WELL-BEING ACROSS AMERICA

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Abstract—This paper uses Behavioral Risk Factor Surveillance System data to study life satisfaction and mental health across the geography of the United States. The analysis draws on a sample of 1.3 million citizens. Initially we control for people's personal characteristics (though not income). There is no correlation between states' regression-adjusted well-being and their GDP per capita. States like Louisiana, plus Washington, D.C., have high psychological well-being levels; California and West Virginia have low well-being. When we control for incomes, satisfaction with life is lower in richer states, just as compensating-differentials theory would predict. Nevertheless, some puzzles remain.

> *By the mid-twentieth century . . . people as a whole were not disease-ridden, and ideas of so-called positive health emerged. This emboldened the WHO to define health in a new way as "physical, mental and social well-being, not merely the absence of disease or infirmity." . . . Medicine would then focus on improving health in the sense of (i) moving people toward the favorable end of the health spectrum, as determined subjectively by responses to questions, and (ii) enhancing the bodily reserves, as determined by screening tests.*
>
> Lester Breslow (1972)

I. Introduction

THE topic of human well-being is important. It is also one of cross-disciplinary interest. Recent research, across a variety of literatures within the social and medical sciences, has attempted to gauge the satisfaction and happiness of a society by drawing on data on citizens' subjective well-being and measurements of variables such as real income. Such work may eventually have policy implications.[1] The Stiglitz Commission (set up by Nicholas Sarkozy of France and downloadable at www.stiglitz-sen-fitoussi.fr) recently completed a report on the issue of how in the future some mixture of economic prosperity and psychological health might be measured and used by governments.

The aim of this paper is to explore the geography of human well-being. It studies mental health and life satisfaction among a recent random sample of 1.3 million U.S. inhabitants.[2] The size of the data set, gathered between 2005 and 2008, provides advantages denied to previous investigators. (The often-used General Social Survey, for example, samples only approximately 3,000 Americans biannually.) We are able to establish some of the first evidence that California, Kentucky, Michigan, Ohio, West Virginia, and Missouri have relatively low levels of psychological well-being. These six states come within the lowest quartile of (regression-corrected) well-being on two separate measures. Using the same criteria, we show that Louisiana, Washington, D.C., Colorado, Alaska, and Tennessee have relatively high well-being. (We are including Washington, D.C., in the category of states in this article.)

The paper discusses the implications of these state-by-state patterns and demonstrates that there is no correlation between states' (regression-adjusted) levels of life satisfaction and their levels of GDP per capita. It also checks, and occasionally disagrees with, some of the famous microfindings in earlier U.S. well-being literature. Following Easterlin (1974, 2003), and an emerging literature that includes Clark (2003), Di Tella, MacCulloch, and Oswald (2001, 2003), Blanchflower and Oswald (2004), Kahneman et al. (2004), Layard (2005), Deaton (2008), Levinson (2009), Daly and Wilson (2009), Stevenson and Wolfers (2009), and Luechinger (2009), we view survey well-being data as proxy utility measures. This paper is complementary to, and covers different ground from, new work by Oswald and Wu (2010), which exploits BRFSS data but uses no mental health information and does not report microeconometric life satisfaction equations.

This paper focuses on four questions:

1. Do some parts of the United States offer higher utility than others? We tackle this by combining information on reported levels of life satisfaction and mental ill health. Our conclusion is, broadly, yes.
2. Are richer states also "happier" states? We find not. When individuals' incomes are held constant, high-GDP states in our data are discernibly less happy. This is what compensating-differentials theory would predict: economists would expect that overall well-being should be the same everywhere (because individuals can be expected to keep moving into attractive places until those are too congested and expensive to be desirable). An arbitrage argument where intrinsically nicer places pay lower wages in equilibrium (see, for example, Roback, 1982; Blomquist, Berger, & Hoehn, 1988; Krupka & Donaldson, 2007), has an intellectual pedigree going back to Adam Smith.
3. Do life satisfaction regression equations have the same econometric structure as mental health equations? The approximate answer is that they do. Some exceptions, noted later, emerge.

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[1] We will not pursue those implications in this paper, which is about spatial patterns, but interested readers might wish to see the arguments in Argyle (2001), Dolan and Peasgood (2008), Gilbert (2006), Layard (2005), and Oswald (1997).

[2] The psychology literature stresses positive affect, negative affect, and life satisfaction (as in Diener et al. 1985); we focus particularly on the third. While this paper was being refereed, Rentfrow, Mellander, and Florida (2009) was published. It examines state-by-state well-being but looks only at raw means (in Gallup data); they did not have access to underlying raw data on individual Americans.

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4. How large are the estimated effects on individuals of personal variables such as income, race, and age? There is, in the literature, continuing debate about these variables' roles.

The neoclassical textbook apparatus would suggest a strong connection between money and well-being: greater income allows individuals access to greater resources and hence to higher utility. By contrast, a common view in the psychology literature, well expressed by the review article of Diener and Biswas-Diener (2002), is that empirically there is only a slight correlation. In the studies those authors describe, the highest correlation between income and subjective well-being that any American research has found is a Pearson's correlation coefficient of $r = 0.18$.

We try to contribute to this issue.

Another debate centers on the connections between aging and well-being. Traditional psychology, represented by sources such as Diener et al. (1999) and Argyle (2001), argues that happiness is either flat or slightly increasing in age. Some work by economists and others, however, has demonstrated signs of a U-shape through the life cycle. This result appears in Theodossiou (1998), Winkelmann and Winkelmann (1998), Frey and Stutzer (2002), Clark (2003), Blanchflower and Oswald (2004), Graham (2005), Oswald (1997), Sacker and Wiggins (2002), Van Praag and Ferrer-i-Carbonell (2004), Shields and Wheatley Price (2005), Oswald and Powdthavee (2007), and Propper et al. (2005).

Use of American data on this issue has not been common. But one approach is that of researchers such as Mroczek and Kolarz (1998) and Easterlin (2006), who hold constant few or no other influences on well-being and instead look at the uncorrected relationship between happiness and age. In a sense, these authors focus on a reduced-form issue. That issue is a descriptive question: How does observed happiness vary over the life cycle? Further analysis includes that of Mroczek and Spiro (2005). The authors conclude in a data set on U.S. veterans that happiness rises into the person's approximately early 60s and then tends to fall away. New work by Glenn (2009) also argues, in his criticism of the multicountry study by Blanchflower and Oswald (2008), that there is no U shape in American data.

We examine this issue in BRFSS data.

More broadly, our paper is in an intellectual tradition that includes Schkade and Kahneman (1998), Plaut, Markus, and Lachman (2002), Gabriel, Mattey, and Wascher (2003), Propper et al. (2005), Weich et al. (2005), Powdthavee (2006), Moro et al. (2008), and Luechinger (2009).[3] Propper et al. (2005) and Weich et al. (2005) find little geographical variation in mental health once they control for individuals' microcharacteristics. Our spatial results are broadly compatible with new European analysis, done independently and with a different statistical method, by Pittau, Zelli, and Gelman (2010).

[3] Moriarty et al. (2009) also draw on several waves of the BRFSS data used in this paper to look at geographical patterns in serious mental illness across U.S. states.

II. Conceptual Issues

An old idea in the economics literature is that different regions within a country can be expected to provide the same level of utility to their inhabitants.[4] If Vermont, for example, offers a more attractive level of well-being to representative individual A than does Ohio, then we would expect to see Ohio citizens like individual A try to move to Vermont. That kind of migratory flow will cease only when a receiving region has become less desirable as an area in which to live. The economic equilibrium ought to be one of strict equality of utility (Roback, 1982; Hoehn, Berger, & Blomquist, 1987). This is a theoretical proposition. It rests on the assumptions of sufficiently low mobility costs and sufficiently accurate levels of information about what it would be like to live in another state.[4] It is also possible that the proposition holds only after a considerable adjustment period (Treyz et al., 1993). If the economist's arbitrage theory across regions is correct and well-being data are a useful proxy for utility, then its prediction should be detectable in an empirical test for state-by-state equality of well-being for a person of given characteristics.

When might such a test ever be expected to fail? One such circumstance would be after a major change in events or the intrinsic attractiveness of individual states or regions. Then a temporary disequilibrium would be expected.

Conceptually, one possible taxonomy is the following:

- A strong version of spatial arbitrage equilibrium. High-income U.S. states offer lower nonpecuniary utility, and there are no detectable econometric differences in regression-adjusted well-being across states.
- A weak version of spatial arbitrage equilibrium. High-income U.S. states offer lower nonpecuniary utility, but there remain some detectable econometric differences in regression-adjusted well-being across U.S. states.
- A rejection of strong and weak forms.

The evidence of the paper tentatively favors the second of these interpretations.

[4] Technically, the standard arbitrage argument is that the marginal values of some variable X should be equated. Consider a much older world where people can live anywhere in the United States, and wherever they go, they can claim some land for free. Early migrants to California claim the beach properties, so even after some years, average happiness in California is higher than in, say, Idaho. In this case, there can be a difference between the marginal and average citizen's utility because early movers have an advantage. But now assume that, in the modern era, everything is tradable. Hence, even a new migrant to California who has sufficient resources can acquire beach property. Then, controlling for people's characteristics, the "marginal" Californians are as happy as all other Californians.

III. Data

We draw on data collected under the auspices of the Behavioral Risk Factor Surveillance System (BRFSS), a state-based system of health surveys that gathers information on risky behaviors, preventive health practices, and access to health care. The BRFSS was established in 1984 by the Centers for Disease Control and Prevention (CDC); currently data are collected monthly in all fifty states, the District of Columbia, Puerto Rico, the U.S. Virgin Islands, and Guam. The data set is meant to "identify emerging health problems, establish and track health objectives, and develop and evaluate public health policies and programs." More than 350,000 adults are interviewed each year; the BRFSS is the largest telephone health survey in the world.

