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Supplementary webappendix

This webappendix formed part of the original submission and has been peer reviewed. We post it as supplied by the authors.

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Web Appendix

Web Appendix 1. Data Used in the Study

Country	Years of Data Availability		
	Mortality	Unemployment	Social Expenditures
Austria	1970-2007	1970-2006	1980,1985,1990-2003
Belgium	1970-1999	1971-2007	1980-2003
Bulgaria	1970-2004	1990-2006	n/a
Cyprus	2004,2006	1974-2006	n/a
Czech Republic	1970-2007	1980-2007	1990-2003
Denmark	1970-2006	1973-2007	1980-2003
Estonia	1981,1982, 1985-2005	1989-2007	n/a
Finland	1970-2007	1974-2007	1980-2003
France	1970-2006	1970-2005	1980-2003
Germany	1990-2006	1991-2006	1980-2003
Greece	1970-2007	1974-2006	1980-2003
Hungary	1970-2005	1990-2007	1999-2004
Ireland	1970-2006	1974-2007	1980-2003
Italy	1970-2003, 2006	1974-2007	1980-2003
Latvia	1980-2007	1992-2007	n/a
Lithuania	1981,1982,1985-2007	1991-2007	n/a
Luxembourg	1971-2005	1975-2007	n/a
Malta	1970-2007	1974-1979,1983,1985-2007	n/a
Netherlands	1970-2007	1970-2006	1980-2003
Poland	1983-1996, 1999-2006	1990-2006	1990-2003
Portugal	1971-2004	1974-2007	n/a
Romania	1989-2007	1991-2006	n/a
Slovakia	1986-2005	1990-2007	1995-2003
Slovenia	1985-2007	1980,1982,1984-2007	n/a
Spain	1970-2005	1974-2006	1980-2003
Sweden	1970-2006	1970-2006	1980-2003
United Kingdom	1970-2007	1974-2005	1980-2003

Notes: Mortality data are from WHO HFA-DB (1970-2007); Unemployment based on ILO KILM reported in WHO HFA-DB (1970-2007); Social expenditure based on OECD Health Data 2008 edition (1980-2003).

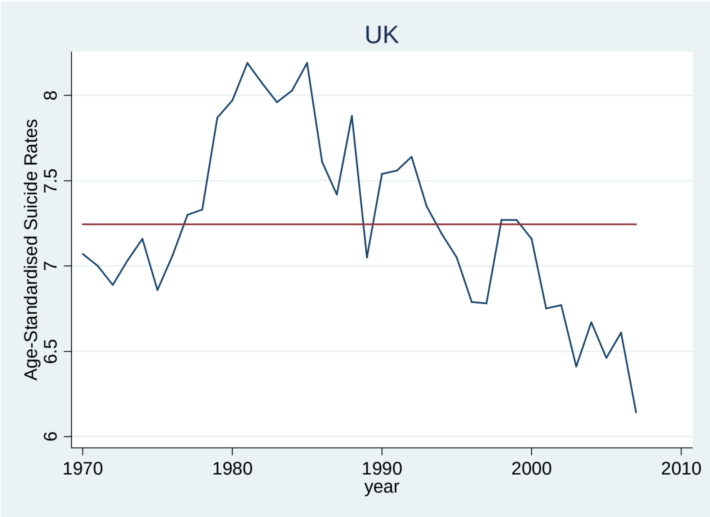
Web Appendix 2. More Details of Estimation Approaches and Replication using Levels

In this Web Appendix we present our modeling approach as contrasted with previous analyses of the unemployment-mortality association. We also replicate our basic model (as shown in figure 1) using the previous analytical approach.

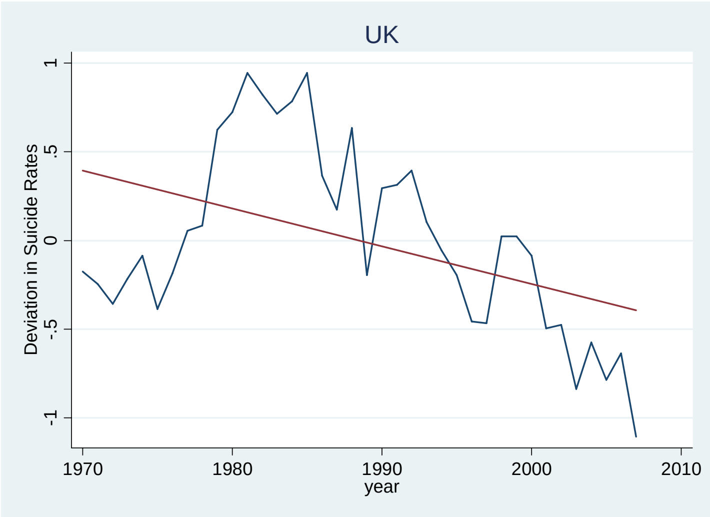
Levels

Previous analyses of population unemployment-mortality associations typically begin with levels of mortality rates (step 1). These data are transformed to a 'fair comparison' by subtracting within-country averages, which effectively removes between-country average differences (step 2). In a final step, year trends are estimated and removed, and similar transformations are taken for independent variables: $\mathrm{H}_{i,t} - \overline{\mathrm{H}}_{i,t} = \alpha + \beta * (\mathrm{U}_{i,t} - \overline{\mathrm{U}}_{i,t}) + \eta_t + \gamma_i * \mathrm{t}_t + \varepsilon_{i,t}$ (see for example, Ruhm 2003).[1]

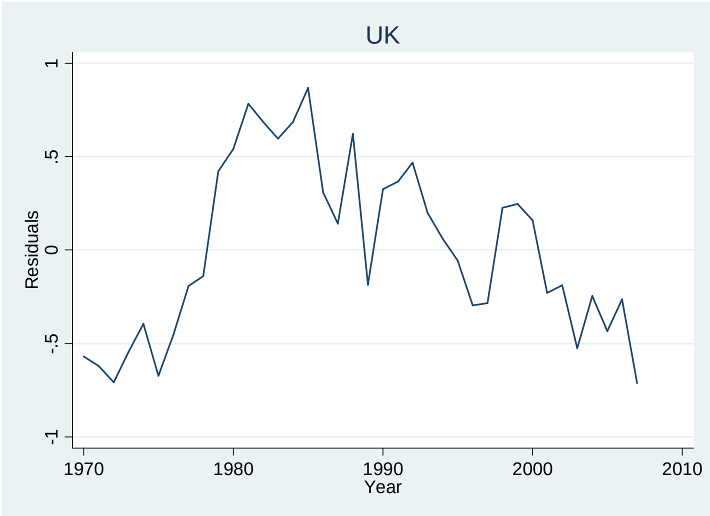
Step 1. Raw data, suicides rates (under 64), levels, UK, line denotes UK average



Step 2. Centered suicide rates, levels, UK. Note the difference in scale. Line denotes year-trends.



Step 3. Final transformed data, levels. Note the difference in scale



However, these models have given rise to some spurious associations. Web Table 3 lists the percentage rise associated with several diseases and their statistical significance (replicating figure 2, see below). As shown, neoplasms, including cancers having a long lag period between exposure and disease, are associated with higher levels of unemployment rates. This implausible result suggests that these models are misspecified.

Table. Replication using Levels

Cause of Death	Coefficient (standard error)
External Causes	0.25 (0.21)
Suicide Rates	0.29** (0.086)
Suicide Rates (under 64)	0.28** (0.088)
Homicide	0.08 (0.07)
Alcohol Abuse	0.13 (0.14)
Accidents	-0.12 (0.22)
Drowning	0.020 (0.018)
Poisoning	0.0069 (0.066)
Ill-defined causes	-0.20 (0.24)
Transport-Related Accidents	-0.11 (0.061)
Falls	-0.033 (0.047)
Cardiovascular Disease	-0.56 (0.46)
Cardiovascular Disease (under 64)	-0.25 (0.22)
Ischaemic Heart Disease	0.80 (0.79)
Cerebrovascular Disease	-0.52* (0.22)
Psychoactive Substance Abuse	-0.038 (0.070)
Liver Cirrhosis	-0.0098 (0.089)
Ulcer	0.023 (0.015)
Neoplasms	0.44*** (<0.001)
Lung Cancer	0.39*** (0.91)
Alzheimer	-0.080 (0.068)

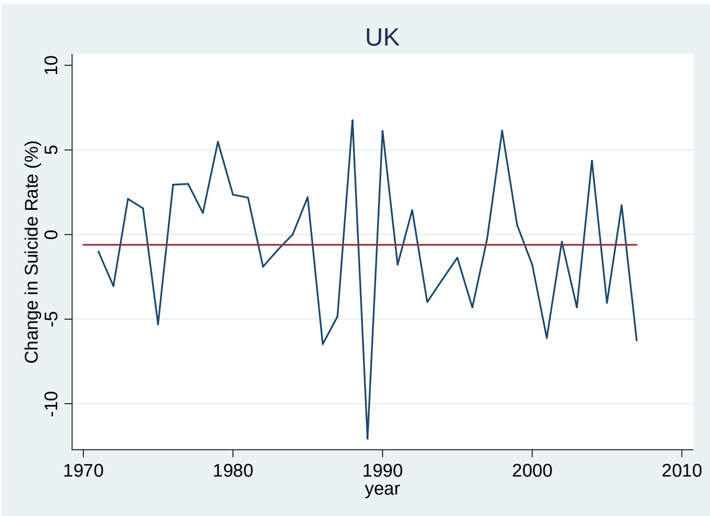
Diabetes	0.080 (0.12)
Diabetes (15-44)	-0.0055 (0.0083)
Maternal Mortality Rates	-0.01*** (0.002)
Infant Mortality Rates	-0.15*** (0.028)
Infectious Diseases	-0.23** (0.069)
Tuberculosis Mortality Rates	0.018 (0.037)
All-Cause Mortality Rates	0.70 (1.30)

Notes: Coefficients presented as semi-elasticities: association of a 1% rise in unemployment with mortality rates per 100,000. Results presented from 28 separate regression models. Robust standard errors in parentheses clustered by country to reflect non-independence of sampling. Models correct for population ageing, past mortality trends, country-specific mortality trends and country fixed effects. Some causes of death overlap (e.g., poisoning and alcohol abuse). Data are from the World Health Organization European Health for All Database 2008 Edition (HFA-DB and HFA-MDB).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

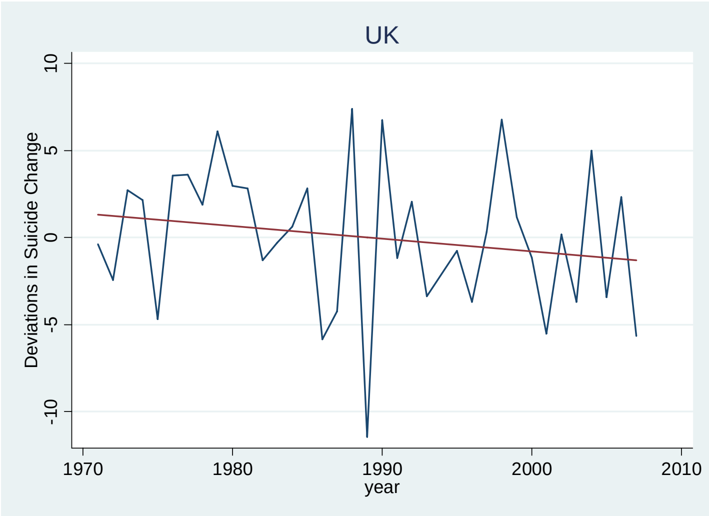
As another limitation, while these models test the hypothesis whether when unemployment rates are relatively high mortality rates are also high, they do not test the relevant hypothesis to our study of whether when unemployment rates are rising relatively mortality rates are also relatively rising. To test the associations of changes in unemployment rates with changes in mortality rates, we identified the associations between changes in mortality and changes in unemployment rates, but using similar transformations as the two-step method above: $\Delta H_{i,t} - \overline{\Delta H}_{i,t} = \alpha + \beta * (\Delta U_{i,t} - \overline{\Delta U}_{i,t}) + \eta * t + \gamma_i * t + \varepsilon_{i,t}$. We present these steps in the figures below.

Changes

Step 1. Raw data, suicides rates (under 64), percentage changes, UK, line denotes UK average



Step 2. Centered suicide rates, changes, UK. Note the difference in scale. Line denotes year-trends.



We note that an alternative, yet mathematically equivalent, notation of our model is as follows:

$$\Delta H_{i,t} = \alpha + \beta \Delta U_{i,t} + \eta * t + \mu_i + \mu_i * t + \varepsilon_{i,t}$$

Modelling short- and long-run dynamics

We did not aim in this paper to fit a comprehensive model that could explain all changes in mortality rates (indeed it is not clear that this would be possible) but to test a specific hypothesis of whether changes in unemployment affect changes in mortality rates (mathematically, as whether the beta coefficient was not equal to zero); the r-squared values, which are reported in the Web Appendix, reflects the way we have transformed the data (and thus the sum-of-squares total variation) to test our hypothesis (which we note has been tested improperly by most existing literature using models specified in levels rather than in terms of changes to the mortality rates).

R-squared values generally decline when assessing relationships between changes rather than between levels. To illustrate this point in our data, we display a well-known relationship in levels between GDP and life expectancy. In levels, which captures long-run average relationships, the R-squared using fixed effects is 0.9153, as shown below.

xi: regress lifexp lgdpc, cluster(num)
β (s.e.) = 2.65 (0.19), $p < 0.00001$
R^2 (SSE/SST)= 0.9153

This replicates the well-established long-run relationship between GDP and health.

