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Predictors of Regional Well-Being: A County Level Analysis

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Abstract The current study takes a novel approach to studying the correlates of subjective well-being. Unlike previous studies, which typically examine group-level well-being at the state or national level, we analyzed correlates of well-being at the county level within the United States. Using nationally representative data, we found that reliable variance in well-being exists across counties. Furthermore, this variance was associated with a number of objective factors, including income, population density, health and education. Continued study of these factors at the regional level may have important implications for developing community programs and public policy.

Keywords Life satisfaction · Subjective well-being · Regional variability

Subjective well-being refers to the subjective evaluation of a person's quality of life (Diener et al. 1995). With the multitude of factors that can influence levels of well-being, research concerning the relationships between objectively measurable factors and subjective evaluations has the potential to inform public policy and to "assist individuals in their everyday life decisions, such as where and how to live" (Diener and Suh 1997, p. 191). In general, researchers interested in well-being have pursued three overarching goals: to catalog the correlates of well-being (Wilson 1967), to use this information to develop strong theories about the causes of well-being (Diener et al. 1999) and to develop programs aimed at improving well-being at the individual or group levels (Lyubomirsky 2007; Seligman et al. 2005; Sin and Lyubomirsky 2009).

To accomplish these goals, the most common approach is to examine the individual level correlates of well-being and then use experimental designs to test hypotheses about the processes that underlie these associations. Considerable progress has been made using this technique, and well-being researchers know quite a bit about who is happy and why (for a review, see Eid and Larsen 2008). A less frequently used approach is to explore how various factors affect the well-being of larger groups. For instance, one may study national

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correlates (e.g., income, access to schools), and then develop and test theories to explain the pattern of correlations that emerges.

This latter approach can be beneficial for a number of reasons. First, it is clear that personality influences well-being (Lucas 2008). Although there are certainly regional differences in personality (e.g., Plaut et al. 2002; Rentfrow et al. 2008), the variance in personality across regions is likely to be less than the variance within a region. Therefore, it may be possible to isolate the external predictors of well-being more clearly when looking at group level differences. Second, if one goal of well-being research is to inspire policy decisions (Diener et al. 2009), then aggregate-level data is needed to inform these debates. Though the idea that correlates at the individual level would mirror those at the state or national level is intuitively appealing, it is not necessarily correct. Different variables have different meanings at different levels of analysis, and it is possible that widely replicated results at the individual level will not generalize to aggregate levels (see van de Vijver et al. 2008, for an overview).

Most of the research that analyzes well-being in groups has been conducted cross-nationally. Such research is important, as nations vary considerably in a number of the factors thought to affect well-being (e.g., income, health, political freedom). For instance, in 2004, the Economist Intelligence Unit presented a quality of life index based upon a cross-national study of objective predictors of life satisfaction. The authors found that objective measures of health, material well-being, political security, family relations, community life, climate, job security, political freedom and gender equality together accounted for 80% of the variance in country level life-satisfaction (also see Diener et al. 1995; Oishi et al. 2009; Schyns 1998; Stevenson and Wolfers 2008).

Although these studies provide valuable information regarding the correlates and predictors of well-being, concerns can be raised about the results that emerge. For instance, language differences may contribute to inconsistent evaluations of survey items, making interpretation of any discrepancies somewhat difficult. Similarly, cultural variations may affect response styles. For example, members of one society may be more apt to select extreme responses, whereas other cultures may tend toward moderate responses (Minkov 2009). There may be no real difference in well-being between the two countries, but systematic variation in survey responses may obscure the similarities (for an example, see Kahneman and Riis 2005). Finally, studies of cross-national well-being cannot address within-nation variance, which may exist despite the cultural and economic homogeneity of a nation. Importantly, this within-nation variance will be most relevant in the use of well-being to determine policy decisions. Poor nations will not be able to quickly improve their economic condition or to emulate the policies of their wealthier (and happier) neighbors. However, given that different areas within those nations vary in subjective well-being, less happy regions could potentially adopt the policies that happier regions have enacted. Thus, understanding the extent to which regional differences in well-being exist—along with the factors that are associated with these differences—is an important goal, both for theoretical and applied reasons.