We study a sample of respondents between the ages of 18 and 85 with nonmissing information. The data set's annual samples provide statistically representative cross-sectional snapshots of the United States.[5] Information on individual life satisfaction was collected in BRFSS for the first time in 2005. Hence there has been little published research on life satisfaction using this data set.

In the remainder of the paper, we rely on two particular survey questions. One provides information about how people feel generally about the quality of their lives; the other gets more narrowly at their mental health. The exact wording of the BRFSS life satisfaction question is: "In general, how satisfied are you with your life?" Here people are able to answer one of the following: very satisfied, satisfied, dissatisfied, or very dissatisfied [questionnaire line code 206]. The wording of the mental health question [questionnaire line code 76] that we use as a complementary source of well-being information is: "Thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" In this case, individuals report an integer between 0 and 30.

Within the BRFSS questionnaire, individuals are asked quite early on about their days of poor mental health. Eight pages (of questions) later, they are asked about their household income. Twelve pages after the income question, they are asked about their feelings of satisfaction with their own life.

The paper's evidence is set out in four main tables that give regression equation results in which the dependent variable is derived from the two kinds of survey answers. To give a sense for the raw patterns in the data, life satisfaction in the United States can be treated in a cardinal way by assigning 1 to 4 to the four answers, where "very satisfied" is assigned a 4. The mean of life satisfaction in modern U.S. data is then 3.4, with a standard deviation of 0.6. The median number of days of mental ill health is 0, while the mean is 3.4 days in the past month, with a standard deviation of 7.7. Well-being answers are thus skewed, in both kinds of measures, toward the upper end of the possible well-being distribution. Table A1 provides descriptive statistics. Table A2 gives the raw mean values of life satisfaction by state.

IV. Results

Life-satisfaction equations, in which the years 2005 to 2008 are pooled, are set out in table 1. For simplicity, we choose an elementary linear OLS estimator in which the four possible values of the dependent variable are assigned the integers from a high of 4 down to a low of 1. However, the later substantive findings are not altered by switching to an ordered estimator. Table 1's method allows coefficient sizes to be read off directly as life satisfaction points.

Column 1 of table 1 reveals a monotonic relationship between household income and people's feelings of satisfaction with their lives. The omitted category is a household income under $10,000 per annum. Seven dummy variables are included, for income bands stretching up to "income greater than $75,000." Perhaps unsurprisingly given the sample size, the null of 0 on these coefficients can be rejected at any conventional level (the implied t-statistic on the upper-income banded dummy, for example, exceeds 200).

The size of the income gradient in table 1 is large. There are four ways to think about this. First, if we compare Americans with the lowest levels of income to those with the highest levels, the difference in life satisfaction in column 1 is approximately 0.6 points. To put this in context, only approximately 5% of the sample put themselves in the two lower satisfaction categories (dissatisfied with life; very dissatisfied with life), so a hypothetical change of 0.6 life satisfaction points is to be thought of as a large move. Second, it can be seen from column 2 of table 1 that although racial dummy variables enter with well-determined coefficients, with both black and Native Americans, for example, having coefficients of approximately -0.14, the size of the race effects in the equation is far smaller than that generated by income differences. This is a way of saying that, statistically, there is much more information in the income dummies than in the race dummies. This has not been the standard view (it could be compared to that in Blanchflower and Oswald, 2004, or an older psychology literature based on simple bivariate patterns) but it is potentially consistent with the finding of Stevenson and Wolfers (2008) that gender and racial differences in Americans' life satisfaction have declined through recent decades. Third, the contribution to the R^2 from income dummies is many multiples of that from race, age, and gender dummies. Fourth, it will be seen later that the income dummy coefficients correspond to large effects when examined against, for example, major life characteristics like being separated or unemployed.

The R^2 in column 1 of table 1 is 0.077. Column 1 has income entered as a control. By contrast, the R^2 is only

[5] This is only approximately true. The data used in the paper appear to slightly oversample women, for example. But our regression equations correct for personal characteristics when deriving the state-dummy well-being coefficients.

TABLE 1.—LIFE SATISFACTION EQUATIONS: BRFSS POOLED DATA 2005–2008

Variables	(1)	(2)	(3)	(4)
Income $10–15K	0.116**	–	0.0871**	0.0648**
	(0.00330)		(0.00333)	(0.00331)
Income $15–20K	0.202**	–	0.175**	0.135**
	(0.00311)		(0.00314)	(0.00314)
Income $20–25K	0.265**	–	0.245**	0.184**
	(0.00298)		(0.00301)	(0.00304)
Income $25–35K	0.338**	–	0.329**	0.248**
	(0.00284)		(0.00288)	(0.00294)
Income $35–50K	0.413**	–	0.423**	0.317**
	(0.00275)		(0.00281)	(0.00292)
Income $50–75K	0.492**	–	0.521**	0.391**
	(0.00273)		(0.00282)	(0.00299)
Income >$75K	0.607**	–	0.652**	0.490**
	(0.00263)		(0.00276)	(0.00302)
Household size	–	0.0471**	0.0234**	0.00101*
		(0.000448)	(0.000460)	(0.000503)
Black	–	−0.127**	−0.00343	0.0335**
		(0.00206)	(0.00214)	(0.00215)
Asian	–	−0.0450**	−0.0385**	−0.0532**
		(0.00428)	(0.00437)	(0.00434)
Hispanic	–	−0.108**	0.0437**	0.0533**
		(0.00239)	(0.00250)	(0.00254)
Native American	–	−0.140**	−0.0120**	0.0146**
		(0.00420)	(0.00429)	(0.00425)
Other minority	–	−0.0662*	−0.0262	−0.0276
		(0.0287)	(0.0284)	(0.0281)
Female	–	−0.00183	0.0372**	0.0393**
		(0.00109)	(0.00112)	(0.00116)
Some high school	–	–	–	−0.00622
				(0.00395)
High school	–	–	–	0.0357**
				(0.00351)
Some college	–	–	–	0.0363**
				(0.00358)
College	–	–	–	0.0984**
				(0.00363)
Married	–	–	–	0.168**
				(0.00204)
Divorced	–	–	–	0.00307
				(0.00224)
Separated	–	–	–	−0.0946**
				(0.00397)
Widowed	–	–	–	0.0488**
				(0.00264)
Partner	–	–	–	0.0526**
				(0.00379)
Self-employed	–	–	–	0.0641**
				(0.00193)
Unemployed	–	–	–	−0.161**
				(0.00290)
Homemaker	–	–	–	0.0621**
				(0.00224)
Student	–	–	–	0.0629**
				(0.00451)
Retired	–	–	–	0.0868**
				(0.00193)
Controls for 5-year age bands?	No	Yes	Yes	Yes
Constant	2.986**	3.217**	2.955**	3.031**
	(0.00259)	(0.00592)	(0.00669)	(0.00774)
Observations	1,249,254	1,383,772	1,215,874	1,213,326
R^2	0.077	0.008	0.093	0.115

Standard errors are in parentheses. *Significant at 5%, **significant at 1%. All regressions include state effects, controls for month and year of survey. Life satisfaction is measured on 1–4 scale: 1 = very dissatisfied to 4 = very satisfied.

0.008 in column 2 of table 1; this column has only a set of demographic characteristics as controls. Put loosely, therefore, money matters a great deal here. An R^2 of 0.077 corresponds arithmetically to a Pearson r coefficient of 0.28, which can be compared to the standard finding, in developed nations, of around $r = 0.15$ (pointed out in the review by Diener & Biswas-Diener, 2002).

Columns 3 and 4 of table 1 show that the income gradient of column 1 is only slightly affected by the inclusion of various sets of control variables. Perhaps most striking, there

continues to be a difference of approximately 0.5 life satisfaction points, even in the long specification of column 4 of table 1, between individuals in the highest income category and those in the lowest income category. This final column includes fifty state dummies, eleven month-of-interview dummies, and an extensive set of personal and demographic dummy variables. Comparing columns 1 and 4, the bivariate association between income and satisfaction is only a little mediated by adjustment for approximately eighty other independent variables.

In these data, there is support for a U shape in life satisfaction throughout most of the life course.[6] Regression adjusted, the age at which minimum life satisfaction is reached is slightly before 50 years old (table A3 in the appendix gives an indication of the shape). An approximate U exists even in raw data. Contrary to the American data in Easterlin (2006) and Glenn (2009), it is not necessary first to control for endogenous variables such as education or marriage or income.

The other variables in column 4 of table 1 have familiarly signed coefficients. Ceteris paribus, a college degree is associated with 0.1 extra life satisfaction points, marriage when compared to being unmarried with 0.17 points, marital separation with −0.1 points, unemployment with −0.16 points, and self-employment with 0.06 points.

Table 2 turns to life satisfaction patterns across the geography of the United States. Here the state dummy coefficients are written out explicitly. Alabama is the omitted, base category. Thus, the first state-dummy coefficient in column 1 of table 2 can be interpreted as showing that satisfaction with life on average in Alaska is 0.0185 life satisfaction points above that in the base case of Alabama. Arizona residents have 0.0494 of extra life satisfaction on this cardinal scale, Arkansas is indistinguishable from Alabama, and so on across the listed states.

However, column 1 of table 2 cannot tell us what life is truly like in each state of the union. Rather, it gives a measure of the average well-being of the typical resident of that state. Because states vary widely in the nature of their inhabitants, a more natural inquiry is to examine the coefficients on state dummies after controlling for personal and demographic features of the populations of each. This is what the later columns of table 2 do.

