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A 'Natural' Suicide Rate, Hysteresis or Suicide Persistence? Evidence from U.S. State-Level Panel Data, 1980-2020

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Abstract

A growing literature probing the natural suicide rate hypothesis appears to have split into two factions. The first focuses on testing the strictly positive rate premise using 'ideal' socioeconomic conditioned empirically predicted values. The second examines the stationarity of the suicide rate time series. By exploiting an expansive (4 decade) panel of U.S. state-level suicide rates and characteristics, this paper aims to debit the inventories of both factions of the literature. Regarding the first, we provide a long-panel (3 decade) test of the strictly positive rate hypothesis where results reinforce the growing consensus that, even under the most pristine socioeconomic state, suicide occurrence endures. Additionally, we test the stationarity of U.S. suicide rates over time. Using panel methods that allow for cross-sectional dependence and structural deviations, we find strong evidence of non-stationarity (unit root) for the common factors of suicide rates in the U.S. This latter finding casts doubt on the usefulness of the natural suicide rate hypothesis.

Keywords: Natural suicide rate, Unit root, Panel data.
JEL Classifications: C32, C33, R12.

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1. Introduction

Emile Durkheim's (1897/1951) *Suicide* remains to be one of the landmark theory treatments in the social sciences. Durkheim's theory centers on two basic tenets: (i) the structure of social relationships form the structure of suicide and (ii) integration and regulation are the focal structural dimensions of social relationships. Durkheim believed, in essence, that societies fostering deep-seated social relationships and a strong collective conscience would be healthier and, in turn, exhibit *lower* suicide rates. Nearly a century later, Maris (1981) more directly affirmed that no society will be free from suicide mortality due to what he described as the "harshness of the human condition." Goldney (2003) bolstered this idea of suicide rates being strictly positive suggesting that biological, genetic and physiological factors determine a community's base rate of suicide. He posits that rates above the biological substrate (substratum) are the result of psychosocial factors and poor socioeconomic conditions.

Drawing on this notion of a base rate of suicide and the vast economic literature probing natural levels of unemployment, Yang and Lester (1991) loosely merged the two and forwarded the 'natural' suicide rate hypothesis. This premise suggests that no society is immune to some level of suicide frequency even when experiencing first-best socioeconomic conditions. In an empirical test of this proposition, Yang and Lester estimated the natural suicide rate for the U.S., in 1980, to be 6.01 per 100,000 population. The 6.01 rate represents a predicted value, from a cross-sectional regression, based on setting each statistically significant covariate to its ideal socioeconomic state. In their conclusion, however, Yang and Lester concede the possibility that omitted covariates or an alternative estimation specification may yield something other than a strictly positive prediction. Notably, this simple one page note in the journal, *Psychological Reports*, has spawned, what appears to be, a growing literature testing the natural suicide rate hypothesis.

The literature, to date, has split into two factions. The first focuses on testing the strictly positive rate premise using 'ideal' empirically predicted values. Positive predicted rates, for several select countries, are affirmed by the cross-sectioned data studies from Yang and Lester (2004) and Lester and Yang (2005). The time-series examinations by Viren (1999) and Andrés and Halicioglu (2011) confirmed positive rates for 15 Organization for Economic Cooperation and Development (OECD) nations. Separate cross-sectioned ecological and time-series regressions put forward by Yang and Lester (2009) and Andriessen, et al (2015) also found positive rates for multiple OECD countries. Efforts exploiting U.S. state-level panel data by Kunce and Anderson (2001-2002) and Collins, et al (2022) uphold the strictly positive suicide rate proposition with robust specification. A more comprehensive review of most of the work cited in this first faction is provided in Yang and Lester (2021). It appears the consensus in this budding faction of the literature finds for a strictly positive suicide rate, even under the most ideal socioeconomic setting, for the U.S. and abroad.

A review of the second faction of the literature is benefited by first setting the stage. In their early work, Yang and Lester (1991) cited seminal economic theory surrounding the natural rate of unemployment hypothesis as motivation for their natural suicide rate theory. Edmund Phelps (1967, 1968) and Milton Friedman (1968) developed the concept of the natural rate of unemployment. In Friedman's own words, "The natural rate of unemployment is the level which would be ground out by the Walrasian system of general equilibrium equations, provided that there is imbedded in them the actual structural characteristics of the labor and commodity markets, including market imperfections, stochastic variability in demands and supplies, the cost of gathering information about job vacancies and labor availabilities, the cost of mobility, and so on" (Friedman 1968, p. 8). The phrase "the level which would be ground out by the Walrasian system of general equilibrium equations" implies that the natural rate of unemployment is an attractor around which unemployment levels, over time, converge. In contrast, Oliver Blanchard and Larry Summers (1987) offered an opposing view of long-run unemployment. They proposed that cyclical fluctuations or economic shocks would have permanent effects on the level of unemployment due to labor market rigidities. In other words, over time levels of unemployment are non-stationary rather than mean reverting. This theory, coined the hysteresis hypothesis, favors path-dependence and the inability of unemployment to return to an initial level after being changed by an external force - even after the force is removed. A vast literature now exists testing the two competing theories empirically by effecting unit root tests on various unemployment time-series or long panels. Finding evidence of a unit root lends support to the hysteresis hypothesis, while rejecting a unit root null tilts evidence towards the natural rate theory. Pissarides (2017) and Özdemir (2021) provide exhaustive reviews of the unemployment hysteresis test literature.

