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The effect of public spending on suicide: Evidence from U.S. state data

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Abstract

This paper investigates the effect of public spending on health and welfare on total, male and female suicide rates using panel data for U.S. states over the time period 1982–1997. We show that the share of health and welfare in total public spending are strong predictors of suicide rates and yield estimated coefficients that are both statistically significant and economically meaningful. In parsimonious specifications, we also find that suicide rates are systematically higher in states with higher divorce rates, but average income level, income inequality and unemployment rates do not have a robust impact on suicide. The model provides a better fit to male than to female suicide data. Our main results hold up to a series of specification tests.

Keywords: Suicide mortality; Public health; Welfare; United States

JEL classification: I12; I18; O51

1. Introduction

A high number of deaths by suicide have been recorded in the United States during the last 30 years: intentional self-harm is not only the eleventh leading cause of death, but it has claimed 745,000 victims between 1978 and 2002 (with an added 30,642 deaths in the year 2003 alone).[1]

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[1] Source: Doan et al. (2003).

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It is the eighth leading cause of death for males, and the nineteenth leading cause of death for females.[2]

In recent years, a number of quantitative studies, using both cross-sectional and panel data, have examined the economic factors that influence suicide mortality rates.[3] Most of the empirical work on the economics of suicide builds on the framework developed by Hamermesh and Soss (1974).[4] The authors define an individual's lifetime utility at a given point in time as the discounted expected gain from living; the decision to commit suicide is made when one's expected lifetime utility reaches zero. Lifetime utility is constructed as a function of age, permanent income, and the cost of maintaining oneself alive.[5] The theoretical implications drawn from this model are then tested against data from a panel of 21 states from the United States. Within this framework, the authors identify three main economic determinants: age, income, and unemployment.

The empirical analyses that were subsequently undertaken focused on the following (aggregate) economic and social determinants of suicide mortality: GDP per capita, unemployment rate and female participation in the labor force as well as divorce rates, fertility rates, alcohol consumption, inequality, and religion. Even institutional variables and cultural factors have been accounted for in the literature (Brainerd, 2001; Chuang and Huang, 1997, 2003; Rodríguez, 2005; Neumayer, 2003a, 2003b; Jungeilges and Kirchgässner, 2002; Helliwell, 2004; Ramstedt, 2001).

Despite the extensive evidence and a growing concern for the relationship between suicide and socio-demographic variables, suicide in the United States has received little attention in the economics literature. There have been, however, some recent attempts in this direction, for example Kunce and Anderson (2002).[6] Using panel data techniques, Kunce and Anderson (2002) find that socioeconomic factors enter their specifications insignificantly. However, they fail to account for important socioeconomic factors, such as income inequality, divorce rate, and female labor participation rate. Furthermore, pooling suicide data across genders can lead to misleading conclusions since the drivers of male and female suicide mortality may not be the same.[7] The results of this study could further be questioned due to the presence of serial correlation in the error term which may cause biased estimates of the slope parameters resulting from the Fixed Effects estimation procedure.

In this paper, we analyze the economic determinants of suicide across states in the United States between 1982 and 1997. We contribute to the literature by extending the typical statistical model of the determinants of suicide to account for the financial effort made by state governments to address public health issues (to which we broadly refer to as 'public action'). We introduce two novel variables which we posit are likely to have an impact on suicide rates, both of which have previously been ignored in the empirical literature. These variables are (a) the proportion of health expenditure and (b) that of welfare expenditure in total public spending. We assess the

[2] Notwithstanding issues of cross-country comparability of suicide data, in a list of 99 countries compiled by the World Health Organization, the United States ranks 45th in terms of number of suicide acts per year (2003 or closest estimate). See http://www.who.int/mental_health/prevention/suicide/country_reports/en/index.html.

[3] An extensive review of the literature can be found in Lester and Yang (1997). Yang and Lester (1996) review modeling frameworks that can be used as a basis for theoretical assessments of suicide.

[4] Most of the empirical work on suicide has been influenced, however, by the conceptual work by Durkheim (1951). He postulated that societal suicide rates were likely to be influenced by social integration and social regulation.

[5] Recently, Marcotte (2003) expanded this model to include the possibility that the utility function may itself be affected by suicide attempts.

[6] Studies of time series for the United States include Yang (1992), and Yang and Lester (1990, 1994), Yang et al. (1992).

[7] On the different determinants of male and female suicide rates, see Rodríguez (2005), Kposowa (2000), Brainerd (2001), Kunce and Anderson (2002) and Helliwell (2004).

contribution of these variables to explaining variation in suicide rates across U.S. states while accounting for the effect of other economic factors (e.g., income level, unemployment rates and economic uncertainty), demographic characteristics (e.g., divorce rates) and geographical differences (e.g., population density).

We find that the share of public health and welfare expenditures in the total state budget are strong predictors of total, male and female suicide rates. The coefficient estimates are statistically significant and their magnitudes are economically meaningful. Our specifications provide a better fit to male suicide data than to female suicide data, but our sensitivity tests could be used as a starting point for future analyses of the determinants of female suicide rates (which have generally received less attention in the empirical literature). The broad conclusions of our study are twofold. First, our findings suggest the importance of accounting for the effects of public spending on health outcomes in empirical analyses of the determinants of suicide mortality. Second, they highlight the role of state-level health and welfare support aimed at assisting those in need.

The remainder of the paper is organized as follows: Section 2 discusses the variables that are included in the baseline specifications. Our model, estimation strategy and empirical results are presented in Section 3. Section 4 presents a series of robustness checks and conclusions are drawn in Section 5. Average suicide rates by state, summary statistics, correlation matrices and regression results are included in the Appendix A.

2. Variables and discussion

2.1. 'Public action' variables

We put forth the hypothesis that the level of effort exerted by the state government in providing health services and improving the health level of its population is correlated with observed suicide rates. The extent of this effort is measured by the share of public health spending in the state budget. This variable is thus a proxy for the amount of medical personnel and medical equipment, as well as for the overall quality of the health system; all of the above may affect (the level and quality of) medical supervision during times when the act of suicide is thought of as an option. In addition to its direct effect on health, this variable can also capture people's perceptions of how generously the state government spends towards their well-being.

The share of welfare spending in total financial outlays of the state government is another variable that measures the extent of 'public action' in any given state. Its direct effect is channeled through income, since welfare aims at improving the financial condition of people in disadvantaged circumstances (i.e., those facing unemployment spells, the prospect of divorce or single motherhood, etc.). Beyond this effect, however, the variable could further explain variation in suicide rates since it captures the government's degree of preference for redistributive policies which compensate disadvantaged social strata. This, in turn, is indicative of the level of social fairness that a given state intends to attain, and will affect satisfaction levels, hence suicide.

In our sample, there is substantial cross-state and cross-time variation in both the health and welfare proportions of public expenditure. For instance, public health expenditure in the state of Colorado varies between 3.6 percent (1997) and 7.4 percent (1986), while public welfare expenditure in the state of New Hampshire varies between 14.9 percent (1983) and 39.5 percent (1992). Furthermore, mean proportions of public health expenditure range between 3.2 percent of the state budget (Alaska) and 10.4 percent (Alabama). Similarly, mean levels of public welfare expenditure range between 8.2 percent of the state budget (Alaska) and 25.2 percent (Maine).