Arguably the most interesting column of table 2 is the fourth. In column 4, we have adjusted for all the nonfinancial features of individuals. This may appear strange, but there is an important reason not to hold constant people's income in statistical work of this sort. It is that if someone leaves West Virginia to live in California, they are likely to earn a larger nominal salary, but other factors, such as house prices and traffic congestion, will tend to be worse. Hence, if we control in a well-being regression equation for their level of income, the structure of the state dummies in the equation will tell us about the remaining intrinsic state disamenities for which compensating higher pay must be offered. The purpose of the exercise here is instead to understand the net benefits or losses from being a citizen of the state.

How much do life satisfaction levels vary from state to state? The answer is, by some standards, fairly widely. The notably poor life satisfaction states are then, in the third column of table 2, after rounding to two decimal points, California (−0.04), Illinois (−0.03), Indiana (−0.07), Kentucky (−0.06), Massachusetts (−0.05), Michigan (−0.06), Missouri (−0.06), Nebraska (−0.05), New York (−0.06), Ohio (−0.06), Pennsylvania (−0.06), Rhode Island (−0.04), and West Virginia (−0.06). The high-satisfaction states are Washington, D.C. (0.02), Florida (0.02), Hawaii (0.04), and Louisiana (0.05). The standard errors correspond in each case, within table 2, to a test of the null hypothesis of 0 on the coefficient.

One warning is in order. It should not be presumed that there is a statistically significant difference between each of the states within these low-satisfaction and high-satisfaction groupings. The null of well-being equality in Indiana and Kentucky, for example, cannot be rejected.

A final concern is whether key state-level economic variables might be missing from the specifications in tables 1 and 2. Following a referee's suggestion, we checked the consequences of including the state unemployment rate, which is somewhat in the spirit of Di Tella et al. (2001), and the population density in the state, in the spirit of Cramer, Torgersen, and Kringlen (2004). Neither of these produced a material alteration in the structure of the state dummies in a life satisfaction equation; typically the two sets of state dummy structures were correlated 0.99. An example table, for unemployment, is given in table A4 in the appendix.

Tables 3 and 4 present equivalent results. In these cases, however, we switch to a dependent variable that measures mental ill health. This is the number of days, in the past 30 days, that people feel they suffered from poor mental health.[7] The median answer is 0, and by the nature of the data, it is not possible for those with good mental health to distinguish themselves from those with sound mental health. For this reason, we use a tobit estimator, but the results are not sensitive to this choice. The first thing noticeable in column 1 of table 3 is the strong income

[6] It is of course possible to fit high-order polynomials, and there is evidence of unhappiness for a few years for people aged 18 and up and again among rather old people. We use a set of banded five-year intervals as an approximation, not because it does every justice to the details of the data set. It is simply that the paper's focus is elsewhere, and midlife is, in these data, characterized by low measured well-being (see table A3). We acknowledge helpful discussions with Danny Blanchflower on these issues.

[7] Moriarty et al. (2009) construct a variable based on the same question in the BRFSS: the number of individuals with "frequent mental distress," defined as having at least fourteen days of poor mental health in the past month. Although a different criterion than we use and closer to a measure of severe mental illness, our rankings of state-level mental well-being are fairly similar to theirs.

TABLE 2.—LIFE SATISFACTION EQUATIONS: BRFSS POOLED DATA 2005–2008

Variables	(1)	(2)	(3)	(4)
Household size	–	0.0471**	0.00404**	0.00373**
		(0.000448)	(0.000482)	(0.000482)
Black	–	−0.127**	−0.0184**	−0.00919**
		(0.00206)	(0.00205)	(0.00204)
Asian	–	−0.0450**	−0.0769**	−0.0718**
		(0.00428)	(0.00417)	(0.00415)
Hispanic	–	−0.108**	−0.00629**	−0.00343
		(0.00239)	(0.00241)	(0.00240)
Native American	–	−0.140**	−0.0473**	−0.0349**
		(0.00420)	(0.00410)	(0.00408)
Other minority	–	−0.0662*	−0.0612*	−0.0566*
		(0.0287)	(0.0279)	(0.0278)
Female	–	−0.00181	0.0214**	0.0212**
		(0.00109)	(0.00108)	(0.00111)
Some high school	–	–	0.0188**	0.0218**
			(0.00358)	(0.00357)
High school	–	–	0.126**	0.123**
			(0.00314)	(0.00313)
Some college	–	–	0.172**	0.166**
			(0.00318)	(0.00317)
College	–	–	0.299**	0.290**
			(0.00317)	(0.00317)
Married	–	–	0.282**	0.268**
			(0.00190)	(0.00190)
Divorced	–	–	−0.00114	−0.00335
			(0.00217)	(0.00217)
Separated	–	–	−0.114**	−0.113**
			(0.00384)	(0.00382)
Widowed	–	–	0.0708**	0.0623**
			(0.00249)	(0.00248)
Partner	–	–	0.0975**	0.0930**
			(0.00367)	(0.00366)
Self-employed	–	–	–	0.0713**
				(0.00187)
Unemployed	–	–	–	−0.239**
				(0.00272)
Homemaker	–	–	–	0.0508**
				(0.00208)
Student	–	–	–	0.0261**
				(0.00418)
Retired	–	–	–	0.0698**
				(0.00181)
Alaska	0.0185*	0.0157*	0.0156*	0.0201**
	(0.00789)	(0.00801)	(0.00778)	(0.00775)
Arizona	0.0494**	0.0329**	0.0137*	0.0110
	(0.00647)	(0.00652)	(0.00633)	(0.00631)
Arkansas	0.00995	−0.0122	−0.0192**	−0.0203**
	(0.00632)	(0.00633)	(0.00615)	(0.00612)
California	−0.0104	−0.0228**	−0.0360**	−0.0363**
	(0.00599)	(0.00607)	(0.00589)	(0.00587)
Colorado	0.0595**	0.0404**	0.00569	0.00415
	(0.00573)	(0.00575)	(0.00559)	(0.00557)
Connecticut	0.0124*	−0.00862	−0.0325**	−0.0288**
	(0.00606)	(0.00607)	(0.00590)	(0.00587)
Delaware	0.0455**	0.0245**	0.00995	0.00798
	(0.00680)	(0.00682)	(0.00662)	(0.00659)
District of Columbia	0.0254**	0.0700**	0.0266**	0.0258**
	(0.00694)	(0.00697)	(0.00680)	(0.00677)
Florida	0.0406**	0.0215**	0.0178**	0.0170**
	(0.00521)	(0.00522)	(0.00507)	(0.00505)
Georgia	0.0270**	0.0166**	0.00128	0.000930
	(0.00604)	(0.00603)	(0.00586)	(0.00583)
Hawaii	0.0531**	0.0481**	0.0467**	0.0404**
	(0.00607)	(0.00683)	(0.00664)	(0.00661)
Idaho	0.0303**	−0.00794	−0.0178**	−0.0216**
	(0.00637)	(0.00639)	(0.00621)	(0.00618)
Illinois	0.00469	−0.0169**	−0.0345**	−0.0328**
	(0.00640)	(0.00640)	(0.00621)	(0.00619)
Indiana	−0.0486**	−0.0701**	−0.0672**	−0.0648**
	(0.00627)	(0.00627)	(0.00609)	(0.00607)
Iowa	0.0239**	−0.0126*	−0.0246**	−0.0261**
	(0.00635)	(0.00635)	(0.00616)	(0.00614)

TABLE 2.—(CONTINUED)

