Unemployment Fluctuations and Regional Suicide: 1980 – 2006

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This study examines the potential link between macroeconomic fluctuations, using the unemployment rate as a proxy, and the probability of a person choosing to commit suicide. It extends the theory and empirical work used in previous studies by delineating the United States into nine sub-regions. This enabled testing as to whether there are significant differences in the incidence of suicides between sub-regions due to changes in general economic activity measured through changes in the unemployment rate. The focus here is to establish if this relationship is unique to any particular region(s) of the country. If so, perhaps there are significant policy implications with regard to suicide prevention by allocating our mental health resources to those areas most affected whenever there is a severe abatement in general economic activity. Examining regional variations in the rate of suicide may inform us regarding the relative causative influence of labor issues and other economic factors on the suicide decision.

Keywords: Suicide, unemployment, regional variation

1. Introduction

This study on regional suicides stems from earlier work (Snipes, Cunha, and Hemley [2011]) that focused on changes in the business cycle and its impact on changes in the incidence of suicides throughout the United States. This study extends the theory used in that previous study. Unlike the previous study, this paper develops a much more robust continuous time, multiple (but finite) period utility maximization model that also allows for the discounting of future consumption, which may also play a role in suicidal decisions. Similar statistical methodology as in the previous work, namely probit analysis, but here we delineate the United States into nine sub-regions. This enabled testing as to whether there are significant differences in the incidence of suicides between sub-regions due to changes in general economic activity measured through changes in the unemployment rate. This was not taken into account in the previous study and could play a significant role in suicide rates. This possible link is discussed much more in depth below.

While that previous research established that there was a relationship between changes in the business cycle and changes in the incidence of suicides, the focus here is to

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establish if this relationship is unique to any particular region(s) of the country. If so, perhaps there are significant policy implications with regard to suicide prevention by allocating our mental health resources to those areas most affected whenever there is a severe abatement in general economic activity.

Although one might assume that good economic times would result in a decrease in suicides and bad economic times result in an increase, Durkheim’s theory on suicide posits a different result. Durkheim asserted that the suicide rate varies inversely with the stability and durability of social relationships and that any economic change, positive or negative, disrupts that status quo and contributes to an increased incidence of suicide. Subsequent studies have suggested that economic cycles as defined by changes in the rate of unemployment may induce increased insecurity and stress and contribute to variations in the rate of suicide (Snipes, Cunha, and Hemley [2011] and sources cited therein).

Researchers have long sought a direct causal link between economic conditions and suicide; Berk, Dodd, and Henry (2006) found a significant association between macroeconomic trends and suicide. Extensive evidence indicates that both unemployment and the fear of unemployment adversely affect the health of individuals (Stuckler et al. [2009], citing Lewis and Sloggett [1998], see also Voss et al. [2004]). There can be no greater adverse affect to individual health than the termination of life itself. The popular media and extensive scholarly literature have identified a correlation between changes in the business cycle and the incidence of suicide (e.g., Feldmann [2010]; Christiano, Trabandt, and Walentin [2010]; Catalano, et al. [2011]; Snipes, Cunha, and Hemley [2011]). A New Zealand study found a “twofold to threefold increase” in the risk of suicide, compared to being employed (Blakely, Collings, and Atkinson [2003]). While unemployment rates can be used as a proxy for the business cycle (see, inter alia, Yang and Lester [1992]) on the assumption that losing one’s job (or the fear of such loss) may be sufficient motivation to end one’s life, job insecurity alone cannot account for such a complex human phenomenon. Myriad other factors may influence such a choice. Examining regional variations in the rate of suicide may inform us regarding the relative causative influence of labor issues and other economic factors on the suicide decision. There is a copious body of literature that focuses on regional variations in suicide in relation to scores of other variables.

2. Literature Review

Our study of correlations between regional variations in the rate of suicide and the rate of unemployment continues a long history of regional suicide studies. Here we discuss that history and then discuss the relevance and importance of studying and understanding the dynamics behind such geographic variations.

Emile Durkheim, in his seminal work published in 1897, concluded “[w]henever serious readjustments take place in the social order, whether or not due to a sudden growth or to an unexpected catastrophe, men are more inclined to self destruction (p. 246).” He differentiated anomic suicides (those resulting from instability caused by erosion of ideals, values, or social standards) from those induced by other personal causes, asserting that it is abrupt or rapid change, rather than any related negative effect of change, that is the critical influence on suicide rates.