2.2. Economic control variables

In specifying our baseline model, we draw on the 'happiness' literature and propose that the process underlying suicide rates is a function of income inequality,[8] which we measure with standard inequality indicators.[9] These are intended to capture several possible effects: in a society with high income equality, people's motivation levels and satisfaction from work may be eroded since equality can be perceived as occupational, and more broadly, social immobility. Furthermore, people's level of satisfaction may be affected by negative social phenomena (such as crime or infringement of property rights) – usually associated with higher inequality. Alternatively, high income equality may give people a sense of social fairness. The empirical analysis will determine which of these effects prevails in the data.[10] It is noteworthy that the literature has found little evidence of a relationship between income inequality and suicide mortality or between income inequality and health (Mellor and Mylio, 2001; Rodríguez, 2005; Neumayer, 2004; Osler et al., 2002; Kennelly et al., 2003).[11]

The empirical evidence on the relation between average income level and suicide mortality has been mixed. As mentioned, Hamermesh and Soss (1974) developed a theoretical model which predicted that age, permanent income, and the cost of maintaining oneself alive are possible predictors of suicide. The intuition provided by the theoretical framework suggests there may be correlations between suicide rates and average per capita income as well. Although some studies indicate that suicide rates have a positive association with income (Hamermesh, 1974), many others identify the opposite effect (Brainerd, 2001; Chuang and Huang, 1997, 2003). To account for the effects of average income (whose role as an explanatory variable remains an open empirical question) on suicide mortality, the statistical model proposed in this paper includes per capita income as a covariate.

Intuition suggests that there may be a relationship between the stability of the economy and suicide rates. Uncertainty associated with changes in the economic environment may constitute a source of stress that plays a role in the act of suicide.[12] Consequently, we choose to include in our model a measure of economic uncertainty. To this end, we use variation on state-level migration flows (expressed as the share of persons who changed residence by moving in or out of each state in that state's total population). This variable is meant to reflect changes in the economic environment that may lead to distress ultimately conducive to suicidal behavior.[13]

Another indicator of economic conditions is the level of unemployment. Unemployment may have both a direct and an indirect effect on suicide mortality. The experience of an unemployment spell can be associated with factors, such as anxiety, depression, and loss of confidence that might directly drive suicide. The psychological effect of an unemployment spell or a high unemployment rate in the economy, hence feeling insecure about one's own employment, are

[8] Alesina et al. (2004) document that higher inequality levels are associated with lower self-reported levels of happiness in a sample of 123,688 individuals from Europe and the US. The effect is weaker for the Americans. Furthermore, Di Tella et al. (2003) report that the level of self-rated happiness is negatively correlated with suicide rates for Europeans and Americans alike.

[9] Throughout the paper, we use the Gini coefficient as our measure of income inequality. We also employed a series of other indicators (e.g., standard deviation of logarithms, relative mean deviation, coefficient of variation and Atkinson indices with parameter values 1, 2 and 3), but the main results shown in the paper remained unaltered. The analysis involving these alternative indicators are thus not reported in the paper, but are available from the authors upon request.

[10] For a description of the channels through which inequality migh affect health, see Kawachi et al. (1999).

[11] For comprehensive surveys of the literature in this area, see Deaton (2003) and Judge and Paterson (2001).

[12] See Henry and Short (1954) for arguments about the effect of environmental factors that lead to frustration.

[13] We thank an anonymous referee for the suggestion of using this proxy for economic uncertainty.

the direct channels through which the level of unemployment may operate on suicide rates. The indirect effect is through the income channel, since periods of unemployment may be characterized by a lower stream of income and increased consumption uncertainty. At the same time, unemployment levels tend to co-move with per capita income growth rates; thus, we include unemployment also as a proxy for periods of boom and recession. We note, in connection with our inclusion of this variable, that empirical studies have found weak evidence of the relationship between unemployment and suicide rates.[14] This is especially the case in cross-country studies. In contrast, some time series analyses for the U.S. (Yang, 1992; Yang and Lester, 1990, 1994; Yang et al., 1992) and Finland (Viren, 1996), have provided evidence of a positive association between the two variables. However, this correlation is weak in other countries (Yang and Lester, 1995). Recent panel data studies have confirmed the hypothesized adverse relationship between unemployment and suicide (Chuang and Huang, 1997, 2003; Brainerd, 2001; Neumayer, 2003a) or unemployment and health (Ruhm, 2000). In contrast, Neumayer (2004), using panel data for German states, reaches opposite conclusions. The author finds that unemployment is negatively and statistically significantly related to total, male and female suicide rates. In light of this mixed evidence, we include unemployment as an economic control variable in this paper in an attempt to provide further evidence on the posited relationships using U.S. state-level data.

2.3. Other control variables

Our next control variable is driven by the observation of an important pattern in our data: there is considerable variation in mean suicide rates (between 1982 and 1997) across states, with some of the states having average suicide rates as high as 1.5 times the mean for the sample (average suicide rates for each state are reported in Table 1 in the Appendix A). These are primarily mountainous states: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming. This pattern suggests that such states share common characteristics that should be accounted for, albeit imperfectly, by a dummy for predominantly mountainous regions.[15] Including this dummy in our model points to the possibility of important omitted variables; we partially address this concern in our specifications by including a demographic control variable (namely, population density[16]). Low population density may be associated with a lower degree of social integration which, in turn, can increase the likelihood of suicide. Studies of the urban–rural differential have emphasized loss of population, marital instability and increasing proportions of persons living alone as factors that reduce social integration in rural settings (Fernquist and Cutright, 1998; Seeman, 1996). Such differential has been increasing in recent years (Singh and Siahpush, 2002). In Section 4, we attempt to address the omitted variables problem by trying alternative specifications with an additional climate control. Climate conditions can influence suicide indirectly as they influence mood or pshychological well-being, which in turn can lead to depression. Robbins et al. (1972), for example, document a positive statistical association between suicide and cold climate. Thorson and Kasworm (1984) find the same association with lack of sunshine, whereas Lester (1988) finds

[14] For a review of the literature relating unemployment to suicide rates, see Platt (1984[0]).

[15] One such dummy is defined for Western U.S. states by Hamermesh and Soss (1974) based on the observation that the average suicide rate in Western states is significantly higher than that in Eastern states. Notably, there is a high correlation between dummies defined for mountain and western states. In the U.S. Mountain states have an average suicide rate of 23.6 per 100,000 population (ranging between a minimum of 16.9 and a maximum of 38.7) whilst non-mountain states have a suicide rate average of 15.3 (ranging from 6.2 to 28.8).

[16] In our sample, population density is negatively correlated with the mountain dummy. The correlation coefficient is −0.11 and it is statistically significant at the 95 percent level of significance.

no such relationship.[17] Recently, Neumayer (2003b), using a panel data approach, found that the average number of sunshine hours is negatively correlated with suicide mortality.

