insignificant on conventional levels.

Heterogeneity by Age - Next, I study effect heterogeneity by dividing the sample in three age groups (i.e., 30-, 30-50, 50+). The results, shown in Figure 5, suggest substantial age-

Figure 5: Estimated relationship between daily helpline call volume and average daily temperature by age



Notes: This figure illustrates the response function between the natural logarithm of daily helpline call volumes and average daily temperatures by age. Younger than 30 years old (A); older than 30 but younger than 50 years old (B); older than 50 years old (C), as estimated by applying the full model in equation (1) to the respective subsample. The response function is normalized with the 10°C - 15°C category set equal to zero. Each coefficient can be interpreted as the percentage change in the number of helpline calls on a day in bin j relative to a day with an average temperature in the base category. Whiskers denote the obtained 95% confidence intervals.

related heterogeneity. The increase in call volume on cold days is caused mainly by people over 50 years of age (Panel C), who record an increase of up to 5.9 percent compared to days in the omitted category. The number of helpline calls from people under 50 years old on cold days does not differ systematically from the number of helpline calls on days with temperatures in the excluded range. However, I find that on extremely cold days, the number of calls from people below the age of 30 (Panel A) drops by 3.6 percent, albeit the coefficient is only weakly significant. At the other end of the temperature distribution, the overall increase in calls on warmer days is primarily attributable to younger individuals, with the impact on days with average temperatures above 25°C being greatest for individuals between 30 and 50 years of age (Panel B). The results suggest a nearly linear relationship between temperature and mental health problems in people younger than 30.

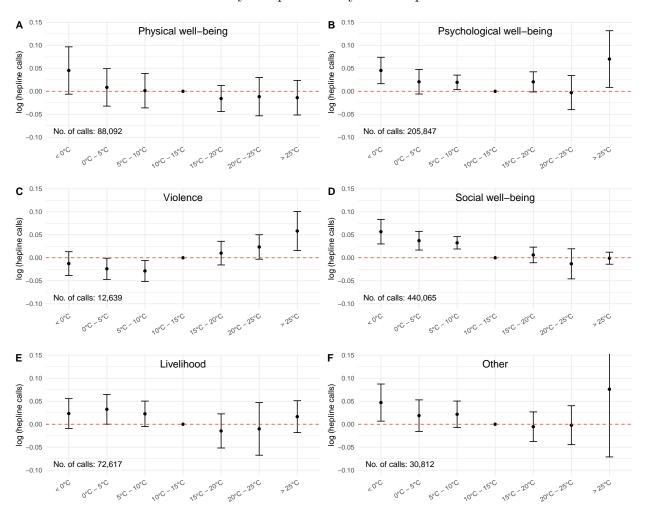
4.3 Mechanisms

To analyze the underlying cause of concern of the consultation, I divide the sample according to the call's main topic. In total there are 34 topics that operators can choose from. As

mentioned above, I group the topics of the call into six main topics (Table A.2). Results of the estimation are depicted in Panel A - F in Figure 6.

Psychological Well-being - Panel B in Figure 6 plots the response function between the natural logarithm of daily helpline call volumes about psychological well-being (e.g., mood, self-harm, stress, self-image) and average daily temperatures. The results identify psychological well-being as an important factor for increasing demand for counseling services on extremely cold days. I find that the number of calls increases significantly on days at the low end of the temperature range by 4.5 percent. Similarly the number of calls increases at

Figure 6: Estimated relationship between daily helpline call volume and average daily temperature by main topic



Notes: This figure illustrates the response function between the natural logarithm of daily helpline call volumes and average daily temperatures by main topic of the conversation. Physical well-being (A); psychological well-being (B); violence (C); social well-being (D); livelihood (E); other (F), as estimated by applying the full model in equation (1) to the respective subsample. The response function is normalized with the 10°C - 15°C category set equal to zero. Each coefficient can be interpreted as the percentage change in the number of helpline calls on a day in bin j relative to a day with an average temperature in the base category. Whiskers denote the obtained 95% confidence intervals.

the high end of the temperature distribution by 7.0 percent, indicating that both extremely hot and cold temperatures indirectly undermine sound mental health through temperature-induced changes in psychological well-being. The nonlinear pattern, which emerges when I split the sample by topic and estimate the model for calls about psychological well-being only resembles evidence on temperature-related mood alterations. Baylis (2020) analyzes the relationship between temperature and expressed mood using Twitter updates in the U.S. and finds a significant drop in expressed sentiment at both ends of the temperature spectrum. Thus, the estimates presented in the mechanism analysis support the existence of a causal psychological link between temperature exposure and mental health problems.

Violence - I document that the number of calls for physical and sexual violence increases significantly by 5.8 percent on hot days compared to days with average temperatures (Panel C), with no increase on the lower end of the temperature range. If anything, the results suggest that the number of calls about violence is lower on colder days, however, the coefficient for the outermost bin is small in magnitude and not statistically significant on conventional levels. The results after estimating the model for physical and sexual violence calls only are consistent with the literature documenting a positive impact of heat exposure on interpersonal aggression, violence, and destructive behavior (Hsiang et al., 2013; Almås et al., 2019; Mukherjee & Sanders, 2021). For example, Mukherjee & Sanders (2021) find that on days with high temperatures, the number of daily violent interactions among detainees increases by 20 percent, and the likelihood of any violent act by up to 18 percent. Almås et al. (2019) find that heat significantly affects the propensity for destructive actions in a laboratory setting. The negative effects in the lower temperature range could be explained by the fact that victims spend more time at home with their abusers and therefore cannot call the telephone counseling service (Leslie & Wilson, 2020; Anderberg et al., 2022).