Beginning with Durkheim, regional differences in the incidence of suicide have intrigued and confounded researchers, with many studies attempting to discern the reasons for these variations even in recent times. These studies focus either on smaller samples
examining individual risk factors over time, such as age (Pearson and Brown [2000], Winfree and Jiang [2010]), psychiatric disorders (Mann [2002], Rowe et al. [2006]), military service (Belik et al. [2010]), gender-related behavior (Murphy [1998], Cutright [2000], Desaulniers [2008], Etxebarria et al. [2009]), or cohort size (Freeman [1998]); or, these studies focus on very large samples to determine the correlation between suicide levels and specific variables in different geographic areas.

For example, there are numerous studies comparing the incidence of suicide in various regions of the United States. Lester, in 1985, considered suicide rates (and homicide rates) in major American cities as indications of their relative level of violence and found differences in race, population density, income, crime rate, longitude, and latitude. Cutchin and Churchill (1999), studied suicide at three different geographic scales: states in the United States, counties within the states of the New England (U.S.) region, and counties within the state of Vermont, and find inconsistent results. In a study examining the effect of socioeconomic factors on state-level suicide rates, little evidence was found to substantiate the hypothesis that aggregate socioeconomic factors matter in understanding regional variations in suicide (Kunce and Anderson [2002]). Suicide rates were found to be higher in regions where sales of alcoholic beverages were higher (Gruenewald et al. [1995]), higher in (U.S.) states with higher relative rates of divorce, interstate migration, and crime, and lower levels of church attendance (Lester [1988], Burr et al. [1999]), and higher in regions with more lax handgun control and higher incidence of gun ownership (Lester [1998], Kaplan and Geling [1998], Molina and Duarte [2006]). Cebula and Zelenskaya (2006) also find a link between the rates of violent crime, finding a positive relationship between the two. They also examined the role of divorce, as we do here.

Given the obvious mental health implications of suicide, it is not surprising that studies have been conducted relating regional variances in suicide with rates of depression (Rihmer [1994], Zonda [1998], Motohashi [2004], rates of alcoholism (Rossow [1995], Walsh [2010]), other psychiatric indicators (Pritchard, JRSH [1995]; Pompioli et al. [2011]), and with other causes of death (Ruhm [2000]). Other geographic deviations in medical factors have also been correlated with suicide, such as fertility (Lester, Psyc. Rep. [1996]) and cancer (Kondrichin, Perceptual [2001]).

Lester (1989, 1994) concluded that the incidence of suicide in the United States was more dependent on the geographic region of origin rather than the region of residence at the time of death. Lester and others continued that research in a comparison of region of birth to suicide rates in Italy (Masocco et al. [2010]). Further studies have posited that genetic differences between regions may partially account for geographic variations in the incidence of suicide (Voracek, Fisher, and Marušič [2003]). Voracek, Loibl, and Kandrychyn (2007) confirmed this finding in a study of Belarus, western Russia, and Ukraine. Voracek and Sonneck (2007) found that regional differences in suicide rates in Austria correspond to variations in the genetic heritage of the population. Shrira (2010) explored a different but similar avenue of inquiry by comparing the rates of suicide amongst residents of and temporary visitors to various United States regions to differentiate between the influence of the place of suicide and the individual characteristics of the suicide victim.

A wealth of studies report the regional variations in suicide rates within particular countries; e.g., inter alia, France (Philippe [1979]); Brittany, France (Batt et al. [1993]); Finland (Lester, Psychiatria [1996]); the United States (Lester, OMEGA [1996]); Queensland, Australia (Cantor and Slater [1997]); the Soviet Union (Wasserman [1998]); Switzerland (Lester, European Journal [1998]); Slovenia (Marusic [1998]); Austria (Lester,
Perceptual [1999]); Poland (Lester and Krysinska, [2004]); South Korea (Park [2007]); and Scotland (Crombie [1989], Lester [2010]). In 1999, Lester reported a meta-analysis of correlates of suicide rates of regions within nations. The analysis of fourteen studies elicited two associations: a positive association of regional suicide rates with the death rate and a negative association with population.

Studies have focused on comparisons of suicide rates between nations, for example, by Lester comparing the United States with Sri Lanka (1989), Italy (1993), and Taiwan (1993). Political events, political institutions, and electoral results have been considered as catalysts for regional differences in suicide rates (e.g., Andress [1976], Kondrichin, Soc. Res. [2001], Voracek [2003]; Fischer and Rodriguez-Andrés [2008]). Voracek has considered the correlation between regional variations in intelligence and the suicide rate in Denmark (2006), the United States (2007), Australia (2007), and Italy (2009). Baker and Lester (1986) analyzed the geographic differences in academic achievement as it relates to rates of suicide. Regional variations in religious practice and belief in life after death have been studied as they relate to the incidence of suicide (Neeleman [1998], Lester [1987, 1989]).