1 Potentially Important Region Level Correlates

Predicting which factors will correlate at the regional level is challenging. On one hand, there is a rich literature on the individual level correlates of well-being, and one might expect that many of these effects would replicate at the aggregate level. Furthermore, existing cross-national studies indicate that certain predictors are robustly (and sometimes quite strongly) linked with well-being when studied at the group level. On the other hand, it is not clear that effects at either higher or lower levels of analysis should always generalize when within-nation regional analyses are conducted.

For instance, one of the most frequently studied correlates of well-being is income, which is expected to be associated with well-being for a variety of reasons (Veenhoven 1995). A high level of income usually ensures that basic needs are met, and it is widely thought that the failure to meet basic needs severely impacts subjective well-being (Diener et al. 1995). Additionally, according to economic theory, income provides choice, and greater choice should lead to greater satisfaction because a wider variety of needs and desires can be fulfilled (Diener et al. 2009). These effects help explain why income is correlated at the individual level, even among rich nations like the United States. The cumulative effect of having many individuals with high incomes may also play a role at the aggregate level. Wealthier regions and nations can provide more services for their citizens, and the wealth of the citizens themselves attracts additional resources and opportunities.

Despite these robust associations, income may not correlate with subjective well-being across regions within a single nation. Diener et al. (1995) showed that there is a clear curvilinear association between income and well-being at the national level: the effect is much steeper among poor nations and it levels out and becomes quite flat among the richest nations. Furthermore, Luttmer (2005) demonstrated social comparison effects in the income/life satisfaction association, such that after controlling for personal income, living in a wealthier area is associated with lower levels of life satisfaction. In other words, relative standing seems to matter, and having rich neighbors is associated with lower levels of life satisfaction once personal income is controlled. Thus, individual and nation level associations with income may not replicate at the regional level.

Importantly, existing research shows that the associations with income do vary considerably at different levels of analysis (see Arthaud-Day and Near 2005, for a review). Within nations, individual income correlates weakly with well-being (with estimates typically falling between .15 and .20; see Lucas and Schimmack 2009). Yet at the national level, these correlations tend to be much stronger. For instance, the most recent analysis with the largest sample of nations studied thus far found a correlation of .83 between national income and national levels of life satisfaction (Deaton 2008). Most studies that have conducted between-nation analyses have found correlations exceeding .60 (e.g., Diener et al. 1995; Diener and Oishi 2000; Schyns 1998). Much less research has been conducted within nations at the regional level, but, in one such study, Rentfrow et al. (2009) found that state level gross regional product and average income correlated .30 with an index of state level “life evaluation.” Thus, this within-nation, between-region correlation is closer to the typical individual level correlation than to the typical between-nation effect.

It is difficult to predict factors beyond income that might relate to well-being because the best source of evidence that justifies these predictions comes from cross-national studies, and the factors typically assessed at the national level tend to correlate quite strongly with income. For instance, Diener, et al. (1995) used national surveys to study the effects of income, social income comparison and civil liberties on well-being in 55 nations. The authors found significant differences in well-being and life satisfaction across nations. Specifically, income, individualism (versus collectivism) and human liberties consistently predicted well-being. However, these three variables correlate between .75 and .80 with one another, making it difficult to tease apart individual effects. Not surprisingly, given these strong correlations, conclusions from studies that examine similar sets of correlates sometimes differ. For instance, Schyns (1998) explored the relationships between economics, culture, freedom and happiness across 40 countries. She found a high degree of variation between the countries studied, in terms of both objective indicators and the subjective happiness variable. Schyns revealed that economic prosperity remained a significant predictor of happiness even when controlling for cultural factors, but as with Diener et al. (1995) findings, economic and cultural indicators were correlated so strongly with each other that it became difficult to tell which was accounting for happiness.

Importantly, when looking within nations, subtler indicators of socio-economic status may emerge as consistent predictors, given that the variance in income is not as great as when a larger sample of nations is used. For instance, Rentfrow et al. (2009), in their analysis of state level effects, examined a variety of factors beyond income that could be considered indicators of socio-economic status. They showed that a variety of educational and occupational indicators (including average educational attainment and percentage of people working in the "creative class" and "super-creative class") were associated with well-being. The effects were strongest when predicting indicators of physical health, but the correlations with the potentially more relevant "life evaluation" measure were moderate (averaging about .25).

Rentfrow et al. (2009) also examined various indexes of inclusiveness as predictors of well-being, including the number of bohemians (people employed in the arts), the percentage of gays and the number of immigrants living in a region. All three indexes were positively correlated with well-being, though, again, the effects tended to be stronger for indicators of physical health and healthy behaviors than for the life evaluation indicator. If replicable, these results suggest that notable within-nation cultural differences are potentially very important for the regional levels of well-being.