Variables	(1)	(2)	(3)	(4)
Kansas	0.0263**	−0.00352	−0.0293**	−0.0306**
	(0.00576)	(0.00576)	(0.00560)	(0.00557)
Kentucky	−0.0522**	−0.0820**	−0.0627**	−0.0635**
	(0.00605)	(0.00605)	(0.00587)	(0.00585)
Louisiana	0.0618**	0.0558**	0.0506**	0.0486**
	(0.00627)	(0.00626)	(0.00608)	(0.00605)
Maine	0.0264**	−0.00403	−0.0115	−0.0101
	(0.00635)	(0.00636)	(0.00617)	(0.00615)
Maryland	0.0356**	0.0185**	−0.0110*	−0.0119*
	(0.00573)	(0.00573)	(0.00557)	(0.00554)
Massachusetts	−0.0221**	−0.0409**	−0.0428**	−0.0374**
	(0.00527)	(0.00528)	(0.00513)	(0.00511)
Michigan	−0.0213**	−0.0420**	−0.0548**	−0.0533**
	(0.00574)	(0.00575)	(0.00558)	(0.00556)
Minnesota	0.0553**	0.0242**	−0.00347	−0.00447
	(0.00680)	(0.00679)	(0.00659)	(0.00656)
Mississippi	−0.00901	−0.0114	−0.00810	−0.00700
	(0.00607)	(0.00605)	(0.00587)	(0.00585)
Missouri	−0.0417**	−0.0666**	−0.0595**	−0.0594**
	(0.00642)	(0.00642)	(0.00623)	(0.00621)
Montana	0.0345**	0.00774	−0.00710	−0.0109
	(0.00622)	(0.00624)	(0.00606)	(0.00603)
Nebraska	0.00442	−0.0340**	−0.0450**	−0.0469**
	(0.00553)	(0.00554)	(0.00538)	(0.00536)
Nevada	−0.00645	−0.0264**	−0.0269**	−0.0278**
	(0.00690)	(0.00705)	(0.00685)	(0.00682)
New Hampshire	0.0397**	0.00501	−0.0119*	−0.0108
	(0.00616)	(0.00617)	(0.00599)	(0.00597)
New Jersey	0.00324	−0.0153**	−0.0331**	−0.0295**
	(0.00553)	(0.00553)	(0.00538)	(0.00536)
New Mexico	0.00792	0.0141*	−0.00935	−0.0120*
	(0.00615)	(0.00623)	(0.00605)	(0.00603)
New York	−0.0286**	−0.0437**	−0.0551**	−0.0534**
	(0.00602)	(0.00604)	(0.00587)	(0.00585)
North Carolina	0.0166**	0.00620	−0.00287	−0.00290
	(0.00524)	(0.00523)	(0.00508)	(0.00506)
North Dakota	0.0230**	−0.00680	−0.0229**	−0.0253**
	(0.00660)	(0.00660)	(0.00641)	(0.00638)
Ohio	−0.0324**	−0.0522**	−0.0566**	−0.0546**
	(0.00568)	(0.00567)	(0.00551)	(0.00549)
Oklahoma	−0.00972	−0.0245**	−0.0285**	−0.0300**
	(0.00571)	(0.00578)	(0.00561)	(0.00558)
Oregon	0.0128*	−0.0171**	−0.0315**	−0.0329**
	(0.00606)	(0.00609)	(0.00592)	(0.00589)
Pennsylvania	−0.0512**	−0.0719**	−0.0611**	−0.0591**
	(0.00538)	(0.00538)	(0.00522)	(0.00520)
Rhode Island	−0.0116	−0.0359**	−0.0388**	−0.0337**
	(0.00671)	(0.00672)	(0.00653)	(0.00650)
South Carolina	0.0335**	0.0236**	0.0117*	0.0139*
	(0.00565)	(0.00564)	(0.00548)	(0.00546)
South Dakota	0.0214**	−0.00704	−0.0182**	−0.0208**
	(0.00603)	(0.00604)	(0.00587)	(0.00584)
Tennessee	0.0104	−0.0111	0.00616	0.00489
	(0.00654)	(0.00653)	(0.00634)	(0.00631)
Texas	0.0309**	0.0261**	0.00502	0.00383
	(0.00559)	(0.00563)	(0.00547)	(0.00545)
Utah	0.0630**	0.00658	−0.0116	−0.0152*
	(0.00639)	(0.00641)	(0.00623)	(0.00620)
Vermont	0.0378**	0.00744	−0.00882	−0.00971
	(0.00601)	(0.00602)	(0.00585)	(0.00583)
Virginia	0.0386**	0.0240**	0.00277	0.00108
	(0.00630)	(0.00631)	(0.00613)	(0.00610)
Washington	0.0218**	−0.00555	−0.0243**	−0.0248**
	(0.00502)	(0.00505)	(0.00490)	(0.00488)
West Virginia	−0.0514**	−0.0832**	−0.0584**	−0.0590**
	(0.00683)	(0.00684)	(0.00664)	(0.00662)
Wisconsin	0.000355	−0.0235**	−0.0270**	−0.0246**
	(0.00622)	(0.00621)	(0.00603)	(0.00601)
Wyoming	0.0551**	0.0249**	0.00684	0.00257
	(0.00618)	(0.00620)	(0.00602)	(0.00599)
Controls for 5-year age bands?	No	Yes	Yes	Yes

TABLE 2.—(CONTINUED)

Variables	(1)	(2)	(3)	(4)
Constant	3.363**	3.216**	3.168**	3.185**
	(0.00500)	(0.00617)	(0.00675)	(0.00686)
Observations	1,423,955	1,383,772	1,379,285	1,379,285
R^2	0.003	0.018	0.077	0.085

Standard errors are in parentheses. *Significant at 5%, **significant at 1%. All regressions include controls for month and year of survey. Life satisfaction is measured on a 1–4 scale; 1 = very dissatisfied to 4 = very satisfied.

TABLE 3.—MENTAL DISTRESS EQUATIONS: BRFSS POOLED DATA, 2005–2008
Poor Mental Health Days per Month and Tobit Regressions Censored at Zero

	(1)	(2)	(3)	(4)
Income $10–15K	−4.003**	–	−2.553**	−2.107**
	(0.102)		(0.102)	(0.102)
Income $15–20K	−6.230**	–	−5.087**	−4.368**
	(0.0969)		(0.0972)	(0.0976)
Income $20–25K	−7.675**	–	−6.827**	−5.780**
	(0.0929)		(0.0935)	(0.0948)
Income $25–35K	−9.512**	–	−9.026**	−7.689**
	(0.0889)		(0.0898)	(0.0922)
Income $35–50K	−10.27**	–	−10.68**	−9.027**
	(0.0859)		(0.0874)	(0.0916)
Income $50–75K	−11.01**	–	−12.28**	−10.35**
	(0.0855)		(0.0878)	(0.0940)
Income >$75K	−12.68**	–	−14.40**	−12.09**
	(0.0824)		(0.0862)	(0.0955)
Household size	–	−0.710**	−0.172**	0.0362*
		(0.0147)	(0.0149)	(0.0162)
Black	–	0.622**	−2.060**	−2.524**
		(0.0677)	(0.0698)	(0.0704)
Asian	–	−3.685**	−3.606**	−3.443**
		(0.148)	(0.149)	(0.149)
Hispanic	–	−0.718**	−3.664**	−3.934**
		(0.0793)	(0.0822)	(0.0838)
Native American	–	3.919**	1.206**	0.782**
		(0.134)	(0.135)	(0.135)
Other minority	–	0.907	−0.0819	−0.0265
		(0.884)	(0.874)	(0.869)
Female	–	4.859**	4.102**	4.012**
		(0.0380)	(0.0383)	(0.0396)
Some high school	–	–	–	0.671**
				(0.130)
High school	–	–	–	−1.185**
				(0.117)
Some college	–	–	–	−0.343**
				(0.119)
College	–	–	–	−1.390**
				(0.121)
Married	–	–	–	−0.933**
				(0.0662)
Divorced	–	–	–	1.121**
				(0.0720)
Separated	–	–	–	4.191**
				(0.121)
Widowed	–	–	–	0.246**
				(0.0888)
Partner	–	–	–	1.479**
				(0.119)
Self-employed	–	–	–	−1.984**
				(0.0661)
Unemployed	–	–	–	3.060**
				(0.0884)
Homemaker	–	–	–	−1.279**
				(0.0735)
Student	–	–	–	0.409**
				(0.138)
Retired	–	–	–	−2.135**
				(0.0687)
Controls for 5-year age bands?	No	Yes	Yes	Yes
Constant	1.529**	−2.863**	4.656**	2.944**
	(0.0804)	(0.193)	(0.212)	(0.249)
Observations	1,276,100	1,417,771	1,241,893	1,239,215

Standard errors are in parentheses. *Significant at 5%, **significant at 1%. All regressions include state effects and controls for month and year of survey.

TABLE 4.—MENTAL DISTRESS EQUATIONS: BRFSS POOLED DATA, 2005–2008
Poor Mental Health Days per Month; Tobit Regressions Censored at Zero

	(1)	(2)	(3)	(4)
Household Size	–	−0.710**	−0.0471**	−0.0394*
		(0.0147)	(0.0158)	(0.0159)
Black	–	0.620**	−1.309**	−1.536**
		(0.0677)	(0.0682)	(0.0681)
Asian	–	−3.686**	−3.012**	−3.183**
		(0.148)	(0.146)	(0.145)
Hispanic	–	−0.720**	−2.826**	−2.873**
		(0.0793)	(0.0810)	(0.0807)
Native American	–	3.917**	2.185**	1.898**
		(0.134)	(0.132)	(0.132)
Other minority	–	0.882	0.891	0.796
		(0.884)	(0.870)	(0.866)
Female	–	4.857**	4.466**	4.420**
		(0.0380)	(0.0379)	(0.0388)
Some high school	–	–	−0.0803	−0.134
			(0.120)	(0.120)
High school	–	–	−3.697**	−3.597**
			(0.106)	(0.106)
Some college	–	–	−3.790**	−3.652**
			(0.108)	(0.108)
College	–	–	−6.366**	−6.123**
			(0.108)	(0.108)
Married	–	–	−3.835**	−3.442**
			(0.0625)	(0.0627)
Divorced	–	–	1.256**	1.328**
			(0.0709)	(0.0707)
Separated	–	–	4.801**	4.817**
			(0.119)	(0.118)
Widowed	–	–	−0.237**	−0.000869
			(0.0853)	(0.0851)
Partner	–	–	0.262*	0.429**
			(0.117)	(0.116)
Self-employed	–	–	–	−2.300**
				(0.0652)
Unemployed	–	–	–	4.917**
				(0.0843)
Homemaker	–	–	–	−1.243**
				(0.0699)
Student	–	–	–	1.337**
				(0.131)
Retired	–	–	–	−2.096**
				(0.0653)
Alaska	−1.914**	−3.132**	−2.990**	−3.041**
	(0.265)	(0.269)	(0.265)	(0.264)
Arizona	−2.454**	−1.541**	−1.123**	−1.034**
	(0.217)	(0.218)	(0.215)	(0.214)
Arkansas	−1.473**	−1.087**	−0.911**	−0.874**
	(0.211)	(0.211)	(0.208)	(0.207)
California	−0.295	0.284	0.533**	0.567**
	(0.196)	(0.198)	(0.195)	(0.195)
Colorado	−2.471**	−2.322**	−1.562**	−1.498**
	(0.191)	(0.191)	(0.189)	(0.188)
Connecticut	−2.494**	−1.893**	−1.296**	−1.381**
	(0.203)	(0.203)	(0.200)	(0.199)
Delaware	−1.534**	−1.432**	−1.047**	−0.972**
	(0.228)	(0.229)	(0.225)	(0.224)
District of Columbia	−2.867**	−3.346**	−2.327**	−2.300**
	(0.233)	(0.233)	(0.230)	(0.229)
Florida	−2.373**	−1.588**	−1.476**	−1.426**
	(0.174)	(0.174)	(0.171)	(0.171)
Georgia	−1.671**	−1.572**	−1.236**	−1.222**
	(0.202)	(0.201)	(0.198)	(0.197)
Hawaii	−3.032**	−1.507**	−1.237**	−1.023**
	(0.205)	(0.232)	(0.228)	(0.227)
Idaho	−1.285**	−1.009**	−0.778**	−0.664**
	(0.212)	(0.212)	(0.209)	(0.208)
Illinois	−1.420**	−1.060**	−0.569**	−0.612**
	(0.213)	(0.213)	(0.209)	(0.208)

