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Are You Okay? Effects of a National Peer-Support Campaign on Mental Health

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Keywords: Peer-to-Peer, Mental Health, Program Evaluation, Suicide Prevention

JEL Classification: I10, I30,

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Are You Okay? Effects of a National Peer-Support Campaign on Mental Health*

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Abstract

Abstract: Peer-to-peer support is often a critical component of mental health programs, but evidence on the effect of peer-based support programs at scale is limited. Using quasi-experimental methods, we examine whether a prominent peer-based support campaign, "R U OK? Day", affects short-term mental health outcomes in Australia. Using variation in daily records and differences in the campaign's intensity over nine years, we find no evidence that "R U OK? Day" reduces suicides and suicidal behaviours in the month after the campaign. However, we find positive effects on mental wellbeing, particularly among middle-aged males, with improved social support the likely mechanism. Our results provide evidence that peer support campaigns may be a practical, low-cost approach to improve population mental wellbeing.

Keywords: Peer-to-Peer; Mental Health; Program Evaluation; Suicide Prevention

JEL classifications: D03,I1,I3

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1 Introduction

Suicide is a leading cause of death worldwide, with over 700,000 suicide deaths each year (World Health Organization, 2021). Many people who experience suicidality do not seek help, and a lack of access to timely and appropriate care can exacerbate the symptoms and negative consequences. Frequently cited barriers to help-seeking include a lack of knowledge about available support services and prejudicial attitudes against people suffering from mental illness, including self-stigmatising attitudes (Henderson et al., 2013; Schnyder et al., 2017). In response to these barriers, mental health awareness campaigns have become central public health policies for preventing suicides and improving mental health. Though they differ in their implementation, such programs typically aim to increase knowledge and reduce the stigma of mental health issues within the community while also rallying support for the prevention of mental illness among governments and other healthcare funders.[1]

A core tenet of mental health-related awareness programs is acknowledging and promoting peers' role in providing at-risk individuals with social support, information, and encouragement to engage with professional services. However, despite the roll-out of these programs around the globe, there is limited evidence directly connecting them to a decrease in suicides or improved mental health. This paper aims to provide this needed evidence by studying the mental health impacts of a national campaign designed to educate and promote peer-to-peer mental health support in the general population.

Our focus centers on "R U OK? Day", the predominant nationwide suicide prevention and mental health awareness campaign conducted annually in Australia. R U OK? Day was launched in 2009 and is centered around one day (the second Thursday) every September. Its unique feature is that it explicitly promotes peer-to-peer mental health support by empowering and encouraging Australians to: (i) ask friends, colleagues, and neighbours, "Are you OK?"; (ii) listen to responses with an open mind; (iii) encourage action if needed, including encouraging people to visit a mental health professional; and (iv) check back in with them over subsequent weeks. The campaign also provides education on how to complete these four steps and to identify signs that a person may be experiencing difficulties, and provides additional resources on professional support services.

Our empirical approach uses three data sources to evaluate the effectiveness of R U OK? Day: daily national administrative records of suicide and accidental poisoning deaths; Google internet search data for terms related to suicide planning and prevention; and self-reported mental wellbeing. Each data source provides daily data from before and after the annual campaign over nine years (2011-2019). To identify the impact of R U OK? Day, we compare changes in years when the campaign was highly active to years when it was not, combined with the narrow window each year when the public's awareness of the campaign peaks. This temporal difference-in-differences approach uncovers short-term behavioural changes that the peer-to-peer aspect of the campaign promotes. A key component of our analysis is to evaluate the effects across different gender and age cohorts, each of which has different incidences of suicide and mental illness, meaning the campaign's impact may differ across these dimensions.

We find no evidence of an effect on suicides or suicidal behaviours. However, we find that the campaign

[1] An example is the WHO's World Mental Health Day, held worldwide each year on October 10th. Another is Mental Illness Awareness Week in the U.S., which takes place annually during the first week of October.

has a small positive effect on self-reported mental wellbeing and that this effect is robust to various model specifications and sensitivity tests. The positive mental health effect is driven mainly by men aged 25-49. This is noteworthy because this subpopulation is known for having insufficient mental healthcare uptake (Meadows et al., 2015; Yousaf et al., 2015). We complement these results with evidence on the mechanism through which R U OK? Day impacts mental health. Among these at-risk populations, the R U OK? Day campaign significantly increased perceived social support. This suggests that the positive impact on mental health likely operates through the intended peer support pathways, including increasing the likelihood of having someone to confide in, having someone to lean on in times of trouble and having someone to cheer up individuals when they are down. Overall, we demonstrate that campaigns that harness peer support may be an effective and low-cost way to improve mental wellbeing before individuals reach a crisis point.

Our work connects to several strands of literature. Evidence on the effect of peers in the context of mental health and suicide prevention is limited to small-scale programs in clinically diagnosed populations (Bowersox et al., 2021). However, there is a broader literature in economics on the effect of peers and social networks on improving health knowledge and behaviours. Existing research connects peers and social networks to improved screening and testing for communicable diseases (Goldberg et al., 2022), feminine hygiene technology adoption (Oster and Thornton, 2012), learning HIV results (Godlonton and Thornton, 2012), child immunization programs (Banerjee et al., 2019), public health insurance (Berg et al., 2019) and flu vaccines (Bronchetti et al., 2015).

Our study also contributes to the small literature on the effects of health awareness campaigns on health or behavioural outcomes. Jacobsen and Jacobsen (2011) examined the effect of breast cancer awareness month on diagnosis rates and found a significant positive influence in the years when breast cancer advocacy was expanding rapidly but had little impact in later years. Similarly, Anderson (2010) examined the effect of a campaign to deter youth from methamphetamine use and found it had no discernible impact. More broadly, evaluations of health awareness campaigns have commonly measured outcomes in terms of self-reported awareness or online activity (e.g., Google searches or Twitter activity relating to the campaign), rather than health outcomes, with most finding positive associations (Vernon et al., 2021).[2]

Finally, our work connects to research that studies the scaling up of a program or intervention to the general population and the problems that arise therein (List, 2022). Peers offer a potentially scalable psychosocial intervention. Previous research has examined the effect of using peers to deliver mental health support programs in small-scale settings (e.g., Maselko et al., 2020; Johnson et al., 2018; Fuhr et al., 2019; Conwell et al., 2021). This study contributes to the evidence on whether peer-based mental health programs are scalable to the wider population.

The remainder of this paper proceeds as follows. Section 2 provides background information on suicide and

[2]Several studies from the public health literature have evaluated suicide prevention campaigns, often targeted to specific population groups (e.g., veterans, police force, college students), and generally find them to be positively associated with self-reported awareness and knowledge of suicides (for systematic reviews see Dumesnil and Verger, 2009; Pirkis et al., 2019; Torok et al., 2017). Studies vary in quality, but many do not involve a comparison group or account for seasonal trends or unobserved factors. We are aware of only two studies that examined the R U OK? Day campaign (Mok et al., 2016; Ross and Bassilios, 2019). Both studies evaluate the campaign in a single year (2014 and 2017, respectively) using online surveys of a sample of approximately 2000 individuals only in the weeks following R U OK? Day. The surveys ask about their awareness of R U OK? Day, their participation and perception of R U OK? Day, and intentions to help others. No comparison group is available for these studies.

mental health in Australia and describes the R U OK? Day campaign. Section 3 details the data collected and used in the study. The estimation strategy is outlined in Section 4. The empirical results are detailed in Section 5, and Section 6 discusses the mechanisms driving the effects. Section 7 concludes the paper and discusses future research directions.

2 The R U OK? Day Campaign

Suicide is the leading cause of death among young Australians aged 15-44, accounting for approximately 25% of deaths annually (Australian Institute of Health and Welfare, 2021). The incidence of suicide in the broad population is 12 deaths per 100,000, which is comparable to incidences in North America and Western Europe, and has been relatively stable over the last two decades (Australian Institute of Health and Welfare, 2022b; World Health Organization, 2021). Males are three times more likely to commit suicide than females, while females are much more likely to be hospitalised due to intentional self-harm Australian Institute of Health and Welfare (2022b). Mental illness is the main risk factor associated with suicide, with approximately one in five Australians suffering from mental illness in a given year.

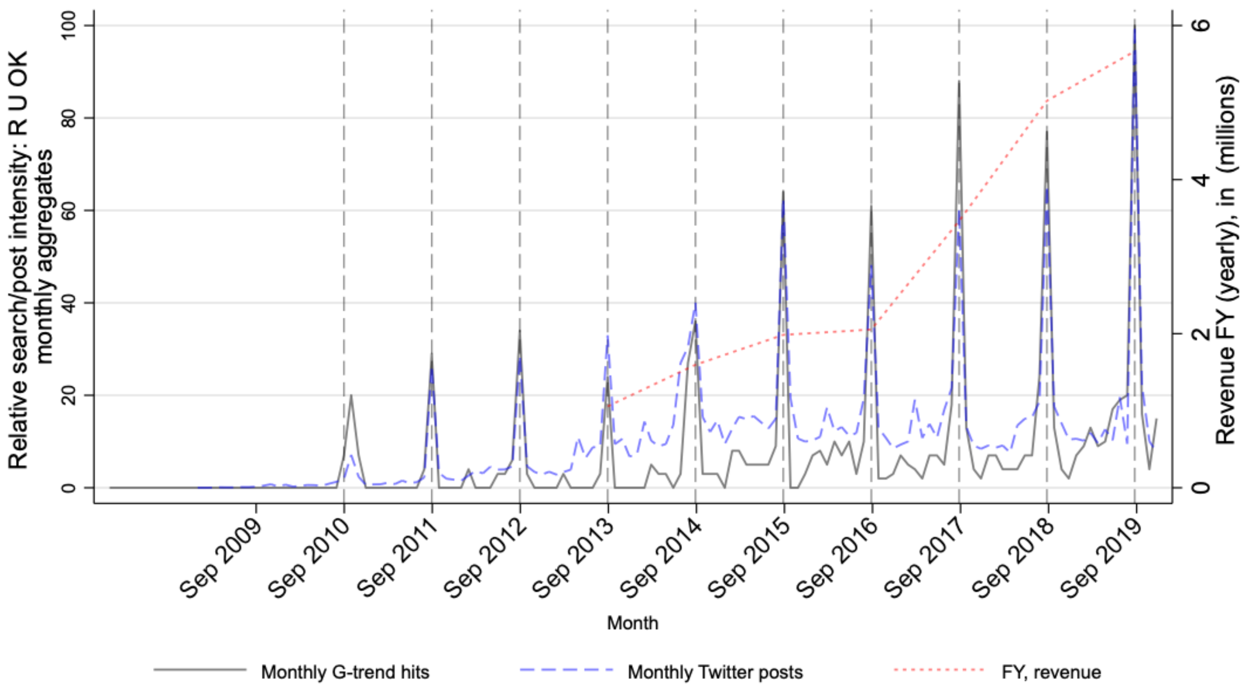

Figure 1: Monthly Google searches "R U OK", Twitter posts, and financial year revenue of the R U OK organisation

Note: Displays the monthly "R U OK" searches on google, twitter posts (divided by maximum monthly posts, 59,968), and the yearly revenue from the organisation's financial reports.
Source: Gtrend search data 2011-2019, Twitter data 2011-2019, R U OK charity financial reports 2013-2019, own calculations.

In response to the high rates of suicide and mental illness, and family experience with suicide, Australian advertiser Gavin Larkin founded the non-profit suicide prevention organisation, 'R U OK?', in 2009. The organisation encourages people to connect with others and have conversations if they identify signs of distress long before they are in crisis. Campaign efforts are concentrated around a national day of action called 'R U

OK? Day', which occurs on the second Thursday of September each year. On this day, the general population is invited and encouraged to reach out to others who might be experiencing personal difficulties, starting with asking, 'Are you ok?'. Through traditional offline marketing strategies and online promotional material, people are provided resources and tips on how to have meaningful conversations that 'could change a life.' People are advised to ask; listen without judgment; encourage the person to take action, such as seeing a mental health professional; and follow up with the person. R U OK? Day is marked in many workplaces, organisations, and schools by activities or events (such as a morning tea) to raise awareness and distribute resources (such as conversation guides).