Some research examines the regional variations in suicide method and choice of weapon (e.g., inter alia, Taylor [1980]; Lester, Crisis [1990]; Kaplan and Geling [1998]; Liu et al. [2007]). Somewhat related research examines regional differences between rates of suicide and homicide (Baker and Lester [1986], Lester [1988], Holinger and Lester [1991], Saucer [1991]; McKenna [1997]).

Various studies have considered the effect on regional suicide rates by economic variables rather than sociological correlates. A Japanese study (Goto et al. [1994]) analyzed the annual variation in suicide deaths and 18 socioeconomic factors of each of the country’s prefectures, and, among other findings, determined that regional differences in savings and bankruptcy were closely related to male suicide. Differences in suicide rates between rural and urban areas were reported in Australia (Burnley [1994]) and in Austria (Kapusta [2008]); regional differences were studied that may contribute to elevated incidences of suicide in rural as opposed to urban areas of Australia (Judd et al. [2006]). Zacharakis et al. (1996) analyzed the relationship of suicides in Greece for a twelve-year period and the socioeconomic variations of the 52 prefectures of Greece. Chuang and Huang (1997) examined suicide rates of 23 Taiwanese cities and counties from 1983 to 1993 and found that, while a combination of economic and sociological variables contributed to variation in the rate of suicide across regions and over time, economic variables had a greater impact than sociological correlates. Viren (2005) also found that changes in the suicide rate are determined by changes in the expected growth rate of income.

Geographic variations in race, ethnicity, and minority status have been analyzed in relation to suicide (Lester, AJP [1980], Lester, Omega [1990], Wissow et al. [2001], Burr et al. [1999]), as have variations in the ages of populations (Seiden [1984], Agbayewa [1993]). Even regional variations in climate (Tsai [2010]), altitude (Haws et al. [2009]), and air pollution and weather (Yang et al. [2011]) have merited the attention of researchers as those factors relate to suicide.

While there have been relatively recent studies of the correlation between suicide and unemployment (e.g., No [2009]; Chen et al. [2010]; Chang et al. [2010]; Snipes, Cunha, and Hemley [2011]), few studies (including Pritchard [1995]) have focused on regional variations in unemployment as a factor of suicide.
This extensive body of knowledge regarding regional variations in suicide raises a critical question: why does it matter? Suicide has a profound negative effect on families, communities, organizations, and the general economy (Snipes, Cunha, and Hemley [2011], and sources cited therein). Several studies illustrate the value of understanding regional variance in the incidence and rate of suicide in the formulation of public policy to reduce or prevent suicide (e.g., Kelleher, Keeley, and Corcoran [1997]; Bellanger and Jourdain [2006]; Bellanger, Jourdain, and Batt-Moillo [2007]; Minoiu and Andres [2008]).

3. A Theoretical Model of Suicide and the Level of Unemployment

To examine the link between the likelihood of a person committing suicide and the national unemployment rate, we develop a continuous time, finite horizon model of utility with discounting and saving. We assume that in every period an individual has a known utility function, $u$, which depends on consumption at the given period, $u(c(t))$, that they maximize in each period. The function $u$ is time-invariant and specific to each individual. We assume further that the individual is able to increase an endowment, $a$, in each period and that the change in the endowment in each period is the difference between the individual’s current endowment and that period’s consumption; that is

$$ a(t) = ra(t) - c(t), $$

where $a(t)$ is the endowment at period $t$, $c(t)$ is consumption in period $t$, and $r$ is the time-invariant market discount rate. We also assume an initial endowment equal to $a(0) = a_0$, and that $a(T) \geq a_T$, where $T$ is the final period. The individual chooses the consumption levels that maximize their utility in each period, while we may regard their endowments, $a$, as state variables. We further assume that the utility function $u(c(t))$ is twice differentiable with decreasing marginal utility and is time additive. Individuals discount future consumption by $\delta$, $\delta \in [0, 1]$ for each period.

In each period, the individual may or may not be fired. The likelihood of the individual being fired is captured by the variable $\rho(t)$, $\rho(t) \in [0, 1]$. Later in the paper, we will use the unemployment rate as a proxy for this variable. The individual does not know what the value of $\rho(t)$ will be until that period, but does have an expectation for the likelihood equal to $E(\rho)$. This expectation is unique to the individual and may be affected by factors such as the type of employment or sector the individual is engaged in or the age and experience of the individual. The individual takes this uncertainty into account through their endowment equation. We assume that the higher the likelihood of the individual is losing their job, the greater the individual will want their savings to be in that period as that will allow for greater future consumption. As they draw consumption based on previous periods’ endowments, we assume that an increase in savings is accomplished through a decrease in consumption. We can then rewrite the endowment function as:

$$ a(t) = ra(t) - (1 - \rho(t))c(t). $$
The individual’s maximization problem is then:

$$\text{Max}_{a,c} \int_{0}^{T} e^{-\delta t} u(c(t)) dt$$

subject to the constraints

$$\dot{a}(t) = ra(t) - (1 - \rho(t))c(t)$$
$$a(0) = a_o$$
$$a(T) \geq a_T,$$

where $\delta$ is the individual’s subjective discount rate on future consumption. The present value Hamiltonian for this problem is then:

$$H(a, c, \lambda, t) = e^{-\delta t} u(c(t)) + \lambda [ra(1 - \rho(t))c],$$

where $a$ and $c$ are the choice variables. The first order conditions are then:

$$\frac{\partial H}{\partial c} = e^{-\delta t} u'(c(t)) - (1 - \rho(t))\lambda(t) = 0;$$

$$r\lambda(t) = -\dot{\lambda}(t);$$
$$\dot{\lambda}(T) \geq 0, \lambda(T)a(T) = 0.$$

Rearranging the first first-order condition, we have

$$\lambda(t) = \frac{e^{-\delta t} u'(c(t))}{(1 - \rho(t))}.$$ 

Totally differentiating this condition with respect to time yields

$$0 = -\delta e^{-\delta t} \frac{u'(c(t))}{(1 - \rho(t))} + e^{-\delta t} \frac{u''(c(t))c(t)}{(1 - \rho(t))} + e^{-\delta t} \frac{u'(c(t))\rho}{(1 - \rho(t))} - \lambda. $$

Define the growth rate of consumption as $g_c = \frac{\dot{c}(t)}{c(t)}$. Then

$$g_c = \left( r - \delta \right) \frac{\rho}{(1 - \rho(t))} \frac{u'(c(t))}{u''(c(t))(c(t))};$$

or
where $\sigma(c(t))$ is the elasticity of intertemporal substitution. Note that $\sigma(c(t)) > 0$. Now that we have the growth rate of consumption, we can note a few interesting implications. First, consumption grows over time whenever the market discount rate, $r$, is greater than the subjective discount rate, $\delta$. There, we can say that the consumer is “less impatient” than the market. More importantly, though, is the relationship between the growth rate and the factors relating to the likelihood of being fired. As $\rho(t)$ increases, $g_c$ decreases (this is seen more clearly in the first equation for the growth rate than the second). That is, as the likelihood of being fired increases, the lower will be the growth in consumption. This is the same as saying they will either decrease the level at which they are consuming or save more. Since utility is based upon consumption levels, this decrease in consumption leads to a decrease in utility.

Once the individual has solved their utility maximization problem, they then compare the results with a baseline or minimum level of utility needed, $U$, in order to not commit suicide. As $u(c(t))$ decreases due to increases in $\rho$, this brings the realized utility level closer to the lower bound $U$. The individual will sum up each periods minimum utility level and compare that with the sum of the utility from their maximization problem. We assume that $U$ is constant across time and is individual specific. In short, if the following condition holds, the individual will choose to end their life in period $t$:

$$\int_0^T e^{-\delta} u(c(t))dt < \int_0^T e^{-\delta} U dt.$$

4. Data and Descriptives

The data examined in this study is comprised of the decedent’s date of death, state of residence, state where death occurred, age, race, gender, marital status, manner of death, and other items, derived from the Public-Use Data File published by the Center for Disease Control (CDC) Division of Vital Statistics. In most cases, the manner or cause of death is reported on the official U.S. Standard Certificate of death by hospitals or other healthcare providers. The Ninth Revision of the *International Classification of Diseases* (ICD-9) published by the World Health Organization has been used to classify the manner of death in statistics published by the National Center for Health Statistics since 1979. The official determination of death can only be certified by a physician, coroner, or other similarly-qualified person, thus making the accuracy and reliability subject to the quality of the diagnosis made. While Gillelsohn and Royston (1982), in a study of scholarly literature spanning 23 years, determine that there is no definitive conclusion about medical proficiency in certifying deaths, they do contend that the proportion of deaths found to be of indeterminable cause suggests the implementation of great care in cause of death determinations (Snipes, Cunha, and Hemley [2011] and sources cited therein).

The Public-Use Data File begins with deaths occurring annually from 1968 through 2006. The cause of death cannot be determined reliably for years 1968 through 1978; therefore, those years have not been included in this analysis (and 1979 was also omitted). The five-digit 282 cause recode is used to identify suicides for 1980 through 1998.
1999 through 2006, the seven different causes of death are identified; an official
determination is required for a death to be characterized as a suicide. The monthly
unemployment levels were retrieved from the St. Louis Federal Reserve website.