TABLE 4.—(CONTINUED)

	(1)	(2)	(3)	(4)
Indiana	−0.869**	−0.749**	−0.701**	−0.755**
	(0.208)	(0.208)	(0.204)	(0.204)
Iowa	−4.252**	−3.746**	−3.325**	−3.290**
	(0.216)	(0.216)	(0.213)	(0.212)
Kansas	−4.042**	−3.605**	−2.978**	−2.930**
	(0.195)	(0.195)	(0.192)	(0.192)
Kentucky	0.333	0.522**	0.147	0.179
	(0.199)	(0.199)	(0.196)	(0.195)
Louisiana	−4.297**	−4.473**	−4.237**	−4.166**
	(0.215)	(0.214)	(0.211)	(0.210)
Maine	−1.774**	−1.541**	−1.305**	−1.316**
	(0.212)	(0.212)	(0.209)	(0.208)
Maryland	−1.746**	−1.522**	−0.857**	−0.809**
	(0.191)	(0.190)	(0.187)	(0.187)
Massachusetts	−1.312**	−1.019**	−0.876**	−1.004**
	(0.175)	(0.175)	(0.172)	(0.172)
Michigan	−0.967**	−0.646**	−0.253	−0.272
	(0.191)	(0.191)	(0.188)	(0.187)
Minnesota	−3.890**	−3.587**	−2.883**	−2.845**
	(0.233)	(0.232)	(0.228)	(0.227)
Mississippi	−0.650**	−0.482*	−0.530**	−0.538**
	(0.202)	(0.201)	(0.198)	(0.197)
Missouri	−0.786**	−0.391	−0.429*	−0.422*
	(0.213)	(0.213)	(0.209)	(0.208)
Montana	−2.221**	−2.026**	−1.614**	−1.490**
	(0.208)	(0.209)	(0.205)	(0.205)
Nebraska	−4.556**	−3.844**	−3.442**	−3.379**
	(0.187)	(0.187)	(0.184)	(0.184)
Nevada	−0.225	0.135	0.203	0.260
	(0.227)	(0.232)	(0.229)	(0.228)
New Hampshire	−2.184**	−1.842**	−1.448**	−1.458**
	(0.206)	(0.206)	(0.203)	(0.202)
New Jersey	−2.636**	−1.910**	−1.376**	−1.446**
	(0.184)	(0.184)	(0.181)	(0.181)
New Mexico	−1.480**	−1.181**	−0.614**	−0.542**
	(0.205)	(0.207)	(0.204)	(0.203)
New York	−1.826**	−1.416**	−1.042**	−1.067**
	(0.200)	(0.201)	(0.198)	(0.197)
North Carolina	−2.334**	−2.083**	−1.875**	−1.870**
	(0.175)	(0.175)	(0.172)	(0.171)
North Dakota	−4.493**	−4.125**	−3.621**	−3.547**
	(0.226)	(0.226)	(0.222)	(0.221)
Ohio	−0.602**	−0.238	−0.0274	−0.0773
	(0.188)	(0.188)	(0.185)	(0.184)
Oklahoma	−0.894**	−0.892**	−0.787**	−0.741**
	(0.190)	(0.192)	(0.189)	(0.189)
Oregon	−1.735**	−1.293**	−0.988**	−0.929**
	(0.202)	(0.203)	(0.200)	(0.200)
Pennsylvania	−1.034**	−0.709**	−0.730**	−0.788**
	(0.179)	(0.178)	(0.175)	(0.175)
Rhode Island	−1.577**	−1.149**	−0.967**	−1.079**
	(0.223)	(0.223)	(0.220)	(0.219)
South Carolina	−1.734**	−1.364**	−1.125**	−1.163**
	(0.189)	(0.188)	(0.185)	(0.185)
South Dakota	−5.017**	−4.622**	−4.222**	−4.128**
	(0.207)	(0.207)	(0.204)	(0.203)
Tennessee	−3.179**	−2.867**	−3.150**	−3.105**
	(0.223)	(0.222)	(0.219)	(0.218)
Texas	−2.444**	−1.902**	−1.485**	−1.443**
	(0.187)	(0.188)	(0.185)	(0.185)
Utah	−0.803**	−0.434*	0.00865	0.122
	(0.212)	(0.212)	(0.209)	(0.208)
Vermont	−2.012**	−1.663**	−1.243**	−1.198**
	(0.201)	(0.201)	(0.198)	(0.198)
Virginia	−2.085**	−1.837**	−1.369**	−1.320**
	(0.211)	(0.211)	(0.208)	(0.207)
Washington	−1.731**	−1.378**	−0.977**	−0.944**
	(0.167)	(0.168)	(0.165)	(0.165)
West Virginia	−0.346	0.0426	−0.359	−0.350
	(0.229)	(0.229)	(0.226)	(0.225)

TABLE 4.—(CONTINUED)

	(1)	(2)	(3)	(4)
Wisconsin	−1.864**	−1.660**	−1.408**	−1.466**
	(0.206)	(0.206)	(0.202)	(0.202)
Wyoming	−2.301**	−2.037**	−1.595**	−1.457**
	(0.207)	(0.208)	(0.204)	(0.204)
Controls for 5-year age bands?	No	Yes	Yes	Yes
Constant	−6.644**	−3.046**	−1.181**	−2.105**
	(0.167)	(0.201)	(0.224)	(0.227)
Observations	1,460,011	1,417,771	1,412,668	1,412,558

Standard errors are in parentheses. *Significant at 5%, **significant at 1%. All regressions include controls for month and year of survey.

gradient. The difference between the lowest and highest income categories is a coefficient of −12.68 days of poor mental health. This column of table 3 is closely reminiscent of the earlier life satisfaction results. Again, there is clear monotonicity in the income dummy variables. This gradient is suggestive of, but stronger than, some equivalent studies on physical health (such as, recently, Pham-Kanter, 2009).

The age structure in these mental health equations is qualitatively consistent with that found in the earlier life satisfaction specifications. There is now a hill-shaped relationship between mental ill-being and age (not reported); these turn at around the mid-30s, so at slightly younger ages than in table 1. Other variables enter in qualitatively predictable ways. For example, unemployment is associated with 3 extra days of poor mental health, a college degree with 1.5 fewer days, and marital separation with 4 extra days.

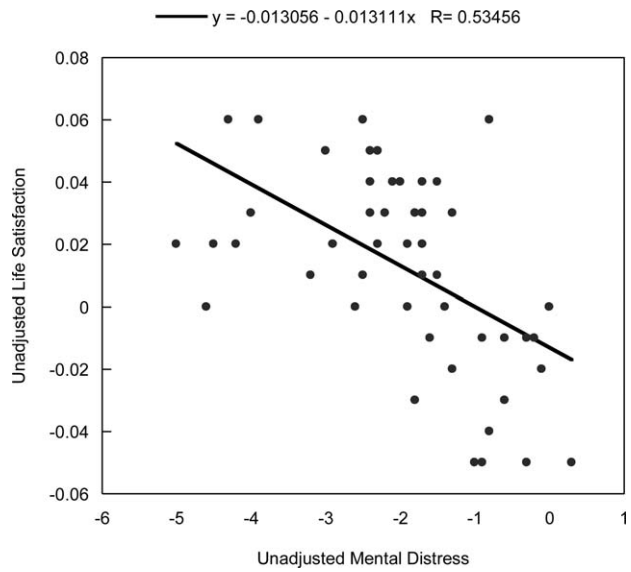
With a few notable exceptions, there is much agreement between the qualitative structure of these American life satisfaction and mental distress equations. A natural comparison is between column 4 of table 1 and column 4 of table 3. The main differences in the coefficient sizes are for Asian, Native American, female, and student. Most variables enter with equivalent effects for each of the two kinds of dependent variable. This finding is against the spirit of Huppert and Whittington's (2003) argument that positive and negative affect are strongly different in character.

Table 4 moves to regressions showing the state-by-state pattern in the number of days of poor mental health. The stand-out case in column 4 of table 4 is California, with the worst mental health across the U.S. states (a coefficient of 0.567). The best mental health, that is, states with the fewest number of poor mental health days, is found in Iowa, Louisiana, Nebraska, the two Dakotas, and Tennessee. Another method is to examine which states are found in the lowest (and highest) quartiles on both measures—the life satisfaction scores and the mental-distress-days scores. Doing so yields the following list of states in the lowest quartile of well-being on both measures: California, Kentucky, Michigan, Ohio, West Virginia, and Missouri.

The states in the highest quartile of well-being on both measures are Louisiana, Washington, D.C., Alaska, Tennessee, and Colorado.

How else might these two forms of well-being measure be combined? Figures 1 to 4 set out various checks and suggest that the two kinds are here, as might be expected, providing reinforcing information. Satisfied U.S. states are noticeably also the mentally healthy ones. To our knowledge, this result is a new one.