There are several potential mechanisms through which R U OK? Day could improve mental health and prevent suicides. First, it empowers and encourages people to check in with their peers and ask them what is troubling them. By doing so, people are providing emotional support to their peers, which in the very short-term, can increase perceived connectedness and a sense of belonging and reduce feelings of hopelessness (Van Orden et al., 2010). Second, there are potential positive effects on mental health that may result from increased engagement with professional health services in the days or weeks following R U OK? Day. The conversations on R U OK? Day can encourage help-seeking behaviour, and peers can provide support in making appointments. Additionally, the campaign may encourage people to access information online (e.g., via the R U OK? website), which may direct people to appropriate mental health services and resources. Another potential channel is by decreasing mental health stigma by raising awareness of mental health issues. Stigma can be a barrier to seeking help and can further increase psychological harm (Yanos et al., 2020).

Figure 1 shows the online engagement around R U OK? Day from its inception in 2009 until 2019. There are two important points to note from this figure. The first is that Google searches (grey line) and Twitter posts (blue dashed line) of "R U OK?" follow a similar pattern, with spikes in activity in the month immediately after the campaign that peak each year on R U OK? Day. This provides supportive evidence of the concentration in the intensity of the R U OK? Day campaign on the national day of action. Second, the intensity of online activity relating to R U OK? Day increased over time, and this was in line with the increase in annual revenue generated by the charity (red dotted line) and a corresponding increase in the reach of the campaigns. Appendix Figure B.1 plots the daily internet search intensities for R U OK? Day along with two other mental health awareness campaigns, Movember and World Mental Health Day, for the 2019 calendar year. The figure highlights that R U OK? Day's peak search intensity is the largest among the three, providing evidence that it is the most extensive mental health awareness campaign in Australia, albeit one that captures attention over only a short time span.

3 Data

In this section, we describe our three primary data sources: daily national administrative records of suicide and accidental poisoning deaths; Google internet search data for terms related to suicide planning and prevention; and self-reported mental wellbeing from a nationally-representative longitudinal survey. Online Appendix A provides detailed information on all data used in the paper, including sources, access conditions, and coverage.

3.1 Deaths via Intentional Self Harm

We utilize the number of deaths per day in Australia, separately for two main cause-of-death classifications – intentional self-harm (suicide) and accidental poisoning – coded according to the ICD-10 classification (WHO, 2019, see also Appendix A). Determining if an injury was intentional is not always straightforward, but most injury deaths in Australia are certified by a coroner. Accidental poisonings mainly involve pharmaceutical drugs, prescribed and illegally obtained, but also include poisonings involving alcohol, carbon monoxide, heroin, and other substances (Australian Institute of Health and Welfare, 2022a). Our data come from the Australian Bureau of Statistics (ABS) Cause of Death Unit Record File,[3] which contains characteristics of the person who died (e.g., age and sex) and characteristics of their death (e.g., cause, date, and place where the person usually lived). Within our sample period of 28 days before and after the R U OK? Day date there is an average of 7.5 intentional deaths and 3.5 accidental poisonings causing death per day.

3.2 Suicide Related Internet Search

Completed suicides are only the 'tip of the iceberg' of self-harm events.[4] For every suicide, many more people plan or attempt suicide. In 2020, an estimated 12.2 million American adults seriously thought about suicide, 3.2 million planned a suicide attempt, and 1.2 million attempted suicide according to the Substance Abuse and Mental Health Services Administration (SAMHSA, 2021). Data detailing suicide plans and attempts are rare. Our approach leverages Google internet search data for terms related to suicide planning and prevention. The internet is a common source of information about mental health and suicide (Parker et al., 2017); unsurprisingly, given the stigma surrounding these issues (Bharadwaj et al., 2017) and that searching for information online is convenient, anonymous, and time-efficient.[5]

Google Trends provides normalized daily search volumes of terms by geographical region, period, and category. We collect daily Google Trends data for searches at the topic- and search- level originating in Australia for the eight-week period immediately surrounding (and including) R U OK? Day for each of the nine years from 2011-2019.[6] We collect data on the Google Trends topic "suicide" in addition to two more specific search queries.[7] The suicide topic provides a general measure of interest in suicide, representing a variety of Google users. For instance, people seeking help for their suicidal thoughts, people seeking information on how to commit suicide,

[3]Findings based on data from the Multi-Agency Data Integration Project (MADIP), 2006 - 2020, MADIP Modular Product, ABS DataLab.

[4]The iceberg model of self-harm (Geulayov et al., 2018) divides self-harm events into: (i) fatal self-harm, an overt and uncommon event (tip of the iceberg); (ii) self-harm that results in a presentation to clinical services, an overt and common event; and (iii) self-harm that occurs in the community, a common but largely hidden event (submerged part of the iceberg).

[5]A similar approach was used by Tefft (2011) to measure depression and anxiety, Frijters et al. (2013) to measure alcohol abuse, and Brodeur et al. (2021) to measure a wide range of mental well-being dimensions (including suicide).

[6]A topic query on Google Trends provides normalized search volumes for a Google-specified collection of terms related to the topic. A search-term query provides normalized search volumes for user-specified terms.

[7]The Google Trends webpage provides lists of the most popular topics and queries related to the search term(s) the user has specified. They describe this as "Users searching for your term also searched for these..." The most common search-term queries related to this topic are "suicide", "suicidal", and "commit suicide", and the most related topics are "death", "suicide prevention", and "depression". These lists suggest that the suicide topic provides a general measure of interest in suicide, representing a variety of Google users.

and people collecting general information on suicide for study or work reasons. We create two more-specific measures using search-term queries: (i) searches related to suicide prevention ("lifeline" + "help suicide" + "hotline suicide" + "suicide hotline"); and (ii) searches related to suicide planning ("commit suicide" + "how to suicide" + "painless suicide" + "quick suicide" + "suicide methods"). The prevention search terms were chosen to reflect the help-seeking behaviour of Australians contemplating suicide (or their friends and families), and the planning search terms reflect information-seeking on suicide methods (see Till et al., 2020).

The data returned via Google Trends are separately normalized for each year in our sample. This necessitates a re-scaling approach so that each of the nine time-series is comparable. We follow the scaling approach used in Brodeur et al. (2021), which we detail for our context in Appendix A. The resulting outcome variables measure the relative likelihood that a random Australian Google user on a particular day will complete a search for information about suicide.

3.3 Self Reported Mental Wellbeing

Most suicides are related to a psychiatric disorder; however, suicide and suicidal ideation are relatively rare among people with poor mental health. For example, Nordentoft et al. (2011) find that the cumulative incidence of suicide in Denmark among people with a mental illness-related hospitalisation is 4.33% for men and 2.10% for women. This suggests that awareness campaigns such as R U OK? Day might affect an individual's mental health and wellbeing without impacting suicide-related outcomes. To explore this possibility, we use individual survey data from a large nationally-representative study.

The Household, Income, and Labour Dynamics in Australia (HILDA) survey is an ongoing annual household-based longitudinal study that commenced in 2001. In each wave, all household members aged 15 years and over are surveyed about their economic and personal wellbeing, labor market dynamics, and family life.[8] These annual surveys are primarily administered in August, September, and October each year, so they are heavily concentrated in the weeks surrounding R U OK? Day.[9] In each HILDA wave, each household member self-completes the Short-Form-36 Health Survey Questionnaire (SF-36). We construct a mental wellbeing index from the SF-36 responses by implementing a principal components analysis using nine of the 36 health questions. These questions measure mental health-related symptoms by asking people how frequently during the past four weeks they have had certain feelings, such as "full of life", "nervous", "so down in the dumps that nothing could cheer you up", and "happy". The six response options for each question range from "all of the time" to "none of the time." The nine questions and the associated weights from the principal component analysis are shown in Appendix Table A.1.

[8]See Watson and Wooden (2021) for a description of the HILDA survey questionnaires and the data collected in waves 1 to 20.

[9]This surveying pattern is displayed in the Online Appendix, Figure B.2.

4 Estimation Strategy

Our empirical design uses two inherent features of the growth and roll-out of the R U OK? Day campaign: (i) the growth in scale over the years, and (ii) a short time window within a year where the campaign is salient. As evident from Figure 1, the campaign has grown substantially over time, not only in resources invested but also in terms of Twitter outreach and search behaviour. In order to maximize power, as most of our outcomes are rare events (suicides) or noisily measured (Google searches), we group the years 2011-2019 into three three-year groups and define two indicators $T_1 = 1[\text{year}_t \in (2014, 2016)]$ and $T_2 = 1[\text{year}_t \in (2017, 2019)]$ that are switched on for the respective years.

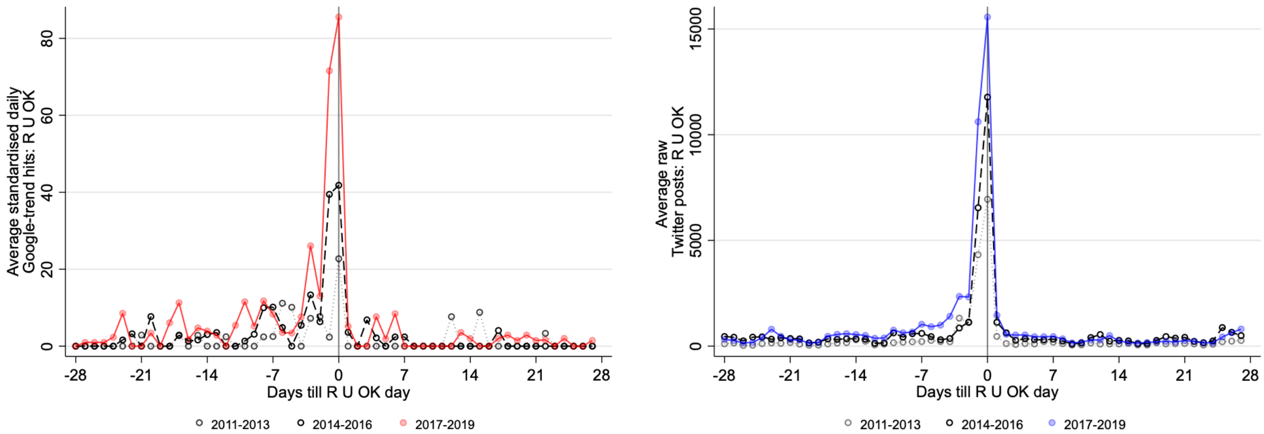

Figure 2: Three year averaged "R U OK" Google searches and Twitter posts relative to R U OK? Day

Note: Left panel displays the three-year averages of the standardized "R U OK" searches on Google, following the standardization of Brodeur et al. (2021), as detailed in the Appendix A. Right panel raw, standardized Twitter post counts.
Source: Google trends search data 2011-2019, Twitter data 2011-2019, own calculations.

The second source of variation is the day the awareness campaign is run; in Figure 2 we use the three-year groupings and show the average daily Google-trends hits and Twitter mentions for each day (-28 to 27, where the actual R U OK? Day is the first "treatment day"). The figure shows that the attention is highly concentrated around the campaign. Consequently, we define $d_{RUok} = 1[\text{day}_t \geq \text{R U OK? Day}]$ that is switched on for all years when the day is on or within the 28 days after R U OK? Day.

4.1 Population-level approach

We specify a simple, highly saturated econometric model to analyze how R U OK? Day impacts the various outcomes we consider. More specifically, we use

$$\begin{aligned} y_{it} = \alpha \quad &+ \quad \tau_1 d_{RUok} \times T_1 + \tau_2 d_{RUok} \times T_2 \\ &+ \quad \delta_{\text{year}} + \delta_{\text{days till RUok}} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where $i = 1, \ldots, n$ indexes individuals and $t = -28, -27, \ldots, 27$ index days relative to R U OK? Day. Our main interest lies in τ_1 and τ_2, which measure the relative change in the outcome variable before versus after R U

OK? Day in each three-year period, with 2011-2013 as our baseline. We interpret our regression specification as a difference-in-differences approach that leverages observations in the first three years, 2011-2013, as a control group and those from 2014 to 2019 as a treatment group. Early years serve as a control group because population awareness around the campaign is low. As a result, we expect a negligible impact on the outcome variables of interest compared to years before R U OK? Day was introduced.[10] The coefficient τ_1 then reports the increase due to higher campaign awareness in 2014-2016 relative to 2011-13, and τ_2 reports the same for 2016-2019. Due to the growth in awareness around the campaign over time, we expect τ_1 to be smaller than τ_2.

To further account for fluctuations that might impact our mental health-related measures, we include a battery of fixed effects in Equation (1). We include year fixed effects, δ_{year} for each year 2012-2019 (2011 omitted) to absorb any possibly-nonlinear annual trends. Day-of-the-year fixed effects, $\delta_{\text{days till RUok}}$ (-27 to 27, -28 omitted) to flexibly account for potential seasonality in the sample window. Finally, ε_{it} is the error term. Unless specified otherwise, the ε_{it}'s covariance matrix is specified to be heteroskedasticity robust.