To account for the multitude of social and economic factors that may affect suicide rates, the divorce rate is usually included in empirical models.[18] According to Durkheim's reasoning, divorce reduces social integration and weakens family ties; therefore, states characterized by a high divorce rate are expected to have a higher suicide rate. The empirical literature provides evidence that divorce rates are positively associated with suicide mortality. Furthermore, it has been argued that the extent to which women are actively involved in economic activities is correlated with divorce rates. Bentzen and Smith (2002) and Stevenson and Wolfers (2006) document a causal relationship between these two variables. To avoid a possible collinearity problem that may arise from including both measures of the degree of women's participation in the labor force[19] and divorce rates in the same specification, we opt solely for the latter.[20]

Some of the variables considered in the analysis are introduced in the regressions in one-period lagged form. This is justified by our conjecture that individuals may have some tolerance level in facing unfavorable conditions. The act of suicide is the final step in coping with misfortune. Therefore, we assume that it takes time for individuals to respond to environmental conditions with the act of suicide. The only economic variables which are not introduced in lagged form are unemployment, share of migrant population and the Gini coefficient of income inequality. This is because unemployment spells are likely to have a contemporaneous effect on suicidal behavior rather than a lagged one. Similarly, the share of migrant population is meant to capture uncertainty about current economic (and future) conditions, while the Gini coefficients evolve very slowly over time.

We also include a second order polynomial function of time in the model in order to capture possible deterministic trends in the data. For instance, the state-level variables on income, the share of health and welfare expenditure in public spending, have upward time trends, with some curvature for the latter variables. Thus, the time polynomial will aid in isolating their idiosyncratic effect on the pattern of state-level suicide rates and will also act as a proxy for common shocks to the model.

3. Empirical strategy and findings

The economic theory of suicide is tested in this paper using data for 47 U.S. states covering the time period 1982–1997.[21] Data on (normalized) suicide rates for the whole population and by gender was obtained from the Centers for Disease Control and Prevention.[22] We use age-adjusted figures for the age group 26–69, since the determinants of teenage, early youth and elderly suicides may well differ from the ones we propose in this study. Another reason to focus on this age group is because we expect teenagers and the elderly to be less sensitive to changes in the

[17] Durkheim (1951), nevertheless, found conditions of the physical environment theoretically unconvincing.

[18] See Chuang and Huang (1997, 2003), Brainerd (2001), Rodríguez (2005), Neumayer (2003a), and Yang et al. (1992)[0].

[19] Indeed, some panel data studies offer evidence that female labor participation is not statistically significantly correlated with suicide rates (Chuang and Huang, 1997, 2003; Neumayer, 2003a).

[20] We introduced alternative measures of women's participation in the labor force as controls in the statistical models. The main findings, however, were not altered, and the regressions are not included in this paper, but they are available from the authors upon request.

[21] The regressions use (unbalanced) panel data for 50 states. The District of Columbia is not included in the analysis because no data for several regressors is available for this administrative unit. Also excluded are state-year cells for which information is not available for at least one of the regressors. Information for the years 1990 and 1992 is lost due to gaps in the public health and welfare expenditure variables. The total number of observations is 665.

[22] The relevant codes for suicide used in this study were: E950-E959 (ICD-9).

economic environment than the (working) age group 26–69. We apply a natural log-transformation to the dependent variable despite little evidence of severe skewness of its distribution.[23] All the coefficients in the model are thus interpreted as semi-elasticities.

Data on state-level economic variables were obtained from the Statistical Abstract of the U.S., Bureau of the Census, 1982–2000. Migration flows were constructed using the individual-level information on state of current and past residence from the Current Population Survey. We retain in our dataset only the observational units for which we have full data on all variables of interest, resulting in a sample of 665 observations. Summary statistics are reported in Table 2 in the Appendix A. Table 14 in the Appendix A reports the data sources.

We report pair-wise correlation matrices among the variables used in the analysis Tables 3 and 4. Table 3 shows that raw correlations between the dependent variables and regressors are all significant at the 99 percent level of significance. As expected, negative and significant correlations are observed between the dependent variables and the share of public health and welfare spending in total state budget, and positive correlations are observed between the dependent variables, divorce rates and the mountain state dummy. These results are suggestive of several substantive correlations which will be subsequently endorsed by regression analysis.

Our baseline, most parsimonious model (three variants of which we implement) takes the following form:[24]

$$\begin{aligned}\ln \text{Suicide\_Rate}_{it} = {} & \alpha_i + \beta_1 \text{Income}_{i,t-1} + \beta_2 \text{Migration}_{it} + \beta_3 \text{Unemployment}_{it} \\ & + \beta_4 \text{Pop\_Density}_{it} + \beta_5 \text{Mountain\_Dummy}_i + \beta_6 \text{Divorce}_{it} + \beta_7 \text{Gini}_{it} \\ & + \beta_8 \text{Health\_Exp}_{i,t-1} + \beta_9 \text{Welfare\_Exp}_{i,t-1} + \beta_{10} \text{Time} + \beta_{11} \text{Time}^2 + \varepsilon_{it}\end{aligned}$$

where the subscripts $i = 1, \ldots, 50$ and and $t = 1982, \ldots, 1997$ represent states and time periods, respectively, α_i are the state-level time-invariant unobserved heterogeneity effects, and ε_{it} is the observation-specific error term and is serially correlated within and between panels. A number of studies have provided evidence on the differential effect of socioeconomic variables on male and female suicide rates (Rodríguez, 2005; Kposowa, 2000; Brainerd, 2001; Kunce and Anderson, 2002; Helliwell, 2004). We therefore estimate the model separately for males and females.

Given the presence of state-level time-invariant unobserved characteristics which may be correlated with omitted variables, a natural estimation method requires a Fixed Effects (or within) transformation of the data through which the α_i's are eliminated. We note two important caveats regarding the within transformation. First, and most importantly, the within-transformed error term (i.e., $\varepsilon_{i\bullet} = \varepsilon_{it} - 1/T \sum_{t=1}^{T} \varepsilon_{it}$) is a function of all the error terms between time periods 1 and T. For the Ordinary Least Squares estimator to be consistent when applied to the within-transformed data, it is necessary that the regressors be strictly exogenous (Wooldridge, 2002, pp. 251–253). In particular, it is required that current shocks to suicide rates are uncorrelated with future values of the regressors. This requirement is very restrictive and unlikely to hold in our setting. For example, it is easy to argue that a current (positive) rise in suicide rates (which is unexplained by the included independent variables and is hence captured by ε_{it}) is likely to be correlated with one-period ahead public health spending.

[23] This transformation is inconsequential for the goodness-of-fit of our models.

[24] A dynamic panel data model version of this model (with fewer explanatory variables) has been proposed by Stack (1992). Estimating that model instead of the one we report does not alter our main findings, but it yields slightly lower coefficient estimates for the 'public action' variables.

For the reasons outlined above, we do not pursue a Fixed Effects estimation strategy. Instead, we opt for the 'system' Generalized Method of Moments estimator (henceforth, 'system GMM') proposed by Arellano and Bover (1995) and Blundell and Bond (1998) and accessibly described in Bond (2002). The estimator, although designed for dynamic panel data models, is appropriate in our case for the following reasons: (1) the variables included in the model in one-period lagged form are correlated with current errors ε_{it} by virtue of serial correlation in ε_{it}. They are therefore endogenous. (2) The unobserved heterogeneity effects α_i may be correlated with included regressors, which would render them endogenous. A first differencing approach is thus necessary to address this omitted time-invariant variable problem. The system GMM estimator is, under mild restrictions on the initial conditions, consistent as it combines instruments based on two types of moment conditions: those arising from orthogonality between endogenous variables (in first differences) and their lagged levels, and those arising from orthogonality between endogenous variables (in levels) and their lagged differences.[25] It is also more efficient than the level and the difference GMM estimators since the latter incorporate only subsets of the instruments used by the system GMM estimator.