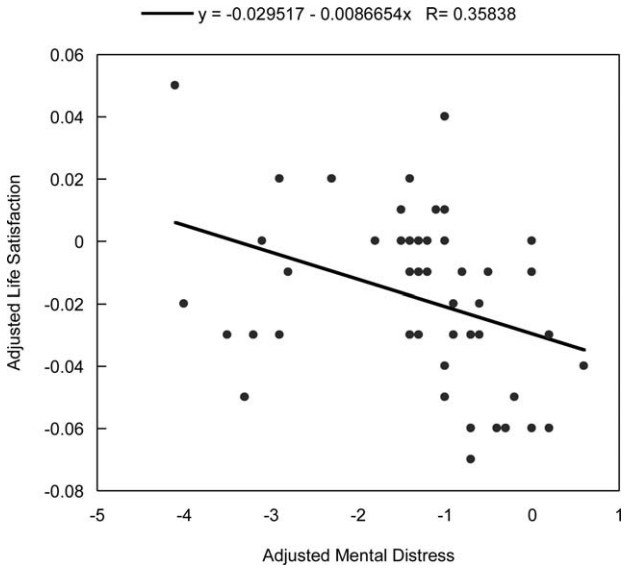
FIGURE 1.—INVERSE CORRELATION BETWEEN LIFE SATISFACTION AND MENTAL DISTRESS DAYS ACROSS THE 51 STATES
BRFSS DATA: 2005–2008; SAMPLE SIZE = 1.3 MILLION APPROXIMATELY



Each dot is a state. The correlation is significant at 1% on a two-tailed test. This figure plots state dummy coefficients from a life satisfaction equation against state dummy coefficients from a number of mental-distress-days equation. In each equation, the regression controls only for year dummies and month-of-interview dummies. Life satisfaction is coded for each individual from 4 (very satisfied) to 1 (very dissatisfied). Mental distress days are coded from 0 (no days) up to 30 (every day in the last month). The bottom right-hand observation is Kentucky. Question wordings in the BRFSS questionnaire are: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" (questions 76–77) and "In general, how satisfied are you with your life?" (question 206), with answers coded from 1 to 4.

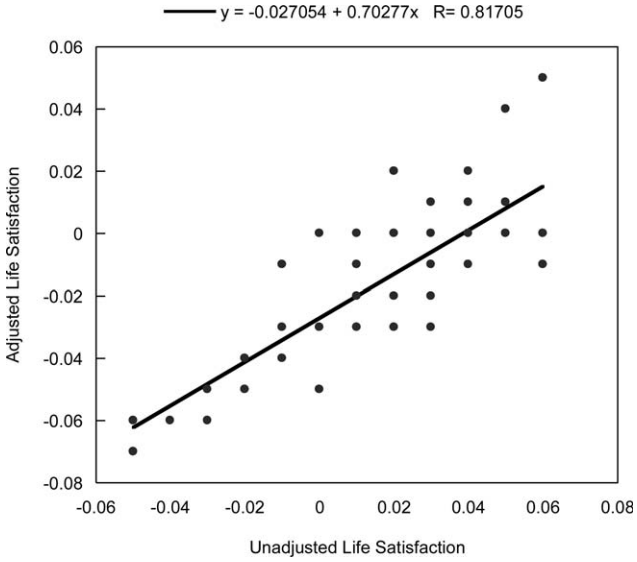
A final issue that deserves consideration is whether the stark results on the states of California (with poor mental health) and Louisiana (with high well-being overall) are caused by the later years in this sample of four years. Might it be, say, that the credit crunch that hit California by 2007–2008 or the aftermath of Hurricane Katrina in Louisiana in the latter part of 2005 somehow led to extreme values in those state dummies? To check this, we reran the key regressions equations for the early year of 2005 data alone. The results for California and Louisiana, for example, were almost identical to those in the full sample. Hence, cru-

FIGURE 2.—THE INVERSE CORRELATION BETWEEN (REGRESSION-ADJUSTED) LIFE SATISFACTION AND (REGRESSION-ADJUSTED) MENTAL DISTRESS DAYS ACROSS THE 51 STATES
BRFSS DATA: 2005–2008; SAMPLE SIZE = 1.3 MILLION APPROXIMATELY



See the figure 1 footnote.

FIGURE 3.—THE CORRELATION BETWEEN ADJUSTED LIFE SATISFACTION AND UNADJUSTED LIFE SATISFACTION ACROSS THE 51 STATES
BRFSS DATA: 2005–2008; SAMPLE SIZE = 1.3 MILLION APPROXIMATELY

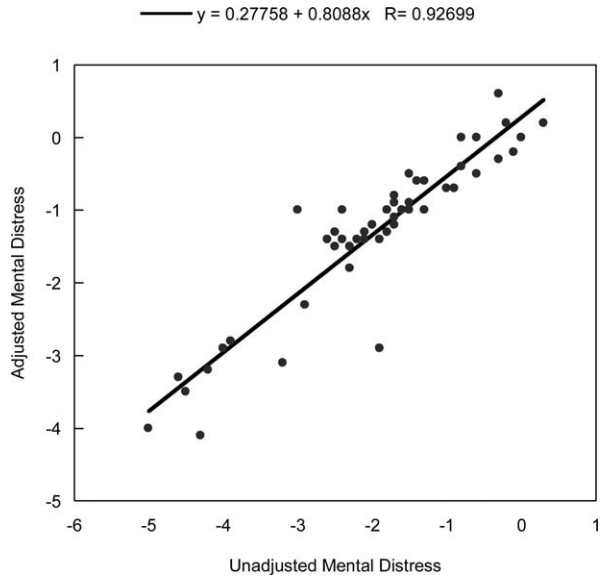


Each dot is a state. In adjusted data, there are regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies. In unadjusted data, there are only year dummies and month-of-interview dummies.

cially, the patterns documented in this paper are not merely the product of the last year or two of data.

As a final and important check that there is not some fundamental problem with the mental health data in BRFSS, Figure 7 reveals a reassuringly similar state pattern, for the interesting case of young people (these other data are necessarily regression uncorrected but that should be less important among nonworking young people), from the National Survey on Drug Use and Health.

FIGURE 4.—THE CORRELATION BETWEEN ADJUSTED MENTAL DISTRESS DAYS AND UNADJUSTED MENTAL DISTRESS DAYS ACROSS THE 51 STATES
BRFSS DATA: 2005–2008; SAMPLE SIZE = 1.3 MILLION APPROXIMATELY



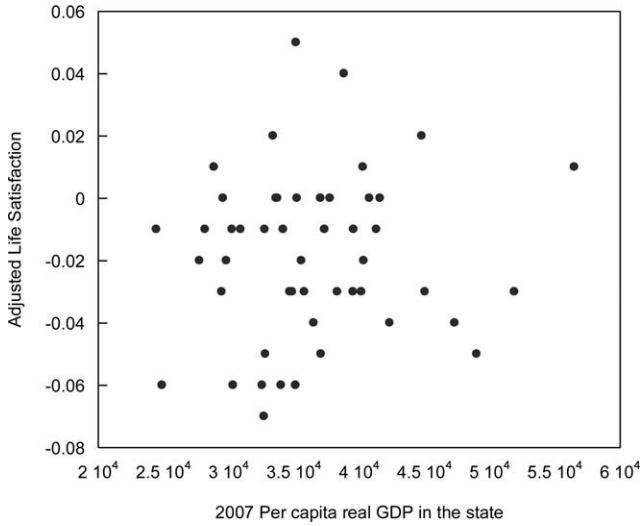
See the figure 3 footnote.

These differences in well-being across states are not minor. In cardinalized terms, they correspond to up to 0.2 life satisfaction points, which is similar in size to the ceteris paribus cross-sectional effect of marital separation or unemployment.[8] The economist's natural null hypothesis of equality of well-being across areas is, in its strict version, rejected by the data. Interestingly, it is not different states' material riches that determine their position in this spatial well-being ordering.

Figure 5 illustrates that fact. There exists no statistically significant correlation, although a best-fitting line would have a very small positive gradient, between state well-being and state GDP per capita. By contrast, and conceptually a different form of comparison, Figure 6 shows that if we control for household income (the microequations are not given in the tables but are available on request), then this gradient is negative. (This result is potentially consistent with the fixed-effects relative income concern finding in Blanchflower and Oswald, 2004, and Luttmer, 2005. Ours, however, is naturally thought of as a correlation between the state fixed effects and other characteristics. Figure 7 is a variant and corroborative check.) This, in a weaker version, is what compensating differentials theory would predict. It should be emphasized that the paper's results do not merely tell us the obvious fact that factors like the climate or air cleanliness or beauty are better in some places than in others. The intellectual question is why the plusses and minuses from innate state differences, such

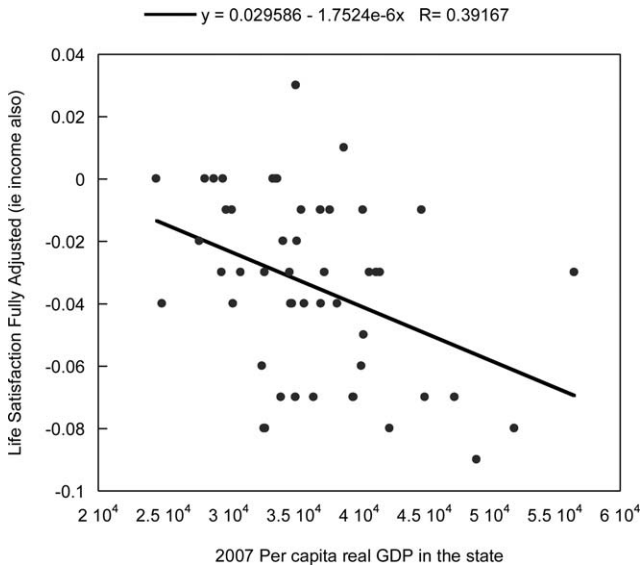
[8] To get to 0.2, we are comparing between the happiest and least happy states, to get an approximate idea of the range within the United States.