Then we assess the short-run change relationships,
xi: regress d.lifexp d.lgdpc, cluster(num)
β (s.e.) = 0.03(0.19), $p = 0.882$
R^2 (SSE/SST) = 0.0253

In this specification, the effect of GDP on life expectancy disappears. Thus, the long-run relationship in levels can differ qualitatively from the short-run relationship in changes. For a broader discussion, see the literature on error-correction models which attempts to differentiate short- and long-run dynamics.[2-4] As an example, we show the results of the short-run and long-run model below, which corroborates our findings:

$\Delta \text{Suicide}_{i,t} = \Phi(\text{Suicide}_{i,t-1} + \beta \text{Unemployment}_{i,t}) + \gamma_1 \Delta \text{Suicide}_{i,t-1} + \gamma_2 \Delta \text{Suicide}_{i,t-2} + \lambda \text{Suicide}_{i,t-2}$
$\mu_i + \varepsilon_{i,t}$

Here Φ is the error correction term, which measures the speed of adjustment to long-run relationships after a short-run perturbation. We note that μ_i represents a set of 26 country dummy variables. We included a set of lags in changes and levels of depth two. We estimated this as dynamic fixed effects:

Table 1a. Estimating Short and Long-Run Relationships between Suicide and Unemployment using Dynamic Fixed Effects Models

Covariate	Suicide Rates	p-value
Long-Run		
Unemployment Level	0.21 (0.20)	0.291
Short-Run		
Unemployment Change	0.88 (0.27)	0.002
Error-Correction Term	0.85 (0.27)	0.002

Notes: Robust standard errors in parentheses clustered by country. Models include 26 country dummy variables.

We see that in the long-run there is no relationship between unemployment rates and suicide rates. We see further that each 1% rise in the unemployment rate is associated with a 0.88% rise in suicide rates. One interpretation of the error-correction term is as the speed of adjustment, as follows. It shows that in the second year, 85% of this effect is gone. By the second year, 85% of remaining effect applies, until the initial unemployment 'shock' is dampened.

```
xtpmg chgsuic064 chgunemp, lr(sdr_suic_064 unemp) cluster(num) dfe
```

If we add in a set of period dummies, the effect remains identical to what we reported in the manuscript:

```
xi: xtpmg chgsuic064 chgunemp $period, lr(sdr_suic_064 unemp) cluster(num) dfe replace
```

Table 1b. Estimating Short and Long-Run Relationships between Suicide and Unemployment using Dynamic Fixed Effects Models, with period effects

Covariate	Suicide Rates	p-value
Long-Run		
Unemployment Level	0.14 (0.20)	0.291
Short-Run		
Unemployment Change	0.71 (0.27)	0.002
Error-Correction Term	0.97 (0.27)	0.023
Period Effects	Yes	Joint Test $\chi^2(25) = 379.65$, $p<0.00001$

Notes: Robust standard errors in parentheses clustered by country.

In this model, 97% of the effect is dampened after the first year. This is consistent with what we show in the figure of web appendix 15: the bulk of the adverse health effects appear to occur within the first two years.

Web Appendix 3 Statistical Addendum

We discuss i) the coding of variables used in the model, ii) the estimation of the model, and iii) perform a series of diagnostic tests.

Given space constraints, we did not present all of the robustness checks in the manuscript, but expand on the methods used in the analysis here.

For illustrative purposes, we show the steps taken for age-standardised suicide rates for both genders among persons under 64, unless otherwise specified. We provide STATA codes to accompany all steps. We also include our data file so that these steps can be replicated.

I. Coding

Our identifier for countries was the variable 'num' and for the year was 'year'.

We set our panel longitudinal data using:

```
tsset num year
```

We took the suicide rates and transformed them to percentage changes, as follows:

```
generate chgsuic064 = 100*((sdr_suic_064 - l.sdr_suic_064)/(l.sdr_suic_064)) if l.sdr_suic_064!=. & sdr_suic_064!=. & sdr_suic_064!= 0 & l.sdr_suic_064!=0
```

We did the same with changes in unemployment rates (noting that unemployment rates were already in terms of percent of the labour force, as is standard).

```
generate chgunemp = d.unemp if l.unemp != . & unemp != .
```

We created our mass rise in unemployment variable based on a 3% or greater rise in unemployment:

```
generate unemp_surge = 0 if unemp != .
replace unemp_surge = 1 if d.unemp >3 & unemp!= . & l.unemp!=.
```

We also created a variable 'trend':

```
generate trend = year -1970
```

We developed a set of 26 country*year trend dummies using the following loop:

```
quietly: for X in num 1/26: gen countryX = 1 if num==X
quietly: for X in num 1/26: replace countryX = 0 if num!=X
quietly: for X in num 1/26: gen countryX_trend = countryX * trend
```

II. Estimation

We estimated our basic model as follows:

```
xtreg chgsuic064 chgunemp year country1_trend-country26_trend if chgsuic064>-150 & chgsuic064<150, fe cluster(num)
```

The 'fe' option denotes fixed effects. This uses the 'within-country' variation – which is equivalent to including a set of 26 country dummy variables in the model (see Wooldridge 2002 for details), and as graphically described in Web Appendix 2.

The 'cluster' option provides unbiased standard errors to serial correlation. As is well-known, serial correlation only affects the efficiency of the model (i.e., the standard errors, not the consistency, or parameter estimates).[a5] While several studies in this literature have attempted to correct for the serial correlation directly, this approach can have “dire consequences for the reliability of inference based on such models”[6] and statisticians offer “a simple message to autocorrelation correctors: Don’t”.[7]

As specified in the methods, we removed potential outlying values based on >|150| percentage change in a given year.

Here we provide representative output from STATA:

Fixed-effects (within) regression			Number of obs =	657		
Group variable: id			Number of groups =	26		
R-sq: within = 0.0554			Obs per group: min =	13		
between = 0.0581			avg =	25.3		
overall = 0.0114			max =	36		
			F(1,25) =	6.62		
corr(u_i, Xb) = -0.9369			Prob > F =	0.0164		
			adjusted for 26 clusters	in num)		
chgsuic064	Coef.	Robust Std Error	t	P>t	[95% Conf Interval]	
chgunemp	0.79053	0.307273	2.57	0.016	0.15769	1.423369
year	-0.05644	0.014521	-3.89	0.001	-0.08635	-0.02653
country1_t~d	-0.08508	0.014339	-5.93	0.000	-0.11461	-0.05554
country2_t~d	-0.14368	0.000792	-181.4	0.000	-0.14531	-0.14205
country3_t~d	-0.70862	0.116559	-6.08	0.000	-0.94868	-0.46856
country4_t~d	(dropped)					
country5_t~d	0.0373	0.008837	4.22	0.000	0.019099	0.0555
country6_t~d	-0.13883	0.002465	-56.32	0.000	-0.1439	-0.13375
country7_t~d	-1.39479	0.039432	-35.37	0.000	-1.476	-1.31357
country8_t~d	-0.03895	0.002536	-15.36	0.000	-0.04417	-0.03373
country9_t~d	-0.0426	0.008057	-5.29	0.000	-0.05919	-0.02601
country10_~d	-0.02479	0.00234	-10.59	0.000	-0.0296	-0.01997

[a] Stock and Watson (2006) point out that the standard heteroskedasticity-robust and heteroskedasticity and autocorrelation consistent-robust covariance estimators are inconsistent for T fixed and T > 2 with fixed effects, but the cluster-robust estimator does not suffer from this problem. If serial correlation is expected, the cluster-robust estimator is the preferred choice (Stock and Watson 2006; see also Nichols and Schaffer, *STATA Journal* 2007). We identified first-order serial correlation in our models using a Durbin-Watson test. Because our data are from multiple panels, we used a modification of the standard Durbin-Watson test to detect the presence of first-order autocorrelation in the residuals using the formula: $DW = \frac{\sum_{t=2}^{n}(\varepsilon_t - \varepsilon_{t-1})^2}{\sum_{t=1}^{n}(\varepsilon_t)^2}$, where ε is the residual and t is the year (See Baltagi-Wu 1999 locally best invariant statistic (BW = 2.64) and Bhargava et al 2001 modified Durbin-Watson (DW = 2.69) (Durbin and Watson 1971).

country11_~d	0.083034	0.010804	7.69	0.000	0.060782	0.105285
country12_~d	0.25722	0.057589	4.47	0.000	0.138613	0.375828
country13_~d	-0.31321	0.005523	-56.71	0.000	-0.32458	-0.30184
country14_~d	-0.14568	0.002233	-65.23	0.000	-0.15028	-0.14109
country15_~d	-0.87025	0.046933	-18.54	0.000	-0.96691	-0.77359
country16_~d	-1.22734	0.085162	-14.41	0.000	-1.40274	-1.05195
country17_~d	-0.53526	0.016162	-33.12	0.000	-0.56854	-0.50197
country18_~d	0.595063	0.022392	26.57	0.000	0.548946	0.64118
country19_~d	-0.03553	0.00467	-7.61	0.000	-0.04515	-0.02592
country20_~d	-0.02206	0.059331	-0.37	0.713	-0.14426	0.100131
country21_~d	0.432423	0.006284	68.81	0.000	0.419482	0.445365
country22_~d	-0.71824	0.044848	-16.01	0.000	-0.81061	-0.62588
country23_~d	0.566596	0.07574	7.48	0.000	0.410606	0.722586
country24_~d	-0.15084	0.024239	-6.22	0.000	-0.20076	-0.10091
country25_~d	-0.06374	0.02343	-2.72	0.012	-0.11199	-0.01548
country26_~d	0.088065	0.013873	6.35	0.000	0.059494	0.116636
_cons	115.6366	29.26933	3.95	0.001	55.35528	175.9179
sigma_u	13.09635					
sigma_e	13.07819					
rho	0.500694	(fraction of variance due to u_i)				

The country21_trend are the indicators coded above. Note root-mean-squared error = 13.078. We note that μ_i refers to the country-fixed effect.

We repeated this process for the each mortality dependent variable (running over 150 statistical models using this basic specification).

As noted above, we could have run this model using:

xi: regress chgsuic064 chgunemp year country1_trend-country26_trend i.country if chgsuic064>-150 & chgsuic064<150, cluster(num)

which displays the country-dummies (the fixed-effects transformation).

chgsuic064	Coef.	Robust Std Error	t	P>t	[95% Conf Interval]	
chgunemp	0.79053	0.313567	2.52	0.018	0.144726	1.436333
year	-0.05644	0.014819	-3.81	0.001	-0.08696	-0.02592
country1_t~d	-0.08508	0.014633	-5.81	0.000	-0.11521	-0.05494
country2_t~d	-0.14368	0.000808	-177.76	0.000	-0.14534	-0.14202
country3_t~d	-0.70862	0.118947	-5.96	0.000	-0.9536	-0.46364
country4_t~d	(dropped)					
country5_t~d	0.0373	0.009018	4.14	0.000	0.018726	0.055873
country6_t~d	-0.13883	0.002516	-55.18	0.000	-0.14401	-0.13364
country7_t~d	-1.39479	0.04024	-34.66	0.000	-1.47766	-1.31191

country8_t~d	-0.03895	0.002588	-15.05	0.000	-0.04428	-0.03362
country9_t~d	-0.0426	0.008222	-5.18	0.000	-0.05953	-0.02567
country10_~d	-0.02479	0.002388	-10.38	0.000	-0.0297	-0.01987
country11_~d	0.083034	0.011025	7.53	0.000	0.060327	0.105741
country12_~d	0.25722	0.058769	4.38	0.000	0.136184	0.378257
country13_~d	-0.31321	0.005636	-55.58	0.000	-0.32482	-0.3016
country14_~d	-0.14568	0.002279	-63.93	0.000	-0.15038	-0.14099
country15_~d	-0.87025	0.047895	-18.17	0.000	-0.96889	-0.77161
country16_~d	-1.22734	0.086906	-14.12	0.000	-1.40633	-1.04836
country17_~d	-0.53526	0.016493	-32.45	0.000	-0.56923	-0.50129
country18_~d	0.595063	0.022851	26.04	0.000	0.548001	0.642125
country19_~d	-0.03553	0.004766	-7.46	0.000	-0.04535	-0.02572
country20_~d	-0.02206	0.060546	-0.36	0.719	-0.14676	0.102634
country21_~d	0.432423	0.006413	67.43	0.000	0.419216	0.44563
country22_~d	-0.71824	0.045767	-15.69	0.000	-0.8125	-0.62399
country23_~d	0.566596	0.077292	7.33	0.000	0.407411	0.725781
country24_~d	-0.15084	0.024736	-6.1	0.000	-0.20178	-0.09989
country25_~d	-0.06374	0.02391	-2.67	0.013	-0.11298	-0.0145
country26_~d	0.088065	0.014157	6.22	0.000	0.058909	0.117222
_Icountry_2	3.187805	0.306846	10.39	0.000	2.555844	3.819767
_Icountry_3	19.04644	3.867492	4.92	0.000	11.08119	27.01169
_Icountry_4	(dropped)					
_Icountry_5	-2.18996	0.159003	-13.77	0.000	-2.51743	-1.86249
_Icountry_6	0.492718	0.339133	1.45	0.159	-0.20574	1.191174
_Icountry_7	37.45076	1.61346	23.21	0.000	34.12778	40.77374
_Icountry_8	0.006251	0.264489	0.02	0.981	-0.53847	0.550977
_Icountry_9	0.979924	0.143272	6.84	0.000	0.68485	1.274998
_Icountry_10	-1.6896	0.423253	-3.99	0.001	-2.56131	-0.81789
_Icountry_11	-0.89881	0.098714	-9.11	0.000	-1.10212	-0.69551
_Icountry_12	-9.5899	2.133665	-4.49	0.000	-13.9843	-5.19553
_Icountry_13	9.857807	0.343257	28.72	0.000	9.150856	10.56476
_Icountry_14	3.556052	0.229256	15.51	0.000	3.083892	4.028213
_Icountry_15	22.64272	1.893995	11.96	0.000	18.74196	26.54347
_Icountry_16	36.4367	3.037516	12	0.000	30.18082	42.69258
_Icountry_17	13.51532	0.030091	449.15	0.000	13.45334	13.57729
_Icountry_18	-4.39452	0.237295	-18.52	0.000	-4.88324	-3.9058
_Icountry_19	1.228319	0.171218	7.17	0.000	0.87569	1.580949
_Icountry_20	0.976605	2.29574	0.43	0.674	-3.75156	5.70477
_Icountry_21	-6.54436	0.173373	-37.75	0.000	-6.90143	-6.18729
_Icountry_22	23.34528	1.805114	12.93	0.000	19.62758	27.06298
_Icountry_23	-17.6636	2.844626	-6.21	0.000	-23.5222	-11.805
_Icountry_24	1.831786	1.094802	1.67	0.107	-0.423	4.086573
_Icountry_25	3.230573	0.814734	3.97	0.001	1.552596	4.90855
_Icountry_26	-3.10615	0.005326	-583.24	0.000	-3.11711	-3.09518
_Icountry_27	-0.00787	0.277877	-0.03	0.978	-0.58016	0.564432
_cons	112.0248	29.23435	3.83	0.001	51.81548	172.234

_lcountry_1 refers to a country dummy variable; these are effectively included in the models above.