4.1 Descriptives

The data sample is comprised of 50.9 percent males and 49.1 percent females, with 86
percent white, about 10 percent black, and 3 percent of another race. Those divorced at death
were 9.3 percent. Slightly more than half (52.9 percent) were over 74 years of age, while
47.1 percent were 74 years old or younger. Of the total observations, approximately 1.4
percent are suicides.

Table 1 shows the percentage of suicide deaths and the percent of all suicides on a
monthly basis. While December and January were the least likely months for suicide, the
most likely times within our sample were the summer months of June, July, and August,
with, a higher percentage (approximately 1.53%) of suicides than in the other months. Data
indicate a fairly even distribution of suicides on a quarterly basis: 24.6 percent in the first
quarter (January through March), 26 percent in the second quarter (April through June), 25.7
percent in the third quarter (July through September), and 23.6 percent in the fourth quarter
(October through December).

Table 1 Percentage of Suicides by Month

<table>
<thead>
<tr>
<th></th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deaths</td>
<td>1.20</td>
<td>1.26</td>
<td>1.34</td>
<td>1.41</td>
<td>1.49</td>
<td>1.55</td>
<td>1.51</td>
<td>1.53</td>
<td>1.48</td>
<td>1.36</td>
<td>1.29</td>
<td>1.16</td>
</tr>
<tr>
<td>Suicides</td>
<td>8.2</td>
<td>7.7</td>
<td>8.7</td>
<td>8.4</td>
<td>8.9</td>
<td>8.7</td>
<td>8.8</td>
<td>8.7</td>
<td>8.3</td>
<td>8.2</td>
<td>7.7</td>
<td>7.7</td>
</tr>
</tbody>
</table>

Table 2 indicates that 1.4 percent of whites in the sample committed suicide, compared to
around 1.36 percent of blacks. Males, with 2.1 percent of all deaths being suicides, were far
more likely to die by suicide than females (0.6 percent). Considering race and gender
together shows that white males (2.5 percent) were the most likely suicides, followed by
black males at slightly more than half that rate (1.36 percent), then white females (0.7
percent), followed by black females (0.3 percent), similarly at half the white female rate.

Table 2 Percentage of Deaths by Suicide by Race and Gender

<table>
<thead>
<tr>
<th></th>
<th>Percentage of Deaths by Suicides</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>1.44%</td>
</tr>
<tr>
<td>Black</td>
<td>1.36%</td>
</tr>
<tr>
<td>White Males</td>
<td>2.5%</td>
</tr>
<tr>
<td>White Females</td>
<td>0.7%</td>
</tr>
<tr>
<td>Black Males</td>
<td>1.3%</td>
</tr>
<tr>
<td>Black Females</td>
<td>0.3%</td>
</tr>
</tbody>
</table>

5. Methodology

For the purposes of this paper, the states are broken up into regions and sub-regions
according to Figure 1. Table 3 also shows what states are included in what region. A random
ten percent sample was taken from the data described above, which left a total of 5,909,885
individual observations. Individuals are categorized as white, black, or other, with Hispanics
counted as white in the data (this was not the choice of the authors, but was simply how the
original data was coded). Only individuals aged fifteen or older are included. We do this as suicides in children are quite uncommon and thus are not included in the analysis.

Table 3 States by Region

<table>
<thead>
<tr>
<th>Region</th>
<th>State</th>
</tr>
</thead>
<tbody>
<tr>
<td>West North Central</td>
<td>IA, KS, MN, MO, ND, NE, SD</td>
</tr>
<tr>
<td>East North Central</td>
<td>IL, IN, MI, OH, WI</td>
</tr>
<tr>
<td>Mid-Atlantic</td>
<td>NJ, NY, PA</td>
</tr>
<tr>
<td>New England</td>
<td>CT, MA, ME, NH, RI, VT</td>
</tr>
<tr>
<td>East South Central</td>
<td>AL, KY, MS, TN</td>
</tr>
<tr>
<td>South Atlantic</td>
<td>DC, DE, FL, GA, MD, NC, SC, VA, WA</td>
</tr>
<tr>
<td>West South Central</td>
<td>AR, LA, OK, TX</td>
</tr>
<tr>
<td>Mountain</td>
<td>AZ, CO, ID, MT, NM, NV, UT, UT, WV</td>
</tr>
<tr>
<td>Pacific</td>
<td>AK, CA, HI, OR, WA</td>
</tr>
</tbody>
</table>

One of the distinctive features of this paper is the use of probit analysis in determining the relationship between macroeconomic fluctuations and suicides. By using probit analysis, we are able to tell the exact magnitude of the effect; probit analysis further provides the associated changes in probabilities. We are then able to tell how the likelihood of a death being ruled a suicide changes with fluctuations in macroeconomic variables (here, the unemployment rates is used as a proxy). We argue that the unemployment rate is an appropriate proxy for macroeconomic fluctuations for several reasons. Perhaps most importantly, most jobs in the United States do not provide many employment guarantees provided by other countries. Thus, we would expect the shock of losing one’s job to be greater. A person’s job is often a source of identity. If this identity is stripped, the individual would be exposed to a greater amount of stress than would be the case if some other macroeconomic indicator were to change.