Social Well-being - The results suggest that on colder days, the number of calls about relationships (e.g., loneliness, partnership, family relationships) increases significantly by 5.7 percent compared to calls in average temperatures (Panel D). However, I find no evidence for an increase in calls about social relations on extremely hot days. The coefficients are close to zero and insignificant. Potentially the results can be explained by limited human mobility on colder days (Clarke et al., 2015). People who live with others may spend more time at home during cold temperatures, which in turn could increase the likelihood of relationship problems. In addition, people who live alone may go out less and socialize less on cold days, which might increase feelings of loneliness and social isolation. Thus, the estimates presented in the mechanism analysis suggest that cold temperatures might indirectly impair

sound mental health by reducing social well-being.

Other Call Topics - The coefficients for the number of physical well-being and livelihood (e.g., work, poverty, finances) calls are not significantly different from zero (Panel A and E, respectively). However, the magnitudes of the coefficients and the shape of the response function for calls related to physical complaints provide suggestive evidence that the number of calls concerned with physical well-being increases on colder days compared to mid-temperature days. I estimate an increase of 4.5 percent for the outermost temperature range, a result that is only weakly statistically significant. In this particular setting, I do not find convincing evidence that exposure to hot temperatures indirectly compromise mental health through worsening physical health. In the short-term livelihood concerns do not seem to be affected by suboptimal temperatures, as the signs of the estimates are inconsistent and the magnitudes do not follow a consistent pattern. It intuitively seems plausible that livelihood concerns are not affected, as the effects presented in this study are short-run impacts of temperature on mental health. However, in the long-term, other temperature-induced effects, such as changes in economic conditions (Dell et al., 2012) or migration (Deschenes & Moretti, 2009), might have indirect impact on livelihood concerns.

Limitations - As noted by Liu & Tsai (2021), the analysis of call topics has some potential shortcomings as the stated topic of the call may not reflect the actual cause of concern, but rather may be a topic the caller wants to discuss with the counselor and the classification of the conversation topic may differ depending on the staff member making the assessment.²⁰

Alternative Explanations - There is a set of potential mechanisms that I cannot test directly in the data. Prior evidence suggests that warmer temperatures reduce sleep (Obradovich et al., 2017; Minor et al., 2022) which in turn causally impacts human health (Jin & Ziebarth, 2020). The relatively large effect size of minimum temperatures (Panel A Table A.7), which are likely to be experienced during nighttime, provide suggestive evidence that temperatures impair mental health through sleep loss in this setting as well. Another alternative mechanism is given by temperature-related decreases in cognitive function. Interestingly, Graff Zivin et al. (2018) also find a nonlinear relationship between temperature and cognitive performance, that resembles the response function between temperature and mental health described in this work. Additionally, there are potential direct biological mechanisms

²⁰While this could be a major issue in cross-national studies, it is not as much of a concern in this work, as all counselors in telephone counseling go through the same training program before they begin their work in telephone counseling.

through which temperature and mental health are linked, such as disruption of central processes involved in maintaining a stable body temperature (Lõhmus, 2018), that cannot be tested with the data at hand.

4.4 Robustness and Validity

I test the validity of the study design and the robustness of my results across multiple dimensions. My main results are consistent with changes in the benchmark specification.

Placebo Tests - Results of the falsification exercises, where I (i) replace daily environmental factors (i.e., temperature, precipitation, sunshine duration, wind speed, humidity, and air pollution) interpolated for each counseling center with the measurements of the same day but of the most distant site, (ii) replace daily environmental factors for each site with the observations recorded 90 days earlier, and (iii) replace daily environmental factors for each counseling center with the observations recorded 90 days earlier of the most distant site, are shown in Table 2. Using a placebo test allows me to check for an association that should be present if the research design is flawed but not otherwise. In this placebo tests, the

Table 2: Effect of average daily temperature on helpline call volume, placebo

		$Dependent\ variable:$	
		helpline calls	
	furthest location	-90 days	furthest location -90 days
	(1)	(2)	(3)
< 0°C	0.004	-0.020	0.015
	(0.018)	(0.020)	(0.022)
0°C - 5°C	-0.006	0.003	-0.003
	(0.011)	(0.014)	(0.012)
5°C - 10°C	-0.005	0.016	-0.002
	(0.012)	(0.013)	(0.011)
10°C - 15°C	Ref.	Ref.	Ref.
15°C - 20°C	-0.006	0.002	0.001
15 C - 20 C	(0.018)	(0.002	(0.016)
20°C - 25°C	-0.023	0.011	0.006
20 C - 23 C	(0.026)	(0.012)	(0.015)
> 25°C	0.020) 0.032	-0.007	0.013) 0.027
25 C	(0.021)	(0.019)	(0.028)
01	01 190	01 120	01 190
Observations	21,138	21,138	21,138
Adjusted R ²	0.455	0.455	0.455
Counseling-center fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Environmental controls	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes
Holiday fixed effects	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the daily number of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in parentheses are two-way clustered at the counseling center and year-month level. In column (1) placebo temperatures are taken from the counseling center that is the most distant. In column (2) placebo temperatures are taken from 90 days earlier. In column(3) placebo temperatures are taken from the most distant counseling center, but 90 days earlier. *p<0.1; **p<0.05;***p<0.01.

magnitude of the coefficients is closer to zero, the signs are inconsistent, and the estimates are insignificant in all specifications.²¹ I interpret the results of in-time and across-space placebos as supporting the causal interpretation of my estimates. In addition, I randomly permute indicators for extreme temperature days (i.e., <0°C and >25°C) across counseling-center-day observations 10,000 times, re-estimate the baseline model for each of these 10,000 generated dataset, and then compare the results to the observed estimate. Results of this simulation exercise are shown in Figure A.6 in the Appendix. The simulation-based distribution of regression coefficients is centered at zero while the observed estimates are far to the right of this null distribution, providing further evidence that suggests there is a significant relationship between extreme temperatures and the number of calls to counseling centers.

