Spatiotemporal Analysis of Australian Suicide Deaths and Other Deaths of Despair Between 2001 and 2020

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Abstract

Analysis of suicide monitoring data at smaller specified units of geography and time, and considering possible associations with other causes of death, has the potential to provide important information upon which to design prevention and intervention initiatives. We constructed and analysed a subset of the National Mortality database which included Australian wide deaths occurring and registered between 2001 and 2020. Deaths data are aggregated to 2016 Australian Statistical Geography Standard (2016 ASGS) Statistical Area Level 2 (SA2) spatial areas, single month time units, sex, and broad age group. Using primary cause, deaths were grouped according to whether the individual died by suicide, another 'death of despair' (alcoholic liver disease and cirrhosis, or accidental poisonings), or any other cause of death. Our study aimed to: 1) describe suicide and other 'deaths of despair'; 2) analyse factors associated with suicide and 'deaths of despair', including socioeconomic status and remoteness; 3) identify spatiotemporal clusters of suicide deaths; and 4) explore whether clusters of suicide deaths are associated with clustering of other 'deaths of despair.'

We find that when we control for population size, there was not a large increase or decrease in suicide over the last twenty-years in Australia, though there is still some year-on-year fluctuation. We find some monthly variability in suicide deaths, with the lowest rate of suicide occurring in mid-late Spring and early Winter. We find similar age and sex patterns to the national level data, but show that remoteness, rather than socioeconomic status is the more consistent predictor of suicide deaths. We show that although some of the spatiotemporal determinants of other deaths of despair (deaths due to alcohol or poisoning) are different than those for suicide, a high rate of other deaths of despair in an area is associated with a high rate of suicide, even when spatiotemporal factors are controlled for. We do show, however, that deaths from all other causes are a better predictor of deaths due to suicide, giving some support to the view that in Australia at least the three categories of deaths of despair do not correlate with each other in a particularly strong way.

Keywords: Suicide, Self-Harm, Australia, Monitoring, Analytic Methods

Introduction and Overview

Suicide is significant public health problem for Australian. In 2021, 3,144 Australians were registered as dying by suicide (preliminary data, Australian Bureau of Statistics, 19/10/2022). In Australia, a total of 107,068 potential years of life were lost to suicide during this period; accounting for more years of potential life lost than by any other cause of death (Australian Bureau of Statistics, 19/10/2022). In addition to the human cost, suicide places a very real monetary burden on the Australian economy. The Productivity Commission (2020, appendix H, pg. 165) estimated that the total economic cost of suicidal behaviour in Australia, is approximately $30.5 billion dollars per annum.

Population health monitoring involves regularly and systemically producing and distributing data and knowledge about the health status of a population for the purposes of informing policymaking (Verschuuren & van Oers, 2019). Analysis of suicide monitoring data at small, specified areas of geography and at as close to real time as possible, enables the rate and ‘spread’ of self-injurious behaviours to be more accurately tracked (Witt & Robinson, 2019). This, in turn provides important information upon which to design and target prevention and intervention initiatives (Productivity Commission, 2020). Effective use of monitoring data may also support accountability and transparency within the systems and services that share responsibility for reducing suicide and self-harm. For this study we are able to use Australian population wide deaths data aggregated to 2016 Australian Statistical Geography Standard (2016 ASGS) Statistical Area Level 2 (SA2) spatial areas and single months. We include deaths occurring and registered between 2001 and 2020. To the best of our knowledge, the most recent country and population wide spatiotemporal analysis of suicide deaths in Australia was published by Robinson et al. (2016) using 2010 to 2012 data.

Yeom (2021) has more recently applied spatiotemporal techniques to South Korean suicide deaths data. Yeom found that small area mortality rates are spatially and temporally dependent on those of neighbouring units, as well as being dependant on a single time-lag without spatial effect. Further, that proxy measures of social integration and regulation significantly impact suicide mortality rates.

To date, as far as we are aware spatiotemporal analyses of suicide deaths in Australia or in other countries have not investigated whether the distribution of suicide deaths is associated with that of deaths by other causes. This is an important avenue for investigation. Firstly, if deaths by other causes are not taken into account, then what appears to be specifically a clustering of suicide deaths, might actually be indicative of a clustering of deaths more broadly (that is, by some or all other causes). Secondly, if clusters of suicide deaths are associated with clustering of deaths by other types of specific causes this has implications for our understanding of what may precipitate these clustered deaths and what most appropriate interventions may be.