The second faction of the natural suicide rate literature centers on testing rates, over time, for a unit root. Yang (1994) was the first to effort a unit root test on several time-series of U.S. suicide rates. Using the first generation Dickey and Fuller (1979) test, she found evidence of a unit root in the preponderance of the time-series tested. In a later paper, Yang, et al (2015) analyzed day-to-day suicide occurrence and year-to-year rate data, for the U.S., by testing the distribution of differences in period-to-period observations for normality. The author's found evidence of a random walk (non-stationary series) for the day-to-day suicide occurrence differences. The year-to-year test rejected the null of normality. They concluded that any shock to suicide occurrence could have lasting, perhaps, permanent effects to the overall suicide rate in the U.S. Chang, et al (2017), utilizing a battery of conventional and panel unit root tests, found mean reversion in 7 out of 23 OECD countries analyzed using data spanning the period 1961-2006. They concluded that the 7 stationary countries exhibited a natural suicide rate and required no government intervention attempting to smooth long-run suicide rate fluctuation. In an examination of age-stratified U.S. quarterly data covering the period 1999-2013, Chen, et al (2018) found mixed results. Using repeat cross-sectioned quantile regressions coupled with quantile unit root tests, the author's found mean reversion for the middle-aged (35-54) and non-stationary behavior for the two tails - young (15-34) and old (55 plus). Focusing on suicides from 1974-2013 in Turkey, Akyuz, et al (2020) stressed the importance of stratifying suicide data by sex (male and female). Using several unit root methods coupled with Fourier approximations, the author's found a unit root for the female time-series and mean reversion for males. Lastly, Anyikwa, et al (2021) applied the sequential panel selection method and three generations of unit root tests to a 1990-2017 panel of G20 countries. They found that only 5 of the G20 nations have stationary suicide rate time-series, the balance followed a unit root. Needless to say, results in this faction of the literature can be characterized as 'mixed' at best. Despite the importance of stationarity to the long-established natural rate reasoning, it seems no consensus has been reached as to its existence in suicide rates.

By exploiting an expansive panel of state-level suicide rates and characteristics, this paper aims to debit the inventories of both factions of the natural suicide rate literature. Section 2 provides a panel test of the strictly positive rate hypothesis where results reinforce the growing consensus that, even under the most pristine socioeconomic state, suicide occurrence endures. Section 3 focuses on the stationarity of suicide rates over time. Using panel methods that allow for cross-sectional dependence and structural deviations, we find strong evidence of non-stationarity (unit root) for the common factors of suicide rates in the U.S. Such findings cast doubt on the usefulness of the natural rate moniker for suicide paths. Section 4 of the paper concludes with thoughts on how to move the research forward.

2. Strictly Positive Suicide Rate

The first part of this examination follows the panel data methods of Kunce and Anderson (2001-2002) and Collins et al (2022) to test the positive suicide rate proposition. Panel data specifications can provide accurate measures of, and controls for, most socioeconomic effects on suicide rates without requiring the collection of vast data sets on the characteristics (many of which are unobservable) of states. The data are a balanced panel comprised of all 50 states and the District of Columbia ($N = 51$) for the years 1990-2019 ($T = 30$). Table 1 describes, provides data sources and shows descriptive statistics for all variables examined. Right-hand-side variables were chosen based on literature convention and ease of setting the slope coefficient (when statistically significant) to an 'ideal' socioeconomic state. A correlation matrix and variance inflation factors for the right-hand-side are provided in Table 2.

Table 1: Data descriptions, sources and descriptive statistics

Suicide Rate. Age Standardized per 100,000 total state population. National Center for Health Statistics, National Vital Statistics System, 1990-2019. Year 2000 age standardization applies. Mean 13.63, STD 4.03. Natural Log Suicide Rate, Mean 2.57, STD 0.30.
Divorce Rate. Based on counts of divorces occurring in a state per 1,000 total state population. National Center for Health Statistics (NCHS), National Vital Statistics System, 1990-2019. California, Georgia, Hawaii, Indiana, Louisiana and Minnesota have stopped consistently reporting divorce occurrence to the NCHS. This missing data can be recovered from the U.S. Bureau of the Census, American Community Survey (ACS), Public Use Microdata Sample (PUMS). See Mayol-Garcia et al. (2021) for a similar application of ACS PUMS data. Mean 3.96, STD 1.13.
Unemployment Rate. Seasonally adjusted average annual rates by state, in percent. U.S. Bureau of Labor Statistics, 1990-2019. Mean 5.48, STD 1.87.
Distilled Spirits Consumption. In gallons per capita, total state population. Beer Institute, Beer Almanac, 1990-2019. Mean 1.53, STD 0.56.
Household Size. Average size of households by state. U.S. Bureau of the Census, 1990-2019. Mean 2.53, STD 0.16.

Table 2: Correlation matrix

	Divorce	Unemployment	Spirits	VIF
Divorce	1.00			1.06
Unemployment	0.07	1.00		1.01
Spirits	-0.17	0.01	1.00	1.12
Household	0.21	0.03	-0.31	1.14

The dependent variable examined is a state's annual age-standardized suicide rate (per 100,000 population). Age-standardized (adjusted) rates are commonly used in the ecological suicide literature to compare relative indexes across groups and over time. Although, there is nothing in socioeconomic suicide theory that dictates functional form, previous examinations have used linear and semilog linear specifications (see Kunce 2021 and Collins et al 2022 for reviews). On a priori grounds, the semilog functional form has considerable appeal relative to the linear form. By taking the natural logarithm of suicide rates, estimates of right-hand-side coefficients vary proportionately with suicide rates rather than impact the overall direct level as in the linear construct. Moreover, semilog form can lessen the effects of vertical outliers on coefficient estimates (see the application in Verardi and Wagner 2011). Consequently, the semilog form was selected for this analysis.