Where the data permits, we present estimates both in aggregate and split by gender (male/female) and age groups (15-24, 25-49, and 50+). Two primary factors drive the decision to present results across these dimensions. First, exposure to R U OK? Day likely differs across these demographics. Advertising for R U OK? Day is a mix of national TV advertising, billboards, and advertising placed directly in schools and workplaces. As a result, different demographic groups will likely encounter information about the campaign at different intensities. Second, R U OK? Day can influence these groups differently. For example, the campaign may have a larger impact on men aged 25-49 because the campaign was originally conceived to target this demographic or because this group has a lower propensity to discuss mental health with peers to begin with. Each of these factors implies the impact of R U OK? Day on mental health-related outcomes might differ across the groups.

Our focus on the eight-week window immediately surrounding the campaign means that the estimated coefficients capture the short-term effects of R U OK? Day. Specifically, the model captures changes in mental health-related outcomes in the four-week window after R U OK? Day compared to the four weeks immediately preceding it. We believe this is a suitable window to evaluate changes. First, the short-term awareness of the campaign among the wider public each year, as documented in Figure 2, suggests that the effects of the campaign are unlikely to persist beyond one month after the focal day. Second, attributing changes to the the campaign is more plausible over a one-month time window compared to longer horizons. This is because during the month after R U OK? Day there are no other population-wide events or campaigns that could similarly influence mental health outcomes.

[10] In a similar vein, Jacobsen and Jacobsen (2011) find no significant change in behavioural outcomes surrounding National Breast Cancer Awareness Month in the US during its early years when breast cancer advocacy was still a grassroots movement. If R U OK? Day did have an effect during the years 2011-2013 compared to earlier years; then, our estimates are isolating any additional effects due to heightened awareness of the campaign in 2014-2019 compared to 2011-2013.

4.2 Individual-level approach

When analysing the HILDA survey data, we augment equation 1:

$$\begin{aligned} y_{it} = \alpha \quad &+ \quad \tau_1 d_{RUok} \times T_1 + \tau_2 d_{RUok} \times T_2 \\ &+ \quad \delta_{\text{year}} + \delta_{\text{days till RUok}} + \delta_r + \delta_{\text{days since first survey}} + \delta_{sex} + \delta_{age} + x'_{it}\beta + \varepsilon_{it} \end{aligned}$$

where y_{it} denotes an outcome variable of interest, τ_1 is the estimate of whether the outcome variable differs before versus after R U OK? Day in 2014-2016, and τ_2 for the years 2017-2019. In this augmented equation we additionally adjust for regional fixed effects δ_r, days since the annual surveying round commenced $\delta_{\text{days since first survey}}$, and in some specifications, time-varying individual characteristics x_{it}.

Table 1: Balance test for observable characteristics: Before vs. After R U OK? Day

Dependent variables: Varying socio-economic characteristics, one regression per line		
	Post R U OK? Day ×	
	2014-2016	2017-2019
	(1)	(2)
Physical health principal component (0-100)	0.096	0.384
	(0.350)	(0.381)
College educated (Yes/No)	-0.000	0.009
	(0.007)	(0.008)
Married/de-facto relationship (Yes/No)	0.003	0.005
	(0.007)	(0.007)
Unemployed (Yes/No)	-0.001	-0.002
	(0.003)	(0.003)
Not-in-labor force (Yes/No)	0.004	-0.004
	(0.006)	(0.006)
Weekly work hours	-0.048	0.052
	(0.279)	(0.296)
Equalized household income	-0.003	-0.006
	(0.005)	(0.006)
Area-level Seifa deciles (1-10)	0.060	0.111
	(0.042)	(0.045)
Living in metropolitan area[a] (Yes/No) urban	-0.042	-0.001
	(0.007)	(0.008)
Missing mental health score[b] (Yes/No)	0.003	-0.003
	(0.004)	(0.004)

Notes: The Table presents coefficients estimates from equation (2). The table reports results for different outcome variables along the row dimension. τ_1 is reported in column (1) and τ_2 in column (2). Conditional age (indicators), sex (indicator), and rurality (indicators)-by-state, and days since the first survey fixed effects, $N = 102,270$. Missings in the covariates are replaced with 0, [a] excludes covariates related to area (otherwise collinear) [b] number of observations uses missing indicator for all potentially answering people (N=151,388). All standard errors are clustered at the individual level.

Source: HILDA 2011-2019 (v19), own calculations.

Within our eight-week analysis period, there is a downward trend in the daily number of completed HILDA interviews, reflecting the gradual completion of the survey wave (see Figure B.2 in the Online Appendix). The interview date is not randomly assigned and is instead negotiated between the respondent and interviewer.[11] This non-random selection of interview dates could potentially introduce bias in our estimated effects. We argue this is not the case for two reasons. First, there are no unusual patterns or mass points in the dates that interviews are conducted, and the trends in sample sizes appear similar for each three-year periods between 2011 and 2019.[12]

Second, Table 1 shows that the observable characteristics of survey respondents interviewed after R U OK? Day in 2014-2016 and 2017-2019 are similar to those interviewed before the day in terms of their physical health, education, marital status, labor market outcomes, and household income. However, there are significant differences in area-level factors: respondents interviewed after R U OK? Day are more likely to reside in non-metropolitan, higher socioeconomic status neighborhoods. It is possible that these differences are only significant by chance. After adjusting for the multiple hypotheses using the Romano-Wolf correction method (Clarke et al., 2020), the p-values associated with the area-level differences in Table 1 are all greater than 0.05 ($p = 0.418$ for the years 2014-2016 and $p = 0.143$ for the years 2017-2019). Even so, to mitigate any potential effects of the non-random interview timing, we present an extended set of estimates from regressions that include all Table 1's listed characteristics in Appendix Table C.2 as additional covariates in our empirical models, including indicators of neighborhood socioeconomic decile. Estimates from these specification(s) are consistent with our main findings reported in the text.

5 Results

We present the results in three parts. First, we evaluate the effects of R U OK? Day on deaths due to intentional self-harm. We then turn to look at internet searches for suicide and suicide-related topics. Finally, we report the effects on self-reported mental wellbeing.

5.1 Deaths due to Intentional Self-Harm and Accidental Poisoning

Figure 3 presents the number of intentional deaths in the eight weeks immediately surrounding R U OK? Day for the years 2011 to 2019, with each point representing the average number of intentional deaths over a 3-day window. The considerable volatility across the eight-week time frame is most apparent, driven by the relatively low frequency of deaths due to intentional self-harm and accidental poisoning. In addition, there is no noticeable difference in the average number of deaths before and after R U OK? Day nor a noticeable change the in the levels over the years.

Estimates presented in Column (1) in Panel A of Table 2 are the estimated effects of R U OK? Day on the total number of deaths due to intentional self-harm, estimated using equation 1. The estimates are small in

[11]Some respondents complete the SF-36 health questions in the HILDA self-completion questionnaire on a date after the face-to-face main interview. The self-completion questionnaire is handed out after the interview and can be either immediately completed and given to the interviewer or mailed back on a later day. For all respondents, we use the date of the interview to minimize potential selection.

[12]In Appendix Figure B.3, we additionally show that the item non-response for the mental health questions is smooth around the R U OK? Day and is similar across years.

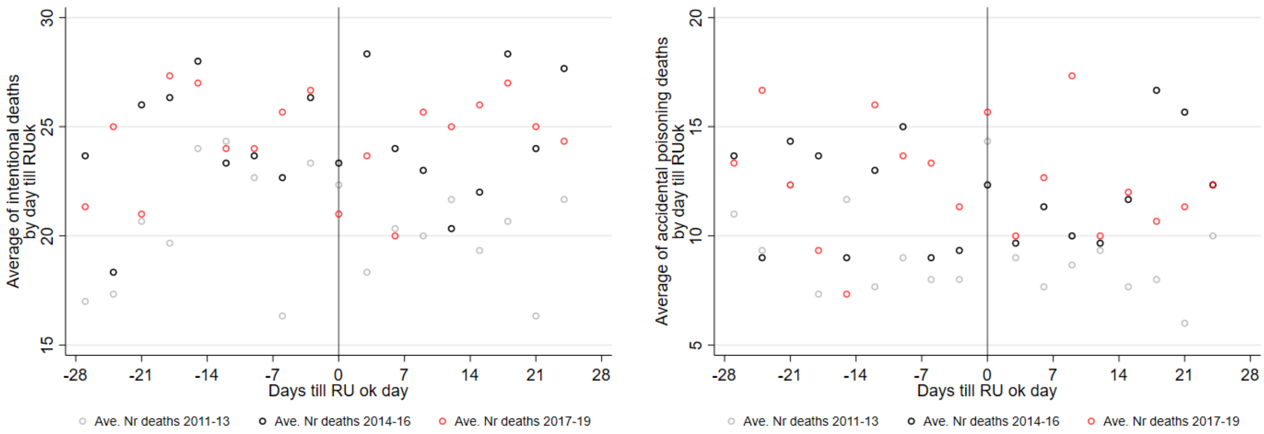

Figure 3: Raw averaged 3-daily deaths, by cause and distance to R U OK? Day

Note: Figure presents an average number of intentional deaths (left) and accidental poisonings (right) by distance to the R U OK? Day. Each dot corresponds to 3 days for confidentiality reasons, i.e., -27 is the 27th day before R U OK? day till the 25th, including the dots being further averaged across the years.
Source: Australian Bureau of Statistics (ABS) Cause of Death Unit Record File 2011-2019, own calculations.

magnitude and imprecisely estimated in both the 2014-2016 period (-0.229) and the 2017-2018 period (-0.267). This finding of imprecise estimates is replicated across columns (2) to (9), which present estimated effects on intentional self-harm by gender and age (15-24, 25-49, and 50+). Similar results are found for accidental poisonings in Panel B.

As discussed in Section 2, we hypothesise that R U OK? Day may cause two temporally separate mental health effects. First, there may be a near-instantaneous effect due to the increased peer support offered on the day. This may cause a reduction in deaths in the days immediately after the focal day. Second, mental health effects may grow in the weeks following R U OK? Day as people access new or additional mental healthcare or reach out to friends and family to receive additional support. To explore these possible responses, we disaggregate our treatment variables into three weekly pre-R U OK? Day indicators (representing three lead terms) and four weekly post-R U OK? Day indicators (representing four lag terms). The estimated effects of the indicators on deaths are presented in Figure 4.[13] Similar to the results in Table 2, the estimates for intentional self-harm and accidental poisoning are all statistically insignificant at the 5% level. Moreover, the point estimates show no perceptible pattern with weeks since R U OK? Day.

The results in Table 2 and Figure 4 suggest that R U OK? Day had no discernible impacts on deaths due to intentional self-harm and accidental poisonings. However, a notable caveat to these results is that our statistical power to detect effects is low, given the low frequency of daily deaths. Ex-post power analysis indicates that if we adopt the conventional 5% statistical significance level and 80% power level, the minimal detectable effects for 2017-2019 are 1.70 for intentional deaths and 1.29 for accidental poisonings (Bloom, 1995). Therefore, the absence of a significant effect on deaths does not necessarily indicate that R U OK? Day does not affect suicide.

[13]We report the results for an eight-week before and eight-week after period in Appendix Figure C.1. These results are consistent with what we report in the main text.

Table 2: Intentional death and accidental poisonings

Dependent variables: Intentional deaths and accidental poisonings									
		Females				Males			
	All	All	15-24	25-49	50+	All	15-24	25-49	50+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Intentional deaths									
2014-2016	-0.203	-0.020	-0.006	-0.095	0.104	-0.183	-0.168	0.134	-0.091
	(0.600)	(0.299)	(0.112)	(0.204)	(0.181)	(0.510)	(0.171)	(0.368)	(0.333)
2017-2019	-0.218	0.479	0.066	0.188	0.249	-0.697	0.005	-0.132	-0.534
	(0.573)	(0.293)	(0.101)	(0.194)	(0.177)	(0.516)	(0.178)	(0.364)	(0.330)
N	504	504	504	504	504	504	504	504	504
R^2	.176	.157	.165	.205	.137	.163	.172	.143	.134
Mean dep.	7.7	2	.29	.9	.76	5.7	.72	2.8	2.2
SD dep.	2.8	1.4	.5	.97	.84	2.4	.84	1.7	1.5
Panel B. Accidental poisoning									
2014-2016	0.271	0.050	-0.013	0.063	-0.011	0.221	0.095	0.122	0.004
	(0.441)	(0.241)	(0.048)	(0.170)	(0.158)	(0.338)	(0.073)	(0.273)	(0.177)
2017-2019	0.006	0.052	-0.035	0.167	-0.091	-0.046	-0.025	-0.150	0.128
	(0.425)	(0.244)	(0.052)	(0.167)	(0.169)	(0.333)	(0.070)	(0.275)	(0.173)
N	504	504	504	504	504	504	504	504	504
R^2	.194	.139	.164	.153	.0844	.212	.0911	.193	.174
Mean dep.	3.7	1.2	.056	.63	.52	2.5	.1	1.7	.7
SD dep.	2.1	1.1	.23	.79	.74	1.6	.32	1.3	.86
Day and year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The Table presents coefficients estimates from equation (1). Panel A for intentional deaths and B for accidental poisonings, according to ICD10 codes, see Appendix A.2. For each regression, we present the two main coefficients for interaction post-R U OK? Day and the respective year indicators. The columns also present N - number of observations, the regression R^2, and the mean and standard deviation of the dependent variable. Column (1) for all individuals in Australia, (2) all females, (6) males. (3)-(5) split the sample by age of females, and (7)-(9) for males.