The term 'deaths of despair' was coined by Case and Deaton (2015, 2017, 2021), to refer to deaths caused by suicide, drug and alcohol poisonings, and chronic liver disease and cirrhosis. They observed, that in the American population, an increase in all-cause mortality for middle aged white non-Hispanic men and woman rose between 2003 and 2013. Further, that the increase in all-cause mortality for this group was largely explained by an increasing death rate due to 'deaths of despair'. More recent US data show that crude population wide rates of 'deaths of despair' doubled between 2000 (22.7 deaths per 100 000) and 2017 (45.8 deaths per 100 000) (US Congress Joint Economic Committee, 05/09/2019). Explanations offered for the rise in these deaths, across the North American population, are increasing economic insecurity, availability of opioids, and a lack of a universal health care (Case & Deaton, 2017). Specifically for white non-Hispanics lack of college education was also a risk factor (Case & Deaton, 2017).

Using data made publicly available by the Australian Institute of Health and Welfare (2020), Bastiampillai et al. (2021) argue that although Australian 'deaths of despair' data is less clear, there are grounds for further investigation. They point-out that nationwide, the Australian aged standardised rate of 'deaths of despair' increased between 2006 and 2018 (Bastiampillai et al., 2021); from 18.8 to 24.1 deaths per 100 000 population (Australian Institue of Health and Welfare, 2020). However, it is also acknowledged that this was preceded by a decline in 'deaths of despair' between 1999 and 2006 (Bastiampillai et al., 2021); from 24.4 to 18.8 deaths per 100 000 population (Australian Institue of Health and Welfare, 2020). As highlighted by Bastiampillai et al (2021), further disaggregated analysis is required to better understand 'deaths of despair' in Australia.

The overall aim of this paper is to build on the work of Bastiampillai et al. (2021) and to update in part the analysis of Robinson et al. (2016) using more recent Australian data. Specifically, we have four study aims, as outlined below:

1. Describe suicide and other 'deaths of despair' that occurred between 2001-2020, across Australia by geography, age, and sex.
2. Analyse factors associated with suicide and 'deaths of despair', including socioeconomic status and remoteness.

3. Identify spatiotemporal clusters of suicide deaths across Australian 2016 ASGS SA2 areas between the years 2001 and 2020 inclusive.
4. Explore whether clusters of suicide deaths are associated with clustering of other 'deaths of despair' (Case & Deaton, 2015, 2017, 2021).

The remainder of the paper is structured as follows. First, we outline the data that we use in the paper, including how it was constructed and, where appropriate, the limitations. We then outline the analyses used, followed by results and discussion. The final section provides some concluding comments with a particular focus on suggestions for further analysis of the dataset constructed for this paper.

Data Sources and Variables

The National Mortality Database (NMD) was the primary data asset used for this study. Data access was facilitated by the Australian Institute of Health and Welfare. The NMD holds individual person level records for all deaths registered in Australia between 1964 and 2020. A subset of the NMD was constructed, which includes all deaths that were both registered and occurred between 2001 and 2020. Data for 2006 to 2017 registered deaths were finalised, 2018 registered deaths were revised, and 2019 to 2020 deaths were preliminary data. No revisions process was in place prior to 2006 registered deaths. The revisions process by year of registration is described below.

Other data sources used were: 2016 ASGS SA2 estimate resident populations (ERP) by sex and age group for the years 2001 to 2020, The Index of Relative Socio-Economic Advantage and Disadvantage for census years, and the Australian Statistical Geography Remoteness Structure for census years.

Study Variables

National Mortality Database Variables

Sex. Defined binarily as male or female.

Age group. Five-year age groups from 15 years to 84 years (deaths under the age of 15 were not included in the analysis), and a single 85 years and older age group. Age group was calculated using the NMD date of birth and date of death variables.

Year of death registration. This variable reflects the year the death was registered with the ABS. From 2007 onwards, ABS 'year of death registration' year includes all deaths registered by an Australian state/territory jurisdiction and received by the ABS before the end of the March quarter of the subsequent year. Prior to 2007, the reference period additionally extended to deaths that were registered by states/territories up to two years prior but not received by the ABS until the ABS year of registration. Due to delays in the registration of deaths and/or lags in the transfer of this information from states/territories to the ABS, year of death registration and year of death are not always the same (Australian Bureau of Statistics, 29/09/2021).

All coroner certified deaths (which includes suicide deaths) registered (with the Australian Bureau of Statistics) after 1 January 2006 are subject to a revisions process (Australian Bureau of Statistics, 29/09/2021). The revisions process produces three iterations of deaths data by year of registration: preliminary data, revised data, and finalised data. The reason the Australian Bureau of Statistics instituted this revisions process was to improve data quality. Previously, data were finalised at a single point in time. However, coronial inquests are often complex and lengthy investigations. The revisions process allows Australian Bureau of Statistics coders to assess new information made available through the coronial process at 12 months and again at 24 months after initial Australian Bureau of Statistics processing of the death.