The model estimated becomes,

$$\ln S_{it} = \alpha + X_{it}\beta + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where α is a scalar intercept, X_{it} are observable socioeconomic variables that vary across states i and over time t, β is a vector of estimated coefficients, μ_i and γ_t are latent state and time specific effects, and ε_{it} denotes the remainder disturbance. The component μ_i is time-invariant and will account for state specific effects not included in the right-hand-side. Likewise, γ_t is state-invariant and accounts for time-specific effects not included in the regression (e.g. economic business cycles). The remainder disturbance ε_{it} varies with states and time and is assumed orthogonal to X_{it}, μ_i and γ_t .

Generally, two specifications of equation (1) are considered. First, fixed effects treats μ_i and γ_t as fixed yet unknown constants differing across states and over time. This specification is easily estimated by including state and year dummy variables in the right-hand-side. If N and T are large, however, the dummy variable approach suffers from the loss of precious degrees of freedom. Alternatively, fixed effects estimates can be obtained by transforming the data into deviations from respective group-state means ('within estimator'). Second, random effects assumes that μ_i and γ_t are random variables, distributed independently across states and over time. Estimates of this specification are based on transformations of the data into deviations from weighted respective group-state means, where the weights are based on the variances of the error components. The potential correlation of μ_i and γ_t with the variables in X_{it} is a primary consideration. If these correlations are present, random effects estimation yields biased and inconsistent estimates of β and the variances of μ_i , γ_t and ε_{it} . Conversely, by transforming the data, into deviations from the simple group-state means, the fixed effects estimator is not impacted by this lack of orthogonality but is not fully efficient since it ignores, in certain cases, variation across states and/or over time. The choice of estimator generally rests on statistical considerations and hypothesis testing. Hausman (1978) outlines a specification test of the null hypothesis of orthogonality between the latent effects and X_{it} . The large Hausman statistic shown in Table 4 favors the fixed effects specification herein.

The question of cross-section dependence naturally arises with panel data, particularly when N is large. Pesaran (2004) suggests a test statistic based on the average of the cross-section pair-wise correlation coefficients. Table 3 shows the Pesaran CD test statistic that rejects the null of no cross-section correlation at the < 10% level. In order to correct for the mild error dependence, we will estimate equation (1) using SUR (PCSE) [2] robust standard errors and covariance as suggested by Beck and Katz (1995). Being, mindful of the 30 year time series in our panel, it is imperative to consider non-stationarity of the variables. Pedroni

[2] Seemingly unrelated regressions (SUR), panel corrected standard error (PCSE).

(2004) proposes several tests for cointegration that allow for heterogeneous intercepts and trends across, in our case, states. Under the null of no cointegration, we provide tests (noting sufficiently large *N* and *T*) for two alternative hypotheses in Table 3. The first is the homogenous alternative (within) and the second shows the heterogeneous alternative (between). Both fail to reject the null at any conventional probability level.[3]

Table 3: Hypotheses tests

Pesaran CD	-1.89	(p 0.06)
Pedroni Cointegration, Panel ADF (within)[a]	-0.67	(p 0.74)
Pedroni Cointegration, Group ADF (between)[a]	-0.47	(p 0.32)
One-way State Effects vs. Pooled OLS	F(50,1446) = 176.08	(p 0.000)
Adding Year Effects vs. One-way model	F(29,1446) = 32.77	(p 0.000)
Pooled Durbin-Watson	1.84	
[a](ADF) augmented Dickey-Fuller. Automatic Akaike information criterion lag length used.		

Careful testing denoted in Table 3 confirms state and year heterogeneity and verifies the importance of controlling for unobservable state and year effects. The test statistic F(50, 1446) = 176.08 firmly rejects the null hypothesis of state homogeneity at the < 1% level. The F(29, 1446) = 32.77 statistic favors the two-way model over the one-way specification, again at the < 1% level. Lastly, the Durbin-Watson statistic (1.84) indicates that serial correlation poses no glaring problem in the pooled sample.

Results from the two-way error components estimators are presented in Table 4.

Table 4: Two-way error components estimates

Variable	Random Effects	Fixed Effects
Constant	2.515***	2.540***
Divorce Rate	-0.0072	-0.0013
Unemployment	0.0010	0.0019
Spirits	0.1325***	0.1075**
Household Size	-0.0616*	-0.0741
R^2	a	0.927
Hausman Test	$\chi_4^2 = 131.67$	
Observations (NT)	1,530	
Both specifications estimated with SUR(PCSE) robust standard errors and covariance.		
[a]No precise counterpart to R^2 in this specification, EViews reports a pseudo R^2 of 0.04.		
Significance at 1% (***), 5% (**), 10% (*) levels.		

[3] A reviewer, of an earlier version of this paper, requested cointegration panel estimates following Pedroni (2001) for comparison. Cointegration estimation results are provided in the Appendix. As expected, results are comparable.

As stated above, the random effects estimates in the first column are easily challenged due to the sizable Hausman test statistic, $\chi_4^2 = 131.67$. The null, $H_0 : E(\mu_i, \lambda_t | X_{it}) = 0$, of latent effects orthogonality is soundly rejected at the < 1% level. The random effects estimator tests biased and inconsistent. The unbiased yet less efficient two-way fixed effects estimates offer little support to the socioeconomic forces hypothesis in explaining the variation in state suicide rates. Only distilled spirits consumption tests significant at any conventional probability level. A marginal increase in distilled spirits consumption per capita increases the suicide rate for the average state by roughly 11%. Interestingly, Durkheim (1897/1951) did not support the presumption that alcohol consumption could explain regional differences in suicide. Durkheim viewed alcoholism as a psychopathic state rather than a symptom of the level of integration. Conversely, strong evidence of an alcohol consumption - suicide link is supported herein. The inconspicuous explanatory power of the fixed effects specification ($R^2 = 0.93$) rests on the latent effects. State and time unobserved effects, captured by the fixed components, hold the explanation to the majority of variation in state-level suicide rates. A note of interpretive caution, however, fixed effects estimation places great demands on the data. For example, μ_i capture any between state variation leaving only within state variation to be picked up by regressors.

