Socioeconomic Factors and Suicide Rates at Large-Unit Aggregate Levels: A Comment

REVISED VERSION

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Summary. Can socioeconomic factors seemingly explain variation in suicide rates at large-unit aggregate levels only due to an ecological fallacy? This is what Kunce and Anderson (2002) suggest based on fixed-effects estimation of US state suicide rates, in which they find little evidence that socioeconomic factors matter. We demonstrate that this result does not hold true for other large-unit aggregate levels in our analysis of suicide at the cross-national level. We find that many socioeconomic factors have a statistically significant impact. We conclude that sociological and economic theories explaining variation in suicide rates at the large-unit aggregate level with the help of aggregate socioeconomic factors cannot simply be dismissed because of an alleged ecological fallacy.

1. Introduction

Kunce and Anderson (2002, p. 160) suggest that a great number of studies, which find evidence that socioeconomic factors matter for the explanation of suicide rates at the large-unit aggregate level (countries, regions, states), are victims of 'an abiding ecological fallacy'. They base their conclusion on fixed-effects estimation of US state age-adjusted suicide rates over the

period 1985-95, in which they find that socioeconomic factors hardly matter. They explain the apparent contradiction between their own result and the established literature as the 'consequence of previous researchers' reliance on cross-sectional data and/or estimation methods' (Kunce and Anderson, 2002, p. 155).

We agree with Kunce and Anderson that cross-sectional data and simple estimation techniques designed for cross-sectional data such as ordinary least squares (OLS) are inappropriate for testing the effect of socioeconomic factors at the large-unit aggregate level. Only panel data allows researchers to control for unobserved time-invariant heterogeneity, so-called fixed effects, as well as aggregate time effects and only panel estimators are appropriate for panel data. However, we demonstrate that Kunce and Anderson's results cannot be invoked to the effect that once fixed effects are controlled for, socioeconomic factors no longer explain suicide at the large-unit aggregate level. We show this by estimating a fixed-effects model for suicide rates at the aggregate country level. At this level, many studies have been undertaken, which are reviewed in Lester and Yang (1997), Stack (2000) and Neumayer (2003). These studies typically fail to control for fixed effects and if Kunce and Anderson's (2002) conclusion was valid, this would put great doubt on their findings.

2. The sociological and economic theory of suicide

What socio-economic factors are usually hypothesised to impact upon suicide? Within this short note, we can merely sketch the modern sociological and economic theory of suicide, which is heavily influenced by Durkheim's (1897/2002) path-breaking book on suicide, as Kunce and Anderson (2002) rightly point out. For Durkheim the key to understanding variation in suicide rates lies in the extent to which individuals are integrated into a social group as well as regulated by its norms and conventions. Following Durkheimian analysis, we would expect, for example, that the (lack of) integration of individuals into the family and the consequent lack of social regulation represents an important determinant of suicide: Higher marriage and fertility rates should be negatively associated, higher divorce rates positively associated with suicide rates. Lower average household size signals a greater potential for feelings of loneliness and lack of integration and should be positively associated with suicide.

Maybe somewhat surprisingly, Durkheim (1897/2002, pp. 25-29) was rather dismissive of alcohol consumption patterns as an explanation of suicide, whereas modern social research has found evidence that heavy consumption of alcohol is strongly related to higher suicide rates, due to both its negative social effects on the individual and others and the higher risk of committing violent acts in a state of acute intoxication (Brainerd, 2001; Ramstedt, 2001). This could be because Durkheim (1897/2002, p. 25)

saw alcoholism more as a ‘psychopathic state’, to which ‘all the ills of our civilization’ were attributed in his time, rather than as a symptom of a lack of integration of the affected individuals.

Even where Durkheim did not develop testable hypotheses himself (perhaps due to the time he was writing in), others have fruitfully used his basic theory to hypothesise that, for example, increased female labour force participation is associated with higher suicide rates. Males are challenged in their role as the bread winners and are less likely to be comforted in their sorrows due to the labour force participation of their female partners, which is particularly problematic for men as their female partners are often their main source of emotional comfort (Stack, 1998). Women are exposed to the stress of the employed work life and often face a double burden of paid outside employment and unpaid housework.

With respect to income levels, Durkheim (1897/2002, p. 214) noted a ‘remarkabe immunity of poor countries’ since ‘poverty protects against suicide because it is a restraint in itself’. Modern sociological theorists have questioned Durkheim’s proposition, arguing that poor people are also confronted with many more personal problems, known to raise the inclination to commit suicide. It stresses the social and psychological deprivations poor people are exposed to and the positive effect of unemployment on suicide (Stack, 2000). Modern economic theory also predicts a negative effect of income on suicide since higher life-time

incomes raise the opportunity costs of committing suicide (Hamermesh and Soss, 1974). Another reason why higher income levels might be associated with lower suicide rates is the generally better quality of emergency medical services in high-income societies, which should lower the success rate of attempted suicides.