Source: Australian Bureau of Statistics (ABS) Cause of Death Unit Record File 2011-2019, own calculations.

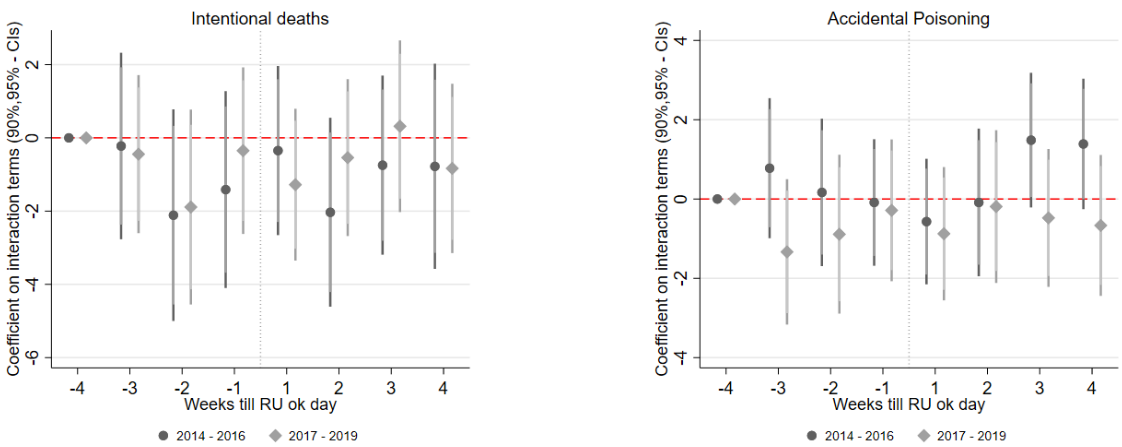

Figure 4: DiD coefficient by weeks relative to 2011-2013

Note: Displays the coefficient estimates analogous to Table 2 Column (1) see notes therein, but interacting the treatment indicators with weeks till R U OK? Day rather than the post-R U OK? Day indicators. See Appendix Figure C.1 for 2-month bandwidth surrounding the R U OK? Day.

Source: Australian Bureau of Statistics (ABS) Cause of Death Unit Record File 2011-2019, own calculations.

5.2 Suicide-related Internet Searches

Completed suicides represent a small fraction of outcomes associated with suicidality. People who commit suicide represent about 10 percent of the population who have thought about committing suicide in a given year, and approximately a third of those who plan a suicide make an attempt, according to the Substance Abuse and Mental Health Services Administration (SAMHSA, 2021). We use internet search terms related to suicide planning and prevention to measure interest in suicide, suicide planning, and help-seeking in the months around R U OK? Day.

Table 3: Google trend results

Dependent variables: Various standardized google search terms			
	Suicide		
	Topic	Prevention	Plan
	(1)	(2)	(3)
2014-2016	4.044	-2.952	-3.869
	(1.306)	(3.766)	(3.878)
2017-2019	0.712	1.389	4.234
	(1.590)	(3.703)	(3.755)
N	504	504	504
R^2	0.31	0.20	0.15
Mean dep.	17.89	33.98	21.23
Std. dep.	7.56	17.65	17.56
Day and year fixed effects	✓	✓	✓

Notes: The Table presents coefficients estimates from equation (1) and robust standard errors in parentheses. Column (1) uses the topic search for suicide ('/m/06z5s'), (2) uses individual search terms related to suicide prevention – 'lifeline + help suicide + hotline suicide + suicide hotline' – and (3) plan – 'commit suicide + how to suicide + painless suicide + quick suicide + suicide methods' – (based on Till et al., 2020)

Source: Google Trends, 2011-2019, own calculations.

The estimated effects of R U OK? Day in 2014-2016 and 2017-2019 on the topic, prevention, and planning variables are presented in Columns (1) to (3) of Table 3. The estimated effects for 2017-2019 are positive for each outcome – indicating increased suicide-related search activity – but have large confidence intervals (p-values equal 0.655, 0.708, and 0.260).[14] For the 2014-2016 period, it is estimated that R U OK? Day significantly increased interest in the suicide topic (p-value equals 0.002) while reducing interest in suicide prevention and planning (p-values equal 0.434, 0.319). Overall, we find little evidence that the campaign reduced suicidal ideation, as represented in Google searches.[15]

We interpret the positive significant effect on the suicide topic in Table 3 as an increase in interest from people

[14] In Table 3, a clear difference across columns is the size of the standard errors. The standard errors are roughly 3x larger in columns (2) and (3) than in column (1). This is explained by the much higher volatility in the prevention and planning variables – which were based on search-term queries – than in the suicide topic variable – which is generated by Google Trends. This volatility limits the statistical power to detect effects.

[15] Additionally, we estimated the effects on the Google Trends 'mental health' topic and found minor, statistically insignificant effects. An explanation for this result is that a non-trivial proportion of searches on the mental health topic are unrelated to the Google user's mental health. For example, common searches concern the mental health of celebrities.

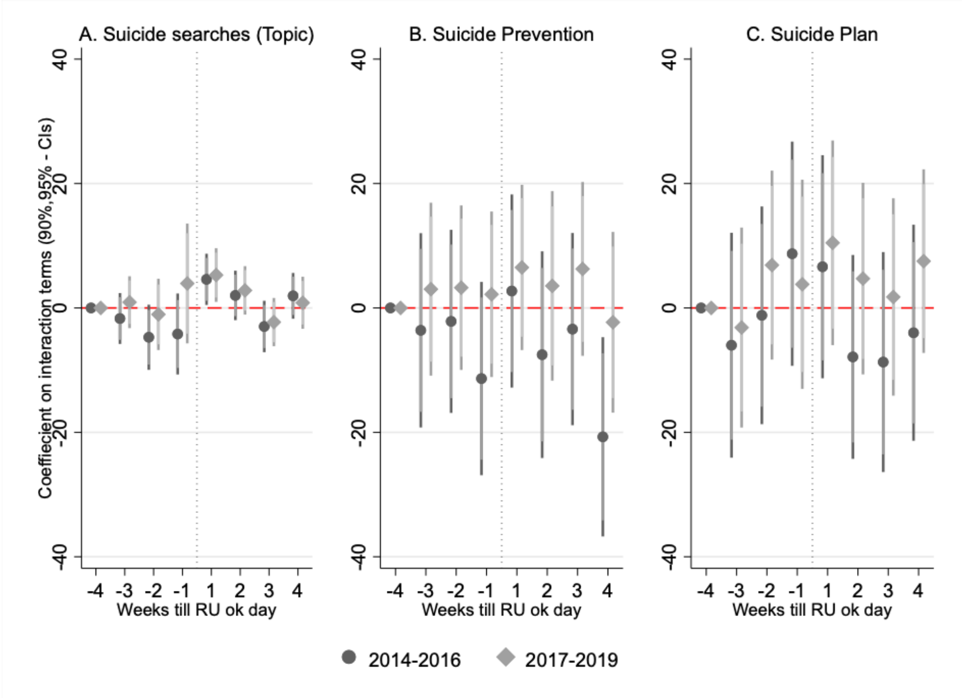

Figure 5: Coefficient by weeks relative to 2011-2013

Note: Displays the coefficient estimates analogous to Table 3, but interacting the treatment indicators with weeks till R U OK? rather than the post-R U OK? indicators, Panel A. corresponds to the Tables Column (1), B to (2), and C to (3).
Source: Google Trends, 2011-2019, own calculations.

seeking to learn about suicide after exposure to suicide-related advertising in the campaign. This interpretation is supported by results in Figure 5, which presents estimated effects for three weeks prior and four weeks including/after R U OK? Day. The estimated effects (for both 2014-2016 and 2017-2019) are significantly positive only for the first post-treatment week – which includes the focal day – suggesting that the additional public health messaging around R U OK? Day increased 'general' searches for suicide-related information. We believe this explanation is more likely than an actual increase in suicidal thoughts and planning. Theoretically, such a positive effect could occur if conversations about mental health issues and suicidality (through R U OK? Day encouraged discussions) increase suicidal tendencies. However, empirical evidence suggests this is unlikely. For example, Dazzi et al. (2014) review the evidence from 13 articles and conclude that none find a statistically significant increase in suicidal ideation due to people being asked about suicidal thoughts. The empirical evidence shown in Figures 5b and 5c similarly indicate no increase in searches related to suicidal thoughts.

5.3 Self-reported Mental Wellbeing

R U OK? Day may positively affect mental wellbeing without impacting suicide-related outcomes. Most people with poor mental health are not suicidal, but nevertheless, may benefit from the increased social support that R U OK? Day encourages. For this reason, we next estimate the effects on self-reported mental wellbeing. Estimates in Panel A of Table 4 indicate that R U OK? Day improved mental wellbeing in 2017-2019 by 0.716 units, equivalent to 4.2% of one standard deviation (p-value = 0.014). This effect appears to be driven by men,

Table 4: R U OK? Day and Self Reported Mental Health

Dependent variables: Principal components of mental health and indicator of lowest 10%, various subsamples									
		Females				Males			
	all	all	15-24	25-49	50+	all	15-24	25-49	50+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Mental health (0-100)									
2014-2016	0.167	0.092	1.213	0.062	-0.283	0.288	-0.834	1.159	-0.134
	(0.275)	(0.390)	(0.976)	(0.605)	(0.613)	(0.387)	(0.923)	(0.602)	(0.620)
2017-2019	0.716	0.574	0.406	0.932	0.241	0.897	0.479	1.485	0.486
	(0.292)	(0.409)	(1.038)	(0.612)	(0.657)	(0.416)	(0.970)	(0.642)	(0.671)
N	102,270	54,119	9,101	22,847	22,171	48,151	8,371	20,151	19,629
R^2	0.03	0.02	0.05	0.02	0.03	0.02	0.04	0.02	0.03
Mean dep.	67.50	65.93	63.71	65.06	67.75	69.26	69.73	68.03	70.32
SD dep.	17.23	17.61	18.21	17.23	17.57	16.62	16.09	16.55	16.83
Panel B. Indicator for bottom decile $\times$100									
2014-2016	-0.257	-0.234	0.329	0.405	-1.411	-0.336	-1.324	-0.403	0.173
	(0.476)	(0.708)	(1.869)	(1.135)	(1.033)	(0.623)	(1.442)	(0.994)	(0.973)
2017-2019	-1.183	-1.439	0.748	-1.535	-2.235	-0.940	-0.334	-1.900	-0.030
	(0.500)	(0.735)	(2.037)	(1.149)	(1.085)	(0.668)	(1.470)	(1.071)	(1.043)
N	102,270	54,119	9,101	22,847	22,171	48,151	8,371	20,151	19,629
R^2	0.01	0.01	0.03	0.01	0.02	0.01	0.03	0.01	0.02
Mean dep.	10.00	11.74	14.93	12.20	9.96	8.04	6.98	8.74	7.77
SD dep.	30.00	32.20	35.64	32.73	29.95	27.19	25.48	28.25	26.77
Day and year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Days since survey start	✓	✓	✓	✓	✓	✓	✓	✓	✓
Basic set of covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The Table presents coefficients estimates from equation (2), see Table 1 notes.