In all our specifications, we report the *p*-values of the Arellano–Bond tests for autocorrelation applied to the first difference equation residuals (in which we expect not to reject the null hypothesis on an autoregressive regression model AR(1) but we are hoping to reject the null hypothesis of second order autocorrelation so as to conclude that lagged values of the endogenous variables are valid instruments). Finally, we report the *p*-values of the standard Hansen *J* statistic for a test of overidentifying restrictions (the null hypothesis is that the instruments used by the system GMM estimator – as a group –are exogenous). These specification tests will confirm whether the system GMM estimator is indeed appropriate in our case.[26] The standard errors calculated are consistent in the presence of heteroskedasticity of unknown form and autocorrelation within panels of unknown form. The population density and the mountain state dummy are used as standard (strictly exogenous) instruments.

The regression results for a panel of 50 U.S. states between 1982 and 1997 are reported in Tables 5–7 in the Appendix A, each corresponding to another dependent variable (total, male and female suicide rates). Each table shows the results for three alternative models (in the first two specifications, we restrict the coefficients on the share of public welfare and health expenditure in total public spending to zero, respectively, the third model is the most encompassing model). The empirical results provide evidence that some of the explanatory variables of interest have an influence on suicide rates (e.g., divorce rates), but many of them (some of which have been identified in the literature as important), do not have a statistically discernible impact on suicide rates (e.g., state income and inequality). The effect of unemployment on suicide rates appears to be zero in our estimations, which is however consistent with empirical evidence from a panel data analysis for the U.S. (Kunce and Anderson, 2002).[27] In relation to control variables other than divorce and unemployment rates, we note that only in one case (Table 6) do we find that

[25] The system GMM estimator is particularly appropriate for specifications containing endogenous variables that are highly persistent since their lagged levels would be weak instruments for their current differences (see Bond et al., 2001). Furthermore, despite the potential "many instruments problem" that might arise with this augmented estimator, it has been shown to be *less* biased than the first differencing and the level estimators when the variance of the individual effects α_i is similar in size to that of the disturbances ε_{it} (Hayakawa, 2005).

[26] We use the one-step estimator so as to avoid the problem of downward biased standard errors which is common in the two-step estimators.

[27] Using gender-specific unemployment rates does not change the results.

lower levels of income per capita are associated with higher suicide rates among men. The result, however, disappears in the model for total suicide rates. This finding hints at one important difference in the underlying stochastic process describing gender-specific suicide rates.

Notably, divorce rates are consistently positively associated with suicide rates (in all specifications and for all dependent variables). It is in fact remarkable that divorce rates appears to be the sole sociological control variable which is statistically significant in the model explaining female suicide rates (Table 7). Furthermore, its coefficient magnitudes are higher for female suicide rates than for male (and total) suicide rates – a finding which is in contrast to that of Stack (1992) for Finnish time series data. Our estimate suggests that every additional divorce (per 1000 persons) is associated with a 4.7 to 5.4 percent increase in female suicide rates. However, this finding might reflect the effect of an omitted variable, such as stress level, which is positively correlated with both suicide rates and divorce rates.

We now turn to describing our findings for the 'public action' variables. The coefficients on the proportion of health in total public expenditure are negative and statistically significant in all regressions (Models 1 and 3) except the ones on female suicide rates. The magnitude of the coefficient estimates is non-negligible: an increase of the share of public health expenditure in total expenditure by 0.01 percentage points (say, from 6 to 7 percent of the total budget) would lead to a reduction in total suicide rates by 1.54 percent (Table 5) in the subsequent year. Consider, for instance, the state of Nevada, which had the highest average suicide rates among all U.S. states (of almost 31 per 100,000 persons per year) between 1982 and 1997. This finding suggests that it would take an increase of the health share in total public spending in the state of Nevada from 3 percent to 6 percent to attain a reduction of the suicide rate by 1 person per 1000. For men, the effect is statistically significant (Table 6) and appears to drive the result for total suicide rates since for females this variable no longer matters statistically, which is further evidence that our proposed model does not fully capture the determinants of female suicide.

The coefficient estimates for the impact of public expenditure on welfare are statistically significant at the 5 percent level of significance in all regressions, including those for females. The coefficient estimates in Table 7 show that an increase in the share of welfare expenditure in total public spending by 10 percentage points is associated with a female suicide rate lower by 10.9 percent. Consider the case of New Mexico, which had an average female suicide rate of 10 acts per 100,000 persons between 1982 and 1997. An increase in its share of welfare expenditure in total public spending from (New Mexico's long-term average) of 11.8 to 21.8 percent would be associated with a lowering of its female suicide rate from 10 to 9 acts per 100,000 persons. New Mexico had an estimated population of 1.9 million in 2005. If we extrapolate our findings (out-of-sample) to more recent years, an increase of the aforementioned magnitude in New Mexico's share of welfare spending would lower the number of female suicide acts in this state by 20 such acts every year.[28]

Regressions using the male suicide rates as a dependent variable are very similar to those on total suicide rates because males account for the bulk of suicide acts, as is illustrated by the average for males of 26 victims (per 100,000 population) as opposed to the average for females of almost 7 (per 100,000 population). Moreover, given the lack of explanatory power of included regressors for female suicide rates, we conclude that male suicide behavior could be more responsive to general economic conditions, as opposed to female behavior, and that the baseline model proposed in this

[28] An interesting area to explore in conjunction with our estimated semi-elasticities (which is however beyond the scope of this paper) would be a cost-benefit analysis of the estimated statistical value of life against the additional public health and welfare spending.

paper does not accurately depict the stochastic model underlying female suicide data. This finding coincides with previous panel data studies of suicide (Chuang and Huang, 1997; Brainerd, 2001).

Finally, demographic control variables, such as population density, and geographical characteristics, are found to be highly statistically significant (at the 1 percent level of significance). As expected, mountain states, mainly located in the Western part of the U.S., systematically have higher suicide rates than non-mountain states.

4. Robustness checks

In this section, we assess the sensitivity of the coefficient magnitudes and statistical significance for the 'public action' variables to influential observations and alternative specifications (involving other control variables).

We begin by identifying outliers using the Huber (1981) procedure.[29] The procedure consists in detecting outliers based on normalized residuals from a 'first-step' regression. Based on these residuals, weights are constructed and assigned to all the observations in the sample, and a weighted estimation procedure is subsequently implemented.[30] Treating the data in this fashion ensures that the impact of influential observations on regression results is down-weighed. To obtain the Huber weights, we run pooled Ordinary Least Squares on our full sample ($N = 665$). We then retain for system GMM regression only those observations with Huber weight lower than fifty percent.[31] This results in samples with at least $N = 640$ observations (total suicide rates), $N = 636$ (males) and $N = 640$ (females). We observe indeed that the coefficient estimates in the three tables which report the results (Tables 8–10) are similar in terms of statistical significance but (often) slightly lower in magnitude than those in Tables 5–7.