After controlling for state and time heterogeneity (by essentially sweeping out all state and time differences) and by setting the only significant covariate (spirits) to zero (reflecting an ideal state where no one imbibes) the log suicide rate is 2.54 − different from zero at a probability value of zero. This result mimics those of the literature reviewed in the introduction of this paper. A reviewer requested that we calculate ideal predictions (rate per 100,000) for each state in the sample. Following Thornton and Innes (1989), Table 5 shows the correct semi-log conversion for each state over the periods: 1990, 2005 and 2019. Results herein are comparable to those found by Collins et al (2022).

Table 5: Ideal state predictions

	Fixed Effect	1990[a]	2005[a]	2019[a]
Constant	2.540	-	-	-
Alabama	0.072	12.68	12.43	16.25
Alaska	0.408	19.07	17.39	22.74
Arizona	0.288	16.91	15.42	20.16
Arkansas	0.169	15.01	13.69	17.91
California	-0.177	10.62	9.68	12.66
Colorado	0.264	16.51	15.06	19.69
Connecticut	-0.356	8.88	8.10	10.60
DC	-0.956	4.88	4.45	5.82
Delaware	-0.207	10.31	9.40	12.29
Florida	0.096	13.96	12.73	16.65
Georgia	-0.067	11.86	10.82	14.15
Hawaii	-0.070	11.83	10.79	14.11
Idaho	0.336	17.75	16.19	21.17
Illinois	-0.311	9.29	8.47	11.08
Indiana [b]	0.012	12.68	11.56	15.12
Iowa	-0.043	12.15	11.08	14.49
Kansas	0.085	13.80	12.58	16.46
Kentucky	0.127	14.40	13.13	17.17
Louisiana	-0.042	12.16	11.09	14.51
Maine	0.082	13.77	12.55	16.42
Maryland	-0.324	9.17	8.36	10.94
Massachusetts	-0.494	7.74	7.05	9.23
Michigan	-0.104	11.43	10.43	13.64
Minnesota	-0.183	10.55	9.62	12.59
Mississippi [b]	-0.012	12.68	11.56	15.12
Missouri	0.092	13.90	12.67	16.57
Montana	0.487	20.63	18.82	24.61
Nebraska	-0.106	11.41	10.40	13.61
Nevada	0.363	18.23	16.62	21.74
New Hampshire	-0.195	10.43	9.51	12.44
New Jersey	-0.580	7.10	6.47	8.47
New Mexico	0.441	19.72	17.98	23.51
New York	-0.516	7.57	6.90	9.03
North Carolina [b]	0.006	12.68	11.56	15.12
North Dakota [b]	0.008	12.68	11.56	15.12
Ohio	-0.081	11.69	10.66	13.95
Oklahoma	0.239	16.11	14.69	19.21
Oregon	0.250	16.28	14.85	19.42
Pennsylvania [b]	-0.018	12.68	11.56	15.12
Rhode Island	-0.346	8.97	8.18	10.69
South Carolina [b]	0.001	12.68	11.56	15.12
South Dakota	0.156	14.82	13.52	17.68

Tennessee	0.129	14.43	13.16	17.21
Texas	-0.056	11.99	10.94	14.30
Utah	0.336	17.73	16.17	21.15
Vermont	0.125	14.36	13.10	17.13
Virginia [b]	-0.010	12.68	11.56	15.12
Washington	0.091	13.89	12.67	16.57
West Virginia	0.239	16.11	14.69	19.21
Wisconsin	-0.093	11.55	10.54	13.78
Wyoming	0.441	19.71	17.98	23.51
[a]1990 period effect insignificant. 2005: -0.0922** 2019: 0.1762**				
[b] Insignificant state effect. **Significant at the < 5% level.				

3. Panel Unit Root Test

Testing for unit roots in single equation, long time-series (T) specifications is now common practice among applied researchers. Single equation tests, however, suffer from a low power defect when examining shorter time spans. A popular remedy for this problem is to use panel unit root tests that augment power by exploiting cross-sectional information. Conventional panel unit root tests have been criticized, of late, for assuming that cross-section cointegrating relationships are not present (Westerlund and Breitung 2013). Assuming cross-section independence, when perhaps dependence is in play, tends to distort the size of the estimated test statistics that reject the null of non-stationarity too often.

Pesaran (2007) proposes a test statistic for cross-section dependence,

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right), \tag{2}$$

where $\hat{\rho}_{ij}$ denotes the pair-wise correlation coefficient from the residuals of cross-sectioned Augmented Dickey-Fuller regressions. The *CD* statistic, testing the null of independence, is distributed asymptotically normal and possesses good small sample properties. Faced with the likelihood of cross-section dependence among suicide rates − we opt for Bai and Ng's (2004, 2010), Panel Analysis of Non-stationarity in Idiosyncratic and Common components (PANIC), method for panel unit root testing.[4] The PANIC unit root test is based on a factor model in which non-stationarity can arise from common factors, idiosyncratic components, or both.

[4] This approach is arguably the workhorse in panel unit root testing, however, can suffer from small sample distortion particularly when the number of cross-sections is 'small'.