When estimating the equations presented below, we use lagged unemployment values. Individuals react to the realization of unemployment in their own lives and not to the generalized news of unemployment. Further, actual unemployment rates may not necessarily be known by the individual until the following month; that is to say, an individual who died in July would not realize the unemployment rate for July but rather would have realized the rate for June. For this reason, a lag of at least one-month is used in all regressions.

In sum, we estimate the following equation:

\[ suicide_i = X_i \beta_i + \Sigma U_i \eta_i + \Sigma (X_i * U_i) \alpha_{i,t} + R_i \lambda_i + \Sigma (R_i * U_i) \delta_{i,t} + \epsilon \]

where \( X_i \) is a matrix of demographic variables, \( U_i \) is the unemployment rate for each month included in the study, \( (X_i * U_i) \) is the interaction between the demographic controls and the unemployment rates, \( R_i \) are region dummies, \( (R_i * U_i) \) is the regional and unemployment interaction, and \( \epsilon \) is an error matrix. The parameters \( \beta, \eta, \alpha, \lambda, \) and \( \delta \) are then the probit estimates for the individual controls. These estimates and their associated changes in probabilities are reported in the following section.

6. Results and Discussion

Results for the probit regressions are found in Tables 4 and 5. The figures for Table 5 are a continuation of the results presented in Table 4; that is, the results presented in Tables 4 and 5 were obtained through the same regression. The columns for each lag for Tables 4 and
5 are meant to be read as one column; each regression included all of the variables included in each table for each lag.

Table 4. Coefficient Estimates for Probit Regression, Demographic Controls and Their Interactions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Probit Estimates, lag = 1</th>
<th>Probit Estimates, lag = 2</th>
<th>Probit Estimates, lag = 3</th>
<th>Probit Estimates, lag = 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Rate, lag = 1</td>
<td>0.033***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment Rate, lag = 2</td>
<td></td>
<td>0.029***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment Rate, lag = 3</td>
<td></td>
<td></td>
<td>0.027***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>Unemployment Rate, lag = 4</td>
<td></td>
<td></td>
<td></td>
<td>0.027***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.008)</td>
</tr>
<tr>
<td>Person was Divorced</td>
<td>0.324***</td>
<td>0.324***</td>
<td>0.324***</td>
<td>0.324***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Person was Black</td>
<td>-0.215***</td>
<td>-0.213***</td>
<td>-0.216***</td>
<td>-0.219***</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.03)</td>
<td>(0.029)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Person was Male</td>
<td>0.66***</td>
<td>0.66***</td>
<td>0.658***</td>
<td>0.657***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.014)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Person was a Black Male</td>
<td>0.004</td>
<td>0.003</td>
<td>0.004</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Unemployment/Black Interaction, lag = 1</td>
<td>-0.006</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment/Male Interaction, lag = 1</td>
<td>-0.026***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment/Black Interaction, lag = 2</td>
<td></td>
<td>-0.007</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment/Male Interaction, lag = 2</td>
<td>-0.026***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment/Black Interaction, lag = 3</td>
<td></td>
<td>-0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment/Male Interaction, lag = 3</td>
<td>-0.027***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment/Black Interaction, lag = 4</td>
<td></td>
<td>-0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment/Male Interaction, lag = 4</td>
<td>-0.026***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Numbers in parentheses are standard errors, *** Estimate is significant at a 99% confidence, ** Estimate is significant at a 95% confidence, * Estimate is significant at a 90 % confidence

As can be seen in Table 4, the coefficient for the unemployment rate is positive and significant in all specifications, indicating that, as the unemployment rate increases, the probability of a death being ruled a suicide increases. The estimate varies between 0.0268 and 0.0329 depending on the lag, which corresponds to an increase of between 7.7 and 9.7 percent in the probability of a death being ruled a suicide. This result is similar to many of the findings discussed in the literature review. An interesting implication can also be drawn from examining the coefficients on each of the lags. For each lag, the coefficient is positive and significant. We argue that this is evidence that the effect is persistent over time, and that the deleterious effects of becoming unemployed affect individuals for many months. The decision to commit suicide may take time. Perhaps the individual is hoping for better times. The positive coefficient estimates for each lag indicate that individuals react to
macroeconomic fluctuations over time: they may react either quickly or take their time in deciding. Either way, the effects are seen over time. This is also implied by our theoretical decision to end one’s life given by the conditions laid out in the model presented in the model above: we need to sum (integrate) an individual’s utility across time.