Week, month, and year of death. Calculated using NMD date of death variable. For weeks, January 1 is always the start of the first week in a given year and each year has 52 weeks. Thus weeks 1 to 51 are 7 days long, and week 52 is either 8 or 9 days long (Cox, 2012). Calendar months and calendar years were used in the analysis.

Primary cause of death. Primary cause of death is recorded using International Classification of Disease Codes tenth Revision (ICD-10). All individuals who died within the study period were retained in the dataset. First, we grouped all deaths according to whether the individual died by suicide (X60–X84, Y87.0) or by a cause other than suicide (all other ICD codes). Next we used the Australian Institue of Health and Welfare (2020) 'deaths of despair' classification to group the other 'deaths of despair': alcoholic liver disease and cirrhosis (K70, K73-K74) and accidental poisonings (X40-X45, Y10-Y15, Y45, Y47, Y49).

Area of usual residence. The location the individual resided in the 6 months prior to death. The smallest geography included within the NMD is the SA2 level; or equivalent for earlier versions of The Australian Statistical Geography Standard (Australian Bureau of Statistics, 20/07/2021) and Australian Standard Geographical Classification (Australian Bureau of Statistics,n.d.). Deaths are assigned to a standard geography of usual residence by year of registration (not year of death).

Variables from other publicly available data sources

Estimate Resident Populations. Estimate resident population (ERP) includes all people, regardless of citizenship or legal status, who usually live within the SA2 area. The Australian Bureau of Statistics has published ERPs by age and sex and adjusted to 2016 ASGS SA2 for the years 2001 to 2020. We accessed ERPs from data.gov.au.

Index of Relative Socio-Economic Advantage and Disadvantage. The Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD) is one of the four indexes that comprise the Socio-Economic Indexes for Areas (SEIFA). The IRSAD summarises area level information about household income and unemployment, occupation, and education. A low score indicates relatively greater disadvantage and a lack of advantage in general. A high IRSAD score indicates a relative lack of disadvantage and greater advantage in general (Australian Bureau of Statistics, 27/03/2018).

We accessed the IRSAD from the Australian Bureau of Statistics Socio-Economic Indexes for Areas website: https://www.abs.gov.au/websitedbs/censushome.nsf/home/seifa) and fix for each area at the 2016 value.

Remoteness. The Australian Statistical Geography Remoteness Structure was used to assign each SA2 a value against each of the five classes of remoteness (on the basis of access to services) (Australian Bureau of Statistics, 16/03/2018). The five classes of remoteness are: Major City, Inner Regional, Outer Regional, Remote, and Very Remote. For the analysis in this paper, remoteness is fixed at the 2016 values. We accessed remoteness files from data.gov.au. The Australian Bureau of Statistics directly supplied a 2001 remoteness to 2016 ASGS SA2 areas correspondence (further details provided at the ‘Geographic time series’ section below).

Data Preparation and Missing Data

Stata (StataCorp, 2021) software was used for data preparation and analysis.

Missing data and data imputation

Individual deaths were included in the dataset if they both occurred and were registered between 2001 and 2020. As such, there were no missing year of death data. While the NMD user guide does specify possible missing values for day and month of death; none were found missing. Date of birth (and subsequently age at death) was missing for 0.007% (192 cases) of the sample. Predictive mean matching (using STATA mi impute pmm) was used to impute the missing date of birth values.

Adjustment for late registration of Victorian deaths

As a result of joint investigations between the Australian Bureau of Statistics and the Victorian Registry of Births Deaths and Marriages, 2 812 death registrations from 2017, 2018 and 2019 were identified that had not previously been provided to the Australian Bureau of Statistics (Australian Bureau of Statistics, 29/09/2021). This issue does not directly impact our substantive analyses and results because we will examine deaths by date of death (not by date of registration). However, this issue does impact the calculation of an adjustment factor to enable estimation of finalised data for 2018, 2019, and 2020 (which are in currently in revised and preliminary form). For this purpose, we applied the Victorian Registry of Births Deaths and Marriages time series adjustment to all causes of death of death groups included in our study. This adjustment places the 2 812 late death registrations back into the registration year that they ought to have been provided to the Australian Bureau of Statistics. (See Australian Bureau of Statistics Technical note: Victorian additional registrations and time series adjustments in Causes of Death, Australia, 2019 for detailed information on this issue.)

Note that applying the time series adjustment for late Victorian registrations to all death groupings included in our study, means that our aggregated dataset is not directly comparable to the publicly available Australian Bureau of Statistics mortality data. This is because the Australian Bureau of Statistics applied the adjustment to some but not all of the causes of death in their publicly available mortality data.