Alternative Specifications and Clustering - I re-estimate the outcomes in column (1) of Table 1 using different transformations of the dependent variable. I estimate alternative specifications using the raw count of the number of helpline calls, the inverse hyperbolic sine (IHS) transformation of the number of helpline calls, and a Poisson specification and compare these to the baseline estimates. Results are shown in Table A.4 in the Appendix. The impact of extreme temperatures on the number of helpline calls remains highly significant and exhibits the same pattern of increasing intensity toward the end of the temperature range, suggesting that my choice of estimator does not drive the results.²² In Table A.5, I explore alternative ways of clustering standard errors and compare these to the results when clustering at the counseling-center and year-month level. I cluster standard errors at larger areas to allow for spatial correlation of standard errors between counseling centers. Results remain robust when clustering at the federal state and year-month level and applying wild cluster bootstrapping to deal with the smaller number of resulting groups.²³

Environmental Conditions - I provide evidence that the results are robust to the exclusion of simultaneous environmental conditions. I exclude one of the daily weather and pollution measurements at a time to check the sensitivity of the temperature coefficients to the individual contemporaneous environmental factors. Results are shown in Table A.6 in the Appendix. Estimated effects remain consistent with the baseline results.

²¹The choice of the 90 day backward shift is purely arbitrary. I repeat the exercises with periods of 60 and 120 days as well as with a forward shift. The results using these alternative placebo observations lead to the same conclusions, with mixed signs, estimates being closer to zero, and insignificant coefficients in all estimations. Results are available upon request.

²²The same applies to the models where I split the sample by gender, age, and topic. The results using alternative specifications mirror the results presented in main part of the paper.

²³See Figure 1 for a visualisation of the spatial level of grouping. The black lines in the map show the borders of the German federal states.

Temperature Exposure - So far, I have relied on average ambient temperatures in order to remain agnostic as to when individuals are exposed to thermal stressors during the day. As additional robustness checks, I define exposure using daily maximum and minimum temperatures. As with average temperatures, the results indicate a pronounced increase in the number of helpline calls on days near the lower and upper ends of the respective temperature distribution. The results are shown in Panels A and B of Table A.7 in the Appendix.

4.5 Dynamic Effects

In this section, I examine the dynamic effects of temperature on mental health. Up until now, this analysis has focused on on-the-day temperature impacts and ignored potential build up effects. It is possible that the increase in call volume on days with extreme temperatures is due to exposure to several days of suboptimal temperature levels. To this end, I follow the approach of Somanathan et al. (2021). I construct new variables indicating the number of days in the last three, five, or seven days that were extremely hot (i.e., $> 25^{\circ}$ C), and the number of days in the last three, five, or seven days that were extremely cold (i.e., $< 0^{\circ}$ C). To test whether past temperatures have an impact on today's helpline call volume, I include the newly constructed variables in the baseline regression equation outlined in equation (1). The results of this empirical exercise are shown in Table 3.

Table 3: Dynamic effect of average daily temperature on helpline call volume

		Dependent variable:	
		helpline calls	
	3 days	5 days	7 days
	(1)	(2)	(3)
< 0°C	0.019	0.018	0.015
	(0.017)	(0.014)	(0.015)
no. of previous days $< 0^{\circ}$ C	0.011***	0.009***	0.006**
v	(0.004)	(0.002)	(0.002)
> 25°C	0.024***	0.024^{*}	0.027**
	(0.009)	(0.013)	(0.011)
no. of previous days $> 25^{\circ}$ C	`0.011	0.008	0.002
-	(0.009)	(0.005)	(0.005)
Observations	20,973	20,863	20,753
Adjusted R^2	0.474	0.478	0.482
Counseling-center fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Environmental controls	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes
Holiday fixed effects	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the daily number of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in parentheses are two-way clustered at the counseling center and year-month level. No. of previous days refers to the count of days in the last (1) three, (2) five, and (3) seven days. *p<0.1; **p<0.05; ***p<0.01.

I do not find convincing evidence of an impact of past exposure to hot temperature extremes on present mental health. Coefficients for the number of hot days in the previous three, five, and seven days are close to zero and statistically insignificant. Magnitude of point estimate for average on-the-day temperature is close to that of the estimates in the baseline specification in absolute value and highly significant. I interpret these findings as supporting evidence of the existence of an instant adverse effect of extremely hot temperatures on mental health. The results provide suggestive evidence of a cold build up. The coefficients for the counts of cold days in the past three, five, and seven days are significant across all specifications. For example, one additional cold day in the previous three days translates to a 1.1 percent increase in on-the-day call volume. The coefficient for the contemporaneous temperature is smaller in magnitude than in the base specification and imprecisely estimated.