Source: HILDA 2011-2019 (v19), own calculations.

for whom there was a 0.897 effect overall (p-value = 0.031) and a 1.485 effect for men aged 25-49 years (p-value = 0.021).The magnitude of the latter effect is of moderate size at 9% of a standard deviation, roughly two-thirds the size of the female coefficient and one-fifth the size of the marriage coefficient (see Appendix Table C.3). The estimated 2017-2019 effects for females overall and for each age group are smaller in magnitude than the corresponding male effect estimates. Interestingly, the largest female effect also occurs for the 25-49 age group, possibly due to a strong emphasis on R U OK? Day messaging in workplaces (through events such as morning teas) and in schools (often with parental involvement) (Woodward, 2020).[16]

The mental wellbeing effects for 2014-2016 are generally smaller. The overall effect for this period equals 0.167 (p-value = 0.544), the effect for females equals 0.092 (p-value = 0.814), and the effect for males equals 0.288 (p-value = 0.416). These results supports the hypothesis proposed in Section 2 that the R U OK? Day effects will have increased over time with the size and reach of the campaign.

There are several potential reasons why males are more strongly affected by R U OK? Day. Men are less likely to use mental healthcare when experiencing psychological distress than women (Wang et al., 2007); thus, R U OK? Day may disproportionately encourage men to seek treatment. Another explanation is that men are less likely to express emotions related to weakness, helplessness, and sadness because of traditional masculinity

[16] Appendix Table C.2 show that these conclusions hold for smaller and larger covariate sets.

norms (Möller-Leimkühler, 2002). So even in the absence of mental healthcare, men may gain more from the peer-to-peer discussions that the campaign encourages. We empirically explore mechanisms driving these effects in Section 6.

In Panel B of Table 4, we repeat the analysis using a dichotomous outcome variable that indicates whether a person's mental wellbeing score is in the bottom decile (i.e., index score < 43.99 units). Similar to Panel A, the estimates indicate that in 2017-2019 R U OK? Day caused an improvement in mental wellbeing: for the full sample, it is estimated to have reduced the probability of an individual suffering poor mental wellbeing at the time of the survey by 1.183 percentage points (p-value = 0.018). Unlike Panel A, this effect is driven more by women than men. The reduction for women is 1.439 percentage points, and the reduction for men is 0.94 percentage points. A possible explanation is gender-based reporting heterogeneity in self-assessed health. Men have been shown to assess health states differently than women (Schneider et al., 2012; Molina, 2016), and this gendered pattern may be especially true for mental health, given the associated social stigmas. However, the results are robust to using gender-specific cutoffs, such that 10% of both men and women are classified as having poor mental wellbeing, In this alternative specification, the estimated effect sizes are 1.586 for women and 1.156 for men. (see Appendix Table C.1.) These additional results suggest that women in the left-hand tail of the mental wellbeing distribution are more likely to be affected by R U OK? Day than are similar men.

The overall conclusion from Table 4 is that R U OK? Day improved the self-assessed mental health of men and women. This result is robust to the inclusion of additional regression covariates. In Appendix Table C.2, we demonstrate that the estimates are broadly similar if we include controls for individual-level socioeconomic characteristics in Column 5 (marital status, number of children, labor market outcomes, and income), weather in Column 6 (20 daily temperature and 20 daily rainfall fixed-effects), and level of neighborhood socioeconomic advantage in Column 7 (decile indicators of the Index of Relative Socioeconomic Advantage and Disadvantage). For example, the estimated full-sample effect of R U OK? Day in 2017-2019 on mental wellbeing equals 0.716 using our main specification (Panel A, Column 1 of Table 4) and equals 0.727, 0.625 and 0.564 in Columns 5-7 of Appendix Table C.2. More generally, these results support the validity of our DiD identification approach. Though there are differences before/after the focal day in the weather (due to seasonality) and the neighborhood socioeconomic status of respondents (due to the non-random roll-out of the survey), the differences did not systematically vary across years.

We additionally test the robustness of our estimates by using pre-2011 survey data. Our main specification uses 2011-2013 as the control period because it is temporally closest to our treatment periods and because HILDA included a top-up sample of 4,009 new respondents in 2011 to capture population sub-groups inadequately covered and to alleviate biases from non-random attrition (Watson and Wooden, 2013). Nevertheless, HILDA survey data exists back to 2001, which can be used to validate our identification approach. Specifically, we introduced placebo R U OK? Day dates back to 2001 (2nd Thursday of each September), and estimated placebo effects for 2002-2004, 2005-2007, and 2008-2010, relative to 2011-2013. The results are presented in Appendix Table C.4, and show that the estimated effects are statistically insignificant during the three placebo time periods, supporting our identification assumptions.

5.3.1 Dynamic impacts

Following our approach in sections 5.1 and 5.2, we explore how the self-assessed mental wellbeing effects vary week-by-week around R U OK? Day. The estimates are presented in Figure 6 and show large effects in weeks 3 and 4, especially for the 2017-2019 period in which the intensity of the campaign was larger. Figure 6A shows that self-assessed mental health was 1.42 units higher in week 3 (8.2% of a standard deviation) and 2.80 units higher in week 4 (16.4% of a standard deviation) during 2017-2019. Similarly, Figure 6B shows that the likelihood of having poor mental wellbeing (bottom decile) drops by 1.7 percentage points in week 3 and 5.1 percentage points in week 4. Mirroring the regression results in Table 4, men drive the Figure 6A results for the continuous mental wellbeing outcome variable, and women drive the Figure 6B results for the binary poor mental wellbeing outcome variable (see Appendix Figure C.2).

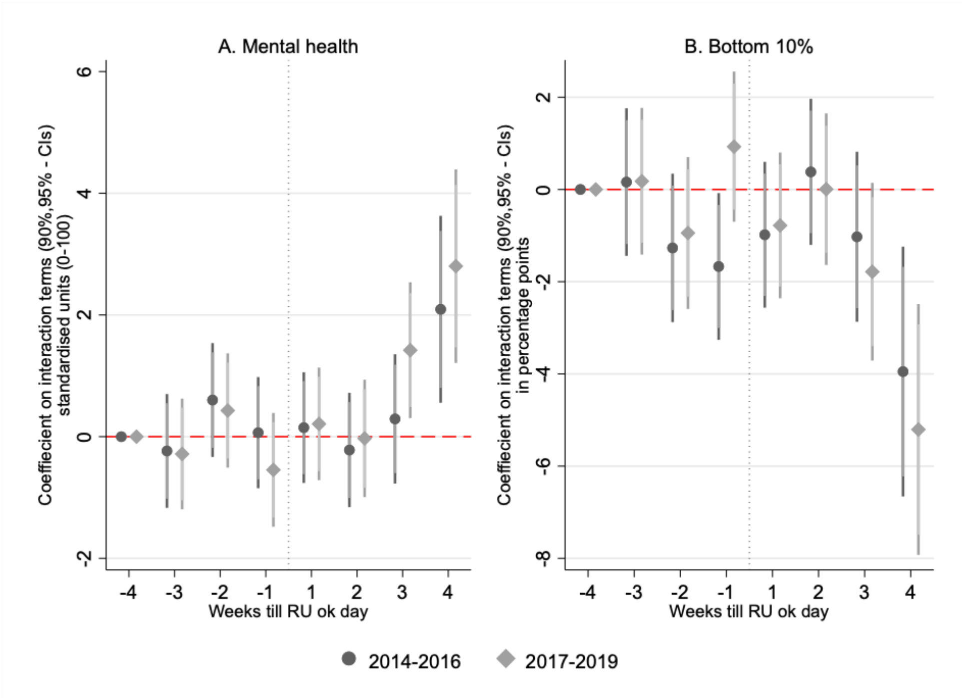

Figure 6: Dynamic Impacts of R U OK? Day Over Time

Note: Displays the raw three-year sums of the number of valid observations (N=109,340) in the overall HILDA population for each day relative to the yearly specific R U OK? Day. Lines are based on locally weighted regressions of the three-year sums on days till RUOK? Day. The gray background depicts the sample period we use in the later regression analysis (N=104,742), corresponding to the 56-days surrounding the R U OK? Day.
Source: Hilda 2011-2019 (v19), own calculations.

Interpreting these dynamic patterns is complicated, as multiple explanations can rationalize the dynamics. The growth over time could reflect the campaign positively impacting mental health by encouraging people to access new mental healthcare (e.g., an initial GP mental health consultation) or additional mental healthcare (e.g., an extra session with a clinical psychologist), which can take time to arrange. However, it could also reflect a feature of the health questionnaire that induces self-assessed mental wellbeing to evolve differently over time than true contemporary mental wellbeing. The HILDA survey measures mental wellbeing by asking people to evaluate their feelings “during the past 4 weeks”. If people obey this instruction, people interviewed within four weeks of R U OK? Day will consider their wellbeing before the focal day, attenuating any positive effects. Exactly how will depend upon the way in which respondents weight feelings experienced in the past. In our interpretation of Table 4, we implicitly assume that self-assessed mental wellbeing is a good measure of genuine wellbeing on the day of the interview (i.e., respondents give zero weight to all previous days). However, respondents may strictly follow the survey instruction and consider all days in the past four weeks equally (i.e., equal weights). In this case, an immediate permanent positive jump in contemporaneous mental wellbeing will result in self-assessed mental health growing linearly over time (see the diagram in Appendix Figure B.5). Another possibility is that respondents follow the peak-end rule (Redelmeier and Kahneman, 1996) and give extra weight to particularly bad mental health days (peak) and recent days (end). If particularly bad days are more likely to have occurred before R U OK? Day, then days further back in time will receive higher weights and self-assessed mental wellbeing may grow according to a convex function.

The relationship shown in Figure 6 is not driven by within-year or between-year differences in respondent characteristics, neighborhood factors, and weather. Repeating the robustness exercise reported for average effects reported in Section 5.3, we demonstrate that the R U OK? Day effects are substantial in weeks 3 and 4, even after including additional regression covariates. These results are reported in Appendix Figure C.3.

6 R U OK? Day & Perceived Social Support

Table 5: Social support

Dependent variables: Principal components of social support, various subsamples									
		Females				Males			
	all	all	15-24	25-49	50+	all	15-24	25-49	50+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2014-2016	0.298	-0.500	1.127	-0.421	-1.281	1.227	-0.899	2.183	1.123
	(0.328)	(0.460)	(1.086)	(0.734)	(0.710)	(0.468)	(1.086)	(0.733)	(0.750)
2017-2019	0.507	-0.141	0.543	0.007	-0.529	1.226	0.167	2.043	0.906
	(0.346)	(0.480)	(1.175)	(0.747)	(0.763)	(0.500)	(1.155)	(0.767)	(0.806)
N	102,974	54,531	9,144	22,990	22,397	48,443	8,427	20,257	19,759
R^2	0.02	0.01	0.04	0.02	0.02	0.02	0.04	0.03	0.02
Mean dep.	77.43	79.04	79.43	79.25	78.67	75.61	77.55	75.56	74.85
SD dep.	20.25	20.30	19.92	20.36	20.39	20.03	19.11	20.14	20.24
Day and year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Days since survey start	✓	✓	✓	✓	✓	✓	✓	✓	✓
Basic set of covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Analogous to Table 4; see notes therein.
Source: HILDA 2011-2019 (v19), own calculations.

The results shown thus far can be thought of as 'reduced form' effects, documenting that R U OK? Day impacts self-reported mental wellbeing abstracting away from mechanisms that could drive the results. In this section, we provide evidence of a mechanism through which R U OK? Day can impact wellbeing via its impact on social support. The campaign emphasizes this as a primary mechanism, and there exists correlational evidence in other contexts linking social support to improved mental health (Olstad et al., 2001; Takizawa et al., 2006; Santini et al., 2016).

HILDA surveys do not directly contain detailed information on whether people have supported their friends' health and wellbeing or whether they have received health-related peer support themselves. However, HILDA does have related information that we can explore. In each wave of the survey, people are asked about their strength of agreement (on a 1 to 7 scale) with the following statements: (i) I don't have anyone that I can confide in; (ii) when I need someone to help me out, I can usually find someone; (iii) I have no one to lean on in times of trouble; (iv) I often need help from other people but can't get it, and (v) there is someone who can always cheer me up when I'm down.[17] We construct a social support index by conducting a principal components analysis using responses to these five statements (see Appendix Table A.1 for more detail) and repeat our main analysis, estimating (1) with this index as the outcome variable.