Data revisions adjustment: For preliminary and revised causes of deaths data

As previously stated, mortality data used for 2006 to 2017 registered deaths were finalised, 2018 registered deaths were revised, and 2019 to 2020 deaths were preliminary.

No revisions process was in place prior to 2006 registered deaths. We calculated an adjustment factor to enable the inclusion of preliminary and revised data in our analysis, in a way that allows for justifiable comparison with finalised data. We will refer to this adjustment as the data revisions adjustment (to distinguish it from the time series adjustment for Late registration of Victorian deaths). The data revisions adjustment was estimated using data that had already been adjusted for late registration of Victorian deaths.

To estimate the adjustment, we calculated the proportion of suicide and non-suicide deaths (including other deaths of despair) that occurred in a given month between 2006 and 2017 that were not registered in the year they occurred (date of death). Instead, these deaths were registered in the subsequent year or subsequent two years after the death occurred.

For 2019 data, we applied an adjustment factor that accounted for the proportion of deaths that were registered in the second year after the death occurred. For 2020 data, we applied an adjustment factor that accounted for the proportion of deaths that were registered in the first and second year after the death occurred. While we note that deaths can be registered more than 2 years after they have occurred, they are a very small proportion of overall deaths and not included in the adjustment factors.

The adjustment factors are given in Table 1 below, with three stylised facts apparent. Adjustment factors are small for most months, apart from December and to a lesser extent November; they tend to be greater for suicide compared to non-suicide deaths; and they are much greater for the first year after the death has occurred rather than the second year.

Table 1 Adjustment factors – By month and year lag

Month	One-year adjustment factors		Two-year adjustment factors	
	Suicide	Non-suicide deaths	Suicide	Non-suicide deaths
January	1.0067	1.0016	1.0012	1.0002
February	1.0080	1.0016	1.0008	1.0003
March	1.0081	1.0015	1.0016	1.0004
April	1.0085	1.0019	1.0013	1.0004
May	1.0098	1.0019	1.0040	1.0003
June	1.0176	1.0025	1.0004	1.0004
July	1.0202	1.0034	1.0018	1.0005
August	1.0294	1.0052	1.0017	1.0005
September	1.0425	1.0096	1.0027	1.0006
October	1.0667	1.0200	1.0038	1.0007
November	1.1574	1.0556	1.0039	1.0009
December	3.4570	2.6367	1.0157	1.0025

Geographic time series

Australian Bureau of Statistics Geographic Correspondences were accessed at data.gov.au and used to standardise all death counts to 2016 ASGS SA2.

The ERP data were matched to NMD death counts by year of death (not by year of registration). It was assumed that ERP and IRSAD remained stable throughout each calendar year.

Analytical Approach

Prior to analysis, a number of other steps were taken to construct a more tractable dataset. The first step was to aggregate deaths across three broader age groups. Specifically, we collapse the five-year age cohorts to those aged: 15 to 29; 30 to 64; and 65 plus. The second step was to take into account the number of days in each calendar month, by creating an average daily death rate. The third step was to calculate age and sex specific rates of death per 100 000 ERP. While some modelling of suicide data uses counts of deaths in a particular area by time period combination (and adjusts for the population at risk using an exposure variable), this is not possible with the data we used as deaths counts are not in integer form due to the application of spatial concordances and data revisions adjustment.

Having constructed the dataset – which has a separate observation by age group, sex, month, and location – our first model estimated suicide mortality rate at time t, in area j, as a function of sex, age group, month of death, and year of death. This basic descriptive model was used to test 1) whether males or females have higher suicide mortality rates; 2) whether there are differences by age and month of death; and 3) whether suicide rates have increased between 2001 and 2020 on average. In addition to the explanatory variables included at model 1, model 2 includes two area-level variables. These are the remoteness category of the area (fixed at the 2016 Census value) and the level of socioeconomic advantage as measured by the IRSAD, estimated for that particular year. Models 1 and 2 use ordinary least squares estimation across the pooled data, without taking into account the correlation in deaths across areas and time.

Our third model includes the same dependant and explanatory variables as Model 2, but is estimated using a random effects panel data model. This takes into account correlation in deaths across time for each area x age x sex unit.

Our fourth model builds upon model 3 by including a set of temporal lags. That is, for a given time period t (measured in months), we include as explanatory variables the suicide mortality rate for each area in time t-1 through to time t-12. This model is used to test whether suicide rates in previous months are predictive of suicide rates at a given point in time.