Table 5. Coefficient Estimates for Probit Regression, Regional Controls and Their Interactions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Probit Estimates, lag t = 1</th>
<th>Probit Estimates, lag t = 2</th>
<th>Probit Estimates, lag t = 3</th>
<th>Probit Estimates, lag t = 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pacific Region</td>
<td>0.291*** (0.042)</td>
<td>0.268*** (0.041)</td>
<td>0.265*** (0.044)</td>
<td>0.264*** (0.045)</td>
</tr>
<tr>
<td>Mountain Region</td>
<td>0.228*** (0.045)</td>
<td>0.208*** (0.044)</td>
<td>0.196*** (0.047)</td>
<td>0.199*** (0.048)</td>
</tr>
<tr>
<td>West North Central Region</td>
<td>-0.03 (0.045)</td>
<td>-0.052 (0.044)</td>
<td>-0.061 (0.047)</td>
<td>-0.063 (0.048)</td>
</tr>
<tr>
<td>East North Central Region</td>
<td>0.023 (0.041)</td>
<td>0.005 (0.043)</td>
<td>0.001 (0.047)</td>
<td>0.006 (0.048)</td>
</tr>
<tr>
<td>West South Central Region</td>
<td>-0.058 (0.042)</td>
<td>-0.08** (0.044)</td>
<td>-0.09** (0.044)</td>
<td>-0.085* (0.046)</td>
</tr>
<tr>
<td>East South Central Region</td>
<td>0.131*** (0.046)</td>
<td>0.109** (0.045)</td>
<td>0.01** (0.048)</td>
<td>0.01** (0.049)</td>
</tr>
<tr>
<td>South Atlantic Region</td>
<td>0.098** (0.041)</td>
<td>0.081** (0.044)</td>
<td>0.081** (0.043)</td>
<td>0.087** (0.044)</td>
</tr>
<tr>
<td>Mid-Atlantic Region</td>
<td>-0.179*** (0.042)</td>
<td>-0.197*** (0.041)</td>
<td>-0.205*** (0.044)</td>
<td>-0.203*** (0.045)</td>
</tr>
<tr>
<td>North East Region</td>
<td>-0.114** (0.049)</td>
<td>-0.131*** (0.048)</td>
<td>-0.145*** (0.05)</td>
<td>-0.139*** (0.052)</td>
</tr>
<tr>
<td>Pacific Region*U_t Interaction</td>
<td>-0.045*** (0.008)</td>
<td>-0.041*** (0.007)</td>
<td>-0.04*** (0.008)</td>
<td>-0.04*** (0.008)</td>
</tr>
<tr>
<td>Mountain Region*U_t Interaction</td>
<td>-0.02** (0.008)</td>
<td>-0.016** (0.008)</td>
<td>-0.014* (0.008)</td>
<td>-0.015* (0.008)</td>
</tr>
<tr>
<td>West North Central Region*U_t Interaction</td>
<td>-0.021*** (0.008)</td>
<td>-0.016** (0.008)</td>
<td>-0.015* (0.008)</td>
<td>-0.015* (0.008)</td>
</tr>
<tr>
<td>East North Central Region*U_t Interaction</td>
<td>-0.025*** (0.008)</td>
<td>-0.021*** (0.007)</td>
<td>-0.20*** (0.008)</td>
<td>-0.201*** (0.008)</td>
</tr>
<tr>
<td>West South Central Region*U_t Interaction</td>
<td>-0.004 (0.008)</td>
<td>0.0004 (0.007)</td>
<td>0.002 (0.008)</td>
<td>0.001 (0.008)</td>
</tr>
<tr>
<td>East South Central Region*U_t Interaction</td>
<td>-0.04*** (0.008)</td>
<td>-0.035*** (0.007)</td>
<td>-0.034*** (0.008)</td>
<td>-0.034*** (0.009)</td>
</tr>
<tr>
<td>South Atlantic Region*U_t Interaction</td>
<td>-0.027*** (0.008)</td>
<td>-0.023*** (0.007)</td>
<td>-0.023*** (0.008)</td>
<td>-0.024*** (0.008)</td>
</tr>
<tr>
<td>Mid-Atlantic Region*U_t Interaction</td>
<td>-0.014* (0.007)</td>
<td>-0.011 (0.007)</td>
<td>-0.009 (0.008)</td>
<td>-0.009 (0.008)</td>
</tr>
<tr>
<td>North East Region*U_t Interaction</td>
<td>-0.0171** (0.008)</td>
<td>-0.014* (0.008)</td>
<td>-0.011 (0.008)</td>
<td>-0.012 (0.009)</td>
</tr>
</tbody>
</table>