The social support estimation results are shown in Table 6. The estimated effects are generally small for women and large for men. R U OK? Day in 2017-2019 is estimated to have increased social support received by men by 1.226 units (6.1% of a standard deviation). This gender difference in the effect of the campaign on social support might be driven by existing differences in social support systems between the genders. Existing research has highlighted that men's friendship circles have shrunk over the last 30 years and that men are low exchangers of social support and invest less in maintaining friendships (Cox, 2021; Reeves, 2022; Liebler and Sandefur, 2002). R U OK? Day can then serve as a 'nudge' for men to (re-)connect with their friends and check in with each other. Corresponding with the results documented in Section 5.3, in which middle-aged men experienced the largest effects, we find the largest social support increase for this same group: a 2.043 unit increase (10.1% of a standard deviation). The results provide suggestive evidence that there is a strong 'first stage' effect where R U OK? Day improves social support, which in turn, improves mental wellbeing.

7 Concluding Remarks

In this paper, we have studied the effectiveness of a nationwide peer-to-peer health awareness campaign that targets suicide prevention and mental health in Australia. Leveraging detailed data and a difference in differences approach, we estimate the short-run causal effects of R U OK? Day on suicides, suicide-related internet searches, and self-reported mental wellbeing. Our main findings are threefold. First, we find no statistically significant effects of R U OK? Day on the number of suicides. The campaign did, however, increase searches for suicide-related information on the internet, suggesting that people seek to learn more about the topic after exposure to suicide-related advertising present in the campaign. Third, we show that R U OK? Day leads to a 4.2 % of standard deviation increase in mental wellbeing during the years the program was most active. This effect is driven by males between the ages of 25-49, whose wellbeing increases by approximately 9% of a standard deviation. Further, we show that higher perceived social support is a plausible channel through which R U OK? Day improves mental wellbeing. In sum, our results suggest that peer-to-peer-based suicide prevention and mental health awareness campaign effectively improves self-reported mental wellbeing for the most at-risk group regarding suicide incidence.

The importance of peer effects has long been recognized in economics. The influence of peers on an individual's

[17] There are also other similar statements included in the survey, such as "I seem to have a lot of friends," "I often feel very lonely," and "I enjoy the time I spend with the people who are important to me." We don't use these as they are less related to the concept of peer support.

choices has been shown across various domains, including in program participation (Dahl et al., 2014), and the take-up of social (Bertrand et al., 2000), and medical (Aizer and Currie, 2004) support programs. More recently, attempts have been made to study interventions to harness peer outreach in small-scale RCTs. Ridley et al. (2020) discuss various approaches to alleviate mental health issues using evidence from such small randomized experiments. How such results –achieved often under eneficial circumstances, such as highly involved training and guidance of peers– might be scaled up has been a topic of recent debate (List, 2022, 2020). Our results contribute to this understanding and the optimal scaling up of peer-to-peer health awareness campaigns.

Our work can be extended in several directions as part of future research. First, we focus on evaluating the short-term impacts of R U OK? Day in the weeks immediately after the campaign. Exploring the long-term impact on suicide prevention, individual mental health, and the de-stigmatization of mental illness within society would complement the findings in our study. Second, our study does not examine the impact of R U OK? Day on individual's uptake of professional healthcare services. Extending our approach to investigate the effects of such a campaign on help-seeking in terms of doctor visits or therapy sessions would be a fruitful avenue for future work. Finally, evaluating the relative effectiveness of national peer-to-peer campaigns that reach a broad audience but with a relatively light touch compared to smaller-scale programs with a heavier intervention can help government policymakers optimize their decision on which type of program best fits their objectives.

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A Additional data information

Next, we lay out the different data sets to capture the potential population-wide responses to the extensive public awareness campaign. We first assess whether there were any structural breaks in the number of suicides or deaths of despair consistent with the design of the awareness campaign. Then we evaluate whether there were any changes in the search or health-seeking behaviours using Google trend data. Finally, we use population-representative data from the largest household panel in Australia, HILDA data, interviewed by chance around the R U OK? Days. All the datasets share the feature of having daily information around the awareness day and, over several years, capturing the increase of the awareness campaign.

Madip Corner data

We use the official death records provided by the Australian Bureau of Statistics [ABS], covering the years 2011-2018. The data includes individual information, age, gender, cause of death, and broad regions. We follow Case and Deaton (2015) and use the leading cause of death and the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD10); see Appendix Table A.2 for details. We use both suicides and the broader measure of death of despair (including suicides). We then calculate the daily aggregates across Australia, overall, by gender and by gender×three broad age groups.

Twitter data

We use the Academic API from Twitter to obtain tweets related to R U, OK? Day in the years 2011 to 2019. The Academic API provides access to the entire history of publicly available tweets at the time of a query. Tweets are collected and returned based on whether they match a Boolean query. We include the terms 'ruok', 'ruokay', 'ruokay' and their hashtag equivalents along with and tweets that mention or originate from the leading mental health organisations that operate within Australia: Lifeline, Beyond Blue, SaneAustralia, Suicide Prevention AU, and Black Dog Institute. We restrict tweets to be composed in the English language. The tweets were collected on September 30th, 2021. The API returns the tweet metadata, including the date and time of each tweet we use in our analysis. We compute the number of tweets per calendar day by counting all tweets posted within each 24-hour period.

G-trend data

Next, to assess whether people are searching for suicide topics or support, we use Google trend data. Google is by far the most widely used search engine in Australia and thus captures any (major) change in search behaviour. The search data measures the over a given period relative to the highest search in that period. Therefore, it needs adjustments on a daily level. In Figure 1, we first used the keyword "R U OK" on the monthly level, which is straightforward to use; 2019 was the highest number of searches. Thus, all others are measured relative to this (if higher than a certain small threshold; otherwise, google does not report the search volume).

When assessing searches on a daily level across years can not be extracted at once. Thus, they need to be standardized to be comparable. We do this following Brodeur et al. (2021) procedure. Since the monthly data has a common scale, these can be used to rescale the daily data – that only has the same scale within a given year. First, we extract the daily counts from the 1st of August till the 31st of October for each year 2011-2019 separately and standardize them by the monthly data. For example, the monthly average of the daily data in August is divided by the monthly August data and then rescaled to 100.

We use suicides (topic), the distinction between planning suicide and seeking suicide help via keywords following Till et al. (2020), health services, and mental health (both categories).[18]

Hilda data

Hilda is a large representative yearly household panel survey that is, by chance, sampled between August and October each year. The sample size is presented in Figure B.2. Thus, we can use our framework to assess whether there were any changes in mental health following the awareness campaign (that may have grown over time). Since here we have the individual data, we use detailed personal information in this part of the analysis.

We focus on two primary outcomes, mental health and social support. To this end, we calculate two principal components one for the mental health questionnaire of the SF36 (and rescaled to 100) and analogously for selected questions capturing social support (cf. Appendix Table A.2). In some analyses, we add covariates to the specification motivated above (as discussed below).

Table A.1: Principal components mental health and social support (rescaled to 0-100)

Questions (Likert 1-7)	Weights	Rel. Weight
Mental health		
Rev-SCQ:A9a Vitality: Feel full of life	0.350	0.117
SCQ:A9b Mental Health: Been a nervous person	0.279	0.093
SCQ:A9c Mental Health: Felt so down in the dumps nothing could cheer you up	0.322	0.108
Rev-SCQ:A9d Mental Health: Felt calm and peaceful	0.345	0.115
Rev-SCQ:A9e Vitality: Have a lot of energy	0.340	0.114
SCQ:A9f Mental Health: Felt down	0.355	0.119
SCQ:A9g Vitality: Felt worn out	0.329	0.110
Rev-SCQ:A9h Mental Health: Been a happy person	0.348	0.116
SCQ:A9i Vitality: Felt tired	0.326	0.109
Component 1: 4.97391 Eigenvalue, Difference 3.89; Component 2: 1.089 (0.181)		
Social support		
There is someone who can always cheer me up	0.373	0.168
When I need someone to help me out, I can usually find someone	0.448	0.201
Rev: I have no one to lean on	0.498	0.224
Rev: Often I need help from others but can get it	0.415	0.187
Rev: I don't have anyone I can confide in	0.490	0.220
Component 1: 2.801 Eigenvalue, Difference 1.94 ; Component 2: 0.085 (0.221)		

Notes: "Rev-" stands for reversed questions.
Source: Hilda 2011-2019 (v19), own calculations.

[18] There are three types of searches in G-Trend data. First is searching for `keywords` that correspond to searches for exactly these words, which we use, for example, for the "R U OK". Second, one can use `topics`; these are a pre-specified collection of keyword searches that might vary over time to reflect the changing nature of what people search for; we use this for the "Suicide" topic (the suicide topic is "/m/06z5s" for example, these can be looked up via pytrends package in python). Finally, the broadest level is `categories`, which are a few pre-specified categories, such as medical facilities and services that capture people searching for doctors.

Table A.2: Description variables

Variables	Information
Coroner data	
Intentional deaths	Following Case and Deaton (2015), we use International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD10) codes suicide: X60-84, Y87.0
Accidental poisonings	International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD10) codes: X40-45, Y10-15, Y45, 47, 49
Google trend data	
R U OK? - monthly	Monthly searches extracted at once (14.06.21)
R U OK? - daily	Daily searches, adjusted via Brodeur et al. (2021) procedure. Aug, Sept, Oct, for each year and standardized by monthly searches.
Suicides topic	Scrapes daily searches in topic /m/06z5s - Suicides, adjusted as above
Suicide plan	'commit suicide + how to suicide + painless suicide + quick suicide + suicide methods' – adjusted as above
Suicide prevention	'lifeline + help suicide + hotline suicide + suicide hotline' – adjusted as above
Hilda data	
Mental health principal component	These questions are about how you feel and how things have been with you during the past 4 weeks. For each question, please give the one answer that comes closest to the way you have been feeling. How much of the time during the past 4 weeks: Feel full of life Been a nervous person Felt so down in the dumps nothing could cheer you up Felt calm and peaceful Have a lot of energy Felt down Felt worn out Been a happy person Felt tired
Social support principal component	The following statements have been used by many people to describe how much support they get from others. How much do you agree or disagree with each? The more you agree, the higher the number of the box you should cross. The more you disagree, the lower the number of the box you should cross. I dont have anyone that I can confide in When I need someone to help me out, I can usually find someone I have no one to lean on in times of trouble I often need help from other people but can't get it There is someone who can always cheer me up when I'm down
Covariates	
Female	Whether or not individual identifies as female in survey
Age	Age in years of the individual
Ruraity	Indicators house hold lives in rural area: 0-5 Major city - Remote
States	Indicators house hold lives in state or territory
Days since survey start	Indicators for days since first within year survey date date
Extended Covariates	
College	Indicator whether individual has a college degree
Married	Indicator whether individual is married/de-facto
Unemployed	Indicator whether individual is unemployed
Not-in-labor-force	Indicator whether individual is not-in-labor-force
Weekly hours worked	Count of hours worked in usual week
Equivalised hh income	Total household income, adjusted by nr. adults and children
Seifa	Deciles of area deprivation - SEIFA (education & occupation)
Precipitation	Precipitation is for the 24 hours before 9 am (local time), in mm. It is estimated using inverse distance weighting using all rainfall stations within 50km of the postcode centroid; see Ireland et al. (2023) for more details
Maximum temperature	Maximum temperature in 24 hours after 9am (local time) in Degrees C, closest weather station, as above
LS weather	Life-satisfaction weighted weather: pre-sample regression index of weather on life satisfaction

B Additional descriptive information

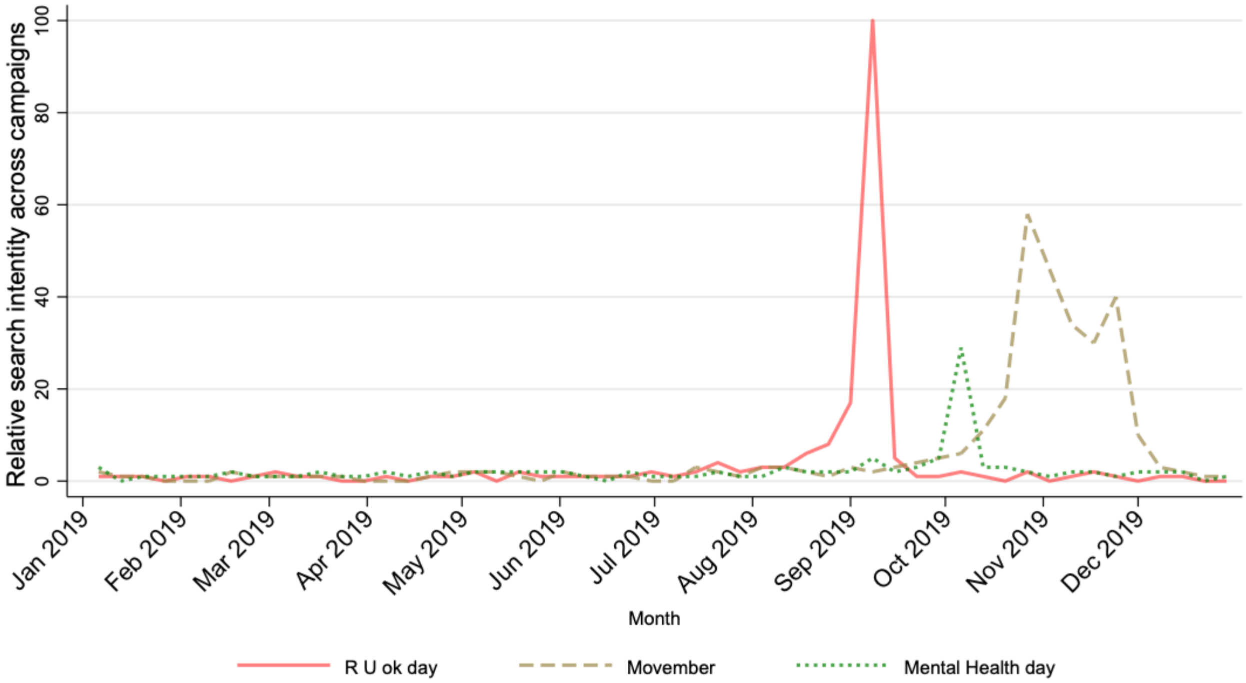

Figure B.1: Size of the campaign relative to other campaigns in the last sample year

Note: Displays Google trends for our last treatment year 2019 (1. Jan - 31. Dec), for the three search terms: "R U ok day", "Mental Health day", and "Movember" in Australia.
Source: Google Trends search data (extracted 2023).