4.6 Other results

The results for the estimation of the model outlined in equation (2), where I employ the natural logarithm of call duration measured in seconds as the dependent variable are shown in Table 4. Results of the semiparametric specification (Panel A) suggest that calls on days with an average temperature in the lower end of the temperature distribution are 5.0 percent longer than calls on a day with an average temperature in the middle range. The magnitude of the estimates increases toward the lower end of the temperature distribution providing consistent evidence of a positive effect of low temperatures on call duration. The relationship between counseling length and warmer temperatures is less accurately estimated, although the negative sign of the coefficients suggests that hot temperatures lead to a reduction in the duration of telephone consultations. Again, I gradually exclude specific fixed effects to test the sensitivity of the results. Significance of estimates strongly depends on the model specification and vanishes when day-of-week, holiday and hour-of-day fixed effects are excluded. A look at the coefficient of the parsimonious model, where temperature enters the regression as a continuous measure, confirms the existence of an inverse linear relationship. In the preferred specification (Table 4, Panel B column (1)), an increase in temperature by 1°C translates to a decrease in call duration by 0.3 percent, a finding that is statistically significant and robust across different specifications.

The finding of shorter call duration on hot days might be explained by temperature-related changes in time preferences with increasing impatience as temperature rises, which, while not unambiguously, have been found to exist in previous research (Carias et al., 2021; Almås et al., 2019). However, I cannot rule out the possibility that the shorter duration of counseling

Table 4: Effect of average daily temperature on helpline call duration

		j	Dependent variable	::	
_			call duration		
	(1)	(2)	(3)	(4)	(5)
Panel A. Nonlinear					
< 0°C	0.050***	0.045***	0.045***	0.051***	0.046***
	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)
0°C - 5°C	0.017*	0.013	0.012	0.018*	0.013
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
5°C - 10°C	0.023***	0.021***	0.021***	0.024***	0.022***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
10°C - 15°C	Ref.	Ref.	Ref.	Ref.	Ref.
15°C - 20°C	-0.010	-0.004	-0.003	-0.009	-0.003
15 C - 20 C	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
20°C - 25°C	-0.053^*	-0.044	-0.044	-0.052^*	-0.043
20 C - 25 C	(0.031)	-0.044 (0.030)	-0.044 (0.030)	-0.032 (0.031)	(0.030)
> 25°C	(0.031) -0.012	(0.030) -0.014	(0.030) -0.014	(0.031) -0.013	(0.030) -0.014
> 25° C					
	(0.022)	(0.023)	(0.023)	(0.022)	(0.023)
Observations	485,274	485,274	485,274	485,274	485,274
Adjusted R^2	0.117	0.117	0.117	0.111	0.110
Panel B. Linear					
Temperature (°C)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
Temperature (C)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	$485,\!274$	485,274	$485,\!274$	$485,\!274$	$485,\!274$
Adjusted R ²	0.117	0.117	0.117	0.110	0.110
Counseling-center fixed effects	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes
Environmental controls	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	No	Yes	Yes	No
Holiday fixed effects	Yes	Yes	No	Yes	No
Hour-of-day fixed effects	Yes	Yes	Yes	No	No

Notes: The dependent variable is the natural logarithm of the duration of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in parentheses are two-way clustered at the counseling center and date level. *p<0.1;**p<0.05;***p<0.01.

is due to temperature-induced effects on telephone counselors, which may also be the cause of the shorter consultation duration. For example, Somanathan et al. (2021) and LoPalo (2022) indicate effects of hot temperatures on worker productivity.

5 Conclusion

This paper investigates the causal link between temperature and mental health concerns. By using data on nearly half a million individual calls to Germany's largest telephone counseling service, I provide novel evidence of the adverse effects of exposure to extreme temperatures on mental health. Since mental health problems involve much more than just clinical diagnosis the use of helpline data makes an important contribution to our understanding of how environmental stressors might erode mental health. I document that the number of calls answered at counseling centers is significantly higher on extreme temperature days than on days with an average ambient daily temperature in the middle of the temperature distri-

bution. I find significant age- and gender-related effect heterogeneity. Results suggest that increasing call volumes on days with a suboptimal temperature level are mainly due to an increase in calls related to social well-being, violence, and psychological well-being. Furthermore, I provide evidence of temperature-induced changes in the intensity of counseling use. Estimates show that the average length of telephone counseling decreases as temperature increases. The findings of this paper add to our understanding of how changes in climatic conditions may impact population mental health in the near future. The results highlight the large potential increase in social costs resulting from deteriorating mental health due to increased exposure to extreme temperatures and draw attention to another, previously overlooked, hidden cost of climate change.

