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On determinants of national suicide rates: evidence from Bayesian model averaging

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ABSTRACT
We aim to establish relative importance of socioeconomic, demographic, geographic and other determinants of national suicide rates. To this aim, we apply Bayesian model averaging (BMA) approach to a dataset of 27 potential determinants in a cross-section of 173 countries. Life expectancy at birth, ambient temperature, age dependency ratio and religious affiliation were found to be the most robust protective factors. Life expectancy at age 65 and unemployment rate are the most robust determinants that are positively associated with suicide mortality.

KEYWORDS
Model uncertainty; Bayesian model averaging; socioeconomic suicide determinants

JEL CLASSIFICATION
I15; C11

I. Introduction

Suicide is one of the leading causes of death worldwide. Globally, more people die due to suicide than to malaria, HIV/AIDS, war or homicide (World Health Organization 2021), and multiple risk and protective factors underly suicide prevalence (Fazel, Runeson, and Ropper 2020). This study aims to establish relative importance of 27 factors as potential determinants of national suicide rates. The variables that we consider fall into four broad categories: geo-climate (e.g. average annual temperature or precipitation), macroeconomic (e.g. GDP per capita or unemployment rate), demographic (e.g. life expectancy or population density) and sociocultural (e.g. internet usage or alcohol consumption per capita).

A search for a satisfactory statistical model of suicide mortality often involves the identification of appropriate variables, lag structure and functional forms. To deal with the large number of potential variables, model selection is often used to find a parsimonious model. Instead of attempting to select a single 'correct model' out of the available set of statistical models, this study relies on the model averaging approach. Model averaging is an alternative that combines inferences from multiple models and incorporates model uncertainty. Prominent overviews of model averaging techniques can be found in the work by Raftery (1995) and Hoeting et al. (1999), whereas more recent advances and applications are reviewed by Moral-Benito (2015) and Steel (2020).

Model averaging techniques are often used where the large number of potential determinants is confronted with the limited number of observations (Clyde 2000; Steel 2020). This approach suits the empirical research on suicide mortality, where only 183 observations are available at the national level, whereas literature proposes numerous factors affecting it (Chen et al. 2012; Fazel, Runeson, and Ropper 2020). A dimensionality reduction approach alternative to ours is to rely on model selection techniques, such as least absolute shrinkage and selection operator (LASSO). For instance, Rockett et al. (2022) apply LASSO to identify important suicide factors among 33 variables measured at US state level.

We employ Bayesian model averaging (BMA) to a dataset covering 27 potential determinants of suicide in a cross-section of 173 countries. BMA computes an unconditional estimate of the parameter of interest as the weighted average of conditional estimates across all possible models. The robustness of a given explanatory variable can be

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assessed on the basis of posterior statistics, such as posterior inclusion probability (PIP). We consider both crude and age-standardized suicide rates, total and stratified by sex.

BMA has been widely used in a range of applications from vaccine effectiveness studies (Oliveira, Shapiro, and Weinberger 2022) to health effects studies for particulate matter (Clyde 2000). Applications of BMA to determine the drivers of complex socioeconomic phenomena extend to economic growth (Brock and Durlauf 2001), political polarization (Grechyna 2016), foreign aid (Bayale 2022). To the best of our knowledge, this study is the first attempt to apply model averaging to the determinants of suicide mortality.

II. Data

We compiled a dataset covering 27 potential suicide determinants across 173 countries with publicly available data. The year 2016 served as the basis. All six suicide mortality variables we considered, along with the 27 variables serving as proxies for suicide determinants, represent aggregated data at the national level. Definitions of the variables and the sources of data are presented in the Supplementary Appendix, Table S.1. Each of the 33 variables used in the analysis has 173 observations corresponding to national aggregates for the 173 countries listed in Table S.3. Table S.2 shows their key summary statistics. As a robustness check, we also considered 3-year averages of suicide rates to stabilize the data.