A second way in which we assess the sensitivity of our results to misspecification relies on including alternative controls and allowing for a potential nonlinearity in the data which may have been captured so far by the quadratic time variable. In particular, we wish to further address the fact that mountain states have higher-than-average suicide rates and deal with a possible omitted variable problem in which that variable reflects difficult-to-observe (and measure) state-level characteristics not accounted for in our models. To this end, we also include in our specifications a climate control, namely the average yearly number of days with sunshine. The sunshine variable is specified as a (strictly exogenous) instrument for the system GMM estimator. We further modify our specifications by including a quadratic term in (one-period) lagged income to allow for a possible non-linearity between per capita income levels and suicide. The results are reported in Tables 11–13.

We find that this richer model appears to provide a superior fit to the data. In particular, a number of variables that have thus far been insignificant, are now correlated with suicide rates. In the first specification in Tables 11–12, higher per capita income is associated with higher suicide rates.

29 In the paper, we only present results based on the Huber (1981) procedure, but we note that Hadi (1992) yields similar results, except that it consistently generates a larger number of outliers, hence smaller restricted samples and lower statistical significance. These results can be obtained from the authors upon request.

30 The weights are based on the (absolute) size of the residuals from the first-stage regression normalized by the median absolute value of the median residual.

31 Admittedly, we choose this cutoff point in a somewhat arbitrary fashion. However, we prefer not to reduce the sample size too much by strengthening the weight requirement on the observations; at the same time, we take this roundabout route of dealing with influential observations because we cannot implement the system GMM estimator with observations additionally weighted by Huber weights.

However, the observed increase in suicide rates associated with higher state-level income occurs at diminishing rates. The quadratic term in (one-period lagged) income is statistically significant in regressions on total and male suicide rates. Income does not appear to make a difference for female suicide rates. In contrast, unemployment rates are positively associated with female suicide rates (Table 13) and the coefficient estimates are statistically significant at the 5 percent level of significance in all models. The extent of income inequality is sporadically statistically significant and positively associated with suicide rates, suggesting that the social mobility argument (in which higher income inequalty signals opportunities for social mobility and should correlate negatively with suicide rates) is unlikely to hold in our data. The more plausible explanation for this finding is that distress associated with large income and social status heterogeneity in the society may be conducive to suicidal behavior. Most importantly, the two ‘public action’ variables coefficient estimates are robustly statistically significant, though of slightly higher magnitude for males, but slightly lower magnitude for females. The estimations presented in Tables 11–13 support our previous conclusions about the importance of public spending in explaining the variation in suicide mortality across U.S. states.

5. Conclusions

Suicide is one of the leading causes of death in the United States. While some dimensions of this phenomenon are of interest to psychologists and sociologists, its economic aspects should be under careful inspection by economists and policy-makers. In this study, we seek to explain variation in total, male and female suicide rates across states in the U.S. between 1982 and 1997 using novel economic variables (namely, the share of health and welfare spending in state budget) whilst controlling for sociological, demographic and geographic characteristics. The model is estimated via system GMM to avoid the pitfalls of a Fixed Effects estimation procedure which would yield biased coefficient estimates in the presence of serial correlation. We subject our estimates to a series of robustness checks, including elimination of influential observations and inclusion of additional controls.

The empirical results show that the proportion of public health and welfare expenditure in the public budget are strong negative predictors of total, male and female suicide rates. The coefficient estimates are statistically significant and their magnitudes are economically meaningful. In our most parsimonious model, only divorce rates are also positively associated with suicide rates. Our baseline specifications provide a better fit to male suicide data than to female suicide data. However, some sensitivitiy analysis of our results shows that unemployment rates, the extent of income inequality and divorce rates have a higher impact (both in terms of statistical significance and magnitude) on suicide for females than for males, providing a point of departure for future research into the determinants of female suicide mortality.

The paper contributes to the literature on the determinants of suicide by showing that public spending variables should be accounted for in causal analyses of the factors associated with aggregate health. Our analysis mirrors cross-country studies, such as Anand and Ravallion (1993) in which the role of public services is considered alongside that of private incomes (and other relevant factors) in assessing human well-being outcomes.

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Appendix A

See Tables 1–14.

Table 1
Average suicide rates for 51 U.S. states, 1982–1997

Rank	State	Average suicide rate
1	New Jersey	9.08
2	District of Columbia	9.12
3	New York	9.71
4	Massachusetts	11.06
5	Connecticut	11.46
6	Illinois	12.53
7	Rhode Island	12.79
8	Hawaii	13.14
9	Maryland	13.28
10	Ohio	13.65
11	Nebraska	14.42
12	Iowa	14.43
13	Minnesota	14.58
14	Michigan	14.62
15	Mississippi	14.87
16	North Dakota	15.09
17	Pennsylvania	15.10
18	Alabama	15.29
19	Kansas	15.50
20	Wisconsin	15.54
21	Delaware	15.55
22	Indiana	15.66
23	South Carolina	15.76
24	New Hampshire	15.78
25	North Carolina	15.85
26	Virginia	15.94
27	California	16.17
28	Georgia	16.31
29	Arkansas	16.50
30	Texas	16.56
31	Tennessee	16.61
32	Maine	16.73
33	Missouri	16.82
34	Kentucky	16.83
35	West Virginia	16.89
36	Louisiana	17.16
37	Washington	17.44
38	South Dakota	17.48
39	Oklahoma	18.03
40	Vermont	18.05
41	Florida	18.73
42	Oregon	19.43
43	Utah	19.93

Table 1 (*Continued*)

Rank	State	Average suicide rate
44	Alaska	20.60
45	Idaho	21.24
46	Colorado	21.75
47	Arizona	22.52
48	Montana	23.84
49	Wyoming	24.58
50	New Mexico	24.96
51	Nevada	30.95

Table 2
Summary statistics ($N = 665$)

Variable	Mean	Standard deviation	Minimum	Maximum
Total suicide rate	2.79	0.25	2.09	3.66
Male suicide rate	3.27	0.25	2.58	4.05
Female suicide rate	1.85	0.32	0.06	2.97
State income – lagged	16.45	4.91	7.73	33.47
Share of migrants in population	0.02	0.02	0.01	0.10
Public health expenditure – lagged	0.07	0.02	0.00	0.13
Public welfare expenditure – lagged	0.17	0.06	0.00	0.40
Gini coefficient of inequality	0.34	0.03	0.27	0.45
Unemployment rate	6.38	2.23	2.40	18.00
Divorce rates – lagged	5.06	1.67	0.80	17.60
Mountain state dummy	0.16	0.37	0.00	1.00
Sunshine	56.61	9.48	23.30	81.10
Population density	184.41	253.67	1.10	1134.40

Table 3
Correlation matrix for variables used in regressions ($N = 665$)

	Suicide rate	Male suicide rate	Female suicide rate
State income – lagged	−0.3326[a]	−0.3062[a]	−0.3781[a]
Share of migrants in population	−0.2571[a]	−0.2878[a]	−0.0912[a]
Public health expenditure – lagged	−0.3556[a]	−0.3535[a]	−0.1768[a]
Public welfare expenditure – lagged	−0.4390[a]	−0.3993[a]	−0.4001[a]
Gini coefficient of inequality	0.0376	0.0597	0.0239
Unemployment rate	0.0789	0.0429	0.2196[a]
Divorce rates – lagged	0.6275[a]	0.6073[a]	0.5447[a]
Mountain state dummy	0.6256[a]	0.6234[a]	0.4627[a]
Sunshine	0.1967[a]	0.1815[a]	0.2331[a]
Population density	−0.4279[a]	−0.4072[a]	−0.3596[a]

[a] Indicates statistical significance at the 1 percent level.