3. Research Design

As mentioned already, we test whether socioeconomic factors can explain variation in suicide rates at the country level. Age-specific numbers of suicide and population data for the period 1980 to 1999 were taken from WHO (2002) and WHO-Europe (2002) and converted into age-standardised rates per 10000 inhabitants using the fictitious European standard population of the World Health Organization's (WHO) Regional Office for Europe as the standard. The choice of the standard population is essentially arbitrary (Barclay, 1958). The European standard population has been taken as it is the reference point for the published age-standardised suicide rates in the 'Health for All' database of WHO-Europe (2002). The WHO has now decided to publish only age-standardised mortality rates, a practice already adopted before by its Regional Office for Europe. Using age-standardised suicide rates has the great advantage that national and, if less relevant, over time differences in the age structure are already controlled for. In other

words, one need no longer include the share of specific age groups in one's analysis of age-standardised suicide rates.[1]

To test for the socio-economic factors suggested by our review in the last section, we include the marriage, divorce and crude birth rate per 1000 inhabitants as well as the average number of persons living in a household. Marriage, divorce and household size data are taken from Euromonitor (2002) and complemented by UN (2001). Data on birth rates and on female labour force participation measured as a percentage of females aged 15 to 64 are taken from World Bank (2001). We also include pure alcohol consumption in liters per capita. This variable is taken from WHO-Europe (2002) and WHO (1999). To test for the impact of income on suicide rates, we include GDP per capita in thousand US$ of purchasing power parity, with data generally taken from World Bank (2001). Missing income data were taken from estimations undertaken for WHO (2000). The income data were converted into constant US$(1997) with the help of the United States GDP deflator. The unemployment rate taken from Euromonitor (2002) has very poor data availability. Pre-testing showed it to be highly insignificant, possibly due to enormous measurement error given national differences in the definition and recognition of unemployment. We therefore do not include this variable in the results reported below. The other variables are hardly affected by the inclusion or exclusion of this variable.

Table 1 provides summary descriptive information on the dependent and independent variables. To check for multicollinearity, we estimated variance inflation factors, which were below 3.2 for all variables with a mean value of 2.08. Since factors above 10 are usually regarded as problematic (Kennedy 1992), there is therefore no reason to be concerned about multicollinearity.

< Insert Table 1 here >

As concerns the estimation technique, like Kunce and Anderson (2002) we use a fixed-effects estimator to estimate basically the same model as they do:

$$Y_{it} = \alpha + \beta X_{it} + \mu_t + \lambda_i + u_{it} \quad (1)$$

Y is the suicide rate, α is a constant, *X* contains the socioeconomic explanatory variables, β is the corresponding vector of coefficients to be estimated. The μ_t variables are T-1 year specific dummy variables, controlling for aggregate time effects. The λ_i variables represent time-invariant country effects, the u_{it} is the error term.[2] The only difference to Kunce and Anderson (2002) is that they log the dependent variable to mitigate potential problems with heteroscedasticity. Instead, for our fixed-

effects estimation we use a more robust and therefore superior way to control for heteroscedasticity in the form of standard errors that are fully robust towards arbitrary heteroscedasticity (as well as autocorrelation). The fixed-effects estimator subtracts from each variable the over-time average of the variable for each cross-sectional unit. Because of this so-called within transformation the individual country effects λ_i are wiped out and the coefficients are estimated based on the time variation within each cross-sectional unit only. The big advantage of the fixed-effects estimator is that any potential correlation of the explanatory variables with the fixed effects is rendered unharmful since the fixed effects and therefore their correlation with the explanatory variables are wiped out from the equation to be estimated. The random-effects estimator estimates all coefficients more efficiently than the fixed-effects estimator in treating unobserved country heterogeneity as random effects and therefore using both the cross-sectional (between) and time-series (within) variation of the data. However, it depends on the assumption that the country effects are not correlated with the explanatory variables so that the individual country effects can be regarded as part of a composite error term $v_{it} = (\lambda_i + u_{it})$. This random-effects assumption can be tested with a so-called Hausman test. This tests whether the coefficients estimated by a random-effects estimator systematically differ from the coefficients estimated by a fixed-effects estimator.