Source: Numbers in parentheses are standard errors, *** Estimate is significant at a 99% confidence, ** Estimate is significant at a 95% confidence, * Estimate is significant at a 90% confidence

The regional controls used here also offer interesting results. The coefficient estimates are positive and significant for four regions (Pacific, Mountain, East South Central, and South Atlantic), implying that individuals in these areas are more likely to commit suicide than others in the other regions. The estimates for a lag of one vary between 0.0982 for the South Atlantic region and 0.2905 for the pacific region, corresponding to between a 28 and 75 percent increase. This is consistent across lags. The effect was greatest for individuals in the...
Pacific region, and smallest for the South Atlantic region. Two of the regions (Mid-Atlantic and North-East regions) had negative estimates, indicating that individuals in these areas were less likely to commit suicide. Three of the regional controls are insignificant (East North Central, West North Central, and West South Central) for a lag of one month, but the estimate for the West South Central region is significant for lags greater than one. This is perhaps an indication that individuals in that region are more patient on their decision to end their life. Both of the North Central areas are in the Mid-West, and in fact constitute the entirety of the Mid-Western states. These coefficients are insignificant for all lags.

One of the secondary focuses of this paper, however, is on the regional interaction terms. From Table 5, we see that all but one region (West South Central) is significant at at least a ninety percent confidence for a lag of one month. Once we allow for more time to pass, other regions begin to lose significance. For all lags, all significant coefficients are negative; however, as the primary focus of this paper is the effects of unemployment on an individual’s choice to commit suicide once regional variations are controlled for, note that for all lags, the unemployment estimate is positive and significant. This was the main focus of the paper.

The impetus of this paper was accounts reported in popular media documenting the correlation between macroeconomic downturns and increases in the suicide rate. The trauma of an individual losing their job might be motivation enough to end their life. This is not the whole story and there are several factors that we cannot control for in the data that may influence the decision (religious views, family controls, and health, for example). There is another way that macroeconomic fluctuations, specifically related to labor issues, may be driving some of the findings with the regional interactions. An alternative to firing someone outright may be to decrease their number of hours worked; instead of losing their job, the individual may become underemployed. The individual is still part of the labor force and counted as having a job and is thus not counted as being unemployed. But the trauma that is associated with the shock not only to income but to ego as well may also drive the decision to end one’s life. If this were the case, that person may still have committed suicide due to the macroeconomic shock, but this would not be picked up in the data. The regions that showed the biggest interaction effects (East North Central region, East South Central region, and the South Atlantic region) each contain major cities with known labor issues (Chicago, Washington, DC) or are often near the top in unemployment. The effects of underemployment may be being picked up here with the negative region interaction variables.

The signs of the other coefficient estimates are also as expected and are consistent across lags. As shown in Table 5, males are more likely to commit suicide overall, as evidenced by the positive estimate, but perhaps surprisingly, are less likely to commit suicide due to changes in unemployment rates, as evidenced by the negative sign on the male/unemployment interaction term. This is true for all lags. Blacks are no more or less likely to commit suicide than are other races. If an individual is divorced, they are also more likely to commit suicide.

7. Conclusions and Implications

Recognizing, identifying, and understanding regional differences in the incidence and causation of suicide can have profound influence on the formulation of public policy and the nature and allocation of resources to intervene in preventing or reducing suicide. Studies have been conducted to assess the efficacy of such programs in a number of countries.
example, in France suicide decreased from 1996 to 1999, with the 11 regions that had implemented suicide prevention programs experiencing a sharper decrease in suicide mortality than the 11 others that had not initiated such programs (Bellanger and Jourdain [2006]; Bellanger, Jourdain, and Batt-Moillo [2007]). Regional trends with regards to suicide prevention programs were also studied in Ireland (Kelleher, Keeley, and Corcoran [1997]) to determine if current resources required redistribution. In 1998, Lester conducted a meta-analysis of 14 studies on regional correlates of suicide rates within nations; this suggests a future study comparing regional variations in unemployment rates with research conducted over the last decade into regional variations in suicide rates.

In an era of severe governmental budgetary constraints, understanding the socioeconomic dynamics related to an increased incidence of suicide as they vary from region to region provides policy makers in both the private and public sectors essential data for the most cost-effective development and allocation of resources designed to reduce suicide and the resulting negative impact on the society and the economy.

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