Consider the following stochastic process for suicide rates,

$$S_{it} = c_i + \lambda_i' F_t + \eta_{it}, \tag{3}$$

where the series S_{it} is the sum of a deterministic component c_i, a common component $\lambda_i' F_t$, and an error η_{it} that is idiosyncratic.[5] Herein, factor selection follows the information criteria proposed by Bai and Ng (2002). Relative to the number of cross-sections (N) and time periods (T), the number of common factors are usually small. Multivariate common factors from equation (3) are tested using the modified version of the, more general, *Qc* test developed by Stock and Watson (1988). For each idiosyncratic component $\hat{\eta}_{it}$, the Augmented Dickey-Fuller test is applied to each cross-section. Accordingly, a pooled panel unit root statistic (distributed $\mathcal{N}(0,1)$) for the idiosyncratic terms can be constructed,

$$P_{\hat{\eta}} = \frac{-2\sum_{i=1}^{N} \ln\left(p_{\hat{\eta}_i}\right) - 2N}{2\sqrt{N}}, \tag{4}$$

where $p_{\hat{\eta}_i}$ denotes the probability values from the cross-sectioned Augmented Dickey-Fuller tests. It is important to note that tests on the common factors are asymptotically independent of tests on the idiosyncratic components. Lastly, a series with a factor structure is non-stationary (unit root) if one or more of the common factors are non-stationary, or the idiosyncratic error is non-stationary, or both.

Data for this part of examination include state-level age-adjusted suicide rates for all 50 states and the District of Columbia over the time period 1980-2020. Natural logarithmic transformations are used as a means to remove growth in variance, of the rates, over time. Table 6 shows the data source and descriptive statistics. Figures 1 - 4 show the suicide path for the United States, California, Ohio and Texas for the last four decades. These select graphs depict a possible structural break at the midpoint of the time-series.[6] A sequence of unit root with structural break tests were performed on the aggregate U.S. time-series.[7] Test results indicated a single structural break at or about the year 2002. Accordingly, we split the entire sample into two sections, 1980-2001 and 2002-2020 for structural comparison to the full sample.

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[5] This factor model focuses on the intercept only specification where no deterministic trend is apparent in each cross-section.

[6] This potential structural deviation calls for further scrutiny. Structural change and unit roots are closely related and unit root tests are biased toward a false unit root null when the data are trend stationary with a structural break (Perron 1989).

[7] For example, an Augmented Dickey-Fuller (minimizing t) test with varying trend and break specifications indicated a break date of 2002.

Table 6: Source and descriptive statistics

Suicide Rate. Age Standardized rate per 100,000 total state population. Year 2000 population standard. National Center for Health Statistics, National Vital Statistics System, 1980-2020.						
	Full Sample		**1980-2001**		**2002-2020**	
	Rate	LN	Rate	LN	Rate	LN
Mean	13.62	2.59	12.99	2.53	14.35	2.62
STD	3.95	0.29	3.45	0.26	4.35	0.31
Observations (*NT*)	2,091		1,122		969	
Pesaran CD	117.68***		37.03***		118.22***	