Dependent variable: suicide rate

We considered two measures of suicide mortality at the country level that have been reported by the World Health Organization (2021): crude suicide rate and age-standardized suicide rate. Crude suicide rate is defined as the number of deaths from suicide per 100,000 population. Age-standardized suicide rate is defined as the weighted average of the age-specific suicide rates. The weights are based on country-invariant population age profile defined by the WHO as 'standard'. They represent the proportions of persons in the corresponding age groups of the standardized population.

We considered total suicide rates as well as male and female suicide rates. In our sample of 173 countries, the mean total suicide rate in 2016 was 9.38 deaths per 100,000 persons. The mean male suicide rate was approximately three times higher than the female suicide rate at 13.97 and 4.90 deaths per 100,000 persons, respectively.

Potential suicide determinants

Table 1 presents the 27 potential suicide determinants selected as regressors for the model averaging approach in the present study. Each explanatory variable is accompanied by references to selected studies that have used it in suicide regressions. These variables have received considerable attention in the literature (see e.g. Fazel et al. (2020) and Chen et al. (2012) for detailed reviews).

The potential factors of suicide prevalence were divided into four broad categories. The first category involves variables related to geographic and climate conditions that might influence suicidal behaviours (Kim et al. 2019; An et al. 2023). These variables include average annual temperature and precipitation, maximum monthly temperature and population weighted latitude in absolute value.

Table 1. Potential suicide determinants.

Variables	Related Studies
Geo-climate factors	
Absolute latitude	An et al. (2023)
Average temperature	Neumayer (2003)
Max. monthly temp.	Fountoulakis et al. (2016)
Precipitation	Fountoulakis et al. (2016)
Macroeconomic factors	
Employment in agriculture	Milner et al. (2012)
Female labor force part.	Jalles and Andresen (2015)
GDP growth	Bussu et al. (2013)
GDP per capita	Meda et al. (2022)
Inflation	Lari and Emamgholipour (2023)
Unemployment	Botha and Nguyen (2022)
Demographic factors	
Age dependency ratio	Matsubayashi and Ueda (2011)
Divorce prevalence	Cai et al. (2022)
Fertility	Okada and Samreth (2013)
International migration	Jalles and Andresen (2015)
Life expectancy at age 65	Breuer (2015)
Life expectancy at birth	Wu and Bond (2006)
Population aged 65+	Milner et al. (2012)
Population density	Oka et al. (2015)
Population growth	Mobley and Taasoobshirazi (2022)
Population sex ratio	Wu and Bond (2006)
Urban population	Ilgun et al. (2020)
Socio-cultural factors	
Alcohol consumption	Ilgun et al. (2020)
Internet usage	Lari and Emamgholipour (2023)
Christianity	Wu et al. (2022)
Islam	Neumayer (2003)
Religiously unaffiliated	Wu et al. (2022)

See Table S.1-S.3 of the Supplementary Appendix for variable definitions, data sources and the list of 173 countries included.

The second group includes macroeconomic factors that have been associated with suicide prevalence (Breuer 2015; Meda et al. 2022). Some of those, such as GDP per capita, fraction of population employed in agriculture and female labour force participation represent common measures of economic development and modernization. Other variables, such as unemployment, GDP growth and inflation, proxy for economic outlook and associated uncertainty.

The last two groups cover a range of demographic and socio-cultural variables. To a varying degree, these variables are associated with often complementary sociological, economic and medical perspectives on suicide. For example, measures of fertility, divorce prevalence or religiosity are often linked to Durkheim's notions of 'social integration' and 'social regulation' as sociological forces affecting suicide (Motillon-Toudic et al. 2022; Stack 2000). Alcohol consumption might affect suicidal behaviour by interfering with several neurotransmitter systems, such as GABA and serotonin (Isaacs et al. 2022). Life expectancy at birth is the key variable associated with economic theories that view suicide as an individual 'rational' decision (Chen et al. 2012).

Our choice of regressors for BMA was influenced by two additional considerations: data availability and computing time. First, aimed to include in the sample as many of the 183 countries for which comparable suicide data are available from the WHO. Second, the dimensionality of the model space grows exponentially with the number of variables, due to which computing time is a limiting factor.