Our fifth model takes into account the spatial structure of the data. Specifically, we include as an additional explanatory variable the suicide mortality rate in the broader SA3 geographic region in which the SA2 area is located. According to the Australian Standard Geographic Structure documentation (Australian Bureau of Statistics 12/07/2016), while an SA2 represents 'a community that interacts together socially and economically … SA3s create a standard framework for the analysis of ABS data at the regional level through clustering groups of SA2s that have similar regional characteristics.' Furthermore, 'In regional areas, SA3s represent the area serviced by regional cities that have a population over 20,000 people. In the major cities, SA3s represent the area serviced by a major transport and commercial hub. They often closely align to large urban Local Government Areas (e.g. Gladstone, Geelong). In outer regional and remote areas, SA3s represent areas which are widely recognised as having a distinct identity and similar social and economic characteristics.'

We exclude '18 non-spatial SA3 special purpose codes comprising Migratory–Offshore–Shipping and No Usual Address codes for each State and Territory' as well as 'The Other Territories of Jervis Bay, Cocos (Keeling) Islands, Christmas Island and Norfolk Island.' For each time period, there remains 2,288 SA2s spread across 336 SA3s, or an average of 5.8 additional SA2s in each of the more aggregated spatial regions (that is, 6.8 SA2s in each SA3, on average). This model is used to test whether suicide rates in neighbouring areas are predictive of suicide rates in a given region.

The estimation of models 1 through to 5 is replicated for deaths due to three (mutually exclusive) additional causes of death as measured by the rate of alcoholic liver disease and cirrhosis (Alcohol Mortality Rate; AMR), rates of accidental poisoning (Poisoning Mortality Rate; PMR) and Other Mortality Rate (OMR). In our sixth and final model for suicide mortality rates we include as additional explanatory variables the AMR, PMR and OMR in the area.

Results

Suicide mortality rates

We begin by discussing results of the first 5 models with suicide deaths as the dependent variable. These are present

For model 1, working down the table, the dummy variables for each year suggest that suicide rates (per 100,000 usual residents) were highest in 2001 (the omitted category) through to 2004, with all other years having a negative and statistically significant coefficient. The lowest rates of suicide were observed in 2009 and 2010, with the rate in 2020 not only lower than that observed in 2001, but also lower than in 2019. There does not appear to be large monthly variation in rates of suicide. May and June were found to have slightly lower suicide death rates compared to January (the omitted category), but coefficient for all other months were not significantly different from zero. Females have lower rates of suicide compared to males. Across age groups, those aged 30 to 64 years had the highest rate of suicide deaths.

Moving onto model 2, analysis of the pooled data suggests that more advantaged areas have lower suicide rates than more disadvantaged areas. Compared to the omitted category (SA2s in a major city), those SA2s in inner-regional and outer-regional areas have higher rates of deaths by suicide, with those SA2s in very remote regions having the highest rates.

In model 3, we take into account the correlation across time for each age x sex x area unit of analysis using the random effects panel model. Results of model 3 show very similar associations between suicide death rate and year, month, sex, age, and remoteness. However, the association with area-level IRSAD is no longer significant.

In Model 4, we can evidence for temporal dependence in the data. Controlling for other factors, a high rate of suicide in one month is associated with a high rate of suicide in a subsequent month. The higher order lagged dependent variables remain statistically significant, but tend to diminish in the size of the association. The only exception to this is the t-5 lag (that is the suicide rate from five months previously), which has the strongest association across all the lagged variables. It is unclear why this might be the case and, if it is not due to random variation in the data, is an area for more detailed analysis.

In Model 5, we introduce a spatial component, showing that even when controlling for other area-level characteristics, there is a strong association with the suicide rate in the surrounding region. Holding other things constant, if suicide rates in the surrounding region go up by one death per 100,000 people per day, then suicide rates in the region in question will go up by 0.173 deaths per 100,000 people per day. This is not direct evidence of regional-level suicide contagion, as there are other unobserved regional-level variables that are not included in the model. However, it does give some indication that knowing about suicide outcomes in neighbouring areas can help when focusing on a particular area.

Comparisons with other causes of death, including deaths of despair.

The sixth and final model includes deaths from three other causes as additional explanatory variables – alcohol, other poisoning, and all other deaths. All three were statistically significant, though to interpret the size of the association, it is important to take into account the standard deviation in the other causes of death (0.020 for AMR; 0.011 for PMR, and 3.263 for OMR). When we do so, we can see that a one standard deviation increase in OMR has the greatest association with the SMR, followed by PMR and AMR. This suggests that deaths by suicide in a particular area, for broad age/sex groupings are driven in part by factors that are driving over-all mortality, above and beyond national yearly and monthly factors, advantage/disadvantage, remoteness, and what is happening in the larger geographical unit. Furthermore, despite the common grouping of the three specific causes of death (suicide, alcohol, and poisoning) it does not appear that there is a particularly strong correlation between them at the small-area level.