Beyond these factors, one must turn to the individual level analyses to derive meaningful predictions about the links between well-being and aggregate characteristics. Social relationships have often been cited as the single most important objective predictor of subjective well-being at the individual level (see Lucas and Dyrenforth 2006, for a review). It is possible that communities with stronger social ties will also show higher levels of subjective well-being. Previous research has demonstrated that married people are happier than single people, who are happier than divorced people, who are in turn happier than widows. For example, in 2005 Bennett used data from the Nottingham Longitudinal Study of Activity and Aging to review the effects of marriage and widowhood on well-being in senior citizens (aged 65 years +). She found that widowhood, especially recent widowhood, reduced well-being. This effect held even when controlling for age. Similarly, Ben-Zur and Michael (2009) found widowhood and divorce to be negatively related to life satisfaction. They reported widows to be less satisfied than divorcees, and married people to be happier than either of the other groups. Although both of these studies utilized relatively small sample sizes, and may not be adequately generalizable to the population at large, Gove et al. (1990) observed similar results across studies in their review (also see Lucas and Clark 2006). In any case, if regions differ in marriage rates, then this factor might reasonably be expected to be associated with the average life satisfaction reported by the residents of that region.

Additionally, at the individual level, a variety of health variables are associated with well-being (Fox 1999). The Centers for Disease Control and Prevention (CDC 1998) reported that substantial geographic differences in health exist, and these differences extend to geographic variance in mental health symptoms (Moriarty et al. 2009). Interestingly, past reviews of the area have noted that subjective measures of health tend to correlate more strongly with reports of subjective well-being than do more objective measures of health (Diener et al. 1999). Using aggregate data provides an important test of these associations because it typically comes from objective measures, such as rates of obesity or death from specific causes. If these measures correlate with subjective ratings of life satisfaction, then this provides particularly strong evidence for the validity and utility of objective reports.

Finally, although such variables are rarely linked with reports of subjective well-being, the characteristics of the region itself may influence well-being scores. When deciding where to live, factors such as whether the location is in an urban or rural area are often important in a person's decision. Long commutes may be balanced with affordable housing in large metropolitan areas, and commuting has been associated with life satisfaction judgments in daily-sampling studies (Kahneman et al. 2004). The current study takes a novel look at regional characteristics such as population size, population density and length of commute as predictors of life satisfaction.

1.1 Summary

Existing research on the individual level correlates of subjective well-being can be augmented with a broader examination of associations at more aggregated levels. Most existing research that takes this approach has been conducted at the national level, which creates an important set of methodological challenges. Thus, an examination of the within-nation, regional level can provide important new theoretical and applied knowledge about the correlates of subjective well-being.

Two major studies have examined these questions in the United States. Oswald and Wu (2010) used the same data analyzed in the current study to show that state level differences in well-being exist, but they did not attempt to address what factors predicted these differences. A second study examined the predictors of state level well-being using data collected by the Gallup organization (Rentfrow et al. 2009).

The current study goes beyond both previous studies in a number of important ways. First, both sets of authors limited their analysis to the state level. Because states themselves are large and heterogeneous, they may not provide the optimal level of analysis. There is likely to be more variance across predictors when narrower units are used, so stronger associations may be identified when county level analyses are used. At the very least, by examining the differences in predictors at different levels, the robustness of the effects can be determined.

Second, one of the previous two studies (that by Rentfrow et al. 2009) used data from the Gallup-Healthways Well-Being Index. The authors' primary analyses focused mainly on a broad index that incorporated ratings from a variety of dimensions including physical health, healthy behaviors and access to resources that can satisfy basic needs. Data from a narrower "Life Evaluation" index was also available, and results diverged considerably from the overall index when this narrow measure was used. Additionally, it is possible that even the life evaluation index does not map cleanly onto existing conceptualizations of life satisfaction or broader well-being. Participants are asked first to evaluate, on a scale from 0—"Worst possible life" to 10—"Best possible life," their present life situation and then their anticipated life situation 5 years in the future (Gallup-Healthways Well-Being Index 2008). Life evaluation scores are then calculated using a complicated formula in which the number of people who are "suffering" (those who report scores between 0 and 4) is subtracted from the number of people who are "thriving" (those who reports scores of 7 or above on the present life item and scores of 8 or above on the future outlook item).