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A Appendix

Table A.1: Summary of sampled helpline crisis centers

Location	Observation period	No. of days	No. of calls	$\frac{\text{Avg.}}{\text{calls/day}}$	Std. calls/da
Aachen	31/12/2018 - 29/02/2020	421	7,632	18.13	5.58
Aschaffenburg	31/12/2018 - 29/02/2020	426	10,924	25.69	4.46
Auerbach	17/12/2018 - 29/02/2020	410	6,776	16.53	7.10
Bad Oeynhausen	01/12/2018 - 29/02/2020	456	10,599	23.24	4.40
Bamberg	16/09/2019 - 29/02/2020	167	4,286	25.66	5.04
Bayreuth	01/01/2019 - 29/02/2020	418	7,153	17.11	7.17
Berlin	31/12/2018 - 29/02/2020	423	7,610	17.99	7.57
Bielefeld		401		26.04	
	15/01/2019 - 29/02/2020		10,442		6.45
Bochum	03/11/2018 - 29/02/2020	483	9,883	20.46	4.94
Bremen	01/02/2019 - 29/02/2020	391	9,505	24.31	7.08
Darmstadt	02/01/2019 - 29/02/2020	424	12,139	28.63	4.55
Dessau	01/01/2019 - 29/02/2020	425	8,943	21.04	5.34
Dortmund	21/02/2019 - 29/02/2020	366	7,267	19.86	5.99
Erlangen	14/01/2019 - 29/02/2020	412	9,795	23.77	7.86
Essen (ev.)	31/03/2019 - 29/02/2020	276	5,928	21.48	5.49
Essen (kath.)	01/01/2019 - 29/02/2020	425	13,443	31.63	10.33
Frankfurt a. M. (ev.)	01/01/2019 - 29/02/2020	425	11,415	26.86	5.19
Frankfurt a. M. (kath.)	23/06/2019 - 29/02/2020	336	6,913	20.57	6.85
Freiburg	21/12/2018 - 29/02/2020	428	14,263	33.32	7.21
Gießen	04/01/2019 - 29/02/2020	381	7,981	20.95	5.97
Greifswald		405	4,607	11.38	6.70
	18/12/2018 - 29/02/2020				
Hagen	10/11/2018 - 29/02/2020	437	8,119	18.58	4.98
Hamburg (ev.)	01/01/2019 - 29/02/2020	425	13,986	32.91	8.21
Hamburg (kath.)	10/01/2019 - 29/02/2020	363	4,314	11.88	6.06
Hamm	02/12/2018 - 29/02/2020	444	10,479	23.60	5.06
Hanau	27/11/2018 - 29/02/2020	460	$10,\!482$	22.79	4.11
Hannover	01/07/2019 - 29/02/2020	244	7,322	30.01	4.91
Ingolstadt	27/02/2019 - 29/02/2020	368	9,894	26.89	5.36
Kaiserslautern	05/11/2018 - 29/02/2020	471	11,699	24.84	6.09
Kassel	16/01/2019 - 29/02/2020	395	7,489	18.96	5.69
Krefeld	20/12/2018 - 29/02/2020	430	9,243	21.50	7.70
Konstanz	01/01/2019 - 29/02/2020	424	8,936	21.08	6.68
Mainz-Wiesbaden	16/10/2019 - 29/02/2020	122	3,243	26.58	7.89
Münster	16/11/2018 - 29/02/2020	454	12,818	28.23	7.13
Neubrandenburg	22/12/2018 - 29/02/2020	408	5,213	12.78	6.25
		244		20.50	5.19
Neuss	01/07/2019 - 29/02/2020		5,002		
Offenburg	20/12/2018 - 29/02/2020	425	9,285	21.85	6.92
Pforzheim	01/01/2019 - 29/02/2020	418	12,076	28.89	5.41
Paderborn	02/12/2018 - 29/02/2020	450	8,333	18.52	3.90
Passau	31/05/2019 - 29/02/2020	274	6,327	23.09	5.28
Recklinghausen	10/12/2018 - 29/02/2020	445	11,162	25.08	4.77
Rosenheim	13/04/2019 - 29/02/2020	276	3,754	13.60	7.15
Rostock	17/12/2018 - 29/02/2020	428	9,527	22.26	6.14
Schwerin	01/01/2019 - 29/02/2020	425	14,142	33.28	6.56
Siegen	04/02/2019 - 29/02/2020	386	7,289	18.88	5.06
Solingen	26/12/2018 - 29/02/2020	420	4,560	10.86	4.87
Stuttgart (kath.)	01/03/2019 - 29/02/2020	352	12,652	35.94	9.67
Sylt	03/09/2019 - 29/02/2020	151	1,270	8.41	2.35
T1 ·	27/09/2019 - 29/02/2020	155	4,300	27.74	5.65
Tubingen Ulm	01/01/2019 - 29/02/2020	425	13,234	31.14	4.68
Wehr	01/01/2019 - 29/02/2020	420	5,475	13.04	4.44
Weiden	23/12/2018 - 29/02/2020	427	12,461	29.18	5.58
Wolfsburg	01/01/2019 - 29/02/2020	424	10,059	23.72	5.85
Wuppertal	01/01/2019 - 29/02/2020	425	10,022	23.58	5.20
Würzburg	01/01/2019 - 29/02/2020	424	13,585	32.04	6.54
55 crisis center			485,274	22.96	8.67

Table A.2: Classification of call topics

Main Topics	Individual Topics
Physical well-being Psychological well-being Violence	Physical well-being (discomfort, illnesses, disabilities) Mood, stress, self-harm, self-image, suicidality, other psychological well-being Physical violence and mental violence, sexual violence
Social well-being	Loneliness, dating, partnership, parenthood, sexuality, pregnancy, family relations, everyday relations, virtual relations, seperation, integration, carework, death, grief
Livelihood Other	Work, poverty, finances, housing, school, volunteering Faith and values, culture, religion, current topics, other topics

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Table A.3: Summary statistics of helpline calls

Panel A: Caller characteristics	Gender	Age group		nployment status	Living situation	
Percentage share of callers	female male 67.35 32.15	30- 30-50 8.76 28.45	55.54 working 55.54 26.17	non-working retired 33.99 20.48	alone not alo 60.88 29.50	
Panel B: Main topics	Physical well-being	Psychological well-being	Violence	Social well-being	Livelihood Othe	er
Percentage share of calls	18.15	42.42	2.60	90.80	14.96 6.35	5

Notes: Percentages do not add up to 100. Panel A: As *TelefonSeelsorge* offers anonymous telephone counseling, the information about the callers is based on the counselor's assessment. Sometimes counselors do not record information on the caller. Panel B: Counselors can choose up to three topics for each call. Therefore some calls have three different topics.