The **xtreg** command automatically makes the necessary adjustment to the degrees of freedom (see Wooldridge 2002) arising from the 26 additional country dummy variables included in the fixed-effects model, accounting for the slight differences in the standard errors.[8] The r-squared is also higher because it reflects the sum-of-squared residuals and sum-of-squared explained for the 'full-variation', as opposed to the 'within-variation' in the output above.

To characterize the statistical properties of the model, we provide added-variable plots, residual-versus-fitted plots, and leverage plots, below.

Distribution of the error-term

Standard OLS regression models assume that observations are independently drawn from a normally and identically distributed sample population. This is typically not the case in cross-national research[9, 10], and, as a result, our analysis proceeds from the assumption of non-normal residuals[11]; systematic reviews have noted that in the social and natural sciences, "normality seems to be the exception rather than the rule" Dietz et al, p. 383). Further, since our dependent variable is close to a non-normal distribution (percentage change in suicide rates, Skewness/Kurtosis test: $z = 11.46$, $p<0.01$), it is not uncommon that the distribution of the error is also non-normal, as is the case in the present study. We also note that, with the relatively rare conditions, there may be over-dispersion in the error terms.

A commonly applied technique for coping with residual non-normality is to delete potential outliers and leverage points[10]; however, this does not correct for non-normality in the parent population that does not manifest itself in the form of outliers. We provide an added-variable plot (also known as a partial-regression leverage plot) and a residual versus fitted plot below to display the possible outlier and influence point structure of our residuals:

Figure 1. Added-variable plot

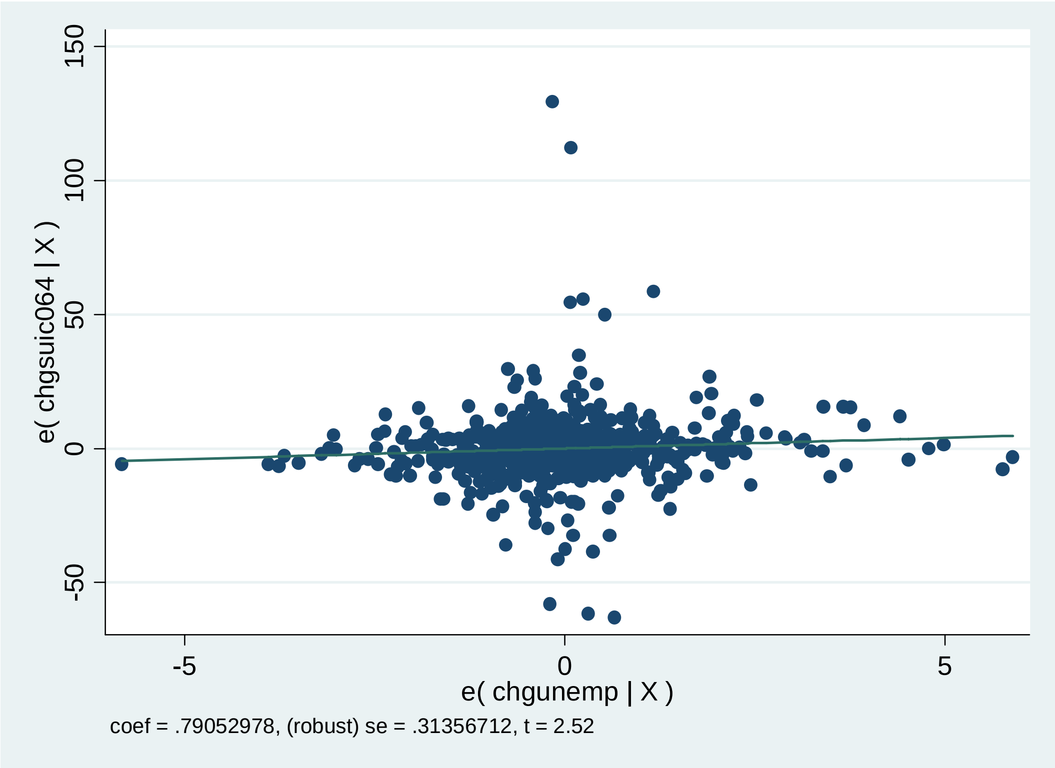
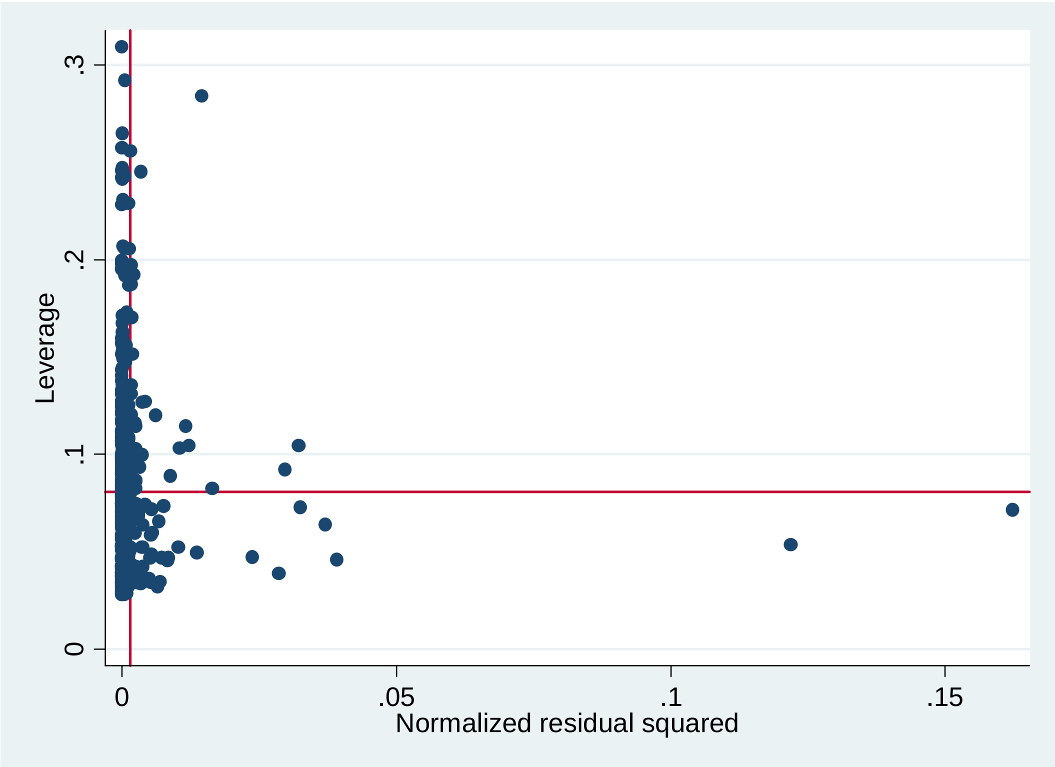


Figure 2. Leverage plot



The added-variable plot shows potential outliers near zero percent changes in unemployment. The leverage plot shows that there were no influence points (as shown by no data points in the upper right hand corner of the model).

We removed potential outliers using a liberal definition of standardised residuals >|2|, as follows:

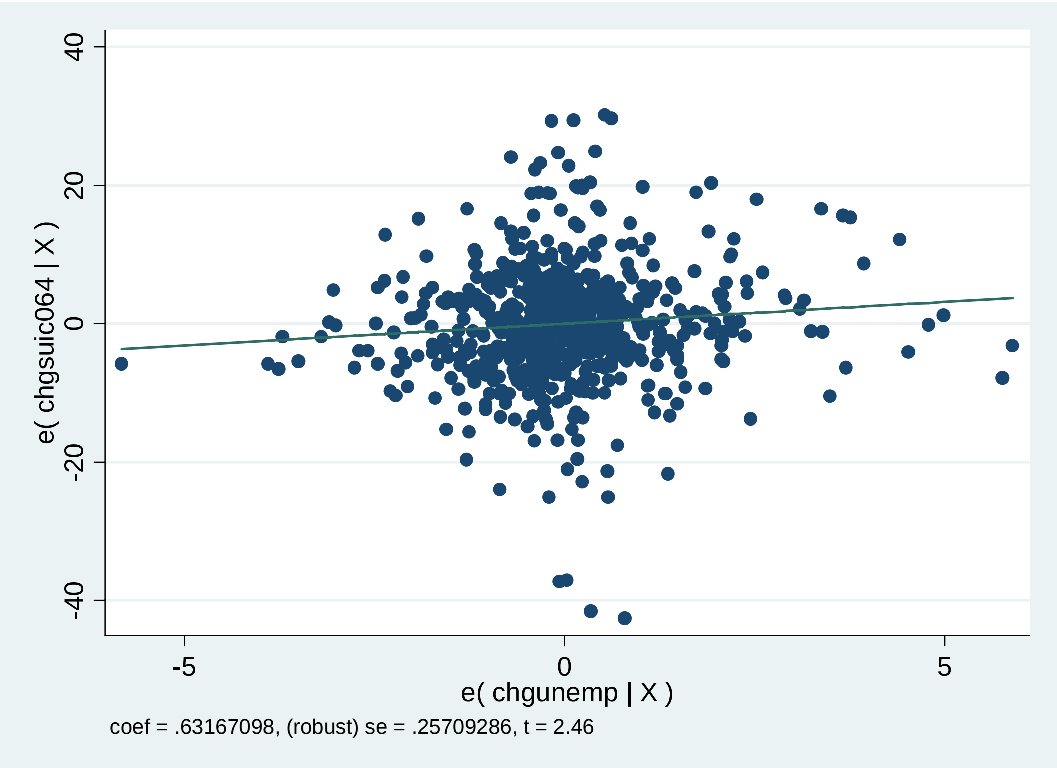
```
predict err, rstandard

xi: regress chgsuic064 chgunemp year country1_trend-country26_trend i.country if chgsuic064>-150 & chgsuic064<150 & err<abs(2), cluster(num)
```

The estimated coefficient for unemployment was statistically indistinguishable from the previous estimate without removing these residuals ($\chi^2(1) = 1.72$, p=0.19).

```
xi: regress chgsuic064 chgunemp year country1_trend-country26_trend i.country if chgsuic064>-150 & chgsuic064<150 & err<abs(2)
eststo t1
xi: regress chgsuic064 chgunemp year country1_trend-country26_trend i.country if chgsuic064>-150 & chgsuic064<150
eststo t2
suest t1 t2
test [t1_mean]chgunemp = [t2_mean]chgunemp
```

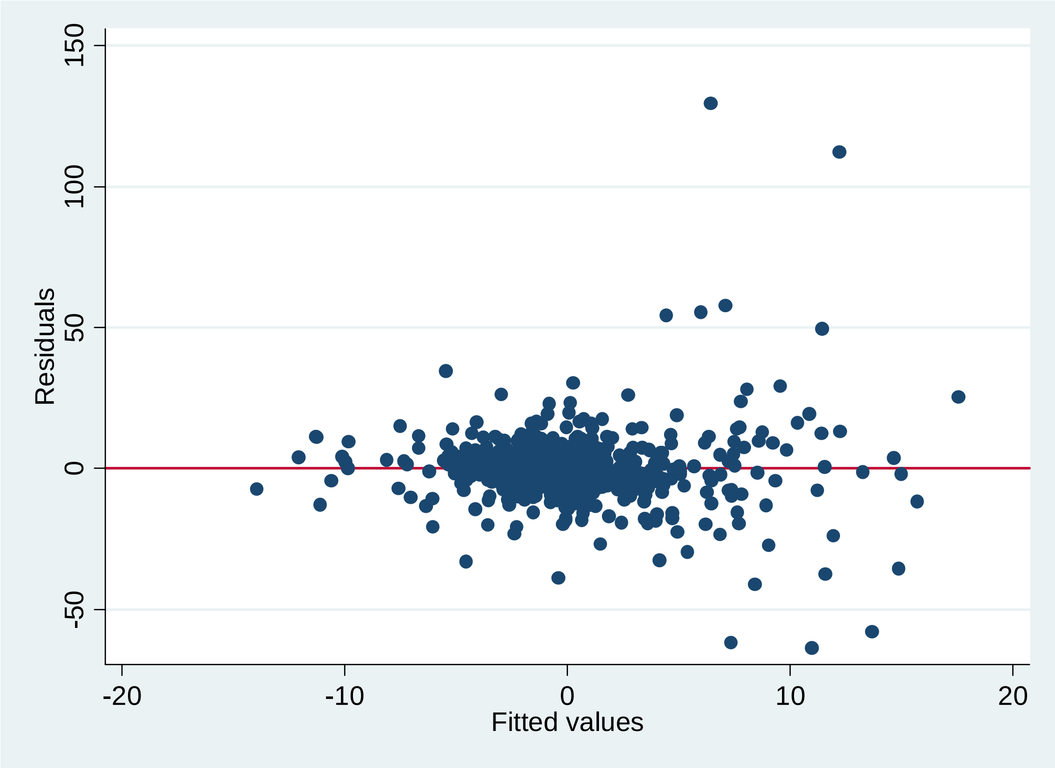
Note the added-variable plot below, and the difference in the y-axis scale.