Finally, we analyze a more comprehensive set of predictors that may contribute to regional differences in well-being. The Oswald and Wu (2010) paper only examined state income and a broad quality of life index. Our study assesses a wide range of variables linked to socioeconomic status, health and social integration. Furthermore, we include a novel look at an understudied regional variable that may be linked with well-being in important ways: the size and density of the population.

2 Method

We used data from the 2005–2008 Behavioral Risk Factor Surveillance System (BRFSS), a national survey organized by the Centers for Disease Control and Prevention (prior waves were not used because they did not include the life satisfaction measure) (CDC 2008a, b). The BRFSS is a system of health surveys, conducted by state health departments, which generate information regarding health practices and health care access within the state. Surveys are conducted throughout the year, using standardized telephone interviews with one adult per household. The full sample for the 4 years that we include consists of over 1.3 million respondents. However, as described below, a smaller sub-sample is used for county level analyses.

Although the BRFSS has primarily been used for state level estimates, it can also be used for county level analyses. Respondents have been sampled from most of the 3,141 counties recognized by the U.S. Census Bureau, but the BRFSS provides weights that enable accurate county level estimates from only 363 of these counties. Although this represents just 12% of counties, these counties tend to be large, which means that they reflect much more than just 12% of the entire population. However, the differences in size and other demographic factors between included and excluded counties can lead to concerns about the extent to which the results from these counties generalize to the broader population. Conversely, if estimates from all counties are used, correlations with other variables could be underestimated because the estimates for the unweighted counties are much less precise.

To address this issue, we took two steps. First, we examined the year-to-year stability in county level estimates to determine whether the imprecise estimates for the smaller counties without weights causes problems with reliability. Presumably, the characteristics that affect well-being do not change dramatically from year to year, and, thus, stability should be relatively high. By comparing the stability for the unweighted estimates to the weighted estimates, we can examine the effects of the lower reliability on correlations. The unweighted stabilities for the full sample of counties ranged from .35 (from 2005 to 2008) to .48 (from 2006 to 2007). However, focusing just on the counties with appropriate weights increased the correlations substantially. The correlations among these counties ranged from .60 (2005–2008) to .66 (2006–2007). This provides evidence that using the smaller subsample of counties with appropriate weights will lead to more reliable estimates.

As a second strategy, we compared the entire profile of correlations between objective factors and life satisfaction scores when all counties were analyzed to the profile of correlations using the smaller, appropriately weighted sample. The profile of correlations for the unweighted analyses correlated .74 with the profile of correlations among the smaller sample of counties with appropriate weights. Because the estimates using these BRFSS-provided weights are technically more appropriate, and because the profiles of correlations were quite similar regardless of the sample that was used, we decided to focus on the latter set of results (those with appropriate weights).

2.1 Life Satisfaction Measure

Participants in the BRFSS were presented with a single-item life satisfaction measure. The item reads, “In general, how satisfied are you with your life?” and respondents are asked to provide answers using a 4-point answer scale ranging from 1—very satisfied to 4—very dissatisfied. To aid interpretation, this item was reverse scored so that high scores reflect higher levels of self-reported life satisfaction. Previous studies have shown that the reliability of single-item life satisfaction measures tends to be reasonable for such a short measure, typically falling around .65 (Lucas and Donnellan 2007). Furthermore, the problems of unreliability are reduced when using aggregated scores, as random measurement error will be averaged out during aggregation.

2.2 Objective Indicators

A variety of publicly available information was used to examine the correlates of life satisfaction. For the most part, we relied on information from the 2000 U.S. Census. The Decennial Census includes demographic, economic and other information from every household in the US. We used these data because of their relative completeness compared to more recent supplemental information—only the complete Census provided data on all variables at the county level. Although it would be useful to have data from the years in which the BRFSS data were collected, not all variables were available for all years. Therefore, we used the 2000 Census for all variables, even if more recent data were available for some variables. Importantly, as a preliminary test of whether this decision reduced the size of the associations, we examined one variable for which good yearly data is available: income. The size of the association with income did not vary depending on whether the 2000 data or 2005–2008 data were used.