Table A.4: Effect of average daily temperature on helpline call volume, other specifications

		Dependent	t variable:	
		helplin	e calls	
	Logarithm	Raw count	IHS	Poisson
	(1)	(2)	(3)	(4)
< 0°C	0.051***	0.420***	0.049***	0.018***
	(0.013)	(0.097)	(0.012)	(0.004)
0°C - 5°C	0.032***	0.374***	0.031***	0.016***
	(0.011)	(0.142)	(0.010)	(0.006)
5°C - 10°C	0.024^{**}	0.360* [*]	0.023**	0.016**
	(0.010)	(0.148)	(0.010)	(0.006)
10°C - 15°C	Ref.	Ref.	Ref.	Ref.
15°C - 20°C	0.004	0.244	0.004	0.010
	(0.008)	(0.144)	(0.008)	(0.006)
20°C - 25°C	-0.001	$0.143^{'}$	-0.001	$0.006^{'}$
	(0.013)	(0.196)	(0.012)	(0.008)
> 25°C	0.034***	Ò.444* [*]	0.033***	0.019***
	(0.009)	(0.178)	(0.009)	(0.007)
Observations	21,138	21,138	21,138	21,138
Adjusted/Pseudo R ²	0.455	0.506	0.460	0.205
Counseling-center fixed effects	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes
Environmental controls	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes
Holiday fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variable is the daily number of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in parentheses are two-way clustered at the counseling center and year-month level. Column (1) is estimated using a log transformation of the dependent variable. Column (2) is estimated using the raw count of answered calls as dependent variable. Column (3) is estimated using the inverse hyperbolic sine (IHS) of the dependent variable. Column (4) is estimated using Poisson regression. *p<0.1;**p<0.05;***p<0.01.

Table A.5: Effect of average daily temperature on helpline call volume, alternate standard errors

		Dependent variable:	
		helpline calls	
	$\begin{array}{c} \text{counseling-center x} \\ \text{year-month} \end{array}$	federal-state x year-month	federal-state x year-month (wild bootstrap)
	(1)	(2)	(3)
< 0°C	0.051***	0.051**	0.051**
0°C - 5°C	(0.013) 0.032^{***}	$(0.018) \\ 0.032^{***}$	(0.024) 0.032***
5°C - 10°C	$(0.011) \\ 0.024**$	$(0.008) \\ 0.024***$	$(0.012) \\ 0.024***$
10°C - 15°C	$\begin{array}{c} (0.010) \\ \text{Ref.} \end{array}$	$\begin{array}{c} (0.007) \\ \text{Ref.} \end{array}$	(0.010) Ref.
15°C - 20°C	0.004	0.004	0.004
20°C - 25°C	$(0.008) \\ -0.001$	$(0.013) \\ -0.001$	$(0.013) \\ -0.001$
> 25°C	$(0.013) \\ 0.034***$	(0.008) 0.034***	$(0.012) \\ 0.034***$
, 20 0	(0.009)	(0.005)	(0.003)
Observations	21,138	21,138	21,138
Adjusted R ²	0.455	0.455	0.455
Counseling-center fixed effects	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes
Environmental controls	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes
Holiday fixed effects	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the daily number of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in Column (1) are two-way clustered at the counseling center and year-month level. The standard errors in Column (2) are two-way clustered at the federal state and year-month level. The standard errors in Column (3) are two-way clustered at the federal state and year-month level and are obtained by wild bootstrap, using 10,000 replications. *p<0.1;**p<0.05;***p<0.01.

Table A.6: Effect of average daily temperature on helpline call volume, environmental factors

			Dependent variable	»:	
_			helpline calls		
	(1)	(2)	(3)	(4)	(5)
< 0°C	0.050***	0.052***	0.051***	0.055***	0.035***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.011)
0°C - 5°C	0.031***	0.033***	0.032***	0.035***	0.032***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)
5°C - 10°C	0.023**	0.024**	0.024**	0.024**	0.025**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
10°C - 15°C	Ref.	Ref.	Ref.	Ref.	Ref.
15°C - 20°C	0.004	0.004	0.004	0.004	0.004
10 0 20 0	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
20°C - 25°C	-0.000	-0.002	-0.001	-0.002	-0.006
	(0.013)	(0.012)	(0.014)	(0.013)	(0.014)
> 25°C	0.035***	0.032***	0.033***	0.033***	0.023***
	(0.009)	(0.007)	(0.011)	(0.010)	(0.009)
Observations	21,138	21,138	21,138	21,138	21,138
Adjusted R ²	0.455	0.455	0.455	0.455	0.455
Precipitation	No	Yes	Yes	Yes	Yes
Relative humidity	Yes	No	Yes	Yes	Yes
Sunshine duration	Yes	Yes	No	Yes	Yes
Surface wind speed	Yes	Yes	Yes	No	Yes
Air pollution	Yes	Yes	Yes	Yes	No
Counseling-center fixed effects	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes
Holiday fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the daily number of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in parentheses are two-way clustered at the counseling center and year-month level. p<0.1; p<0.05; p<0.05; p<0.01.

Table A.7: Effect of minimum and maximum daily temperature on helpline call volume