Although there is definitely an association between deaths from other causes and deaths by suicide, some quite different temporal and spatial patterns emerge when we analyse AMRs, PMRs, and OMRs separately (essentially replicating Model 5 with the different dependent variables, Appendix Table 2). We can see that like with suicide, AMRs have declined over the 20-year time horizon, but that PMRs have stayed more constant over the period. Deaths from other causes declined between 2009 and 2020.

Within-years, there are higher AMRs between May and October, with these months tending to have lower suicide mortality rates. There is very little variation across months in

PMRs, whereas OMRs peak in the colder months with December through to March having the lowest mortality rates.

Females have lower mortality rates for the two additional deaths of despair (remembering that females also had lower suicide mortality rates) as well as other causes of death. Age patterns are also different with the two older age groups having much larger AMRs and OMRs than those aged 15 to 29, but PMRs following a similar age distribution to the suicide mortality rates. It should be noted also that we do not age standardise the death rates within the broad age categories, which may be influencing some of the results.

Socioeconomic advantage had the strongest (negative) relationship with AMRs and PMRs, with no significant relationship in the random-effects models for OMRs. There were also different spatial patterns by remoteness. Inner regional areas had the highest AMRs, PMRs and OMRs with no difference or a small negative between major cities and the other three broad remoteness regions (outer regional, remote, and very remote). This is in contrast to the suicide mortality rates presented earlier, where the largest rates were in very remote areas.

Concluding comments and limitations

This paper is, in some ways, a proof-of-concept report, as applied to Australian data. Specifically, we consider to what extent analysis of highly disaggregated data on suicide deaths in Australia, at relatively small time periods, and for small geographic units can produce coherent and plausible findings. We would argue that analysis of data disaggregated by month, small geographic region, age group, and sex can tell us something in addition to what is found using national-level or yearly data. Furthermore though, we would also argue that the longer time series (twenty-years of data) that is available for areas rather than for individuals also has research insights.

Broadly speaking, we find that when we control for population size, there was not a large increase or decrease in suicide over the last twenty-years in Australia, though there is still some year-on-year fluctuation. We do show that there is monthly variation in suicide, with summer tending to have the highest rates of suicide, and late autumn/early winter the lowest rates. We find similar age and sex patterns to the national level data, but show that remoteness, rather than socioeconomic status is the more consistent predictor of suicide deaths. This may be picking up the high rates of suicide amongst Aboriginal and Torres Strait Islander Australians as a relatively high share of people who live in remote and (particularly) very remote areas are Aboriginal and Torres Strait Islander.

Another innovation in this paper is the analysis of the spatial distribution of other deaths of despair alongside suicide. We show that although some of the spatiotemporal determinants of other deaths of despair (deaths due to alcohol or accidental poisoning) are different than those for suicide, a high rate of other deaths of despair in an area is associated with a high rate of suicide, even when spatiotemporal factors are controlled for. We do show, however, that deaths from all other causes are a better predictor of deaths due to suicide when we adjust for the variation in the specific causes of death, giving some support to the view that in Australia at least the three categories of deaths of despair do not correlate with each other in a particularly strong way.

There is substantially more analysis that could be undertaken on the data that we constructed. While we showed that there is spatial-clustering of deaths due to suicide, a more flexible specification with contiguous spatial lags could potentially demonstrate more accurately the functional form of the relationship. Second, we chose to aggregate deaths to months rather than weeks, and deaths into three broad age groups. Aggregation could be ‘dialled-up or dialled-down’ for the different dimensions, testing for the more predictive data structure. Third, we have included two geographic factors (remoteness and advantage/disadvantage) whereas other measures or the component parts of the measures used might also add insight. A fourth direction of extension could also be to include different groupings of non-suicide deaths, with deaths grouped by preventability one avenue that we have begun data construction for. Fifth, we have assumed that the relationship between spatiotemporal factors and suicide deaths is consistent across age, sex, and geographic region. Separate models could be estimated for population sub-groups.

A final area of future analysis would be to focus on specific geographic areas. The use of concordances and changing geographic structures mean that there is likely to be measurement error for some of the individual geographic units in the analysis. This is particularly the case when comparing suicide deaths to the population estimates. However, there is still significant information for each area, and there would be significant policy merit in identifying those areas with relatively high suicide rates both with and without controlling for spatiotemporal factors.