III. Method

We identify the underlying factors that explain suicide mortality by using a BMA approach within a context of a linear regression model (see Luca and Magnus (2011) and Magnus et al. (2010) for detailed description). Inference is based on the posterior distribution of the parameter of interest, which is a weighted average of posterior distributions under the various models weighted by posterior model probabilities (Steel 2020).

In this study, BMA considers 2^{27} regression models based on 173 observations on suicide rates $(n = 173)$ and 27 regressors $(k = 27)$. It obtains ith model M_i by including a subset of regressors and estimates posterior mean coefficients as a weighted average of the estimates conditional on model M_i. Model weights representing the probability that M_i is the 'true' model given the data $p(M_i|y)$ are based on both prior probabilities $p(M_i)$ and observed data, y.

Posterior variance estimators take into account model uncertainty arising from both parameter estimation and model selection. The probability that a variable belongs to the 'true' model, also known as posterior inclusion probability (PIP), is defined as the sum of the posterior probabilities of the model specifications $p(M_i|y)$, which contain that particular variable. Importance of a specific variable in BMA applications is most often measured by its PIP (Moral-Benito 2015; Steel 2020).

An equal prior probability, $p(M_i) = 2^{-k}$, was assigned for each model M_i in this study, thus not prioritizing any variables associated with any particular theory and allowing BMA find the most probable ones. We used the Stata implementation of BMA developed by Luca and Magnus (2011) which relies on $g-$priors. In particular, it follows Fernández et al. (2001) by selecting the same $g_i = 1/\max(n, k)$ for all models M_i (Magnus, Powell, and Prufer 2010).

IV. Results and discussion

Tables 2 and 3 present the most important determinants of crude and age-standardized suicide rate identified by BMA. Three key statistics are shown for each explanatory variable: PIP, unconditional (posterior) mean and ratio of posterior mean to standard deviation (t-statistics). Variables are ranked according to PIP, which indicates the extent to which a variable is a robust determinant of suicide rate. Values of PIP > 0.5 indicate evidence for a regressor, whereas values of PIP > 0.75 indicate positive/strong evidence (Raftery 1995). Estimation results for all 27 potential determinants are presented in Tables S.4 and S.5 of the

Table 2. Robust determinants of crude suicide rates.

Variables	PIP	Mean	*t*-Statistic
Total suicide rates			
Life expectancy at birth	0.999	−0.649	−3.859
Population aged 65+	0.950	0.526	2.722
Age dependency ratio	0.889	−0.124	−2.206
Unemployment	0.822	−0.164	−1.713
Average annual temperature	0.730	−0.142	−1.332
Alcohol consumption per capita	0.521	0.215	0.906
Male suicide rates			
Life expectancy at birth	0.961	−0.791	−2.952
Alcohol consumption per capita	0.886	0.779	2.040
Population aged 65+	0.820	0.654	1.706
Age dependency ratio	0.814	−0.177	−1.730
Unemployment	0.799	−0.265	−1.621
Average annual temperature	0.679	−0.223	−1.119
Female suicide rates			
Life expectancy at birth	1.000	−0.456	−3.946
Christianity	0.958	−0.039	−2.997
Islam	0.920	−0.038	−2.382
Population aged 65+	0.770	0.180	1.491
Life expectancy at age 65	0.746	0.540	1.421
Average annual temperature	0.501	−0.065	−0.883

Posterior inclusion probability (PIP), unconditional (posterior) mean and the ratio of posterior mean to standard deviation (*t*-statistics) are reported for each robust regressor (PIP > 0.5). Values of PIP > 0.5 indicate evidence for a regressor, whereas values of PIP > 0.75 indicate positive/strong evidence (Raftery 1995).

Table 3. Robust determinants of age-standardized suicide rates.