Figure 3. Added-variable plot, potential outliers (>|2| standardised residuals) removed



As expected, the residual-versus-fitted plot revealed a fan-shaped pattern, which is evidence of heteroskedasticity, and was confirmed using a Breusch-Pagan test. This can arise from mis-specification but also from sub-group differences, which we address explicitly in our interaction models.

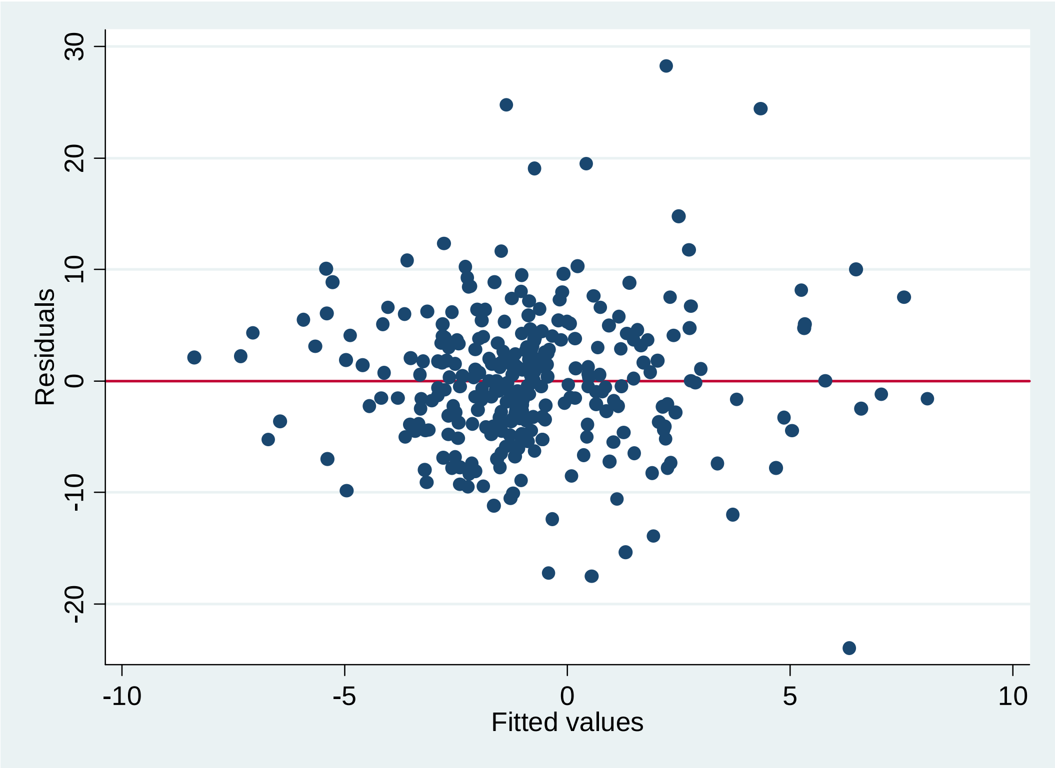
Figure 4. Residual-versus-fitted plot and heteroskedasticity



Once we included the interaction terms with social protections, the residuals shape was changed considerably, which provides further supportive evidence of the important of social protections in modifying the effect of unemployment:

```
generate inter_labmkt= chgunemp * socexp_labmkt
xi: regress chgsuic064 chgunemp socexp_labmkt inter_labmkt year country1_trend-country26_trend i.country if chgsuic064>-150 & chgsuic064<150, cluster(num)
rvfplot, yline(0)
```

Figure 5. Residual-versus-fitted, after specifying modifying effects of social protections



We also note that heteroscedasticity does not bias the coefficients, but causes inferential problems associated with biased standard errors. We coped with the problem of non-constant variance by using robust standard errors (STATA automatically specified the Huber/White estimator or so-called 'sandwich estimators' or variance).[12, 13] Such a procedure is the standard and most recommended practice for ecological models.[8]

We used two methods to ensure robustness to non-normality of the error structure: robust regression, using bootstrapping, and non-parametric estimation, using quantile regression – two estimation techniques which are not sensitive to the Gauss-Markov normality assumption [9, 10, 14]; for a health-related discussion regarding SF-36, see Walters and Campbell, 2004.[15]

First, as a robustness check (not presented in the manuscript), we used bootstrapped standard errors, a commonly applied correction for residual non-normality in time-series data, and the estimated coefficient and confidence intervals were nearly indistinguishable to those presented in the main text.[16, 17b] As noted by Watson and Campbell, the use of bootstrapping methods which are insensitive to distributional assumptions tends to be chimerical [18];

[b] Bootstrapping is a nonparametric method for estimating standard errors (Efron 1981). For a sample of size n, a bootstrap sample of size n is drawn from the sample with replacement (that is, any observation can be sampled more than once). The regression coefficients are estimated using this bootstrap sample. Then a second bootstrap of sample size n is drawn, and the process is repeated (here 50 times) until enough bootstrap samples have been drawn to provide an estimate of the standard error of the parameter of interest. The bootstrap estimate of the standard error is simply the standard deviation of the coefficient across bootstrap replications. Since the technique makes no assumptions about the distribution of residuals in the parent population, it can be applied to OLS as well as other non-parametric estimation methods such as LAD. Bootstrapping typically doesn't provide better parameter estimates but does provide standard error estimates that don't depend on distributional assumptions (Freedman 1981;Dietz 1987).

nonetheless, they do add confidence to the inferences that have been drawn from the more conventional methods presented in the manuscript.

```
bootstrap: xtreg chgsuic064 chgunemp year country1_trend-country26_trend if chgsuic064>-150 & chgsuic064<150, fe
```

Table 1. Bootstrapping Estimation, using 50 replications		
Bootstrapping	Bootstrap Coefficient (Bootstrap Std. Error)	P-value
Percentage Change in Unemployment	0.79 (0.28)	0.006
Main Model	Coefficient (Robust Clustered Std. Error)	P-value
Percentage Change in Unemployment	0.79 (0.31)	0.016

Second, we applied quantile regression, a non-parametric approach, which also produced similar results. Quantile regression is estimated using "least absolute deviations" regression (LAD), which minimizes the sum of the absolute values of the residuals (as opposed to the sum of squares in OLS), and uses medians, rather than means; as a result, quantile regression is robust to residual outliers and non-normality.

```
xi: bsqreg chgsuic064 chgunemp year country1_trend-country26_trend i.country if chgsuic064>-150 &
chgsuic064<150
```

Table 2. Quantile Regression		
Covariate	Quantile Coefficient (Bootstrap std. Error)	P-value
Percentage Change in Unemployment	0.72 (0.37)	0.049

These two complementary robust regression methods, quantile regression and bootstrapping, provide efficient and unbiased parameter estimates and unbiased estimates of standard errors. Statisticians note that "this solves the problem of nonnormal residuals" (Dietz 1987, p. 385).

Missing Data

As detailed in Web Appendix 1, data on mortality for some countries were missing between years. We considered the potential issues associated with these data. We checked the assumption that these were missing-at-random by recoding the change in suicide as 0 for missing data and creating a dummy variable, 'missing', if the mortality data were unavailable. None of the results was changed, and the coefficient on missing' was not significant, as shown below. More sophisticated methods of imputing the data based on predictors also did not change the patterns. Thus we chose to maximize our sample by using all of the available data, even though this rendered our panel unbalanced (that is, some countries had more observations than others), while noting that under fixed effects or "within-country" estimation our results would be robust.

```
generate missing = 0
```

```
replace missing = 1 if chgsuic064 == .
replace chgsuic064 = 0 if missing ==1
xtreg chgsuic064 chgunemp missing year country1_trend-country26_trend if chgsuic064>-150 & chgsuic064<150, fe
cluster(num)
```

Table 3. Missing Data		
Covariate	Coefficient (std. error)	P-value
Percentage Change in Unemployment	0.67 (0.26)	0.016
Missing Dummy	2.02 (1.52)	0.197

Further notes on fixed effects estimation

We wish to note that in the unadjusted correlation matrix our measure of unemployment and suicide have qualitatively different effects (table below). We believe this finding merits further discussion that space constraints in the text precluded. Our theory does not suggest that a high unemployment rate is harmful but rather that a rise in unemployment may be for those populations affected.

When we replicate the correlation matrix using the first difference terms, or the change in each variable from the previous year, the direction of the effect associated with unemployment on suicide rates reverses.

Table 4. Correlations, Level and Change

Pearson Correlation Level	Suicide under-64 (level)
Unemployment (level)	-0.02 (p = 0.51, n= 694)
Pearson Correlation Change	Suicide under-64 (change)
Unemployment (change)	0.14 (p = 0.003, n = 662)

We can specify this finding at a mathematical level. Consider a standard regression model, where

(1) $\mathrm{SUIC}_{it} = \beta UNEMP_{it} + \varepsilon_{it}$

In longitudinal studies, we can decompose the error term of this standard model into two components, country-specific heterogeneity (υ) and a i.i.d. error term of random noise or measurement error (μ):

(2) $\varepsilon_{it} = \mu_i + \sigma_{it}$;

Now the revised specification becomes:

(2) $\mathrm{SUIC}_{it} = \beta UNEMP_{it} + \mu_i + \sigma_{it}$

Applying the first-differencing operation shown in Table W3b yields

(3) $\Delta\mathrm{SUIC}_{it} = \Delta\beta UNEMP_{it} + \Delta\mu_i + \Delta\sigma_{it}$

Since μ_i does not change over time, it drops out of the model. As an example, we present these regressions here:

```
regress sdr_suic_064 unemp, cluster(num)
regress d.sdr_suic_064 d.unemp, cluster(num)
```

WB4. Effect of Unemployment on Age-Standardised Suicide Rates (under 64)		
	Undifferenced	First-Differenced
Unemployment Rate	-0.04 (0.07)	0.15* (0.05)

Note: Robust standard errors in parentheses clustered by country to reflect non-independence of sampling and robustness to serial correlation. * - denotes significant at p<0.001

In the regression, the unemployment rate has no effect on suicides. Once we difference the models to net out country heterogeneity, however, the coefficient is strongly significant.

The fixed effects transformation also removes all time-invariant components of the model:

$$(4)\ (\mathrm{SUIC}_{it} - \overline{SUIC}_{i}) = \beta(\mathrm{UNEMP}_{it} - \overline{UNEMP}_{i}) + (\mu_i - \bar{\mu}_i) + (\sigma_{it} - \bar{\sigma}_i)\,;$$

It is often called the "within estimator" because it essentially evaluates variation within each country, while holding constant differences between countries (i.e., using country-specific slopes).

Testing Random versus Fixed Effects

We can justify our decision to use fixed effects (FEM) theoretically, and show support for this decision empirically.

Theoretically, FEM copes with between-country limitations to the existing unemployment data. As the International Labour Organization notes, "there are a host of reasons why measured unemployment rates may not be comparable *between countries*" (ILO 2007, p. 8, italics added)[19], including different sources of data, varying numbers of observations per year, different conceptual bases of measuring unemployment, and collection methodology. One issue is that the propensity to register as unemployed at an employment office differs across countries, although this gap tends to be fairly stable over time among countries. By using fixed effects, and removing these between-country differences from the analysis, we are able to isolate how relative annual changes in unemployment in the UK affect mortality changes in the UK, those in Sweden to Sweden, and so on for all countries.

Empirically, we can test whether the more conservative fixed effects modelling approach is justifiable. Since fixed effects includes an additional 26 dummy control variables, the models lose degrees of freedom and are less efficient – making it harder to detect an effect, should one exist. Random effects models are therefore more sensitive detectors of effect, while FEM approaches are more conservative. The standard way to test the assumptions that the unobserved country-specific effects are not confounders is first to estimate both random effects and fixed effects models, and then to test whether the coefficients significantly differ between the two (a "Hausman-Taylor" test of endogeneity, see page 123 Rabe-Hesketh and Skrondal, 2008 *Multilevel and Longitudinal Modeling using*

STATA).[20] Performing this test[c], we obtain $\chi^2(1) = 4.32$, $p = 0.0377$. Thus, we find that we cannot safely assume that the unobserved country-specific factors are not potential confounders to the unemployment-mortality association, and therefore we remove these from the analysis by using a FEM approach.[d]

Testing Effect Homogeneity

We tested cross-model hypotheses by using the STATA routine on seemingly unrelated estimation (using robust clustered standard errors). Category-wise testing of significance is not appropriate. Our approach accounts for the differing variance and sample size across the separately estimated models. The test has one degree of freedom because it tests two coefficients.

Further discussions are available from STATA 2003. In STATA 8 Reference S-Z. College Station, TX: Stata Press; 2003. "Seemingly Unrelated Estimation—Suest". pp. 126–47[21], as well as Greene WH. 2003. Econometric Analysis. Upper Saddle River, NJ: Prentice Hall; 2003[22] and Veazie 2006.[23]

See also http://www.stata.com/support/faqs/stat/testing.html for a description of the STATA module we used. (Briefly, we use a three step method: first we regress female suicide on unemployment, and create a dummy to indicate the observations that were included this sample. Second, in a separate dataset, we run a model of male suicide on unemployment. We then append this male suicide-unemployment sample to the first female suicide-unemployment sample. We create an interaction term between unemployment and the female estimation. Third, using the combined dataset, we regress suicide (both male and female) on unemployment, unemployment * the male sample dummy, and the male sample dummy. If there is no significant interaction with gender, the male sample dummy and the male sample interaction with unemployment should be zero (indicating that being part of the male sample does not affect the coefficient describing the relationship between unemployment and suicide). The results of this test are reported below.