Table 4
Correlation matrix of independent variables ($N = 665$)

	State income – lagged	Share of migrants in population	Public health expenditure – lagged	Public welfare expenditure – lagged	Gini coefficient of inequality	Unemploy-ment rate	Divorce rate – lagged	Mountain state dummy	Sunshine
Share of migrants in population	0.1379[a]								
Public health expenditure – lagged	−0.0215	0.08							
Public welfare expenditure – lagged	0.4713[a]	0.3364[a]	0.1357[a]						
Gini coefficient of inequality	0.2125[a]	0.3050[a]	0.1382[a]	0.1304[a]					
Unemployment rate	−0.4514[a]	0.1031[a]	−0.08	−0.2397[a]	0.1373[a]				
Divorce rate – lagged	−0.2882[a]	−0.1701[a]	−0.2921[a]	−0.4416[a]	0.1583[a]	0.2495[a]			
Mountain state dummy	−0.1117[a]	−0.1808[a]	−0.3253[a]	−0.3758[a]	−0.02	−0.0127	0.4523[a]		
Sunshine	−0.0916[a]	0.1045[a]	0.1601[a]	−0.1010[a]	0.3007[a]	−0.1452[a]	0.2589[a]	0.4267[a]	
Population density	0.2376[a]	−0.05	0.2051[a]	0.2487[a]	−0.08	0.1010[a]	−0.1349[a]	−0.1134[a]	−0.04

[a] Significant at 1%.

Table 5
System GMM estimation results

	Model (1)	Model (2)	Model (3)
State income – lagged	−0.0049	−0.0043	−0.0060
	[0.0069]	[0.0082]	[0.0067]
Share of migrant population	−1.2044	−1.7504	−1.4550
	[1.7695]	[2.0211]	[1.7469]
Unemployment	0.0022	0.0064	0.0044
	[0.0056]	[0.0049]	[0.0053]
Population density	−0.0003***	−0.0003***	−0.0003***
	[0.0001]	[0.0001]	[0.0001]
Mountain state dummy	0.2399***	0.2266***	0.2117***
	[0.0365]	[0.0374]	[0.0349]
Divorce rate – lagged	0.0414***	0.0393***	0.0376***
	[0.0099]	[0.0108]	[0.0081]
Time squared	0.0009	0.0021	0.0022
	[0.0018]	[0.0022]	[0.0019]
Gini coefficient	0.2812	0.0670	0.0901
	[0.4009]	[0.4270]	[0.3712]
Public health expenditure – lagged	−1.8901**		−1.5440*
	[0.8530]		[0.8538]
Public welfare expenditure – lagged		−0.8025**	−0.7394**
		[0.3154]	[0.2945]
Constant	−0.7146	−5.4397	−5.7666
	[7.1846]	[8.3996]	[7.2330]
p-value Hansen *J* test of overidentifying restrictions	1.000	1.000	1.000
p-value Arellano–Bond test for AR(1) in first differences (m1)	0.001	0.001	0.001
p-value Arellano–Bond test for AR(2) in first differences (m2)	0.601	0.722	0.480
Observations	665	665	665
Number of groups	50	50	50

Dependent variable: total suicide rates. Robust standard errors in brackets. The linear term of the time polynomial is dropped due to collinearity.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 6
System GMM estimation results.

	Model (1)	Model (2)	Model (3)
State income – lagged	−0.0087	−0.0090	−0.0111*
	[0.0065]	[0.0078]	[0.0066]
Share of migrant population	−1.2545	−1.5758	−1.2731
	[1.5635]	[1.7440]	[1.4906]
Unemployment	0.0000	0.0046	0.0022
	[0.0056]	[0.0048]	[0.0052]

Table 6 (*Continued*)

	Model (1)	Model (2)	Model (3)
Population density	−0.0003***	−0.0003***	−0.0003***
	[0.0001]	[0.0001]	[0.0001]
Mountain state dummy	0.2312***	0.2219***	0.2079***
	[0.0366]	[0.0390]	[0.0361]
Divorce rate – lagged	0.0393***	0.0378***	0.0364***
	[0.0095]	[0.0108]	[0.0083]
Time squared	0.0023	0.0037*	0.0038**
	[0.0017]	[0.0020]	[0.0018]
Gini coefficient	0.3123	0.0174	0.1045
	[0.3832]	[0.4153]	[0.3602]
Public health expenditure – lagged	−1.7104**		−1.4796*
	[0.8587]		[0.8301]
Public welfare expenditure – lagged		−0.6691**	−0.5970**
		[0.2890]	[0.2757]
Constant	−5.9915	−11.1257	−11.5901*
	[6.8160]	[7.9017]	[6.9726]
p-value Hansen *J* test of overidentifying restrictions	1.000	1.000	1.000
p-value Arellano–Bond test for AR(1) in first differences (m1)	0.000	0.001	0.001
p-value Arellano–Bond test for AR(2) in first differences (m2)	0.076	0.078	0.053
Observations	665	665	665
Number of groups	50	50	50

Robust standard errors in brackets. Dependent variable: male suicide rates. The linear term of the time polynomial is dropped due to collinearity.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 7
System GMM estimation results

	Model (1)	Model (2)	Model (3)
State income – lagged	−0.0036	−0.0005	0.0011
	[0.0117]	[0.0143]	[0.0112]
Share of migrant population	−0.2340	−1.0313	−1.4014
	[2.7712]	[3.1217]	[2.8948]
Unemployment	0.0099	0.0112	0.0135
	[0.0077]	[0.0082]	[0.0086]
Population density	−0.0002	−0.0002	−0.0002
	[0.0001]	[0.0002]	[0.0001]
Mountain state dummy	0.2492***	0.2192***	0.2176***
	[0.0480]	[0.0489]	[0.0510]
Divorce rate – lagged	0.0541***	0.0467***	0.0483***
	[0.0183]	[0.0163]	[0.0155]

Table 7 (*Continued*)

	Model (1)	Model (2)	Model (3)
Time squared	−0.0023	−0.0017	−0.0020
	[0.0031]	[0.0036]	[0.0030]
Gini coefficient	0.4837	0.5567	0.2869
	[0.6726]	[0.5903]	[0.5464]
Public health expenditure – lagged	−1.1281		−0.3704
	[1.2787]		[1.4438]
Public welfare expenditure – lagged		−1.0952**	−0.9228**
		[0.5337]	[0.4406]
Constant	10.5774	8.2909	9.3865
	[11.9161]	[14.0069]	[11.5830]
p-value Hansen *J* test of overidentifying restrictions	1.000	1.000	1.000
p-value Arellano–Bond test for AR(1) in first differences (m1)	0.002	0.002	0.002
p-value Arellano–Bond test for AR(2) in first differences (m2)	0.182	0.149	0.149
Observations	665	665	665
Number of groups	50	50	50

Dependent variable: female suicide rates. Robust standard errors in brackets. The linear term of the time polynomial is dropped due to collinearity.
** Significant at 5%.
*** Significant at 1%.