FIGURE 5.—THE ABSENCE OF CORRELATION BETWEEN ADJUSTED LIFE SATISFACTION AND GDP PER CAPITA ACROSS 50 STATES
BRFSS DATA: 2005–2008; SAMPLE SIZE = 1.3 MILLION APPROXIMATELY



Each dot is a state. Washington, D.C., is omitted (for compositional reasons, its GDP per head is hard to compare with that of other states). GDP data are for 2007 and are from the standard Bureau of Economic Analysis source. Pearson's r here is positive but below 0.1. In adjusted data, there are regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies.

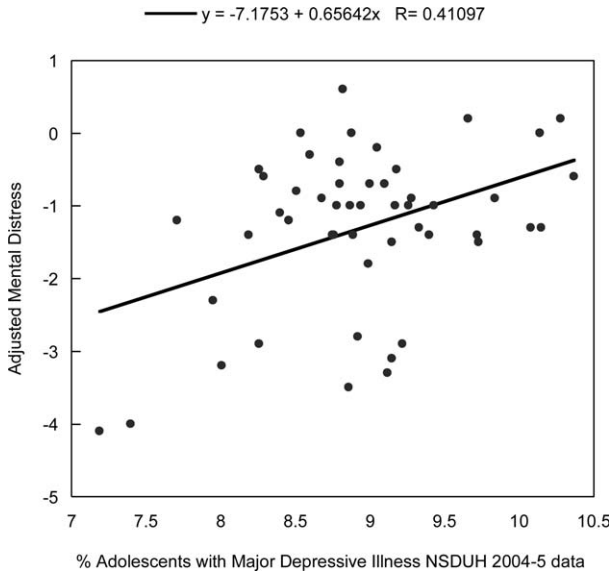
FIGURE 6.—THE INVERSE CORRELATION BETWEEN FULLY ADJUSTED LIFE SATISFACTION AND GDP PER CAPITA ACROSS 50 STATES
BRFSS DATA: 2005–2008; SAMPLE SIZE = 1.3 MILLION APPROXIMATELY



Each dot is a state. The correlation is significant at 1% on a two-tailed test. Washington, D.C., is omitted (for compositional reasons, its GDP per head is hard to compare with that of other states). GDP data are for 2007 and are from the standard Bureau of Economic Analysis source. In fully adjusted data, there are regression controls for household income as well as the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies.

as perhaps sunshine hours or beautiful lakes, are not entirely eroded—right back up to the point where all areas provide the same net utility. Even after adjusting for individuals' backgrounds and characteristics, there remain some significant unexplained differences state by state in Americans' well-being.[9] Future work may have to address this apparent puzzle.

FIGURE 7.—THE CORRELATION BETWEEN ADJUSTED MENTAL DISTRESS AND THE PROPORTION OF YOUTHS AGED 12–17 WITH A MAJOR DEPRESSIVE EPISODE IN THE PAST YEAR, NSDUH DATA
BRFSS DATA: 2005–2008; SAMPLE SIZE = 1.3 MILLION APPROXIMATELY



Each dot is a state. The correlation is significant at 1% on a two-tailed test. The data on rates of adolescent depression come from Mental Health America and the SAMHSA, Office of Applied Studies, National Survey on Drug Use and Health 2004-5. The bottom left-hand observation is Louisiana. In adjusted data, there are regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies.

V. Conclusions

This paper examines information on 1.3 million randomly sampled U.S. citizens for the years 2005 to 2008. It uses data on life satisfaction scores and on people's recorded numbers of days in poor mental health.

Some states exhibit low levels of mental well-being, while relatively high levels are found among others. Particularly notable in the data is, for example, the unusually happy state of Louisiana.[10] In contrast, and against some common perceptions, Californians are not happier than the inhabitants of other states (consistent with the data on college students studied in Schkade & Kahneman, 1998). In fact, we show that they lie below the mental well-being of people living in the majority of places in the United States.

Importantly, these BRFSS data reveal (see especially figure 5) no correlation between U.S. states' mental well-being and their GDP per capita. Correcting for people's incomes, satisfaction with life is low in the rich states. Our results are thus consistent with a weak version of the arbitrage theory that

[9] Pittau et al. (2010) find something similar. In current work, we are exploring ideas from Putnam (2000).

[10] Because we were initially surprised to find Louisiana doing so well in these rankings, we checked for any corroborative evidence in the psychiatric literature. We discovered that Louisianan adolescent mental health, as measured by SAMHSA, Office of Applied Studies, National Survey on Drug Use and Health 2004–5, is the best of all the states in the United States. See the notes to figure 7.

areas should in equilibrium provide equal utility across space. Unlike informal quality-of-life rankings of the U.S. states (such as Rampell, 2009, or Thompson Healthcare, 2007), which primarily reveal the types of individuals who live in a place, and produce rather different rankings from ours, this paper adjusts for the nature of the citizens in the state.

Although, for completeness, we present a variety of regression-equation specifications, perhaps the most natural ones to focus on are those in the final columns of tables 2 and 4. These specifications control for the detailed demographic backgrounds of individuals but not for their incomes.[11] This is because a principal aim of the paper is to inquire into the overall well-being, not an income-held-constant level of utility, that is provided in a geographical area.[12]

There is empirical support for a far stronger income gradient than promulgated in the psychology literature. This result is in the same spirit as the argument of Deaton (2008) on international cross-section data (see also Kapteyn, Smith, & Soest, 2008). It might seem natural for economists to expect a powerful connection between income and happiness, but a recent review of the evidence in the psychology literature, for example, argues: "Within most economically developed nations, richer people are only slightly happier than most others" (Diener & Biswas-Diener, 2002). Our empirical results for individuals in the United States do not greatly accord with this view. But they do agree with such a view, or an even stronger version of it, for the states themselves.

Whether there are intellectual connections between the lack of a correlation in figure 5 and the famous Easterlin paradox (1974, 2003) remains to be understood, and, importantly, the observed patterns in U.S. state-by-U.S. state well-being demand an explanation.

[11] For completeness, figure A1 reports a state cross-section plot of adjusted life satisfaction against fully adjusted life satisfaction (controlling for personal household income), and there remains a strong positive correlation.

[12] Oswald and Wu (2010), which was written after this paper but published more quickly because of the speed of science journals, is concerned with that issue; its contribution is partly methodological and attempts to show a match with the objective pattern found in Gabriel et al. (2003).

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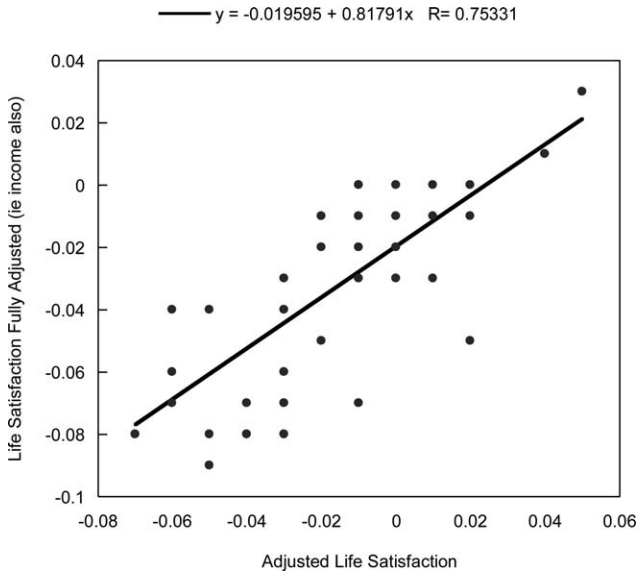
TABLE AND FIGURE APPENDIX

FIGURE A1.—THE CORRELATION BETWEEN ADJUSTED LIFE SATISFACTION AND FULLY ADJUSTED LIFE SATISFACTION (FOR INDIVIDUAL HOUSEHOLDS' INCOME LEVELS) ACROSS 51 STATES
BRFSS DATA: 2005–2008; SAMPLE SIZE = 1.3 MILLION APPROXIMATELY



Each dot is a state. In adjusted data, there are regression controls for the survey respondent's gender, age, age squared, education, marital status, unemployment, and race, and also year dummies and month-of-interview dummies. Fully adjusted life satisfaction also controls for household income.

TABLE A1.—SUMMARY STATISTICS

Variable	Mean	S.D.
Life satisfaction (1–4 Scale)	3.386	0.629
Poor mental health days per month	3.400	7.688
Income $10–15K	0.058	0.235
Income $15–20K	0.076	0.265
Income $20–25K	0.096	0.295
Income $25–35K	0.128	0.335
Income $35–50K	0.164	0.370
Income $50–75K	0.172	0.378
Income >$75K	0.253	0.435
Age	52.711	16.315
Black	0.081	0.273
Asian	0.018	0.135
Hispanic	0.063	0.242
Native American	0.017	0.128
Other minority	0.001	0.035
Female	0.619	0.486
Some high school	0.066	0.248
High school	0.304	0.460
Some college	0.265	0.441
College	0.330	0.470
Married	0.567	0.496
Divorced	0.142	0.349
Separated	0.023	0.149
Widowed	0.118	0.323
Partner	0.024	0.154
Self-employed	0.090	0.286
Unemployed	0.040	0.195
Homemaker	0.079	0.269
Student	0.019	0.135
Retired	0.240	0.427
Observations	1,483,403	

Data from the 2005–2008 waves of BRFSS.