***Significant at the < 1% level.

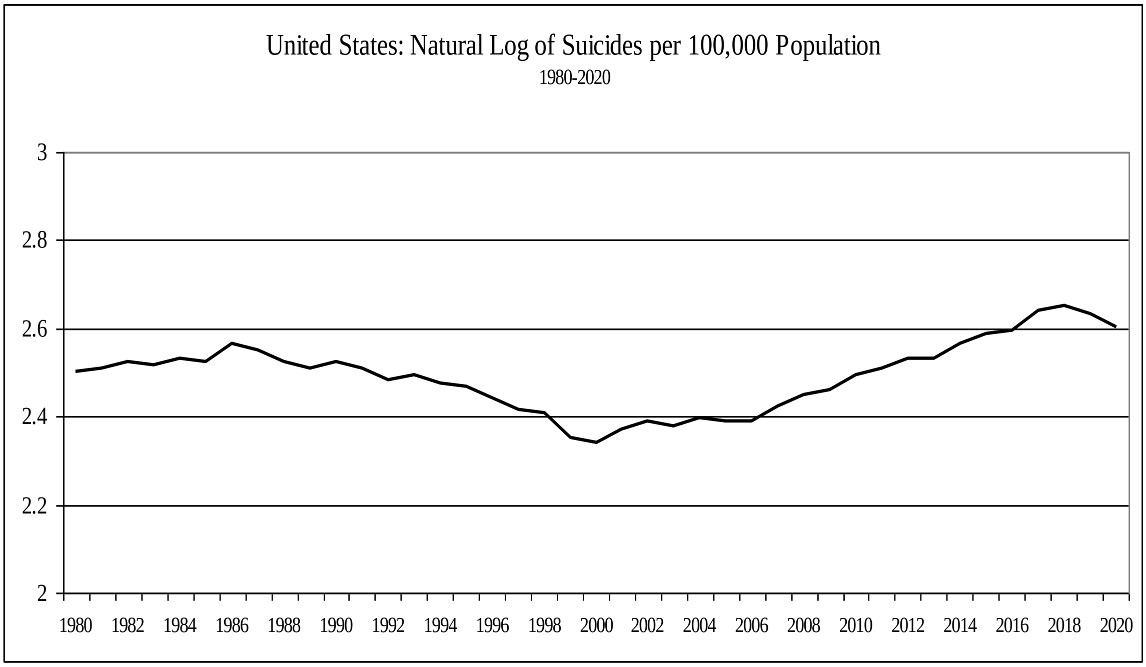

Figure 1: United States, natural log of age-adjusted suicide rates

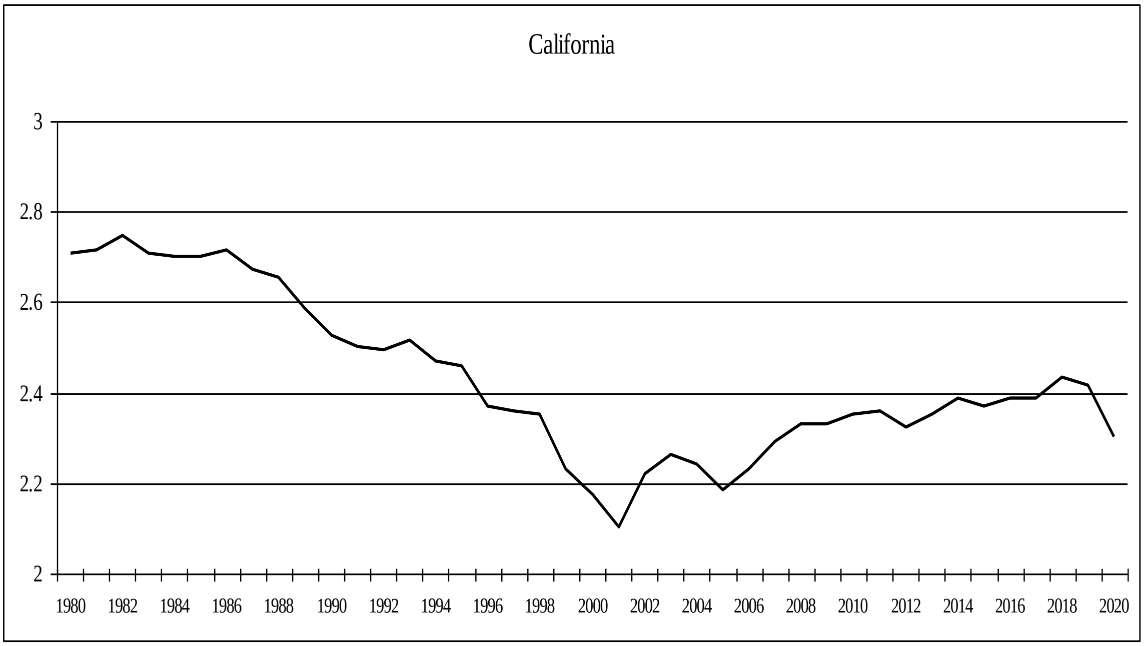

Figure 2: California, natural log of age-adjusted suicide rates

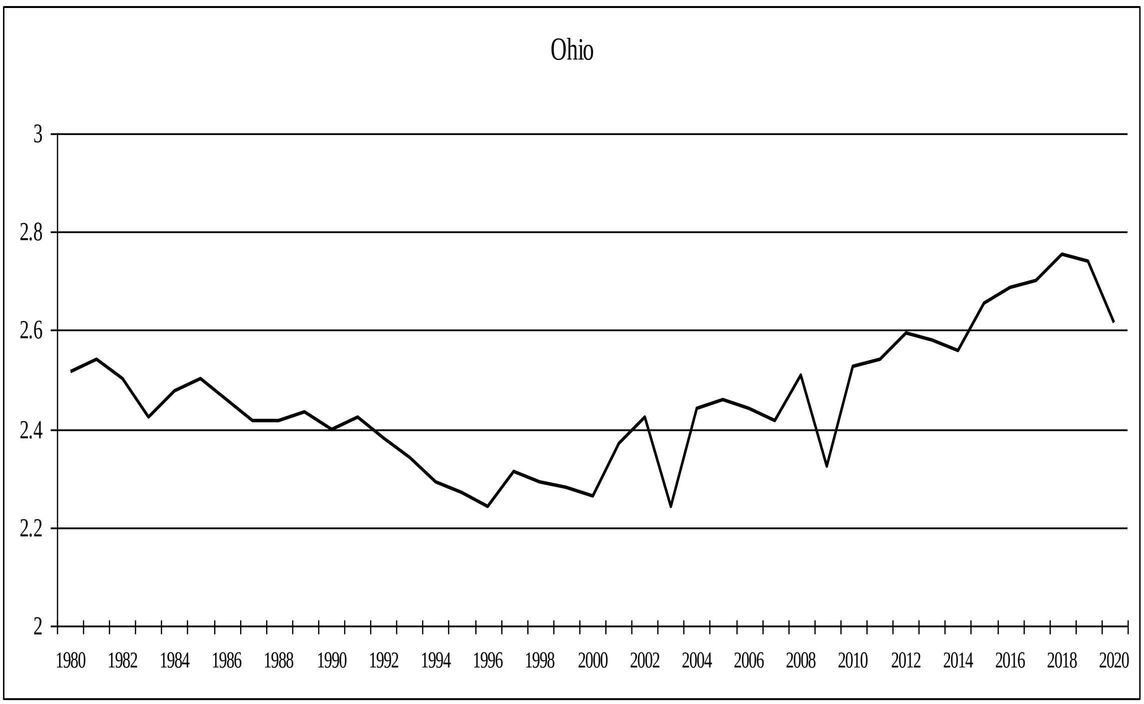

Figure 3: Ohio, natural log of age-adjusted suicide rates

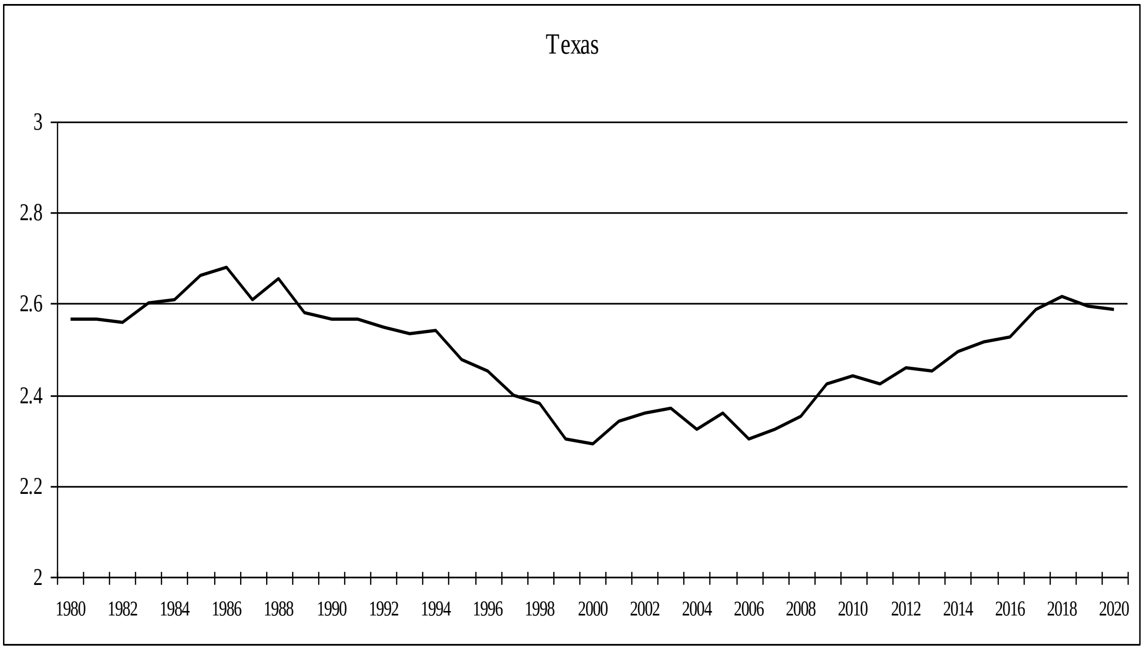

Figure 4: Texas, natural log of age-adjusted suicide rates

The last row of Table 6 shows the Pesaran (2007) test statistics for each sample. The tests reject the null hypothesis of cross-section independence at any conventional significance level. Now we instigate PANIC − which does not require cross-section independence nor the stationarity of common components, for the full sample as well as the sub-samples separated by the possible structural deviation. Results are reported in Table 7.

Table 7: PANIC results

	Full Sample		1980-2001		2002-2020	
	Lags	**Stat**	**Lags**	**Stat**	**Lags**	**Stat**
Alabama	1	0.37	0	-0.87	0	1.02
Alaska	4	-0.07	0	-1.69*	5	-2.14**
Arizona	1	-1.73*	1	-1.25	0	-2.65***
Arkansas	8	0.60	8	1.77	0	-0.62
California	2	0.95	2	2.35	7	1.43
Colorado	1	-1.29	0	-0.86	4	2.43
Connecticut	1	-3.10***	0	-0.75	0	-3.72***
DC	8	-0.40	8	-2.05**	7	-2.97***
Delaware	1	-1.05	0	-1.44	1	0.17
Florida	2	0.88	1	-1.49	2	2.06
Georgia	2	-1.03	3	0.93	7	-0.20
Hawaii	6	-0.72	8	-0.40	0	-1.38
Idaho	6	0.94	2	-1.01	2	1.87