In STATA, the test is operationalised using the suest module (seemingly-unrelated estimation), as follows:

```
xi: regress chgsuic_fem chgunemp year country1_trend-country26_trend i.country if

chgsuic_fem>-150 &  chgsuic_fem<150
eststo t1
xi: regress chgsuic_male chgunemp year country1_trend-country26_trend i.country if

chgsuic_male>-150 &  chgsuic_male<150
eststo t2
suest t1 t2, cluster(num)
test [t1_mean]chgunemp = [t2_mean]chgunemp
```

$\chi^2(1) = 2.06$, $p = 0.1509$

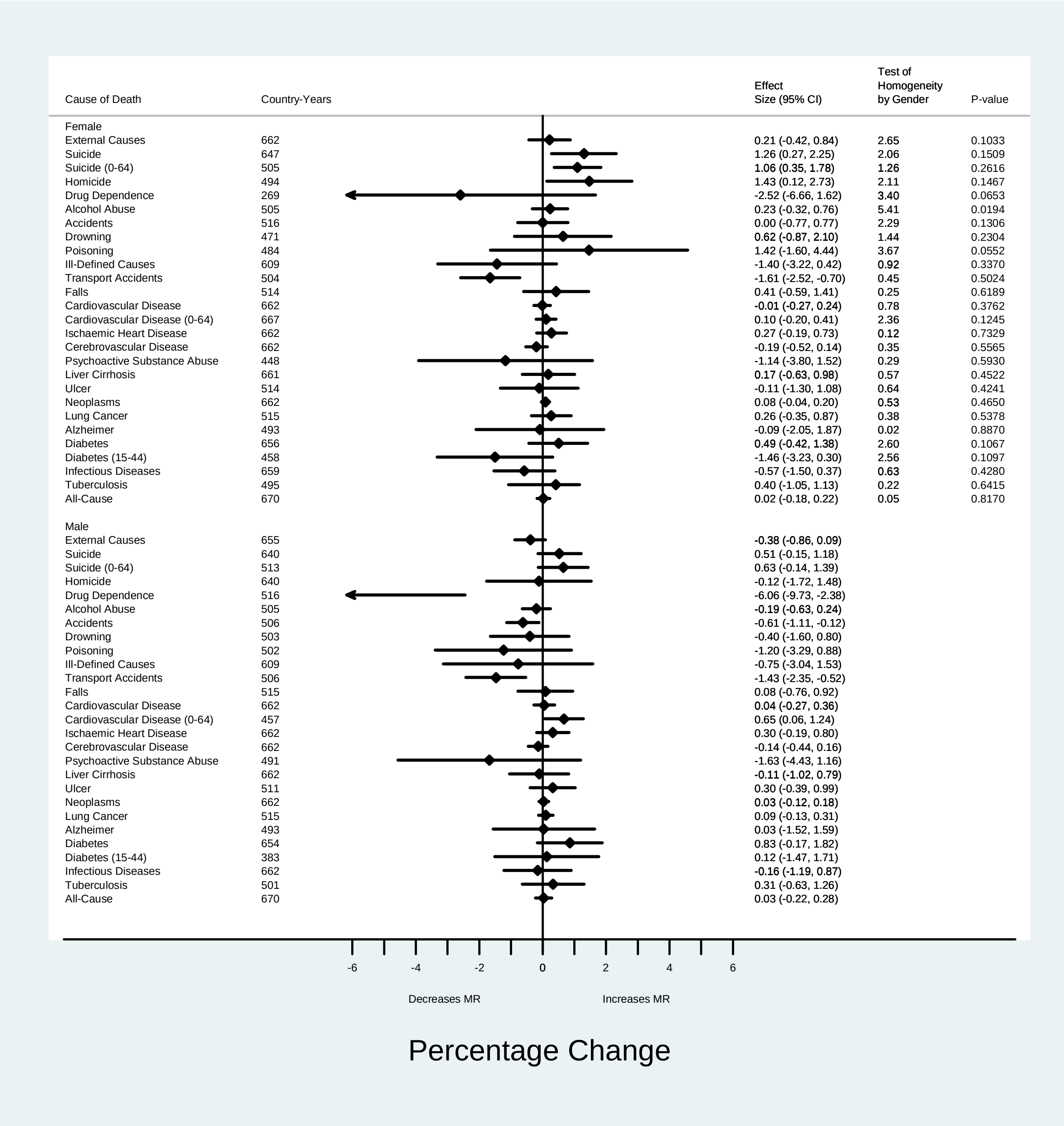
We did this test 55 more times and added the results as additional columns to Web Appendices 2 and 3, the replication of Figures 1 and 2 by gender

---

[c] Hausman test statistic $h = (\beta\hat{}^{fixed} - \beta\hat{}^{random})^2/[(s.e.\ \beta\hat{}^{fixed})^2 - s.e.(\beta\hat{}^{random})^2]$, which has a χ^2 distribution with 1 degree of freedom. (note: ^, 'hat', denotes the estimated coefficient).

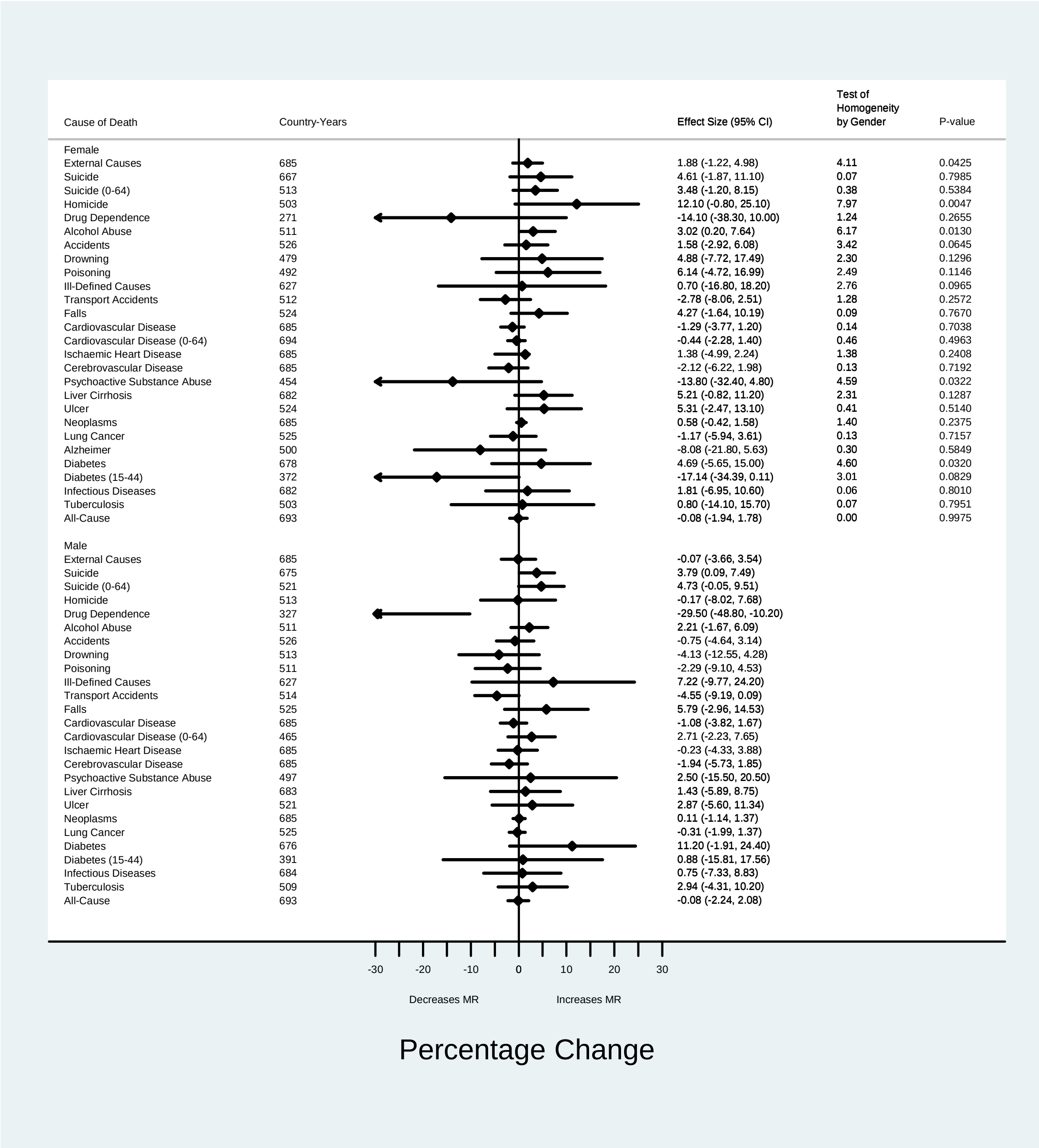
[d] The pooled OLS produces β (s.e.)= 1.04(0.29), p<0.001 and the fixed effects model produces β (s.e.)= 0.79 (0.31), p=0.018.

Web Appendix 4. Replication of Figure 1, by Gender



Notes: Coefficients are presented from fifty-four separate regression models (see Web Appendices 2,3, 10 and 11 for representative models and more details). Models correct for population ageing, past mortality trends, country-specific mortality trends and country fixed effects. Error bars are 95% confidence intervals based on robust standard errors clustered by country to reflect non-independence of sampling. Homogeneity of effect Wald test $\sim\chi^2(1)$ and calculated based on robust standard errors clustered by country using STATA suest module. Some causes of death are overlapping (e.g., poisoning and alcohol abuse). Data are from the World Health Organization European Health for All Database 2008 Edition (HFA-DB and HFA-MDB).

Web Appendix 5. Replication of Figure 2, by Gender



Notes: Coefficients are presented from fifty-four separate regression models (see Web Appendices 2,3, 10 and 11 for representative models and more details). Models correct for population ageing, past mortality trends, country-specific mortality trends and country fixed effects. Error bars are 95% confidence intervals based on robust standard errors clustered by country to reflect non-independence of sampling. Homogeneity of effect Wald test $\sim\chi^2(1)$ and calculated based on robust standard errors clustered by country using STATA suest module. Some causes of death are overlapping (e.g., poisoning and alcohol abuse). Data are from the World Health Organization European Health for All Database 2008 Edition (HFA-DB and HFA-MDB).

Note: Web Appendix 4 and 5 disaggregate all mortality rate variables in Figures 1 and 2 by gender except for maternal mortality, which only applies to female, and infant mortality, for which reliable data by gender were not available.

Web Appendix 6. Periods of Mass Rises in Unemployment and Changes in Suicide Rates

Country	Year	Percentage Rise in Unemployment	Percentage Change in Standardised Suicide Rates (Ages 0-64)
Ireland	1975	4.3	25.2
Romania	1992	5.4	23.8
Latvia	1993	3.5	23.8
Estonia	1993	4.9	21.5
Bulgaria	1992	4.2	17.7
Slovenia	1991	3.5	17.1
Spain	1993	4.3	13.4
Lithuania	1992	3.2	12.2
Netherlands	1983	4.2	9.8
Spain	1980	3.6	6.5
Poland	1991	5.3	6.2
Bulgaria	1991	9.4	3.3
United Kingdom	1981	3.6	2.8
Slovakia	1999	3.6	2.1
Czech Republic	1991	3.4	1.8
Hungary	1992	3.8	1.3
Slovakia	1992	4.8	0.1
Finland	1992	5.1	0.1
Finland	1991	3.4	-2.1
Hungary	1991	6.8	-3.1
Finland	1993	4.6	-5.4
Lithuania	1998	6.5	-5.9
Slovakia	1991	5.1	-6.9
Bulgaria	1999	3.8	-8.6
Sweden	1992	3.6	-12.0
Slovenia	1992	3.3	-15.0

Notes: Table arranged from greatest rise in suicides (Ireland, 1975) to the lowest rise (Slovenia, 1992).