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Appendix tables – Model results

Appendix Table 1 Factors associated with suicide deaths – 2001 to 2020

Explanatory variables	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Year (omitted 2001 (Models1-3) 2002 (Models 4-6))												
2002	-0.00927		0.00282		0.00098							
2003	-0.00798		0.00279		0.00206		0.00670		0.00655		0.00588	
2004	-0.00453		0.00202		0.00156		0.00493		0.00491		0.00484	
2005	-0.02173	***	-0.01001	*	-0.00961	*	-0.00277		-0.00284		-0.00281	
2006	-0.02433	***	-0.01367	***	-0.01369	***	-0.00493		-0.00502		-0.00532	
2007	-0.01095	*	-0.00122		-0.00306		0.00200		0.00180		0.00142	
2008	-0.02267	***	-0.01291	**	-0.01371	***	-0.00360		-0.00376		-0.00445	
2009	-0.04090	***	-0.02793	***	-0.02908	***	-0.01452	***	-0.01475	***	-0.00989	*
2010	-0.04185	***	-0.02870	***	-0.02958	***	-0.01317	***	-0.01344	***	-0.00856	*
2011	-0.03331	***	-0.02022	***	-0.02057	***	-0.00654		-0.00660		-0.00087	
2012	-0.04132	***	-0.02816	***	-0.02868	***	-0.01323	***	-0.01342	***	-0.00718	
2013	-0.02789	***	-0.02497	***	-0.02631	***	-0.01012	**	-0.01045	**	-0.00390	
2014	-0.03475	***	-0.02141	***	-0.02233	***	-0.00715		-0.00724		-0.00082	
2015	-0.03434	***	-0.02099	***	-0.02202	***	-0.00788		-0.00797		-0.00134	
2016	-0.03083	***	-0.01762	***	-0.01753	***	-0.00489		-0.00495		0.00203	
2017	-0.02570	***	-0.01231	**	-0.01218	**	-0.00040		-0.00046		0.00646	
2018	-0.03201	***	-0.02163	***	-0.02146	***	-0.00999	**	-0.01005	**	-0.00235	
2019	-0.02741	***	-0.01419	***	-0.01405	***	-0.00161		-0.00166		0.00549	
2020	-0.03622	***	-0.02337	***	-0.02332	***	-0.01145	**	-0.01756	***	-0.00585	
Month (omitted January)												
February	0.00485		0.00478		0.00478		0.00506		0.00447		0.00476	
March	0.00077		-0.00029		-0.00029		-0.00078		-0.00078		-0.00100	
April	-0.00372		-0.00866	**	-0.00866	**	-0.01014	**	-0.01035	***	-0.01064	***
May	-0.00869	*	-0.00880	**	-0.00880	**	-0.00830	**	-0.00831	**	-0.00989	**
June	-0.00804	*	-0.00771	*	-0.00771	*	-0.00798	**	-0.00819	**	-0.01073	***
July	-0.00007		-0.00012		-0.00012		-0.00043		-0.00044		-0.00398	
August	-0.00103		-0.00101		-0.00101		-0.00049		-0.00050		-0.00392	
September	-0.00468		-0.00616		-0.00616		-0.00522		-0.00545		-0.00805	**
October	-0.00017		-0.00327		-0.00327		-0.00160		-0.00165		-0.00314	
November	0.00262		-0.00009		-0.00009		-0.00087		-0.00118		-0.00164	
December	-0.00353		-0.00631		-0.00631		-0.00569		-0.00928	**	-0.00720	*
Female	-0.06059	***	-0.05811	***	-0.05988	***	-0.03803	***	-0.03797	***	-0.03711	***
Age group (omitted 15 to 29)												
30 to 64	0.02130	***	0.01897	***	0.01756	***	0.01265	***	0.01250	***	0.00780	***
65 plus	-0.00196		-0.00069		-0.00339		0.00059		0.00005		-0.04298	***
Continuous SEIFA			-0.00002	**	0.00001		-0.00003	**	-0.00002	**	-0.00002	