Table 8
Regressions without outliers. System GMM estimation results

	Model (1)	Model (2)	Model (3)
State income – lagged	−0.0001	−0.0029	−0.0020
	[0.0058]	[0.0068]	[0.0058]
Share of migrant population	−1.2277	−2.1275	−1.6756
	[1.7953]	[2.0581]	[1.7602]
Unemployment	−0.0044	0.0002	−0.0012
	[0.0051]	[0.0052]	[0.0053]
Population density	−0.0004***	−0.0003***	−0.0004***
	[0.0001]	[0.0001]	[0.0001]
Mountain state dummy	0.2556***	0.2495***	0.2306***
	[0.0339]	[0.0315]	[0.0331]
Divorce rate – lagged	0.0337***	0.0344***	0.0322***
	[0.0067]	[0.0065]	[0.0065]
Time squared	−0.0008	0.0008	0.0005
	[0.0015]	[0.0017]	[0.0015]
Gini coefficient	0.2210	−0.0030	0.0733
	[0.4123]	[0.4241]	[0.3557]
Public health expenditure – lagged	−1.6332**		−1.5648**
	[0.8118]		[0.7036]

Table 8 (*Continued*)

	Model (1)	Model (2)	Model (3)
Public welfare expenditure – lagged		−0.4952**	−0.5024**
		[0.2354]	[0.2320]
Constant	5.9952	−0.2868	1.0114
	[5.6621]	[6.7215]	[5.9418]
p-value Hansen *J* test of overidentifying restrictions	1.000	1.000	1.000
p-value Arellano–Bond test for AR(1) in first differences (m1)	0.000	0.000	0.000
p-value Arellano–Bond test for AR(2) in first differences (m2)	0.456	0.615	0.352
Observations	642	640	642
Number of groups	50	50	50

Dependent variable: total suicide rates. Robust standard errors in brackets. The linear term of the time polynomial is dropped due to collinearity. Influential observations (with Huber weights lower than 50 percent) have been eliminated from the sample.

** Significant at 5%.

*** Significant at 1%.

Table 9

Regressions without outliers. System GMM estimation results

	Model (1)	Model (2)	Model (3)
State income – lagged	−0.0032	−0.0058	−0.0063
	[0.0064]	[0.0065]	[0.0061]
Share of migrant population	−1.5935	−2.1893	−1.9473
	[1.7029]	[1.8304]	[1.6017]
Unemployment	−0.0052	−0.0007	−0.0017
	[0.0043]	[0.0041]	[0.0041]
Population density	−0.0004***	−0.0004***	−0.0004***
	[0.0001]	[0.0001]	[0.0001]
Mountain state dummy	0.2602***	0.2470***	0.2286***
	[0.0352]	[0.0330]	[0.0343]
Divorce rate – lagged	0.0236***	0.0263***	0.0241***
	[0.0074]	[0.0070]	[0.0072]
Time squared	0.0002	0.0017	0.0019
	[0.0014]	[0.0015]	[0.0015]
Gini coefficient	0.3957	0.2504	0.2405
	[0.3963]	[0.4192]	[0.3527]
Public health expenditure – lagged	−1.0858		−1.2249*
	[0.7490]		[0.6983]
Public welfare expenditure – lagged		−0.4373**	−0.5112**
		[0.2175]	[0.2443]
Constant	2.3689	−3.4752	−3.9770
	[5.4229]	[5.9595]	[5.7227]
p-value Hansen *J* test of overidentifying restrictions	1.000	1.000	1.000
p-value Arellano–Bond test for AR(1) in first differences (m1)	0.000	0.000	0.000

Table 9 (*Continued*)

	Model (1)	Model (2)	Model (3)
p-value Arellano–Bond test for AR(2) in first differences (m2)	0.514	0.547	0.403
Observations	637	636	637
Number of groups	50	50	50

Dependent variable: male suicide rates. Robust standard errors in brackets. The linear term of the time polynomial is dropped due to collinearity. Influential observations (with Huber weights lower than 50 percent) have been eliminated from the sample.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 10
Regressions without outliers. System GMM estimation results

	Model (1)	Model (2)	Model (3)
State income – lagged	−0.0065	−0.0059	−0.0055
	[0.0113]	[0.0127]	[0.0103]
Share of migrant population	−0.0793	−0.5026	0.4543
	[2.7355]	[3.1666]	[2.7659]
Unemployment	0.0077	0.0075	0.0113
	[0.0068]	[0.0076]	[0.0077]
Population density	−0.0002*	−0.0002*	−0.0002*
	[0.0001]	[0.0001]	[0.0001]
Mountain state dummy	0.2766***	0.2478***	0.2390***
	[0.0442]	[0.0485]	[0.0485]
Divorce rate – lagged	0.0347**	0.0289*	0.0310*
	[0.0167]	[0.0162]	[0.0161]
Time squared	−0.0025	−0.0015	−0.0010
	[0.0028]	[0.0031]	[0.0027]
Gini coefficient	0.7554	0.8282	0.5332
	[0.6422]	[0.7077]	[0.5607]
Public health expenditure – lagged	−1.1133		−0.4315
	[1.0966]		[1.1451]
Public welfare expenditure – lagged		−1.0109*	−1.1326**
		[0.5464]	[0.4710]
Constant	11.6276	7.4938	5.6911
	[10.7291]	[12.1330]	[10.4698]
p-value Hansen *J* test of overidentifying restrictions	1.000	1.000	1.000
p-value Arellano–Bond test for AR(1) in first differences (m1)	0.000	0.000	0.000
p-value Arellano–Bond test for AR(2) in first differences (m2)	0.710	0.617	0.616
Observations	640	640	641
Number of groups	50	50	50

Dependent variable: female suicide rates. Robust standard errors in brackets. The linear term of the time polynomial is dropped due to collinearity. Influential observations (with Huber weights lower than 50 percent) have been eliminated from the sample.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 11
Tests of misspecification. System GMM estimation results