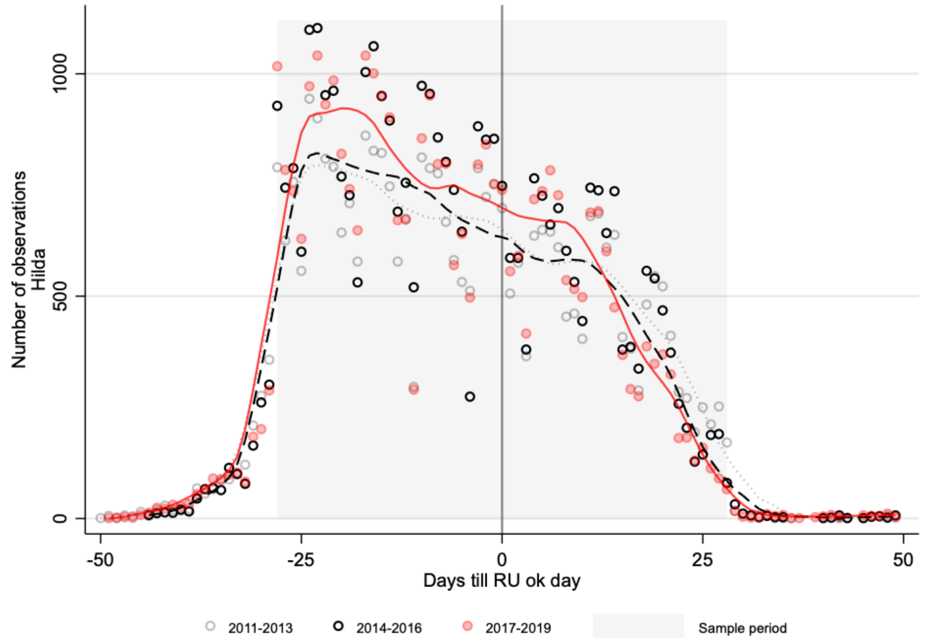

Figure B.2: Sampling time and observations HILDA across years relative to R U OK? Day

Note: Displays the raw three-year sums of the number of valid observations (N=109,340) in the overall Hilda population for each day relative to the yearly specific R U OK? Day. Lines are based on locally weighted regressions of the three-year sums on days till R U OK? Day. The gray background depicts the sample period we use in the later regression analysis (N=104,742)

Source: Hilda 2011-2019 (v19), own calculations.

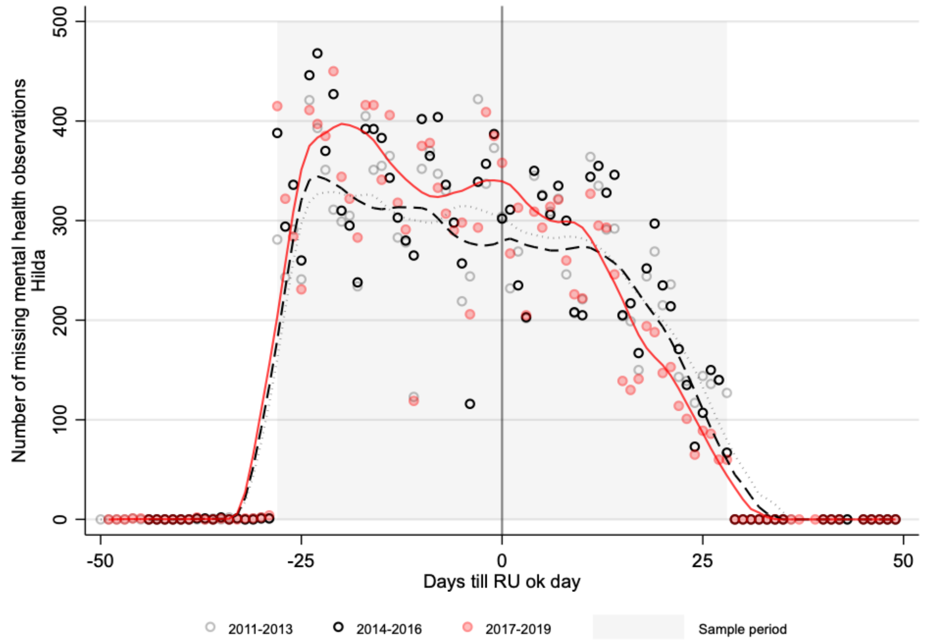

Figure B.3: Sampling time and observations HILDA across years relative to R U OK? Day: Item non-responses

Note: Displays the raw three-year sums of the number of invalid item responses for mental health.

Source: Hilda 2011-2019 (v19), own calculations.

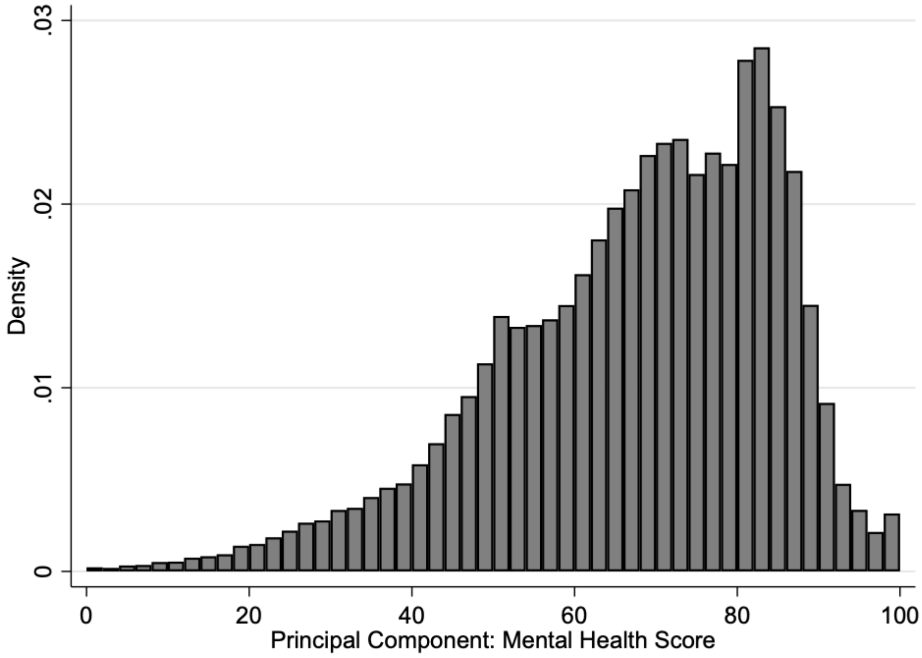

Figure B.4: Histogram

Note: Displays the raw distribution of standardized PCA-based mental health outcome.
Source: Hilda 2011-2019 (v19), own calculations.

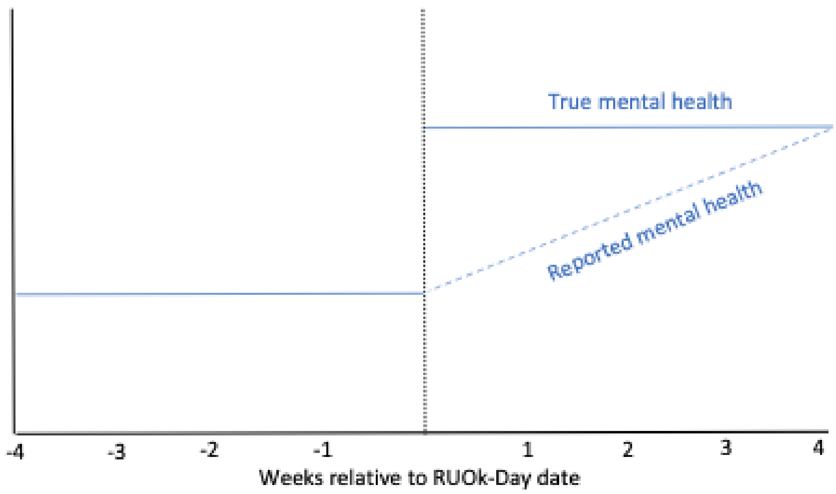

Figure B.5: Hypothetical reporting time dependence

C Additional estimation results

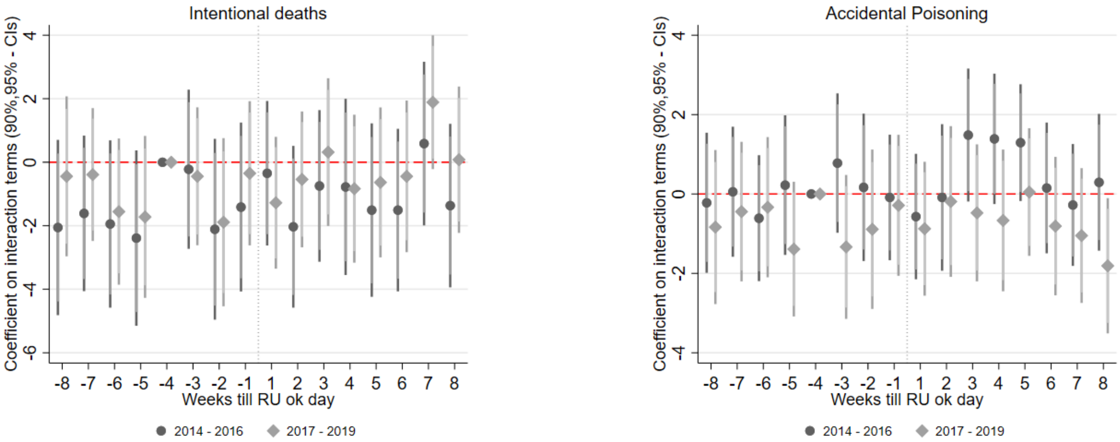

Figure C.1: Coefficient by weeks relative to 2011-2013, 2 months around cutoff

Note: Displays the coefficient estimates analogous to Table 2 Column (1) see notes therein, but interacting the treatment indicators with weeks till R U OK? Day rather than the post-R U OK? Day indicators.
Source: Australian Bureau of Statistics (ABS) Cause of Death Unit Record File 2011-2018, own calculations.

Table C.1: Heterogeneity by age and sex: Hilda

Dependent variables: Principal components of mental health and indicator of lowest 10%, various subsamples									
		Females				Males			
	all	all	15-24	25-49	50+	all	15-24	25-49	50+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B. Indicator for bottom decile ×100 gender specific									
2014-2016	-0.202	0.071	-0.082	0.789	-0.873	-0.577	-0.430	-1.034	-0.202
	(0.474)	(0.656)	(1.721)	(1.062)	(0.949)	(0.685)	(1.556)	(1.092)	(1.097)
2017-2019	-1.352	-1.586	0.406	-1.802	-2.236	-1.156	0.099	-1.997	-0.637
	(0.497)	(0.678)	(1.902)	(1.068)	(0.993)	(0.730)	(1.636)	(1.182)	(1.142)
N	102,270	54,119	9,101	22,847	22,171	48,151	8,371	20,151	19,629
R^2	0.01	0.01	0.03	0.01	0.02	0.01	0.02	0.01	0.02
Mean dep.	10.01	10.00	12.82	10.45	8.38	10.02	8.72	10.87	9.70
SD dep.	30.01	30.00	33.44	30.59	27.71	30.03	28.22	31.13	29.60
Day and year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Days since survey start	✓	✓	✓	✓	✓	✓	✓	✓	✓
Basic set of covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Analogous to Table 4 see notes therein.