Remoteness (omitted major city)												
Inner Regional			0.02071	***	0.02841	***	0.01014	***	0.00722	***	0.00692	***
Outer Regional			0.01951	***	0.02219	***	0.01242	***	0.01064	***	0.01400	***
Remote			0.00999		0.01078		0.00735		0.00415		0.00928	
Very Remote			0.03146	***	0.03613	**	0.02029	***	0.01554	***	0.02168	***
One month lag							0.03112	***	0.03077	***	0.02656	***
Two month lag							0.02533	***	0.02498	***	0.02087	***
Three month lag							0.02990	***	0.02955	***	0.02395	***
Four month lag							0.02786	***	0.02746	***	0.02153	***
Five month lag							0.05100	***	0.05061	***	0.04759	***
Six month lag							0.02454	***	0.02417	***	0.02033	***
Seven month lag							0.01515	***	0.01474	***	0.01303	***
Eight month lag							0.02141	***	0.02100	***	0.01461	***
Nine month lag							0.01501	***	0.01459	***	0.01131	***
Ten month lag							0.02160	***	0.02117	***	0.01667	***
Eleven month lag							0.02246	***	0.02206	***	0.01841	***
Twelve month lag							0.01223	***	0.01180	***	0.00879	***
Region death rate									0.17261	***	0.06326	***
Alcohol Mortality Rate											0.03934	***
Poisoning Mortality Rate											0.14976	***
Other Morality Rate											0.00369	***
Constant	0.10337	***	0.10706	***	0.07820	***	0.07702	***	0.07065	***	0.06382	***
Sample size	3,190,800		3,150,300		3,150,300		2,989,428		2,989,428		2,989,428	
R-Squared	0.0004		0.0005		0.0005		0.0124		0.0127		0.0183	

Appendix Table 2 Factors associated with other causes of death – 2001 to 2020

Explanatory variables	Alcohol		Poisoning		Other causes	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Year (omitted 2002)						
2003	-0.00252		0.00531	***	0.04693	
2004	-0.00600	***	0.00297	*	0.04448	
2005	-0.00326	*	0.00256		0.02709	
2006	-0.00479	**	0.00399	**	0.02697	
2007	-0.00304		0.00524	***	0.01718	
2008	-0.00301		0.00590	***	0.03029	
2009	-0.01106	***	0.00200		-0.42061	***
2010	-0.00983	***	0.00137		-0.11763	**
2011	-0.00854	***	0.00191		-0.17152	***
2012	-0.01311	***	0.00063		-0.20338	***
2013	-0.00922	***	0.00227		-0.18558	***
2014	-0.00970	***	0.00323	**	-0.18332	***
2015	-0.00946	***	0.00301	*	-0.18664	***
2016	-0.00969	***	0.00402	**	-0.19594	***
2017	-0.00737	***	0.00322	**	-0.19051	***
2018	-0.00913	***	0.00409	**	-0.23477	***
2019	-0.00832	***	0.00529	***	-0.19987	***
2020	-0.00905	***	0.00264		-0.25877	***
Month (omitted January)						
February	0.00126		-0.00027		0.10588	***
March	0.00245		-0.00004		0.24231	***
April	0.00214		-0.00145		0.35114	***
May	0.00511	***	0.00021		0.54826	***
June	0.00476	***	0.00203		0.65966	***
July	0.00409	***	0.00198		0.77898	***
August	0.00777	***	-0.00021		0.64106	***
September	0.00292	*	0.00085		0.36118	***
October	0.00401	***	-0.00075		0.13094	***
November	0.00112		-0.00080		0.04461	
December	-0.00125		-0.00075		0.05874	
Female	-0.01377	***	-0.00602	***	-0.05286	***
Age group (omitted 15 to 29)						
30 to 64	0.01634	***	0.01232	***	0.06790	***
65 plus	0.03031	***	-0.00144	**	1.23975	***
Continuous SEIFA	-0.00002	***	-0.00002	***	-0.00012	
Remoteness (omitted major city)						
Inner Regional	-0.00232	***	0.00019		-0.02242	
Outer Regional	-0.00206	**	-0.00200	**	-0.05552	**
Remote	-0.00065		-0.00468	**	-0.05384	
Very Remote	-0.00115		-0.00702	***	0.00824	

One month lag	0.02554	***	0.03410	***	0.33404	***
Two month lag	0.05113	***	0.00691	***	0.26250	***
Three month lag	0.03427	***	0.04325	***	0.08805	***
Four month lag	0.03400	***	0.01685	***	0.08709	***
Five month lag	0.06285	***	0.00771	***	-0.00437	***
Six month lag	0.03280	***	0.00084		0.01777	***
Seven month lag	0.01931	***	0.00747	***	0.02010	***
Eight month lag	0.05277	***	0.05111	***	-0.00755	***
Nine month lag	0.01229	***	0.01004	***	0.04312	***
Ten month lag	0.01198	***	0.00511	***	0.02120	***
Eleven month lag	0.00799	***	0.01708	***	0.00911	***
Twelve month lag	0.01952	***	0.00941	***	0.01033	***
Region death rate	0.53809	***	0.34626	***	0.08593	***
Constant	0.02623	***	0.01839	***	-0.18827	*
Sample size	2,989,428		2,989,428		2,989,428	
R-Squared	0.0276		0.0083		0.6574	