Variables	PIP	Mean	*t*-Statistic
Total suicide rates			
Life expectancy at birth	1.000	−1.876	−5.970
Life expectancy at 65	0.978	2.500	3.312
Unemployment	0.743	0.247	1.413
Age dependency ratio	0.679	−0.133	−1.265
Average annual temperature	0.640	−0.251	−1.183
Male suicide rates			
Life expectancy at birth	1.000	−3.061	−5.339
Life expectancy at 65	0.943	3.778	2.635
Unemployment	0.886	0.558	2.068
Age dependency ratio	0.725	−0.248	−1.395
Islam	0.629	−0.064	−1.106
Average annual temperature	0.546	−0.349	−0.979
Female suicide rates			
Life expectancy at birth	1.000	−0.728	−6.469
Life expectancy at 65	0.994	1.075	4.040
Average annual temperature	0.798	−0.132	−1.718
Employment in agriculture	0.557	−0.026	−0.977

Posterior inclusion probability (PIP), unconditional (posterior) mean and the ratio of posterior mean to standard deviation (*t*-statistics) are reported for each robust regressor (PIP > 0.5). Values of PIP > 0.5 indicate evidence for a regressor, whereas values of PIP > 0.75 indicate positive/strong evidence (Raftery 1995).

Supplementary Appendix. The ratio of posterior mean to standard error in absolute terms (t−ratio) can serve as an alternative measure of robustness: $t > 1$ is roughly equivalent to PIP > 0.5 (Masanjala and Papageorgiou 2008).

Depending on the measure of mortality and the level of disaggregation, several variables proved to be robust determinants of suicide. Out of 27 potentials determinants, we found no evidence in favour of 17 regressors for all six mortality measures.

Life expectancy at birth and life expectancy at age 65

The most robust variable among the potential suicide determinants is life expectancy at birth. It is the only variable that exhibits strong evidence of robustness (PIP > 0.95) for all measures of suicide mortality. Higher life expectancy at birth is associated with lower male, female and total crude or age-standardized suicide rates.

This finding offers some empirical support to the permanent income view of suicide advocated Hamermesh and Soss (1974). Their theoretical framework postulates that the likelihood of suicides diminishes with higher life expectancy or income per capita. However, our empirical support is only partial. First, we found no evidence that GDP per capita or its growth rate are robust determinants of suicide. Second, life expectancy at age 65 was found to be the second most robust determinant of age-standardized suicide rates (PIP > 0.94). Unlike life expectancy at birth, higher life expectancy at age 65 is associated with higher male, female and total suicide rates. This might indicate the importance of health-adjusted measures of life expectancy in understanding suicide patterns.

Unemployment

Unemployment is the only macroeconomic variable that our application of BMA classified as a robust determinant of suicide. This conclusion applies to male and total suicide rates, both crude and age-standardized. Unemployment positively correlates with age-standardized rates in the present study. This finding is consistent with Koo and Cox (2008), who extend the theory of Hamermesh and Soss (1974) to include human capital depreciation during unemployment spells.

Unemployment's relation with crude rate is the opposite. Adjustment for differences in the age distribution reversed the sign, indicating the importance of disaggregation by age or potential nonlinearities (Antonakakis and Collins 2018).

Ambient temperature

Average annual temperature was found to be a robust determinant of all six suicide rates. However, the evidence was weaker than that obtained for life expectancy ($0.5 < PIP < 0.8$ and $|t| > 1$). In all cases, higher temperatures were associated with lower suicide rates, but the effects differed based on sex.

Our results contrasts with those of Fountoulakis et al. (2016), who reported a positive correlation between temperature and suicide in a sample of 29 European countries. This might indicate importance regional disparities or nonlinearities in the relationship between temperature and suicide. For examples, Kim et al. (2019) report inverted-J relationship between environmental temperature and suicide in their multi-country study.

Other robust regressors

Besides those discussed above, several factors proved to be robust determinants of at least one measure of suicide mortality. These factors are fraction of population aged 65+, age dependence ratio, alcohol consumption, employment in agriculture and affiliations with Islam or Christianity.