Source: HILDA 2011-2019 (v19), own calculations.

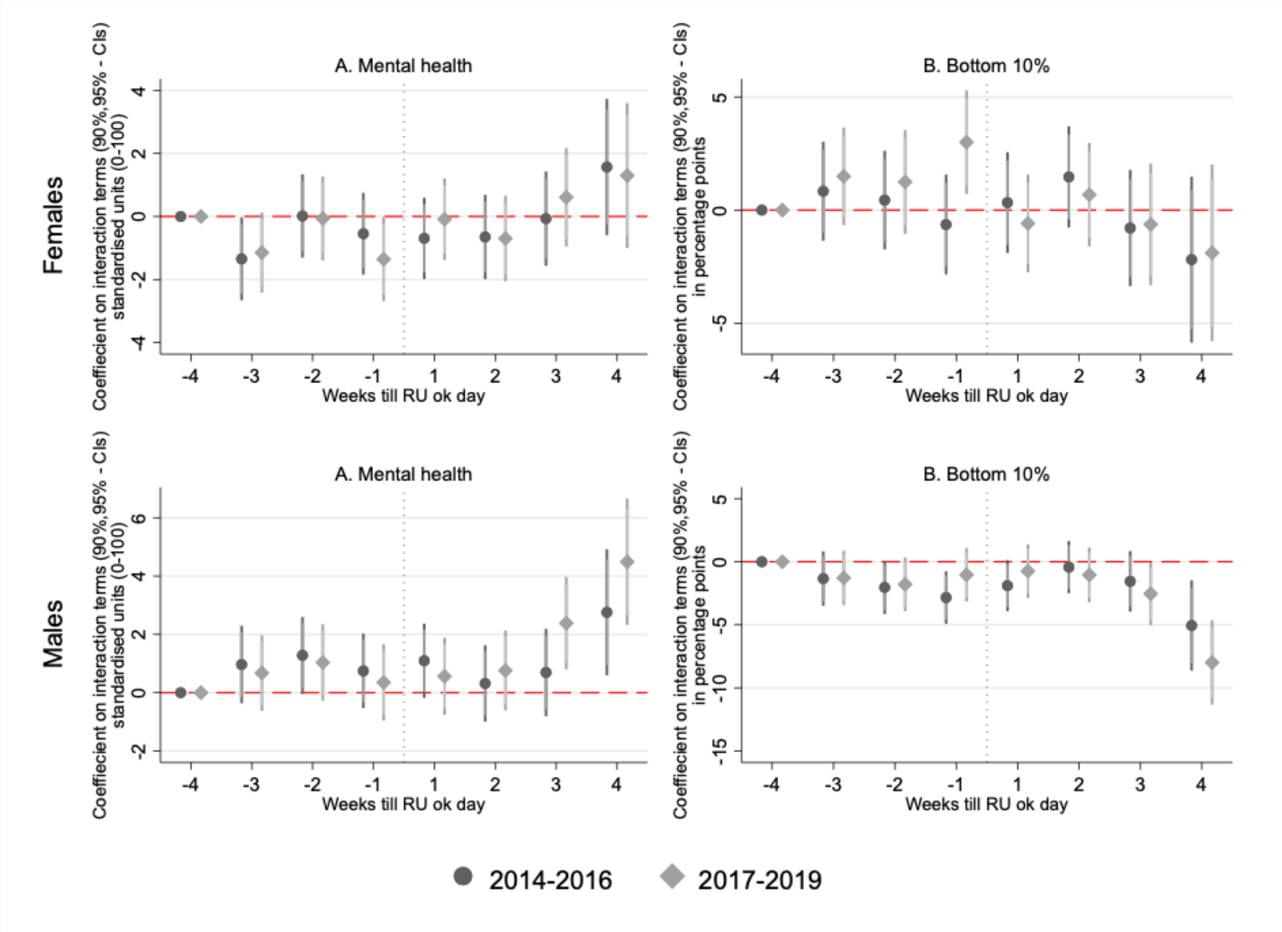

Figure C.2: Over weeks, by gender

Note: See Figure 6 and notes therein.

Source: Hilda 2011-2019 (v19), own calculations.

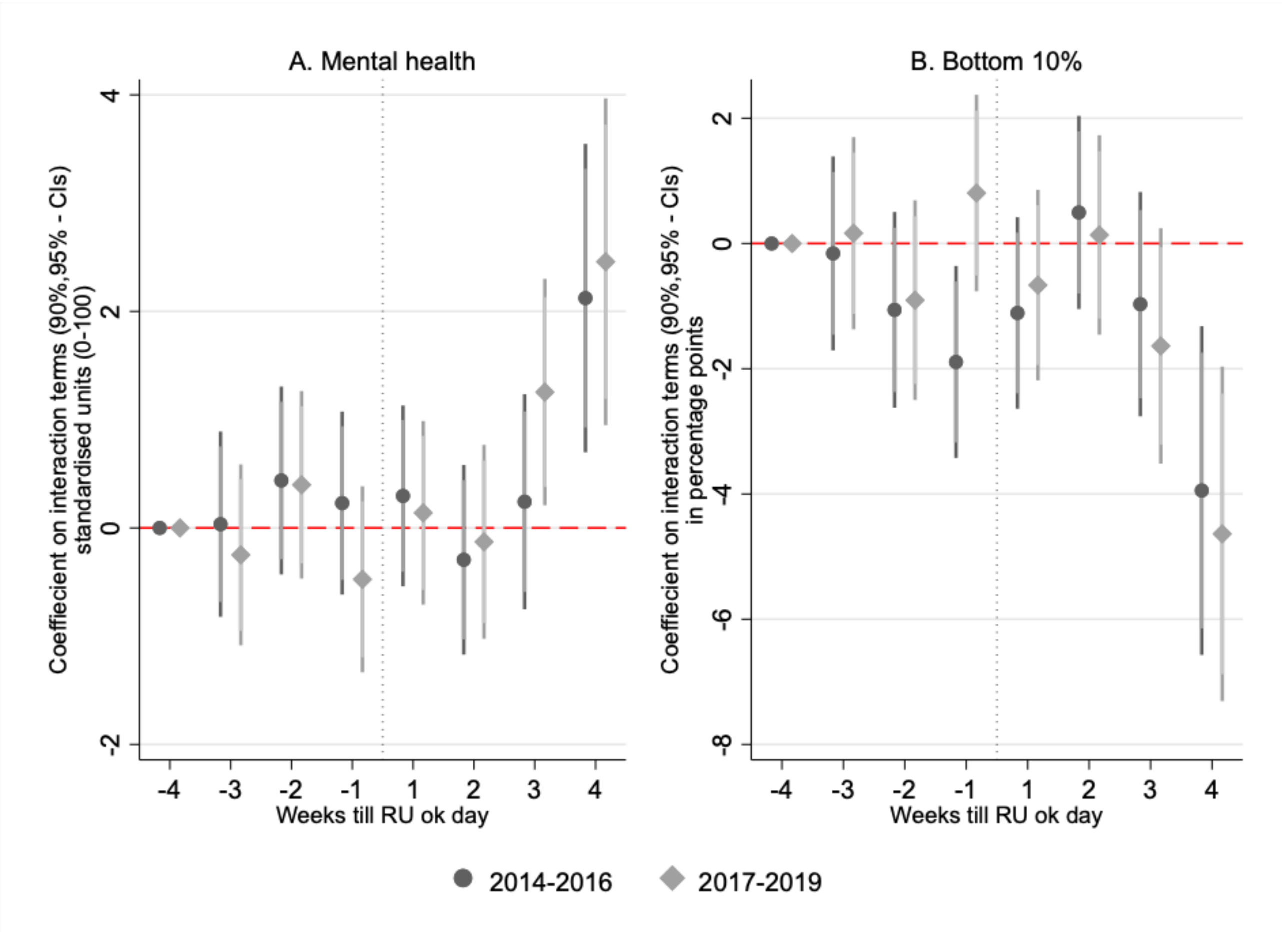

Figure C.3: Over weeks, including extended set of covariates

Note: See Figure 6 and notes therein.

Source: Hilda 2011-2019 (v19), own calculations.

Table C.2: Robustness

Dependent variables: Principal components of mental health							
		+Basic covariates			+Extended	+Weather	+Seifa
	DiD	+Age/gender	Area	Survey start	covariates	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2014-2016	0.258	0.284	0.325	0.167	0.127	0.156	0.123
	(0.270)	(0.268)	(0.267)	(0.275)	(0.256)	(0.276)	(0.273)
2017-2019	0.734	0.706	0.641	0.716	0.564	0.727	0.625
	(0.293)	(0.291)	(0.289)	(0.292)	(0.269)	(0.293)	(0.290)
N	102,276	102,276	102,270	102,270	102,270	102,270	102,270
R^2	0.00	0.02	0.02	0.03	0.17	0.03	0.04
Day and year fixed effects	✓	✓	✓	✓	✓	✓	✓
Age & gender		✓	✓	✓	✓	✓	✓
Area FE			✓	✓	✓	✓	✓
Day of survey FE				✓	✓	✓	✓
Extended set of covariates					✓		
Weather percentile fixed effects						✓	
Seifa decile fixed effects							✓

Notes: The Table presents coefficients estimates from equation (1) and individual-level cluster-robust standard errors. Column (1) is based only on the post-R U OK? and three-year-band indicators and their interaction (shown). Column (2) shows our *main model*, which is conditional age (indicators), sex (indicator), regional - state × rurality (indicators); column (3) adds the full set of variables presented in Table 1. Column (4) alternatively adds 40 indicators for weather, i.e., 20 percentile maximum temperature and 20 percentile precipitation; column (5) alternatively uses SA4 fixed effects. The mean and standard deviation of the mental health principal component (standardized to 0-100) are 67.50 and 17.23, respectively (N=102,582), and for social support, 77.44 and 20.25 (N=103,294).

Source: HILDA 2011-2019 (v19), Australian Bureau of Meteorology, own calculations.

Table C.3: Extended regression results Table C.2 - Col 5

Dependent variables: Varying socio-economic characteristics, one regression per line	PCA	10% Indicator
	(1)	(2)
2014-2016	0.127	-0.216
	(0.256)	(0.462)
2017-2019	0.564	-0.996
	(0.269)	(0.483)
Physical health principal component (0-100)	0.259	-0.281
	(0.004)	(0.008)
College educated (Yes/No)	-0.174	-0.110
	(0.215)	(0.337)
Married/de-facto relationship (Yes/No)	2.652	-3.922
	(0.222)	(0.366)
Unemployed (Yes/No)	-3.122	5.681
	(0.377)	(0.716)
Not-in-labor force (Yes/No)	-2.436	4.824
	(0.268)	(0.453)
Weekly work hours	0.039	-0.053
	(0.006)	(0.010)
Equalized household income	0.477	-2.061
	(0.286)	(0.454)
Area-level Seifa deciles (1-10)	0.226	-0.323
	(0.036)	(0.055)

Notes: The Table presents coefficients estimates from equation (2) and individual-level cluster-robust standard errors, conditional age (indicators), sex (indicator), and rurality (indicators)-by-state fixed effects, and a day since the start of survey fixed effects $N = 102,270$. Missing in the covariates are replaced with 0.

Source: HILDA 2011-2019 (v19), Australian Bureau of Meteorology, own calculations.

Table C.4: Pre-trends

Dependent variables: PCA mental health and bottom 10% indicator		
	PCA	10% Indicator
	(1)	(2)
2002-2004	-0.175	0.182
	(0.487)	(0.867)
2005-2007	-0.047	0.510
	(0.486)	(0.867)
2008-2010	0.424	-0.780
	(0.470)	(0.845)
2011-2013		omitted cat.
2014-2016	0.274	-0.389
	(0.270)	(0.476)
2017-2019	0.668	-1.046
	(0.290)	(0.509)
N	182,134	182,134
R^2	0.02	0.01

Notes: The Table presents coefficients estimates from equation (1) and individual-level cluster-robust standard errors, conditional age (indicators), sex (indicator), and rurality (indicators)-by-state fixed effects, and a day since the start of survey fixed effects $N = 102,270$.

Source: HILDA 2002-2019 (v19), own calculations.