With respect to sample size, because the divorce, marriage and household size variables have smaller data availability than the other variables, we estimate two models, namely one with and one without these variables. The size of the sample of our analysis is dictated entirely by the availability of data. No country is excluded *per se*. Appendix 1 lists the countries included in the two different samples, where for some countries data are not available for all years. It is clear that even in the larger sample, which covers 79 as opposed to 62 countries, many countries are still missing, particularly from the developing world. This is because they do not report reliable suicide data to the WHO. Since their exclusion, which cannot be remedied, might lead to sample selection bias, we additionally estimate a two-stage sample selection model using Heckman's (1979) full maximum-likelihood estimator. In this model, we first explain the selection of countries into the sample using per capita income, autocracy (Freedom House 2002), the urbanisation rate and the natural log of population size (World Bank 2001) as explanatory variables. In the second stage, a fixed-effects model then explains variation in suicide rates. Note that because both stages are estimated jointly, the error terms from both stages are allowed to be correlated and this is taken into account in Heckman's estimator.

4. Estimation Results

Column I of Table 2 presents our large sample estimation results with fixed-effects due to the exclusion of the divorce, marriage and household size variables. Income has a statistically significantly negative impact on suicide rates as modern sociological and economic theory would predict. The coefficient of the female labour force participation rate is statistically insignificant. The two remaining variables test in accordance with Durkheimian theory: Higher per capita alcohol consumption is associated with higher suicide rates, whereas a higher birth rate lowers suicide rates. If we control for potential sample selection bias with the help of Heckman's two-stage sample selection model, then our results are all upheld (see column II). Our first-stage explanatory variables are all highly significant predictors of whether a country could be included in our sample due to available suicide data. A Wald test cannot reject the hypothesis of independent equations at both stages, providing additional evidence that sample selection is not a problem here. Our results are also confirmed if a random-effects estimator is used instead of fixed-effects estimation (column III).[3] The only difference is that the coefficient of the female labour force participation rate becomes significant with the expected positive sign in random-effects estimation. The Hausman test, which tests the random-effects assumptions fails to reject the hypothesis that the differences

between the fixed-effects and random-effects estimation results are down to chance and not systematic.

< Insert Table 2 here >

Column I of table 3 presents fixed-effects estimation results of the smaller sample size, as we now additionally include the divorce, marriage and household size variables. All the existing variables test as before with the exception of the female labour force participation rate, the coefficient of which is now statistically significant with the expected positive sign. With respect to the newly included variables, a higher divorce rate is positively associated with suicide, whereas the opposite holds true for the marriage rate and the average household size, all in line with expectation. Heckman's sample-selection model leads to very similar results, which are reported in column II, and the Wald test clearly fails to reject the hypothesis of independent equations. Results are also very similar in random-effects estimation reported in column III. Given the strong congruence in results from the fixed-effects and random-effects estimation, we are not surprised to find that the Hausman test fails to reject the random-effects assumption.

5. Conclusion

All socio-economic factors are statistically significant and according to expectation in our estimation results with the exception of the female labour force participation rate in fixed-effects estimation in the large sample. We do not know why socioeconomic factors turn out to be mostly insignificant in Kunce and Anderson's (2002) analysis of US state suicide data. We note that they do not include either the marriage rate, birth rate, female labour force participation rate or alcohol consumption patterns. The first two figure prominently in Durkheim's original analysis of suicide and the latter two are well established variables in modern suicide research. They therefore fail to include four important socioeconomic factors in their analysis of the impact of socioeconomic factors on US state suicide rates. On the other hand, we readily admit that Kunce and Anderson (2000) control for a few other variables, which we cannot include due to lack of data.

In any case, our results clearly show that socio-economic factors are relevant for explaining variation in suicide rates at the country-level even after controlling for country-specific fixed effects. We fully agree with Kunce and Anderson (2002) that a failure to control for fixed effects can lead to spurious regression results. We also agree with their and Kposowa, Breault and Singh's (1995) call for more studies to be undertaken with individual-level data where such data are available. However, our results demonstrate that the sociological and economic theories explaining

variation in aggregate large-unit suicide data cannot be dismissed out of hand because of an alleged ecological fallacy.

We would like to extend the present analysis and test the power of socio-economic factors to explain suicide rates in fixed-effects estimation at the sub-national level outside the US. One of the problems is that there are few federations made up of multiple jurisdictions similar to the US and fewer still that would have sufficient data available. Such an extension of our research remains a task for future research.

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Table 1.

Descriptive statistics of variables.

	N	Mean	Std. Dev.	Min.	Max.
suicide rate	1097	14.9	10	0.1	48.5
gdp p.c.	1097	12.2	7.5	1.3	41.6
birth rate	1097	17.1	7.3	7.6	42.1
female labour force participation	1097	37	9.8	11.1	52.7
alcohol consumption	1097	7.3	3.5	0	17.7
divorce rate	951	1.9	1.1	0.1	6
marriage rate	1028	6.7	1.9	2.4	17.7
household size	917	3.3	1	2	9.1
autocracy	1097	5.6	4	2	14
urbanisation rate	1097	67.5	16.9	17	100
population size (logged)	1097	15.9	1.5	12	19.4

Table 2. Estimation results (large sample).