In addition to the Census data, we also used information from the CDC on obesity and rates of death from specific causes within regions. Finally, we used one measure of self-reported health-related quality of life from the BRFSS survey itself. This measure asks respondents to provide the number of days out of the last 30 in which their physical health, including illness and injury, was poor (for a detailed discussion of this measure, see Moriarty et al. 2003). In all cases (whether from the Census, CDC, or the BRFSS), variables with severely skewed distributions (including household income, housing values, population size and population density) were log transformed before analysis.

3 Results

The first major goal of our analyses was to examine the association between economic conditions and life satisfaction at the county level. Results are presented in Table 1. As expected, median household income correlates moderately with life satisfaction at the county level. However, additional economic factors beyond median household income are also associated with life satisfaction. For instance, the percentage of people living under the poverty line exhibits a stronger correlation than median income, and unemployment rates for counties correlate −.46 with average life satisfaction. The effects of unemployment and poverty remain moderate in size, even after controlling for median household income, with a partial correlation of −.32 for unemployment rate and −.31 for poverty rate.

Table 1 Correlations between economic factors and life satisfaction for counties

	Mean	SD	Correlation
Income			
Median household income[a]	.25	.23	.35**
% Persons in poverty	.08	.04	−.46**
Employment			
Unemployed	5.44	1.94	−.45**
Household expenses			
Home Value[a]	.46	.39	.17**
Median mortgage[b]	1083.80	279.65	.11*
% Mortgage >35% of income	.22	.06	−.32**
Median rent[b]	602.62	136.25	.17**
% Rent >35% of income	.28	.04	−.14**

* $p < .05$, ** $p < .01$

[a] Variable was log-transformed before analysis

[b] In US Dollars

Table 1 also shows that economic indicators related to housing costs are sometimes associated with life satisfaction, though the effects tend to be weaker than for the indicators discussed above. Conceptually, this makes sense, as housing prices can be seen as an indicator of both affluence and cost of living (Easterlin 1994). Thus, high housing prices are somewhat of a mixed blessing for residents. In support of this interpretation, the indicators that assess the housing prices as a percentage of income (the percent of people whose mortgage exceeds 35% of their income and the percent of people whose rent exceeds 35% of their income) are negatively correlated with life satisfaction. In addition, housing values, median mortgage, and median rent are all negatively associated with life satisfaction once median household income is controlled (partial *r*s for housing values, median mortgage and median rent are −.15, −.30, and −.24), though the effects are not large.

In addition to these more direct indicators of wealth, it is also possible to look at alternative indicators of socio-economic status, including information about education and occupation. In fact, Rentfrow et al., found that a measure of educational attainment (which they labeled "human capital") exhibited the strongest correlations with the well-being indexes of any of the predictors they examined (with correlations of .79 and .30 for the overall and life evaluation indexes, respectively). In addition, they found moderate to strong correlations between their well-being indexes and occupational indicators, including the percentage of people in the creative class, super-creative class, service class and working class. We examined these effects by looking at education and a series of more specific occupations and industries reported by the Census. Table 2 shows these results.

First, this table shows that the education effect is replicated—the percentage of high school graduates and the percentage of college graduates are both strongly associated with average life satisfaction. In fact, these are among the strongest correlations for any predictors that we examined. As with the other indicators described above, the effects hold when controlling for median household income: the partial correlation with high school and college graduate percentages, controlling for income, are .41 and .24. These moderate to strong effects replicate those found in the Rentfrow et al. (2009) paper and are important because much existing work at the individual level has found that education is, at most, weakly associated with subjective well-being (Diener et al. 1999). These replicable results suggest that at aggregate levels the associations are much stronger.

Table 2 also shows the associations between life satisfaction and various occupational variables. Keeping with the reporting practices of the Census, these variables are divided

Table 2 Correlations between education and occupation factors and life satisfaction for counties

	Mean	SD	Correlation
Education			
% High school graduate or higher	82.53	7.00	.52**
% with bachelor's degree or higher	25.59	9.31	.41**
Occupations[a]			
Construction	.10	.03	.04
Farming	.01	.02	−.21**
Production	.13	.04	−.35**
Professional	.34	.07	.37**
Sales	.27	.02	.07
Service	.15	.03	−.28**
Industry[b]			
Agriculture	.02	.03	−.13*
Arts	.08	.03	.00
Construction	.07	.02	.24**
Educational	.20	.04	−.01
Finance	.07	.02	.09
Information	.03	.01	.10
Manufacturing	.12	.06	−.14**
Other	.05	.01	−.13*
Professional	.09	.03	.17**
Public	.06	.03	.04
Retail	.12	.02	.17**
Transportation	.05	.02	−.17**
Wholesale	.04	.01	−.06