		Dependen	t variable:	
_		helplir	ne calls	
	(1)	(2)	(3)	(4)
Panel A. Minimum Temperatures				
< -4°C	0.065***	0.068***	0.068***	0.070***
	(0.023)	(0.025)	(0.022)	(0.024)
-4°C - 1°C	0.043**	0.045**	0.044**	0.045**
	(0.020)	(0.021)	(0.020)	(0.021)
1°C - 6°C	0.032**	0.032**	0.032**	0.032**
000 1100	(0.015)	(0.016)	(0.015)	(0.015)
6°C - 11°C	Ref.	Ref.	Ref.	Ref.
11°C - 16°C	-0.016	-0.017	-0.017	-0.017
	(0.017)	(0.017)	(0.017)	(0.017)
> 16 °C	0.060**	0.063**	0.061**	0.064**
	(0.028)	(0.028)	(0.028)	(0.028)
Observations	21,138	21,138	21,138	21,138
Adjusted R^2	0.455	0.454	0.455	0.454
Panel B. Maximum Temperatures	0.040***	0.040***	0.045444	0.045***
$< 2^{\circ} C$	0.043***	0.043***	0.045***	0.045***
2°C - 12°C	$(0.012) \\ 0.024***$	$(0.013) \\ 0.026***$	$(0.013) \\ 0.024***$	(0.014) $0.026***$
2°C - 12°C	(0.007)	(0.008)	(0.007)	(0.008)
12°C - 22°C	(0.007) Ref.	(0.008) Ref.	(0.007) Ref.	(0.008) Ref.
12 C - 22 C	nei.	nei.	nei.	nei.
22°C - 32°C	0.004	-0.001	0.003	-0.002
	(0.008)	(0.008)	(0.008)	(0.008)
> 32°C	0.025**	0.022**	0.025**	0.023**
	(0.012)	(0.010)	(0.012)	(0.010)
Observations	21,138	21,138	21,138	21,138
Adjusted R ²	0.455	0.454	0.455	0.454
Counseling-center fixed effects	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes
Environmental controls	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	No	Yes	No
Holiday fixed effects	Yes	Yes	No	No

Notes: The dependent variable is the natural logarithm of the daily number of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in parentheses are two-way clustered at the counseling center and year-month level. *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Effect of average daily temperature on helpline call volume by gender and age group

_			Dependent variable		
			helpline calls		
_	gen	ider			
	female	male	30-	30-50	50+
	(1)	(2)	(3)	(4)	(5)
< 0°C	0.044***	0.033	-0.036*	0.014	0.059***
	(0.013)	(0.028)	(0.020)	(0.018)	(0.011)
0°C - 5°C	0.024**	0.031**	-0.010	[0.024]	0.024**
	(0.011)	(0.015)	(0.019)	(0.017)	(0.011)
5°C - 10°C	0.020**	0.023**	-0.011	0.017	0.022**
	(0.010)	(0.011)	(0.012)	(0.014)	(0.009)
10°C - 15°C	Ref.	Ref.	Ref.	Ref.	Ref.
15°C - 20°C	0.005	0.008	0.009	0.023*	-0.006
	(0.009)	(0.006)	(0.010)	(0.013)	(0.009)
20°C - 25°C	-0.001	-0.004	0.014	0.003	-0.004
	(0.017)	(0.013)	(0.016)	(0.019)	(0.012)
$> 25^{\circ}\mathrm{C}$	0.013	0.045**	0.035**	0.053***	0.010*
	(0.013)	(0.020)	(0.017)	(0.017)	(0.005)
Observations	21,138	21,138	21,138	21,138	21,138
Adjusted R ²	0.439	0.323	0.120	0.272	0.428
Counseling-center fixed effects	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes
Environmental controls	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes
Holiday fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the daily number of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in parentheses are two-way clustered at the counseling center and year-month level. Columns (1) and (2) present the results when the sample is split by gender. Columns (3) - (5) present the results when the sample is split by age cohorts. *p<0.1; **p<0.05; ***p<0.01.

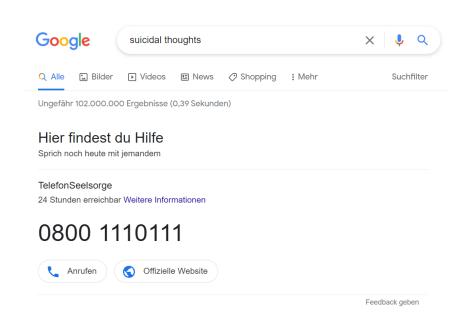
Table A.9: Effect of average daily temperature on helpline call volume by main topic

			D 1			
	Dependent variable: helpline calls main topic					
	physical well-being	psychological well-being	violence	social well-being	liveli- hood	other
	(1)	(2)	(3)	(4)	(5)	(6)
< 0°C	0.045*	0.045***	-0.013	0.057***	0.023	0.047**
	(0.026)	(0.015)	(0.013)	(0.014)	(0.017)	(0.021)
0°C - 5°C	0.008	0.021	-0.024**	0.037***	0.033**	0.019
	(0.021)	(0.014)	(0.012)	(0.010)	(0.017)	(0.018)
5°C - 10°C	0.001	0.019**	-0.029**	0.033***	0.023	0.022
	(0.019)	(0.008)	(0.012)	(0.007)	(0.014)	(0.015)
10°C - 15°C	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
15°C - 20°C	-0.016	0.020*	0.010	0.006	-0.015	-0.005
	(0.014)	(0.011)	(0.013)	(0.009)	(0.019)	(0.016)
20°C - 25°C	-0.012	-0.003	0.023^{*}	-0.013	-0.010	-0.002
	(0.021)	(0.019)	(0.014)	(0.017)	(0.029)	(0.022)
$> 25^{\circ}\mathrm{C}$	-0.014	0.070**	0.058***	-0.001	0.017	0.076
	(0.019)	(0.031)	(0.022)	(0.007)	(0.018)	(0.075)
Observations	21,138	21,138	21,138	21,138	21,138	21,138
Adjusted R ²	0.218	0.268	0.083	0.377	0.208	0.103
Counseling-center fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Environmental controls	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Holiday fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the daily number of answered helpline calls. The sample period is November 3, 2018 to February 29, 2020. The standard errors in parentheses are two-way clustered at the counseling center and year-month level. Columns (1) - (6) present the results when the sample is split by main topic of the conversation. *p<0.1; **p<0.05 ***p<0.01.