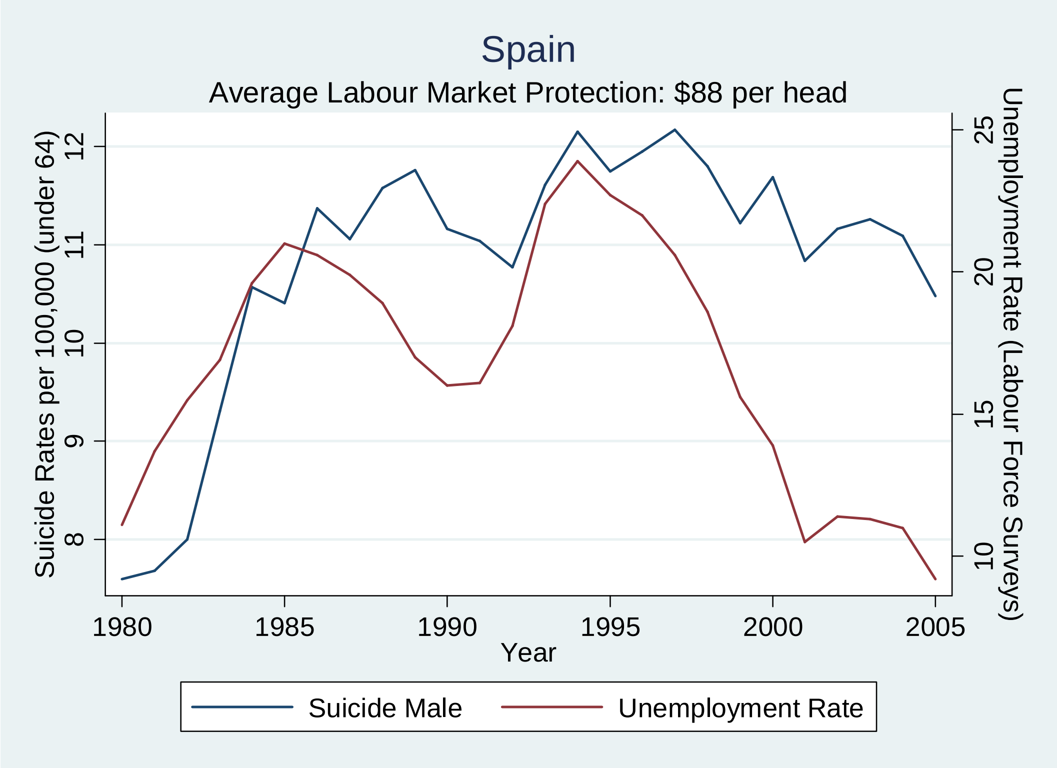
Web Appendix 7. Relationship between Change in Unemployment Rates and Age-Standardised Suicide Rates (under 65), EU countries 1970-2007

Country	Correlation	Elasticity
Austria	0.08	0.86
Belgium	0.51	3.8
Bulgaria	0.45	1.14
Czech Republic	0.15	0.86
Denmark	-0.04	-0.31
Estonia	0.51	3.52
Finland	-0.02	-0.07
France	0.44	2.46
Germany	0.08	0.28
Greece	-0.12	-1.81
Hungary	-0.1	-0.18
Ireland	0.11	0.86
Italy	0.09	0.69
Latvia	0.64	4.55
Lithuania	0.24	0.97
Luxembourg	0.12	10.85
Malta	0.15	10.04
Netherlands	0.44	1.68
Poland	0.63	0.93
Portugal	0.22	4.44
Romania	0.53	2.24
Slovakia	-0.09	-0.26
Slovenia	0.31	1.91
Spain	0.59	1.88
Sweden	-0.13	-0.89
United Kingdom	0.13	0.45

Web Appendix 8. Comparisons among EU countries unemployment-mortality associations

Spain: direct correlation between rises in unemployment and rises in suicide rates. Spain previously had among the lowest suicide rates in western Europe (note y-axis in early-1980's), but a combination of AIDS and high rates of injuries against a backdrop of economic and political turbulence post-Franco with low social protections ($88 per head) left the population more exposed to economic shocks.

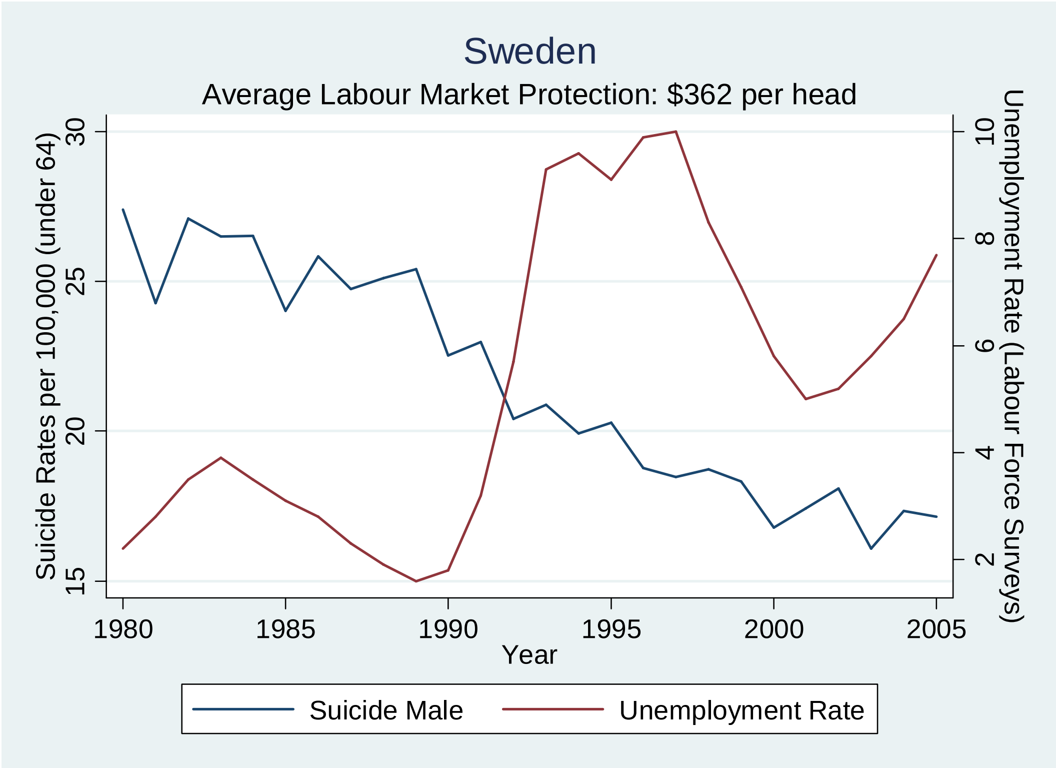
Web Figure 8a. Direct Association of Unemployment with Suicide, Spain 1980-2005



Notes: Unemployment rates based on labour force surveys from the International Labour Organisation Key Indicators of the Labour Market Database 2006 edition. Male suicide mortality rates (ages 0-64) are from the World Health Organisation European Health for All Database 2008 edition.

Sweden: de-coupled unemployment rise (coinciding with the 1992 financial crisis) from rises in suicide rates (ages 0-64) altogether, in part through high social protections on active labour market programmes.

Web Figure 8b. No Association of Unemployment with Suicide, Sweden 1980-2005



Web Appendix 9. Further Interaction Tests

We also compared different types of social expenditure, observing that active labour market programmes had the strongest effect. The table below presents the interaction coefficients from five models (note all units of social protections are comparable in 1 USD).

We note that family support was also significant but delivered a less strong effect for an additional 1 USD spending on active labour market programmes.

Table 1. Comparison of alternative social protections: Modifying Effects on the Change in Unemployment-Suicide Rate Associations

Covariate	Change in Under-64 Suicide Rates (excluding CEE countries)	P-value	Sample Size	Akaike Information Criterion	Bayesian Information Criterion
Change in Unemployment Rate x 10 USD Spending on Active Labour Market Programmes	-0.038% (0.016)	0.028	300	1958.36	1969.47
Change in Unemployment Rate x 10 USD Spending on Unemployment Cash Benefits	0.0088% (0.012)	0.489	310	1969.28	1980.49
Change in Unemployment Rate x 10 USD Spending on Healthcare	-0.0068% (0.0065)	0.314	334	2197.48	2208.92
Change in Unemployment Rate x 10 USD Spending on Family Support	-0.023% (0.0076)	0.007	326	2144.19	2155.55
Change in Unemployment Rate x 10 USD Spending on Housing Support	-0.068% (0.040)	0.108	294	1943.14	1954.19

Notes: Robust standard errors in parentheses clustered by country. Results control for the full specification as in the table above. Interaction terms presented from five separate regression models.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Below we show that the interaction effect is significant when analysing only the western EU members before 2004 (i.e., excluding CEE countries).

When we analyzed each block separately, we observed that the effects were prominent in Western Europe.

Table 2. Replication of Interaction Model using only western non-CEE EU countries (members post-2004).

Covariate	Change in Under-64 Suicide Rates (excluding CEE countries)
Change in Unemployment Rate (%)	1.53* (0.55)
Spending on Active Labour Market Programmes	-0.0034 (0.0065)
Change in Unemployment Rate x Spending on Active Labour Market Programmes	-0.0053** (0.0016)
Year	-0.0057 (0.039)
Country-Year Trends	Yes
Observations	257
R^2	0.076

Notes: Robust standard errors in parentheses clustered by country.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We also observed a dose-response relationship: the lower the degree of social protections, the greater was the effect of rising unemployment on short-term suicide fluctuations. This was not simply the result of a non-linear employment effect; if it were, we would have seen significant associations with all the interaction terms.

Thus, these lines of evidence enabled us to specify that social protections, as opposed to other potential effect modifiers, were the main interacting factor for offsetting the health impacts of rising unemployment rates – population-evidence which is consistent with some individual studies we cite in the main text.

In the course of our analysis, we found evidence consistent with three major possible interacting factors that modified the relationship between rises in unemployment and fluctuations in mortality:
1) Baseline rates of unemployment
2) History of institutional differences in Central and Eastern Europe dating to the Communist era
3) Degree of social protections

We tested these interactions further by including them all in the model. We found that, even when including an interaction between changes in unemployment and central & eastern Europe and between the baseline rate of unemployment, only active labour market programmes exerted a protective effect:

Table 3. Tests of competing explanations for effect modification, age-standardised under-64 suicide rates

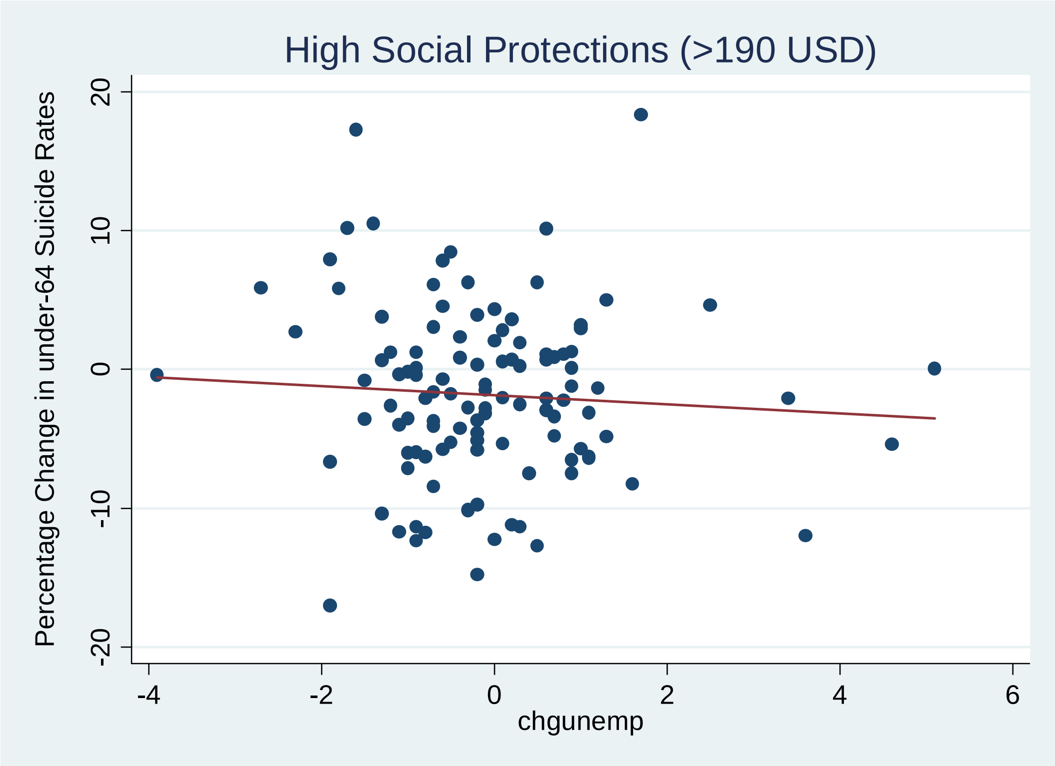
Covariate	Coefficient (Robust standard error)	P-value
Change in Unemployment Rate	0.84 (0.82)	0.320
Social Expenditures on Active Labour Market Programmes	-0.0013 (0.0075)	0.863
Changes in Unemployment Rate x Social Expenditures on Active Labour Market Programmes	-0.00450 (0.00186)	0.028
Baseline Unemployment Rate	-0.18 (0.19)	0.344
Change in Unemployment Rate x Baseline Unemployment Rate	0.049 (0.055)	0.387
Change in Unemployment Rate x Dummy for CEE country	-0.802 (0.503)	0.130
Year	-0.07 (0.08)	0.374
Country-Year Trends	Included	<0.00001

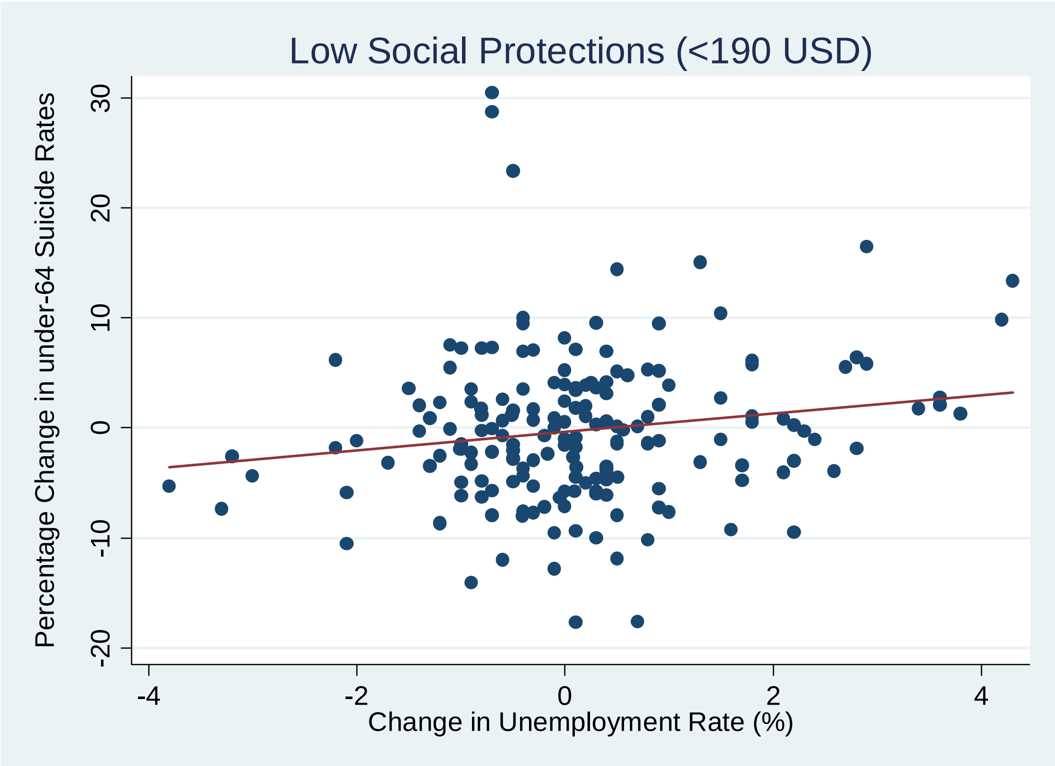
We note that the effect attributed to being a central and Eastern European country was already captured by the model's country fixed effects.