TABLE A2.—RAW UNADJUSTED MEANS OF LIFE SATISFACTION BY STATE, GROUPED BY REGION

State	Mean Life Satisfaction	Census Division
New England		
Connecticut	3.387	1
Maine	3.400	1
Massachusetts	3.352	1
New Hampshire	3.414	1
Rhode Island	3.363	1
Vermont	3.412	1
Mid-Atlantic		
New Jersey	3.378	2
New York	3.345	2
Pennsylvania	3.323	2
East North Central		
Illinois	3.379	3
Indiana	3.325	3
Michigan	3.351	3
Ohio	3.341	3
Wisconsin	3.374	3
West North Central		
Iowa	3.398	4
Kansas	3.405	4
Minnesota	3.430	4
Missouri	3.332	4
Nebraska	3.379	4
North Dakota	3.397	4
South Dakota	3.395	4
South Atlantic		
Delaware	3.419	5
District of Columbia	3.400	5
Florida	3.412	5
Georgia	3.401	5
Maryland	3.410	5
North Carolina	3.390	5
South Carolina	3.408	5
Virginia	3.412	5
West Virginia	3.322	5
East South Central		
Alabama	3.373	6
Kentucky	3.322	6
Mississippi	3.365	6
Tennessee	3.384	6
West South Central		
Arkansas	3.384	7
Louisiana	3.437	7
Oklahoma	3.362	7
Texas	3.404	7
Mountain		
Arizona	3.424	8
Colorado	3.433	8
Idaho	3.404	8
Montana	3.409	8
Nevada	3.368	8
New Mexico	3.382	8
Utah	3.437	8
Wyoming	3.430	8
Pacific		
Alaska	3.392	9
California	3.365	9
Hawaii	3.427	9
Oregon	3.384	9
Washington	3.395	9

TABLE A3.—THE U-SHAPE IN AGE IN BRFSS LIFE SATISFACTION DATA

Variable	(1)	(2)
age23_27	0.0150**	−0.128**
	(0.00410)	(0.00422)
age28_32	0.0570**	−0.155**
	(0.00384)	(0.00411)
age33_37	0.0495**	−0.181**
	(0.00372)	(0.00405)
age38_42	0.0349**	−0.188**
	(0.00366)	(0.00402)
age43_47	0.00765*	−0.201**
	(0.00360)	(0.00399)
age48_52	−0.00200	−0.205**
	(0.00356)	(0.00401)
age53_57	0.0126**	−0.196**
	(0.00355)	(0.00407)
age58_62	0.0610**	−0.157**
	(0.00357)	(0.00414)
age63_67	0.104**	−0.121**
	(0.00363)	(0.00429)
age68_72	0.109**	−0.113**
	(0.00372)	(0.00446)
age73_77	0.0875**	−0.121**
	(0.00380)	(0.00459)
age78_82	0.0627**	−0.125**
	(0.00395)	(0.00477)
age83p	0.0434**	−0.125**
	(0.00487)	(0.00556)
Full set of other controls?	None	Yes
Observations	1,423,955	1,379,285
R^2	0.003	0.085

Standard errors are in parentheses. **Significant at 1%. Life satisfaction is measured on 1–4 scale; 1 = very dissatisfied to 4 = very satisfied. Column 2 includes controls for race, marital and employment status, household income, and state and time effects. The omitted age group is 18–22 year olds (the youngest group).

TABLE A4.—LIFE SATISFACTION ACROSS U.S. STATES (WITH AND WITHOUT STATE UNEMPLOYMENT RATES AS A CONTROL)

Variables	(1)	(2)
Household size	0.00373**	0.00373**
	(0.000482)	(0.000482)
Black	−0.00919**	−0.00919**
	(0.00204)	(0.00204)
Asian	−0.0718**	−0.0718**
	(0.00415)	(0.00415)
Hispanic	−0.00343	−0.00345
	(0.00240)	(0.00240)
Native American	−0.0349**	−0.0349**
	(0.00408)	(0.00408)
Other minority	−0.0566*	−0.0567*
	(0.0278)	(0.0278)
Female	0.0212**	0.0212**
	(0.00111)	(0.00111)
Some high school	0.0218**	0.0218**
	(0.00357)	(0.00357)
High school	0.123**	0.123**
	(0.00313)	(0.00313)
Some college	0.166**	0.166**
	(0.00317)	(0.00317)
College	0.290**	0.290**
	(0.00317)	(0.00317)
Married	0.268**	0.268**
	(0.00190)	(0.00190)
Divorced	−0.00335	−0.00334
	(0.00217)	(0.00217)
Separated	−0.113**	−0.113**
	(0.00382)	(0.00382)
Widowed	0.0623**	0.0623**
	(0.00248)	(0.00248)
Partner	0.0930**	0.0930**
	(0.00366)	(0.00366)

TABLE A4.—(CONTINUED)

Variables	(1)	(2)
Self-employed	0.0713**	0.0713**
	(0.00187)	(0.00187)
Unemployed	−0.239**	−0.239**
	(0.00272)	(0.00272)
Homemaker	0.0508**	0.0508**
	(0.00208)	(0.00208)
Student	0.0261**	0.0261**
	(0.00418)	(0.00418)
Retired	0.0698**	0.0698**
	(0.00181)	(0.00181)
Alaska	0.0201**	0.0253**
	(0.00775)	(0.00853)
Arizona	0.0110	0.0122
	(0.00631)	(0.00636)
Arkansas	−0.0203**	−0.0180**
	(0.00612)	(0.00632)
California	−0.0363**	−0.0322**
	(0.00587)	(0.00649)
Colorado	0.00415	0.00510
	(0.00557)	(0.00561)
Connecticut	−0.0288**	−0.0270**
	(0.00587)	(0.00599)
Delaware	0.00798	0.00775
	(0.00659)	(0.00659)
District of Columbia	0.0258**	0.0304**
	(0.00677)	(0.00746)
Florida	0.0170**	0.0178**
	(0.00505)	(0.00507)
Georgia	0.000930	0.00333
	(0.00583)	(0.00606)
Hawaii	0.0404**	0.0381**
	(0.00661)	(0.00681)
Idaho	−0.0216**	−0.0226**
	(0.00618)	(0.00621)
Illinois	−0.0328**	−0.0295**
	(0.00619)	(0.00659)
Indiana	−0.0648**	−0.0623**
	(0.00607)	(0.00630)
Iowa	−0.0261**	−0.0262**
	(0.00614)	(0.00614)
Kansas	−0.0306**	−0.0296**
	(0.00557)	(0.00562)
Kentucky	−0.0635**	−0.0593**
	(0.00585)	(0.00653)
Louisiana	0.0486**	0.0486**
	(0.00605)	(0.00605)
Maine	−0.0101	−0.00823
	(0.00615)	(0.00627)
Maryland	−0.0119*	−0.0120*
	(0.00554)	(0.00554)
Massachusetts	−0.0374**	−0.0357**
	(0.00511)	(0.00524)
Michigan	−0.0533**	−0.0465**
	(0.00556)	(0.00725)
Minnesota	−0.00447	−0.00347
	(0.00656)	(0.00660)
Mississippi	−0.00700	−0.00132
	(0.00585)	(0.00701)
Missouri	−0.0594**	−0.0568**
	(0.00621)	(0.00647)

TABLE A4.—(CONTINUED)

Variables	(1)	(2)
Montana	−0.0109	−0.0115
	(0.00603)	(0.00605)
Nebraska	−0.0469**	−0.0485**
	(0.00536)	(0.00548)
Nevada	−0.0278**	−0.0255**
	(0.00682)	(0.00700)
New Hampshire	−0.0108	−0.0118*
	(0.00597)	(0.00600)
New Jersey	−0.0295**	−0.0282**
	(0.00536)	(0.00543)
New Mexico	−0.0120*	−0.0115
	(0.00603)	(0.00603)
New York	−0.0534**	−0.0514**
	(0.00585)	(0.00600)
North Carolina	−0.00290	−0.000161
	(0.00506)	(0.00539)
North Dakota	−0.0253**	−0.0270**
	(0.00638)	(0.00649)
Ohio	−0.0546**	−0.0505**
	(0.00549)	(0.00615)
Oklahoma	−0.0300**	−0.0296**
	(0.00558)	(0.00559)
Oregon	−0.0329**	−0.0290**
	(0.00589)	(0.00646)
Pennsylvania	−0.0591**	−0.0573**
	(0.00520)	(0.00533)
Rhode Island	−0.0337**	−0.0299**
	(0.00650)	(0.00699)
South Carolina	0.0139*	0.0188**
	(0.00546)	(0.00637)
South Dakota	−0.0208**	−0.0228**
	(0.00584)	(0.00599)
Tennessee	0.00489	0.00816
	(0.00631)	(0.00669)
Texas	0.00383	0.00547
	(0.00545)	(0.00556)
Utah	−0.0152*	−0.0167**
	(0.00620)	(0.00629)
Vermont	−0.00971	−0.00993
	(0.00583)	(0.00583)
Virginia	0.00108	−0.000286
	(0.00610)	(0.00617)
Washington	−0.0248**	−0.0225**
	(0.00488)	(0.00513)
West Virginia	−0.0590**	−0.0578**
	(0.00662)	(0.00666)
Wisconsin	−0.0246**	−0.0233**
	(0.00601)	(0.00607)
Wyoming	0.00257	0.000863
	(0.00599)	(0.00610)
State Unemployment Rate	–	−0.00216
		(0.00147)
Constant	3.185**	3.194**
	(0.00686)	(0.00926)
Observations	1,379,285	1,379,285
R^2	0.085	0.085

Standard errors are in parentheses. *Significant at 5%, **significant at 1%. All regressions include controls for month and year of survey, and five-year age bands. Life satisfaction is measured on a 1–4 scale: 1 = very dissatisfied to 4 = very satisfied.