	I Fixed effects	II Heckman with fixed effects	III Random effects
gdp p.c.	-0.28	-0.28	-0.26
	(3.91)**	(4.10)**	(5.12)**
female labour force participation	0.06	0.06	0.17
	(0.83)	(0.88)	(3.12)
birth rate	-0.32	-0.32	-0.38
	(5.07)**	(5.33)**	(7.74)**
alcohol consumption	0.49	0.48	0.41
	(4.92)**	(5.15)**	(5.59)**
gdp p.c. (first stage)		0.05	
		(9.63)**	
autocracy (first stage)		-0.05	
		(6.42)**	
urbanisation rate (first stage)		0.02	
		(17.51)**	
ln(population) (first stage)		0.09	
		(16.47)**	
R^2 (within)	0.1623		
Log likelihood		-3995.8	
R^2 (overall)			0.2635
Wald test chi^2 (independent eqs.)		0.31	
Wald test p-value		0.5783	
Hausman test chi^2			12.28
Hausman test p-value			0.9659
Number of countries	79	79	79
Number of observations	1097	1097	1097

Dependent variable is age-standardised suicide rate (suicides per 100,000 inhabitants). Absolute t statistics and z statistics in brackets. Coefficients of period and country specific dummies not shown. ** significant at .001% level.

Table 3. Estimation results (small sample).

	I Fixed effects	II Heckman with fixed effects	III Random effects
gdp p.c.	-0.36	-0.36	-0.40
	(4.25)**	(4.49)**	(6.35)**
female labour force participation	0.21	0.21	0.19
	(2.63)*	(2.79)*	(2.84)*
birth rate	-0.32	-0.32	-0.29
	(3.86)**	(4.09)**	(4.07)**
alcohol consumption	0.52	0.52	0.49
	(3.88)**	(4.10)**	(5.27)**
divorce rate	2.22	2.22	2.32
	(5.47)**	(5.79)**	(7.06)**
marriage rate	-1.18	-1.18	-1.14
	(5.70)**	(6.04)**	(7.13)**
household size	-2.43	-2.44	-2.20
	(3.88)**	(4.11)**	(4.07)**
gdp p.c. (first stage)		0.06	
		(11.10)**	
autocracy (first stage)		-0.05	
		(6.12)**	
urbanisation rate (first stage)		0.03	
		(18.93)**	
ln(population) (first stage)		0.17	
		(11.62)**	
R^2 (within)	0.3553		
Log likelihood		-2786.6	
R^2 (overall)			0.5028
Wald test chi^2 (independent eqs.)		0.14	
Wald test p-value		0.7114	
Hausman test chi^2			10.12
Hausman test p-value			0.9978
Number of countries	62	62	62
Number of observations	812	812	812

Dependent variable is age-standardised suicide rate (suicides per 100,000 inhabitants). Absolute t statistics and z statistics in brackets. Coefficients of period and country specific dummies not shown. * significant at .01%; ** significant at .001% level.

Appendix 1: Countries included in sample.

Albania, Armenia, Australia, Austria, Azerbaijan, (Bahamas), Bahrain, Barbados, Belarus, Belgium, (Belize), Brazil, Bulgaria, Canada, Chile, (Colombia), Costa Rica, Croatia, (Cuba), Czech Republic, Denmark, Dominican Republic, Ecuador, (El Salvador), Estonia, Finland, France, (Georgia), Germany, Greece, (Guatemala), (Guyana), Hungary, Iceland, (Ireland), Israel, Italy, (Jamaica), Japan, Kazakhstan, Kuwait, (Kyrgyz Republic), Latvia, Lithuania, Luxembourg, (Macedonia), (Malta), (Mauritius), Mexico, Moldova, Netherlands, New Zealand, Norway, Panama, (Peru), Poland, Portugal, Romania, Russian Federation, Singapore, Slovak Republic, Slovenia, South Korea, Spain, Sri Lanka, Suriname, Sweden, Switzerland, (Tajikistan), Thailand, Trinidad and Tobago, Turkmenistan, Ukraine, United Kingdom, United States, Uruguay, (Uzbekistan), Venezuela.

Note: Countries in brackets included in larger sample only.

NOTES

[1] We do not understand why Kunce and Anderson (2002) include the percentage of state population aged 15-24 given that their suicide rates are already age-adjusted.

[2] Like Kunce and Anderson (2002) and practically all other studies of variation in suicide rates, we include the explanatory variables without lags. Lagging these variables by a number of years does not change our major results.

[3] Note that there is no easy way to estimate an unbalanced random-effects model with robust standard errors. The reported standard errors therefore are non-robust.