Table 4. Country-specific active labour market spending and associated estimated effects of an hypothetical 1% rise in unemployment rates with suicide rates.

Country	Investment in Active Labour Market Protections (2003)	Estimated Effect Size on Suicides Rates (under 64) (if a 1% rise occurred in 2003)
Poland	22	2.84
Czech Republic	30	2.71
Slovakia	38	2.57
Greece	41	2.52
Hungary	57	2.26
United Kingdom	150	0.72
Spain	169	0.41
Italy	181	0.21
Austria	197	-0.06
Ireland	233	-0.65
Finland	248	-0.9
France	291	-1.61
Germany	321	-2.11
Netherlands	336	-2.36
Belgium	365	-2.84
Sweden	375	-3.01
Denmark	495	-4.99

Figure 1: Association between Changes in Suicide Rates (under 64) and Unemployment, by Social Protections per capita





Web Appendix 10. Replications without year controls and further robustness checks

We include these models as representative tabular presentations of our basic figures and also as a replication of our models but without using country-year time trends. As shown, we have presented our most conservative estimates in the main text and figures.

In tables 1 and 2 we replicate models for selected causes of death without year controls. As shown, all the results are consistent in direction, albeit the effects are slightly greater and more significant.

In tables 3 and 4 we replicate models for suicide rates stratified by age and gender. All results were again consistent with our basic models, although the effect sizes were larger. This again reiterates that the results presented in the main text are from our most conservative models (reducing the probability of type-I errors).

In table 5 and 6 we evaluate the unemployment-mortality associations within west EU (members pre 2004) and east EU (members post 2004), finding that the unemployment-mortality associations were generally stronger in the latter group of countries although, as we note in Web Appendix 16, these differences were not significant.

Table 1. Representative Associations of a 1% Rise in Unemployment with Percentage Change in Age-Standardised Death Rates, EU Countries 1970-2007, without year controls

	(1) Suicide	(2) CVD	(3) Homicide[a]	(4) Ulcer[a]	(5) Road Accidents[a]	(6) Alcohol Poisoning[a]	(7) Life Expectancy
Unemployment Rate	1.16%*** (0.25%)	0.28%* (0.13)	1.21%** (0.37)	0.54% (0.29)	-1.03%*** (0.22)	1.22% (1.97)	-0.013% (0.018)
Average Rate of Year-to-Year Change*	-0.49%*** (0.052)	-2.85%*** (0.027)	1.77%*** (0.054)	-2.23%*** (0.043)	-2.48%*** (0.032)	4.33%*** (0.23)	0.30%*** (0.0038)
Nation-Years	635	635	487	493	494	203	641
Nations	25	25	25	25	25	25	26
R^2-within	0.03	0.01	0.01	<0.01	0.02	0.002	<0.01

Notes: Results presented from seven regression models. Robust standard errors in parentheses clustered by country. * - average rate of change is the trend in the health outcome conditional on changes in unemployment rates. Model estimated as: $\Delta H_{i,t} - \Delta\overline{H}_{i,t} = \alpha + \beta * (\Delta U_{i,t} - \Delta\overline{U}_{i,t}) + \varepsilon_{i,t}$. [a] – data are from WHO-HFA MDB covering 1981-2006. Countries include Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 2. Associations of a Mass Rise in Unemployment with Percentage Change in Mortality Rates, EU Countries 1970-2007, without year controls

	(5) Suicide	(6) CVD	(7) External Causes	(8) Life Expectancy at Birth
Mass Rise in Unemployment	6.32%** (2.09)	1.00% (1.38)	1.88% (1.92)	-0.21% (0.19)
Average Rate of Year-to-Year Change*	-0.41%*** (0.083)	-2.69%*** (0.055)	-1.49%*** (0.076)	0.30%*** (0.0074)
Nation-Years	655	655	655	661
Nations	25	25	25	26
R^2-within	0.015	0.002	0.003	0.006

Notes: Results presented from four regression models. Robust standard errors in parentheses clustered by country. Mass rise in unemployment is defined as a period when unemployment rates rise by greater than 3%. Model estimated as: $\Delta H_{i,t} - \Delta\overline{H}_{i,t} = \alpha + \beta * (\Delta U_{i,t} - \Delta\overline{U}_{i,t}) + \varepsilon_{i,t}$ * - average rate of change is the trend in the health outcome conditional on changes in unemployment rates (α). Countries include Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 3. Representative Table: Effects of a 1% Rise in Unemployment on Percentage Change in Male Suicide Rates, EU Countries 1980-2007, by Age, without year controls

Male	Under-14	15-29	30-44	45-59	60-74	75+
Change in Unemployment Rate (%)	2.40 (1.39)	0.39 (0.40)	1.66*** (0.38)	1.31* (0.53)	0.49* (0.22)	0.77 (0.47)
Average Rate of Year-to-Year Change*	3.84 (2.67)	0.26 (0.70)	0.54 (0.67)	0.42 (0.50)	0.14 (0.75)	1.79* (0.87)
Nation-Years	379	493	494	494	494	491
R^2-within	0.008	0.001	0.023	0.013	0.002	0.004

Notes: Robust standard errors in parentheses clustered by country. Models also control for changes in the percentage of the population over age-65. * - average rate of change is the trend in the health outcome conditional on changes in unemployment rates (α in equation #1). Countries include Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 4. Representative Table: Effects of a 1% Rise in Unemployment on Percentage Change in Female Suicide Rates, EU Countries 1980-2007, by Age, without year controls

Female	Under-14	15-29	30-44	45-59	60-74	75+
Change in Unemployment Rate (%)	-1.39 (2.23)	1.74^{*} (0.81)	1.84^{**} (0.63)	0.94 (0.50)	1.08^{*} (0.40)	-0.22 (0.77)
Average Rate of Year-to-Year Change*	-2.57 (3.64)	-0.25 (0.86)	0.18 (0.88)	-0.89 (1.55)	0.29 (1.43)	1.32 (1.87)
Nation-Years	251	479	493	490	487	478
R^2-within	0.009	0.009	0.013	0.004	0.008	0.003

Notes: Robust standard errors in parentheses clustered by country. Models also control for changes in the percentage of the population over age-65. * - average rate of change is the trend in the health outcome conditional on changes in unemployment rates (α in equation #1). Countries include Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Models are estimated by extending equation #1 to include *k,* or the age-specific death rate data, as follows:

(2) $$\Delta H_{i,t,k} - \Delta\overline{H}_{i,t,k} = \alpha + \beta * (\Delta U_{i,t} - \Delta\overline{U}_{i,t}) + \varepsilon_{i,t}$$

Table 5. Associations of Unemployment with Suicide, CEE versus non-CEE

	(1) 0-14	(2) 15-29	(3) 30-44	(4) 45-59	(5) 60-74	(6) 75+
Change in Unemployment Rate (%)	0.53	1.28	2.12^{*}	2.09^{**}	0.74	0.46
	(1.53)	(0.61)	(0.64)	(0.52)	(0.39)	(0.44)
Constant	4.61^{***}	-1.71^{***}	-1.55^{***}	-0.83^{**}	-1.52^{***}	1.42^{***}
	(0.59)	(0.23)	(0.24)	(0.19)	(0.14)	(0.16)
Observations	110	129	129	129	129	129
R^2-within	0.000	0.034	0.085	0.109	0.012	0.001

Notes: Robust Standard errors in parentheses clustered by country to reflect non-independence of sampling

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 6. Non-CEE (Western Europe)

	(1) 0-14	(2) 15-29	(3) 30-44	(4) 45-59	(5) 60-74	(6) 75+
Change in Unemployment Rate (%)	3.83	-0.23	1.34^{**}	0.76	0.31	0.98
	(1.94)	(0.51)	(0.43)	(0.81)	(0.26)	(0.74)
Constant	-0.36^{***}	1.20^{***}	0.82^{***}	0.61^{***}	0.13^{***}	0.38^{***}
	(0.075)	(0.032)	(0.027)	(0.052)	(0.017)	(0.048)
Observations	269	364	365	365	365	362
R^2-within	0.010	0.000	0.011	0.003	0.001	0.004

Notes: Robust Standard errors in parentheses clustered by country to reflect non-independence of sampling

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Web Appendix 11. Representative Dynamic Associations of Rises in Unemployment with Changes in Suicide Rates

Change in Unemployment Rate (%)	All-Cause	Suicide (under 64)
Contemporary	0.10	0.45
	(0.12)	(0.37)
One-Year Lag	-0.18	0.52*
	(0.15)	(0.20)
Two-Year Lag	-0.028	-0.94
	(0.13)	(0.54)
Three-Year Lag	-0.063	0.18
	(0.10)	(0.46)
Average EU Trend	-0.031***	-0.11***
	(0.0060)	(0.024)
Country-Specific Time-Trends	Yes	Yes
Country-Years	491	580
R^2	0.071	0.046

Notes: Robust Standard errors in parentheses clustered by country to reflect non-independence of sampling
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Web Appendix 12. Reconciling Individual and Population Level Findings

We further test the plausibility of the magnitude of our findings by comparing predictions based on individual models with those of ours at the population level.

Individual-level studies have found that unemployment increases risks of suicide by roughly 2.6 fold in England.[24] In 1995, in the UK, the rate of suicide among males between age 30-44 was 18.57/100,000 population and the unemployment rate was 8.6%. Based on the individual findings from longitudinal studies, we would expect a rise in unemployment of 10% to be associated with an increase in suicides of 14.1%. Our population model estimates a rise of 11.7% for age 30-44 males (95% CI: 2.4% and 20.9%), which is sufficiently similar.

With regard to the current economic crisis, if unemployment continues to rise to 3 million (or close to 10% of the labour force), our models suggest an increase of between 25 and 290 suicides will occur in the UK in the next year, over and above historical trends, as a result of the financial meltdown.[5]

Consider our basic model set out in equation 1 on page 9:

$$\Delta H_{i,t} - \overline{\Delta H}_{i,t} = \alpha + \beta * (\Delta U_{i,t} - \overline{\Delta U}_{i,t}) + \eta * t + \gamma_i * t + \varepsilon_{i,t}$$

Now, take the partial derivative with respect to unemployment, or $\partial \Delta H / \partial \Delta U$.

Note that the country-year, year trend, delta-H-bar and delta-U-bar terms drop out in a steady state (where the change in H-bar and U-bar are on average 0). This leaves us with:

$$\partial \Delta H_{i,t} = \beta * \partial \Delta U_{i,t}$$

Thus a 1% rise in unemployment in steady-state gives rise to a β effect on the percentage change in mortality rates.

However, for a regression decomposition, one would need to plug in the values accordingly. We could do this to provide a 'local' estimate based on the UK's baseline parameters. Conducted in this way, we would plug in the average UK unemployment rate, which was 0.07% per year for unemployment. A 10% rise in suicide rates as presented in the text would thus imply:

9.93* 1.17 = 11.6% estimated rise in suicides for ages 30-44 (where we presented 11.7%). We present the general comparative statics provided in the former example, the current one in the text, so that readers and health policymakers could easily conduct a similar exercise for their own countries.

[5] There were 3,897 suicides in the UK in 2007, which is then multiplied by a 4.45% increase associated with a >3% rise in unemployment rates. Other calculations, such as using the under-65 suicide rate of 6.14/100,000 in the UK in 2007, scaled to the number of people under-65 (British population in July 2008 was 60,943,912; under-65 was 83.96% according to latest available 2007 data), yields similar estimates.