Illinois	0	-2.23**	0	-1.31	5	-1.94*
Indiana	3	0.57	2	-0.90	7	-1.41
Iowa	0	-1.61	0	-2.91***	1	2.55
Kansas	2	0.52	8	-1.12	2	1.55
Kentucky	1	-1.09	5	-1.03	1	0.77
Louisiana	1	-1.66*	7	2.01	7	1.93
Maine	1	-2.34**	8	-0.06	0	-0.52
Maryland	2	-0.26	0	-0.73	0	-1.70*
Massachusetts	1	-1.53	0	-1.29	7	-2.21**
Michigan	0	-1.71*	0	-0.06	2	0.62
Minnesota	5	-2.24**	6	-3.09***	6	2.20
Mississippi	3	-0.18	3	0.18	7	-1.86*
Missouri	2	1.10	2	-1.00	7	0.37
Montana	8	1.31	5	2.68	0	-0.47
Nebraska	0	-2.17**	4	-0.09	1	-1.37
Nevada	2	-1.31	1	-1.84*	0	-2.27**
New Hampshire	6	1.98	0	-1.29	0	0.24
New Jersey	6	0.07	7	-0.43	6	1.86
New Mexico	0	-0.89	8	-2.24**	2	-1.33
New York	8	0.08	8	1.63	1	-1.07
North Carolina	1	-2.13**	8	-1.81*	7	-1.41
North Dakota	1	0.61	8	0.97	7	-1.25
Ohio	2	-0.57	0	-0.10	7	4.66
Oklahoma	3	1.86	8	-3.08***	6	-1.18
Oregon	2	-0.07	8	-0.88	7	3.37
Pennsylvania	0	-0.96	0	-0.94	0	-0.59
Rhode Island	3	1.60	0	-0.57	0	-1.82*
South Carolina	1	0.60	3	-0.92	0	2.45
South Dakota	0	-2.80***	8	-2.29**	5	2.04
Tennessee	8	1.77	4	-0.69	0	0.26
Texas	0	-0.53	1	-0.65	7	0.93
Utah	2	-1.06	3	0.73	1	-0.01
Vermont	1	-0.56	0	0.07	0	1.48
Virginia	8	-0.86	2	0.89	6	-0.76
Washington	6	-1.35	8	0.57	7	-0.44
West Virginia	0	-0.25	1	-1.51	0	-1.31
Wisconsin	2	-0.73	0	-1.33	2	0.92
Wyoming	8	0.03	8	-2.61*	0	-0.87
Null Rejections		10		10		10
Common Factors	6	91.92	7	-12.90	7	-29.69
Idiosyncratic		2.01**		3.35***		1.69*

Significance at 1% (***), 5% (**), 10% (*) levels.