	Model (1)	Model (2)	Model (3)
State income – lagged	0.0434**	0.0297	0.0353
	[0.0206]	[0.0201]	[0.0224]
State income^2 – lagged	−0.0012***	−0.0009**	−0.0010**
	[0.0004]	[0.0004]	[0.0004]
Share of migrant population	−2.1498	−2.0091	−1.9246
	[1.8822]	[2.2453]	[2.0049]
Unemployment	0.0101*	0.0110**	0.0102*
	[0.0056]	[0.0054]	[0.0056]
Population density	−0.0003***	−0.0003***	−0.0003***
	[0.0001]	[0.0001]	[0.0001]
Mountain state dummy	0.2611***	0.2569***	0.2274***
	[0.0396]	[0.0467]	[0.0485]
Divorce rate – lagged	0.0322***	0.0323***	0.0270***
	[0.0086]	[0.0072]	[0.0073]
Sunshine	−0.0007	−0.0016	−0.0003
	[0.0019]	[0.0018]	[0.0020]
Time squared	−0.0004	0.0012	0.0008
	[0.0024]	[0.0024]	[0.0025]
Gini coefficient	0.8787**	0.6260*	0.7064*
	[0.3475]	[0.3740]	[0.3809]
Public health expenditure – lagged	−1.9330**		−1.8491*
	[0.9480]		[0.9665]
Public welfare expenditure – lagged		−0.8271**	−0.7921**
		[0.3709]	[0.3480]
Constant	3.6688	−2.4078	−0.8854
	[9.2436]	[9.2262]	[9.6681]
p-value Hansen *J* test of overidentifying restrictions	1.000	1.000	1.000
p-value Arellano–Bond test for AR(1) in first differences (m1)	0.001	0.001	0.001
p-value Arellano–Bond test for AR(2) in first differences (m2)	0.672	0.830	0.520
Observations	665	665	665
Number of groups	50	50	50

Dependent variable: total suicide rates. Robust standard errors in brackets. The linear term of the time polynomial is dropped due to collinearity.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 12
Tests of misspecification. System GMM estimation results

	Model (1)	Model (2)	Model (3)
State income – lagged	0.0333*	0.0210	0.0260
	[0.0202]	[0.0202]	[0.0221]
State income^2 – lagged	−0.0011***	−0.0008**	−0.0009**
	[0.0004]	[0.0004]	[0.0004]
Share of migrant population	−2.0080	−1.8803	−1.8045
	[1.7155]	[1.9968]	[1.7990]
Unemployment	0.0079	0.0087	0.0080
	[0.0056]	[0.0054]	[0.0056]
Population density	−0.0003***	−0.0003***	−0.0003***
	[0.0001]	[0.0001]	[0.0001]
Mountain state dummy	0.2594***	0.2554***	0.2290***
	[0.0418]	[0.0500]	[0.0508]
Divorce rate – lagged	0.0302***	0.0303***	0.0255***
	[0.0079]	[0.0069]	[0.0069]
Sunshine	−0.0012	−0.0020	−0.0009
	[0.0018]	[0.0020]	[0.0020]
Time squared	0.0014	0.0028	0.0025
	[0.0023]	[0.0023]	[0.0024]
Gini coefficient	0.7586**	0.5309	0.6029
	[0.3650]	[0.3949]	[0.4087]
Public health expenditure – lagged	−1.7337*		−1.6579*
	[0.9114]		[0.9260]
Public welfare expenditure – lagged		−0.7470**	−0.7156**
		[0.3545]	[0.3374]
Constant	−2.5778	−8.0571	−6.6922
	[8.9177]	[8.8470]	[9.2804]
p-value Hansen *J* test of overidentifying restrictions	1.000	1.000	1.000
p-value Arellano–Bond test for AR(1) in first differences (m1)	0.000	0.000	0.000
p-value Arellano–Bond test for AR(2) in first differences (m2)	0.090	0.117	0.070
Observations	665	665	665
Number of groups	50	50	50

Dependent variable: male suicide rates. Robust standard errors in brackets. The linear term of the time polynomial is dropped due to collinearity.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 13
Tests of misspecification. System GMM estimation results

	Model (1)	Model (2)	Model (3)
State income – lagged	0.0569	0.0443	0.0480
	[0.0382]	[0.0370]	[0.0392]
State income^2 – lagged	−0.0015*	−0.0012	−0.0013
	[0.0008]	[0.0007]	[0.0008]
Share of migrant population	−1.7309	−1.5384	−1.4832
	[2.7375]	[3.0810]	[2.9490]
Unemployment	0.0173**	0.0180**	0.0174**
	[0.0085]	[0.0085]	[0.0086]
Population density	−0.0002	−0.0002	−0.0002
	[0.0001]	[0.0001]	[0.0002]
Mountain state dummy	0.2362***	0.2184***	0.1992***
	[0.0550]	[0.0552]	[0.0592]
Divorce rate – lagged	0.0461***	0.0438***	0.0404**
	[0.0174]	[0.0148]	[0.0163]
Sunshine	0.0019	0.0014	0.0023
	[0.0027]	[0.0022]	[0.0028]
Time squared	−0.0043	−0.0027	−0.0030
	[0.0038]	[0.0038]	[0.0039]
Gini coefficient	1.4299**	1.1881*	1.2405*
	[0.6909]	[0.6626]	[0.6706]
Public health expenditure – lagged	−1.2985		−1.2062
	[1.4390]		[1.4842]
Public welfare expenditure – lagged		−0.8938*	−0.8709*
		[0.5156]	[0.5020]
Constant	17.6594	11.6587	12.6518
	[14.4387]	[14.4036]	[15.0199]
p-value Hansen *J* test of overidentifying restrictions	1.000	1.000	1.000
p-value Arellano–Bond test for AR(1) in first differences (m1)	0.002	0.002	0.002
p-value Arellano–Bond test for AR(2) in first differences (m2)	0.178	0.158	0.147
Observations	665	665	665
Number of groups	50	50	50

Dependent variable: female suicide rates. Robust standard errors in brackets. The linear term of the time polynomial is dropped due to collinearity.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 14
Variable definitions and sources

Variable	Source
Age-adjusted total, male and female suicide rates The age group considered is 20–69; the base year for age adjustment 1980. Unit of measurement: the normalization is 100,000. Thus, it represents the total no. of committed acts per 100,000 persons	Centers for Disease Control and Prevention
Income inequality variables The unit is the household. The inequality indicators are computed using family pretax income (between 1982–1997) from the March Current Population Survey	Wu et al. (2002)
Total and by-gender unemployment rates Unit of measurement: the normalization is 100. Thus, it represents the total no. of people in involuntary unemployment per 100 persons.	Bureau of Labor Statistics, US Department of Labor, Geographic Profile of Employment and Unemployment
Mountain state dummy Takes value 1 if the state is mostly covered by mountains. Mountain states are: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah and Wyoming	Classification of the Statistical Abstract of the United States, US Census Bureau, US Department of Commerce, 1998
Divorce rates Unit of measurement: the normalization is 1,000	Statistical Abstract of the United States, US Census Bureau, US Department of Commerce, 1985–2000
Per Capita Personal Income Unit of measurement: US$ (constant)	Bureau of Economic Analysis
Share of migrants in total population Computed by the authors using data from the March Current Population Survey. It is equal to the ratio between the total flow of migrants, i.e., the number of individuals that changed residence (by moving either in or out of a state) and the total population of each state.	Current Population Survey
Share of health and welfare expenditures in total public spending Computed as proportion of health and welfare expenditure, respectively, in total state government expenditure.	Statistical Abstract of the United States, US Census Bureau, US Department of Commerce, 1985–2000
Population density Population per square mile of land area.	Statistical Abstract of the United States, US Census Bureau, US Department of Commerce, 1985–2000
Sunshine Average percentage of possible annual sunshine in any given state. For states with several weather stations, we computed averages.	Statistical Abstract of the United States, US Census Bureau, US Department of Commerce, 1985–2000

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