Figure A.1: Visibility of telephone counseling services, Panel (A): online search; Panel (B): information poster

Α



В



Notes: Panel A: This figure presents a representative example of an online search for mental health concerns in Germany. The search term is 'suicidal thoughts'. The phone number of *TelefonSeelsorge* is prominently placed on top of the search page. Above the phone number it says, 'You can find help here - Talk to someone today'. Panel B: This figure presents a representative example of an information poster for telephone counseling services offered by *TelefonSeelsorge*. In the top right corner it says, 'Worries can be shared.'.

TS Osnabrück Bad Bentheim Osnabrück Niederlande Tecklenburg Ochtrup • Emsdetten Steinfurt TS Münster Ostbevern Telgte Münster Nottuln Warendorf Borken Sendenhorst Bocholt Oelde Ascheberg

Figure A.2: Catchment area of TelefonSeelsorge Münster

This figure presents the catchment area of *TelefonSeelsorge* Münster. Maps can be obtained from some of the crisis center's website. See https://www.telefonseelsorge.de/unsere-stellen/ for a list of all locations and their websites.

Haltern am See

TS Recklinghausen

TS Wesel

Lüdinghausen

TS Hamm

~105 km

3000 1000 1000 0 20 40 60 Number of calls

Figure A.3: Distribution of the number of calls per day

Notes: This figure illustrates the distribution of the number of helpline calls answered at any given counseling-center-day in the study sample. The horizontal dashed line represents the sample mean (22.96).

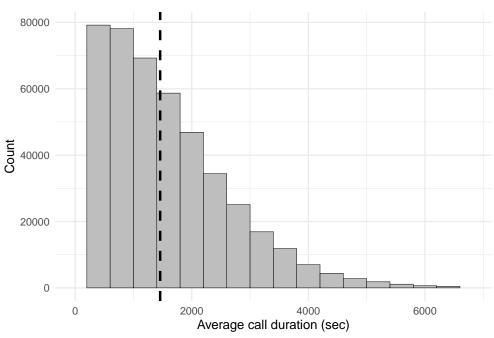
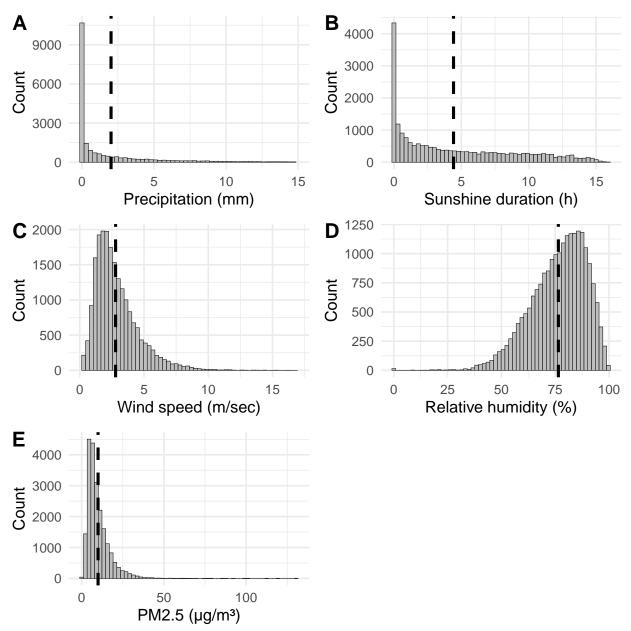


Figure A.4: Distribution of helpline call duration

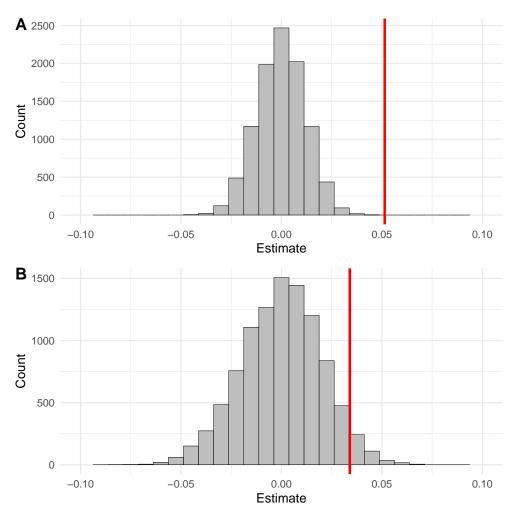
Notes: This figure illustrates the distribution of the length of the calls answered at any given counseling center in the study sample. The horizontal dashed line represents the sample mean (1457.71 $\sec \equiv 24 \min 18 \sec$).

Figure A.5: Distribution of concurrent environmental factors, Panel (A): precipitation; Panel (B): sunshine duration; Panel (C): surface wind speed; Panel (D): relative humidity; Panel (E): air pollution



Notes: This figure illustrates the distribution of realized daily average (A) precipitation, (B) sunshine duration, (C) wind speed, (D) humidity, and (E) air pollution at any given counseling-center-day in the study sample. The horizontal dashed line represents the respective sample mean.

Figure A.6: Simulation-based null distribution of regression coefficients for extreme temperature days, Panel (A): $<0^{\circ}$ C; Panel (B): $>25^{\circ}$ C



Notes: This figure illustrates the simulation-based null distribution of the regression estimates for (A) $<0^{\circ}$ C and (B) $>25^{\circ}$ C. The horizontal red line represents the observed estimate, (A) 0.051 and (B) 0.034. Proportion of simulated coefficients that lie below the slope estimated on the real data is (A) 1 and (B) 0.960. Extreme temperature days are randomly permuted 10,000 times across counseling-center-day observations and the baseline model outlined in equation (1) is re-estimated for each of these 10,000 simulated datasets.