For each sample, estimates in 10 differing state cross-sections reject the null hypothesis of unit root at conventional levels. Moreover, within each sample, multiple common factors are determined and tested using an iterative procedure. Herein, we apply the more general *MQc* test which corrects for serial correlation, of arbitrary form, through non-parametric estimation. *MQc* parallels the multivariate procedure suggested by Phillips (1987). The null hypothesis states that r common factors have at most r common stochastic trends. As in our case, failure to reject the null of retaining the common factors (in each sample) indicates that *all* common factors are non-stationary. The last row of Table 7 shows the pooled idiosyncratic component test (see equation (4)) for each sample. The null hypothesis of this test is all cross-sections have a unit root (non-stationary). Note that the null holds only if *no* stationary combination of the S_i exists. As such, the pooled test mirrors a panel test for no cointegration. In all three of our samples, the null is rejected − though the sub-sample 2002-2020 test result is not statistically imperious. Results are consistent with non-stationarity in U.S. suicide rates, pervasive in the common factors and finite in the idiosyncratic components. The structural comparison is mildly helpful showing that the stochastic nature of U.S. suicide rates (at least the idiosyncratic components) has been affected by certain phenomena in the last two decades. At the 5% significance level, the 2002-2020 sub-sample confirms non-stationarity in both the common and idiosyncratic components.

4. Concluding Remarks

It appears we are at a crossroads going forward in the natural suicide rate literature. Strong evidence suggests, even under the most ideal steady-state, suicide rates will be positive in societies across the globe − yet referring to the positive rate as 'natural' is problematic on borrowed theoretical grounds. Natural, in the purest sense, implies stationary time paths. No clear evidence exists that suicide rates follow strict mean reversion. More often than not, non-stationarity (hysteresis) has been confirmed in the literature cited in the introduction and of course herein. Recall, hysteresis implies that cyclical fluctuations and shocks have permanent effects on suicide trajectories. This implication alone is problematic for those galvanized to reduce or prevent suicide occurrence. In the study, reviewed herein, that also focused on U.S. data, Chen et al (2018 p. 813) concluded "that positive shocks have significant impacts on various suicide rates, and the persistence of suicide was confirmed for all… quantiles except for the suicide rate of the middle age (aged 35-54) group." For the stationary middle age series the authors recommended that suicide prevention efforts should target this group *during* periods of economic downturn. Anyikwa et al (2021) found that all but five G20 countries exhibit what they call suicide persistence (unit root) and recommended that the advanced nations of the G20 move toward adopting formal suicide prevention strategies which are tailored to each countries' social, religious and economic standards. The use of the term 'persistence' by Chen et al (2018) and Anyikwa et al (2021) is also contentious. Within the borrowed economic framework, the existence of hysteresis should not be confused with persistence. Given the proper context, persistence implies that, though the adjustment process is very slow, suicide rates follow mean reversion. Therefore, persistence is a special carve out of the natural rate hypothesis where suicide rates are simply *near* unit root. If persistence prevailed in U.S. and G20 suicide rates, cycles and shocks would have long lasting but not permanent effects. Again, no clear evidence exists that all suicide rates follow strictly hysteresis or persistent paths. More long run, focused research in the second faction of this literature is warranted. In the mean time, recommendations that costly prevention efforts should chase stationary or non-stationary stochastic processes are simply misguided.

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Appendix

Table A1: Cointegration estimation

Variable	Panel Fully Modified Least Squares (FMOLS)	
Constant	Deterministic Coefficient	
Divorce Rate	-0.033	
Unemployment	-0.0008	
Spirits	0.164***	Ideal state - 0 gallons/capita
Household Size	-0.091*	Ideal state - 2 people
Pseudo R^2	0.861	
Observations	1,479	
Estimated using robust sandwich covariance structure.		
Significance at 1% (***), 5% (**), 10% (*) levels.		

Table A2: Cross-section deterministic coefficients (ideal state)

Alabama	15.27	Montana	20.47
Alaska	16.20 [a]	Nebraska	11.47
Arizona	16.78	Nevada	13.90 [a]
Arkansas	17.10	New Hampshire	8.08a
California	10.19	New Jersey	6.38
Colorado	15.05	New Mexico	20.46
Connecticut	8.18	New York	7.51
DC	3.57 [a]	North Carolina	13.95
Delaware	7.98 [a]	North Dakota	11.18 [a]
Florida	12.86	Ohio	12.90
Georgia	11.65	Oklahoma	18.39
Hawaii	11.39	Oregon	16.45
Idaho	18.98	Pennsylvania	13.28
Illinois	8.91	Rhode Island	8.37
Indiana	12.69	South Carolina	12.30
Iowa	12.59	South Dakota	14.12
Kansas	14.73	Tennessee	16.12
Kentucky	15.83	Texas	12.49
Louisiana	11.45	Utah	18.98
Maine	13.60	Vermont	14.82
Maryland	8.28	Virginia	13.44
Massachusetts	6.88 [a]	Washington	14.24
Michigan	11.17	West Virginia	19.72
Minnesota	9.19 [a]	Wisconsin	9.82 [a]
Mississippi	13.01	Wyoming	18.51
Missouri	14.08		

[a] Differs from two-way fixed effects estimate by more than 15% (+ or -).