Web Appendix 13. Representative Results Set, including R-Squared statistics, of Figures 3 and 4

Cause of Death	Gender	Age	Effect Size	Lower 95% Bound	Upper 95% Bound	Sample Size (country-years)	Test of Homogeneity	P-value	R^2-within
All-Cause	Male	Under-14	0.07	-0.37	0.5	521	0	0.9442	0.016
All-Cause	Male	15-29	-0.88	-1.53	-0.22	521	9.8	0.0017	0.038
All-Cause	Male	30-44	0.07	-0.55	0.68	521	0.01	0.9431	0.069
All-Cause	Male	45-59	0.1	-0.25	0.46	521	0.31	0.5795	0.051
All-Cause	Male	60-74	0.02	-0.23	0.26	521	ref	ref	0.07
All-Cause	Male	75+	0.07	-0.21	0.35	521	ref	ref	0.02
Suicide	Male	Under-14	2.43	-1.49	6.34	379	1.72	0.1901	0.039
Suicide	Male	15-29	-0.18	-1.38	1.03	508	0.13	0.7193	0.037
Suicide	Male	30-44	1.17	0.24	2.09	510	5.26	0.0218	0.045
Suicide	Male	45-59	0.58	-0.69	1.85	504	0.9	0.3433	0.066
Suicide	Male	60-74	-0.04	-0.67	0.58	504	ref	ref	0.072
Suicide	Male	75+	0.02	-1.3	1.34	496	ref	ref	0.071
Ischaemic Heart Disease	Male	Under-14	-0.45	-1.51	0.61	429	1.84	0.1744	0.021
Ischaemic Heart Disease	Male	15-29	0.49	-2.18	3.17	434	0.01	0.9062	0.049
Ischaemic Heart Disease	Male	30-44	0.85	0.06	1.64	513	2.92	0.0874	0.023
Ischaemic Heart Disease	Male	45-59	0.48	-0.06	1.02	516	1	0.3171	0.023
Ischaemic Heart Disease	Male	60-74	0.38	-0.16	0.91	516	ref	ref	0.089
Ischaemic Heart Disease	Male	75+	0.29	-0.29	0.86	516	ref	ref	0.065
All-Cause	Female	Under-14	-0.33	-1	0.34	521	1.07	0.3005	0.024
All-Cause	Female	15-29	0.01	-0.37	0.38	520	0.06	0.8063	0.029
All-Cause	Female	30-44	-0.01	-0.42	0.4	521	0.17	0.6826	0.052
All-Cause	Female	45-59	0.13	-0.19	0.44	521	0.27	0.6031	0.02
All-Cause	Female	60-74	0.06	-0.14	0.25	521	ref	ref	0.033
All-Cause	Female	75+	0.04	-0.24	0.33	521	ref	ref	0.02
Suicide	Female	Under-14	-1.78	-7.21	3.66	251	0.5	0.4783	0.052
Suicide	Female	15-29	2.07	0.05	4.08	482	4.4	0.0359	0.045

Suicide	Female	30-44	1.51	-0.06	3.08	502	3.01	0.0827	0.026
Suicide	Female	45-59	0.88	-0.31	2.08	500	1.5	0.2213	0.018
Suicide	Female	60-74	0.75	-0.22	1.72	488	ref	ref	0.041
Suicide	Female	75+	-0.91	-2.61	0.79	479	ref	ref	0.02
Ischaemic Heart Disease	Female	Under-14	-0.03	-1.93	1.88	456	0.18	0.6745	0.049
Ischaemic Heart Disease	Female	15-29	1.53	-1.75	4.81	331	0.56	0.4555	0.047
Ischaemic Heart Disease	Female	30-44	-0.14	-1.95	1.67	496	0.3	0.5852	0.044
Ischaemic Heart Disease	Female	45-59	0.1	-1.09	1.3	512	0.24	0.6272	0.017
Ischaemic Heart Disease	Female	60-74	0.23	-0.22	0.68	516	ref	ref	0.091
Ischaemic Heart Disease	Female	75+	0.42	-0.15	0.98	516	ref	ref	0.065

STATA code:

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format p %9.4fc
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la var n "Country-Years"
la var r2 "R-squared"
la var p "P-value"
la variable test "Test of Homogeneity (age-group vs. over-60)"

metan medium low high if male=="Male",by(type) xlabel(-6, -4, -2, 0,2,4,6) xtick(-
5, -3, -1, 1, 3, 5) lcols(age n) rcols(test p) astext(45) force boxsca(120) nowt
nooverall nohet favours(Decreases MR # Increases MR) xtitle(" " "Percentage
Change", size(small)) nobox effect("Effect Size")
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Web Appendix 14. Alternative Economic Measures

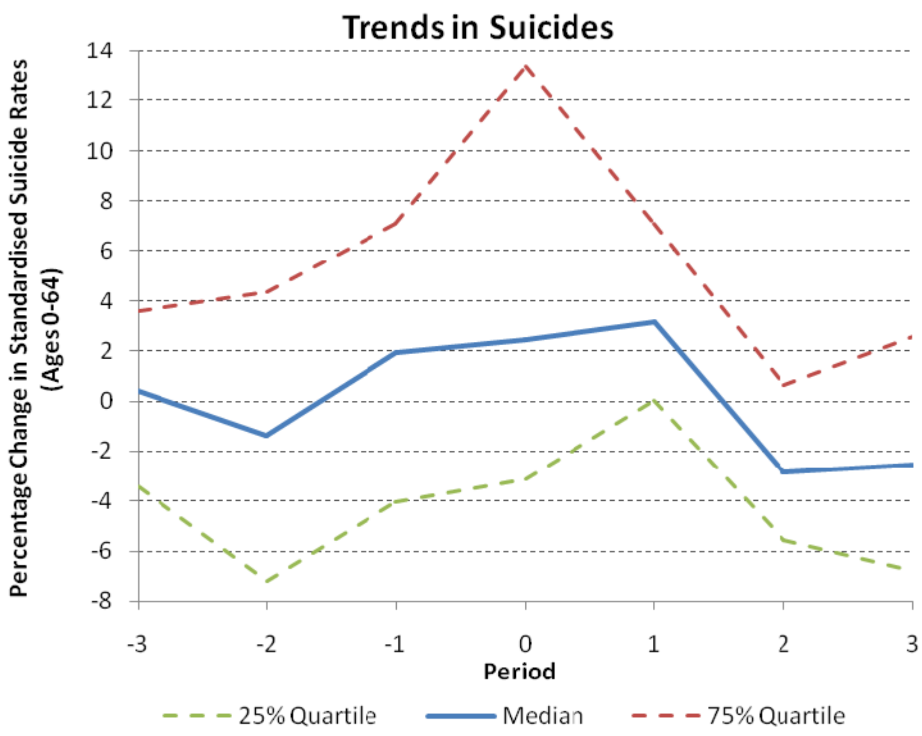
Table 1 presents results from thirty statistical models of the effects of alternative measures of economic change on health, including the number of hours worked, chronic unemployment, underemployment, unemployment based on labour force surveys, GDP per capita and the magnitude of the change in the unemployment rate (whether positive or negative). We found that rises in long-term unemployment were strongly associated with reductions in road-traffic accidents (-2.26%, 95% CI: -1.09 to -3.44, p = 0.0006), but had no effect on other causes of death. We found that short-term rises in hours worked were connected with a reduction in cardiovascular death rates of 0.29% (95% CI: 0.06 to 0.52, p = 0.016), but had no effect on suicides, homicides or road-traffic accidents. Underemployment, defined as working fewer hours than one is allowed to work and wishing to work more hours if possible, had no effect on any of the health outcomes studied. We also found that a 1% greater change in the unemployment rate, whether positive or negative, was significantly associated with a 1.19% reduction in transportation-related mortality rates (95% CI: -2.13 to -0.26, p = 0.014), which statistically indistinguishable to that associated with an increase in unemployment of 1.39% (test of effect homogeneity: $\chi^2 = 0.45$, p = 0.5007).

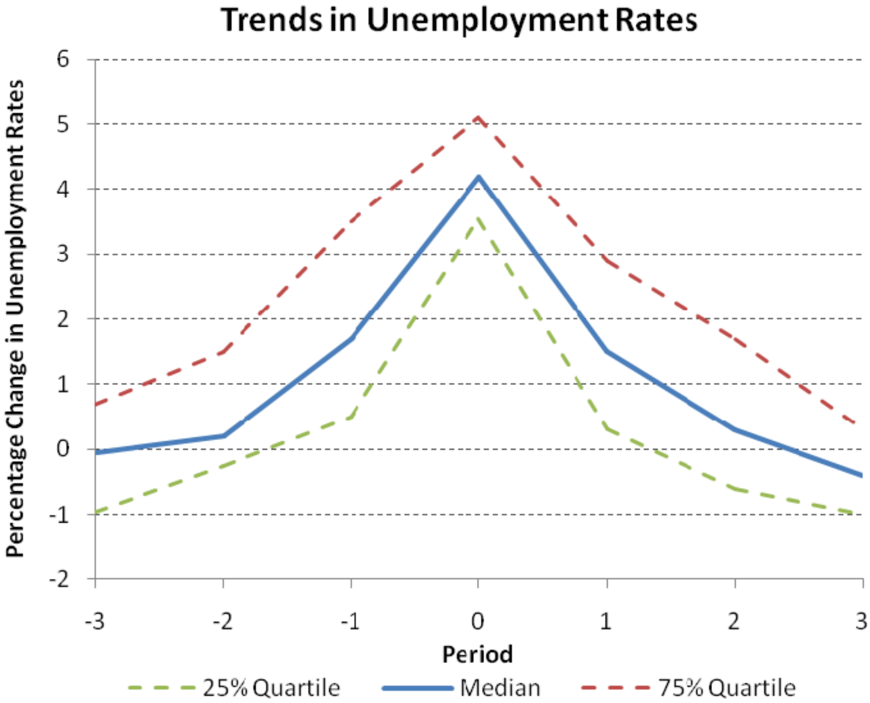
Web Appendix 15. Trends in Suicides and Unemployment. Period 0 is the year of rise in unemployment rates by > 3%.

Time-Trends

Figure 1 depicts trends in suicide rates before- and after- the period of mass rises in unemployment. Period 0 on the x-axis marks the year when unemployment rates rose by >3%. Positive periods are years after the crisis, whereas negative periods are the years leading up to the crisis. The Figure also compares the suicide rate trajectories of countries in the 25th quartile of suicide rates to those in the 75th quartile to compare how suicide rates were differentially affected in more and less vulnerable populations. Only those countries in the highest quartile of suicides experienced substantial increases in suicide rates, of about 6%, while countries in the lowest quartile experienced declines in suicide rates, albeit at slower rates than before the economic crisis. As shown in figure 1, after about two years, on average, rates of suicide in these higher-risk countries return to their prior trend.

Figure 1. Trends in Suicides and Unemployment. Period 0 is the year of rise in unemployment rates by > 3%.

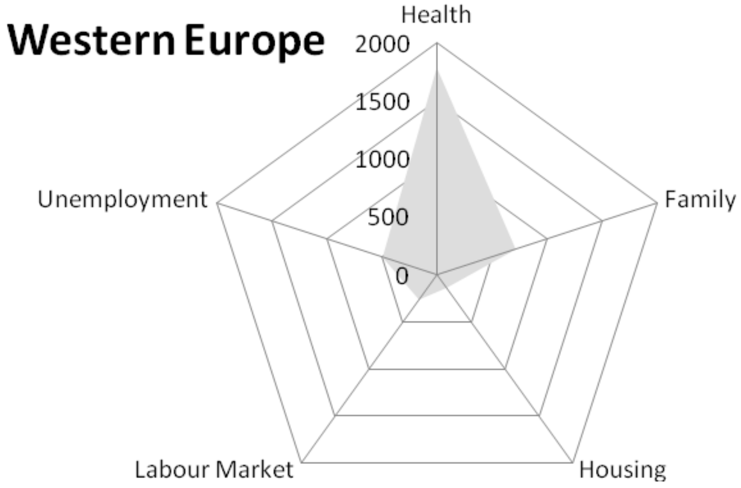


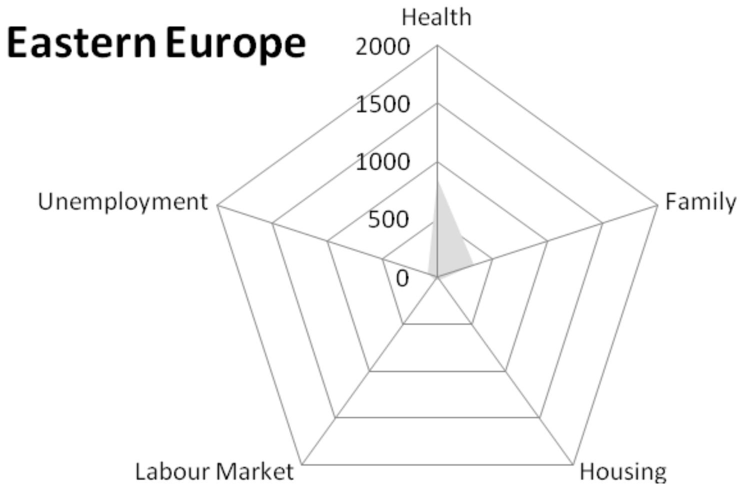


Notes: Period 0 on the x-axis marks the year when unemployment rates rose by >3%. Percentiles are based on the level of suicides rates in each year in the sample of countries. Positive periods are years after the crisis, whereas negative periods are the years leading up to the crisis. Unemployment rates tended to rise in the year before the large wave of job losses, but the rise in unemployment and mortality accelerated in the year of the mass rise in unemployment.

Web Appendix 16. Size and Distribution of Social Welfare Spending in eastern and western Europe, 2003, USD purchasing-power-parity per capita

Figure 1.





Notes: Eastern Europe includes Czech Republic, Hungary, Poland and Slovakia. Western Europe includes EU member OECD countries that are not in eastern Europe (14 countries). Data are from the OECD Health Data 2008 edition. Panel 1 defines all data on social protections.

It has been argued that the commitments of the governments of Sweden and Finland to social support during times of crises played a role, for instance through the use of active labour market programmes. One modifying factor could therefore be national institutional differences. We first compared the effects of an unemployment rise of greater than 3% in countries of central and eastern Europe (CEE) to those in the rest of western Europe. We found that unemployment surges were linked with a 5.30% rise in suicides in CEE countries but insignificant 3.10% rise in non-CEE countries; however, we found no evidence of a statistically significant difference between western and eastern Europe ($\chi^2 = 0.35$, $p = 0.5560$).

One explanation for the significant increase in CEE countries could be differences in social protection. Figure 1 above depicts the amount and distribution of welfare spending for health, labour market programmes, family, housing and unemployment across western and eastern Europe. In 2003, western European countries (excluding CEE) spent on average US$7,129 per head of population on social welfare, in the areas of family, health, education, labour market and unemployment (definitions are given in Panel 1). CEE countries for which data were available from the OECD (Hungary, Poland, Slovakia, and Czech Republic) spent less than half, or US$ 3,071 per head, and in all categories of expenditure, government intervention in Eastern Europe is much smaller (in part reflecting differences in GDP).

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