We find support for age dependence ratio as a robust predictor of age-adjusted male and total suicide rates, both crude and age-standardized. In line with prior research, posterior coefficient estimates reveals that a higher ratio of the dependent population to the working age population is associated with lower suicide mortality (Matsubayashi and Ueda 2011). This result is consistent Durkheim's notion of protective effects of social integration and family ties.

Alcohol consumption positively correlates with crude male and total suicide rates. This result is in line with a recent meta-analysis by Isaacs et al. (2022) which highlights alcohol use as a risk factor for death by suicide. However, alcohol consumption is not a statistically robust determinant of age-standardized measures of male suicide mortality. This suggest that association of alcohol consumption with male suicide mortality substantially varies depending on the age.

Consistent with protective effects of religiosity reviewed by Lawrence et al. (2016), we find that a higher proportion of Christians or Muslims decreases crude female rate. Moreover, a higher proportion of Muslims negatively correlates with age-standardized male suicide rates. Our results suggest substantial variability in the protective influence of religiosity for different segments of population depending on age and sex.

We find some weak evidence ($PIP = 0.557$) that a fraction of population employed in agriculture is a robust determinant negatively correlated with female age-standardized rates. While population aged 65+ was found to be statistically robust for all crude rates, this result did not apply to age-standardized rates.

Robustness and limitations of the study

To enhance the validity of our findings, we address two potential concerns. First, given the low probability of occurrence for events such as suicide, relying on a short observation period could lead to erroneous inferences. To mitigate this concern, we replicate our analysis using the 3-year average of age-standardized suicide rates (2015–2017). Table S.8 in the Supplementary Appendix confirms the stability of the BMA estimates for total, male and female suicide rates.

Second, our measure of population density is based on the total land area rather than habitable land. To address this potential issue, we re-estimate all the specifications after replacing population density with an alternative measure that takes into account uninhabitable areas. We use physiological or real population density, which is defined as the number of people per unit of arable land area. Tables S.6 and S.7 in the Supplementary Appendix show that our results are robust to this change in the definition of the variable that proxies for population density.

Our analysis has several limitations besides its ecological design. First, we focused on a cross-section of countries rather than a panel due to data availability. Second, because our study uses national-level data, it is susceptible to potential cross-level bias. For example, per capita alcohol consumption, identified as a factor associated with suicide mortality, may vary significantly across different groups. Research based on more granular data, for example individual-level data, is better positioned to mitigate this potential issue (see Isaacs et al. (2022) and references therein). Third, we included only a limited number of potential determinants due to the computing time required for BMA. Finally, we did not consider nonlinear effects or the effects of lagged variables due to both data availability and computing time requirements. We intend to address some of these challenges in future research.

V. Conclusion

Life expectancy at birth, ambient temperature, age dependency ratio and religious affiliation were found to be the most statistically robust protective factors. Life expectancy at age 65 and unemployment rate are the most robust determinants that are positively associated with suicide mortality. We document some variability in robustness of suicide determinants depending on sex and age. However, robust factors maintain the signs of their association for both male and female suicide rates.

Due to the dimensionality of the problem and data availability, several important evidence-based predictors of suicide mortality have been left beyond the scope of this study. Some of these factors, discussed by Stack (2021) and Rockett et al. (2022), include metrics of political effort (such as spending on social welfare), measures of availability of lethal means (such as firearms restriction laws), social isolation proxies (such as homelessness and incarceration rates), World Values Survey measures referring to religious beliefs and behaviours as well as acceptance of suicide. Some of these factors could be used in future studies based on WHO national suicide mortality data.

WHO data that we use in this study, while facilitating understanding of global suicide mortality patterns, differ in their quality across several dimensions. For instance, given the illegality of suicidal behaviour in some countries, under-reporting or misclassification is likely to be a greater problem there for suicide than for other causes of death (Wu et al. 2022). On the other hand, the problem of undercount tends to be more severe for female rather than male suicides, given a disproportional use of poisons and drugs by females in their suicides (Rockett et al. 2020).

Disclosure statement

No potential conflict of interest was reported by the author(s).

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