* $p < .05$, ** $p < .01$

[a] % Persons who perform specific occupational duties

[b] % Persons working in an industry

into percentages of people who perform specific occupational duties and the percentages of people working in different industries. Results show that these associations tend to be smaller than the more direct indicators of socio-economic status, with many correlations close to zero. There is a general trend for counties with a high percentage of residents working in professional occupations to report higher levels of life satisfaction, and these correlations are still small to moderate even after controlling for median household income (partial $r = .18$). In addition, counties with high percentages of people working in production or service have lower levels of life satisfaction. Finally, in contrast to the results from Rentfrow et al. (2009), communities with high levels of people working in industries like the arts, education, finance, or other professional industries were not typically happier than communities where few people worked in these industries.

Table 3 shows the results for marital status as an indicator of the average life satisfaction of counties. Consistent with existing individual level data, aggregated marital status variables exhibit weak to moderate associations with life satisfaction. In particular, the percentage of people who are married correlates moderately strongly with average life satisfaction. Additionally, the percentages of people who are widowed and separated are moderately to strongly correlated with life satisfaction (though the associations with divorce are quite weak). Two alternative explanations of this effect are (a) that married people have higher incomes than unmarried people and income is driving these differences, or (b) that married people are older than unmarried people (but younger than widowed

Table 3 Correlations between marital status and life satisfaction for counties

	Mean	SD	Correlation
% Divorced	.10	.02	−.11*
% Married	.55	.06	.42**
% Separated	.02	.01	−.45**
% Single	.26	.06	−.26**
% Widowed	.06	.02	−.31**

* $p < .05$, ** $p < .01$

people) and that age is responsible for these effects. To test these possibilities, we examined the associations controlling for income and the quadratic effect of age, and the results were quite similar (and even stronger in some cases). Average age was only weakly correlated with life satisfaction ($r = .06$). In addition, controlling for age and age squared led to only small changes in the marital status effects. The correlation between percent married and life satisfaction controlling for the quadratic effect of age was .42, and the partial correlation was .37 when controlling for median income. Similarly, the associations with widowhood remained when controlling for these potentially explanatory variables. The correlation between percent widowed and life satisfaction controlling for the quadratic effect of age was −.18. This correlation was −.50 when controlling for median income. Thus, there appear to be moderate associations between family structure variables and life satisfaction even after controlling for the potentially explanatory variables of age and income.

Rentfrow et al. (2009) also found that a variety of indicators of inclusiveness correlated positively with well-being at the state level. For instance, the percentage of immigrants living within a state correlated .48 and .45 with the overall index and life evaluation index, respectively. Similarly, a “gay index” created by Florida (2002) correlated .30 with the overall well-being index and .26 with life evaluation. These results suggested that communities that were more welcoming to individuals with diverse backgrounds were happier than those that were less welcoming. The current analyses did not replicate these results. In fact, the results for the number of foreign-born residents predicted average life satisfaction in the opposite direction, with a moderate negative correlation. Similar results were obtained with a measure of the percent of English-speaking residents in the county (see Table 4). In addition, in contrast to the results from Rentfrow et al., the percent of households consisting of same-sex partners was only weakly (and negatively) correlated with aggregate life satisfaction.

Table 5 reports the correlations between aggregate life satisfaction scores and a variety of indicators of health. The first line shows that at the aggregate level, self-reports of health-related quality of life correlate with self-reports of life satisfaction. Of course, these reports come from the same sources and could reflect shared method variance. Therefore, a more impressive demonstration of the links with health comes from the objective measures. The additional lines in Table 5 show that these measures also correlate with aggregate life satisfaction, often at moderate to strong levels. For instance, obesity rates

Table 4 Correlations between inclusiveness factors and life satisfaction for counties

	Mean	SD	Correlation
% of gay couples cohabiting	.01	.00	−.15**
% English as first language	.85	.14	.27**
% Foreign born	.09	.08	−.28**

* $p < .05$, ** $p < .01$

Table 5 Correlations between health factors and life satisfaction for counties

	Mean	SD	Correlation
Physical health[a]	9.94	1.46	−.31**
Obesity	25.45	4.01	−.36**
Disability			
% Persons with disability, aged <20 years	.08	.01	−.37**
% Persons with disability, aged 21–64 years	.19	.04	−.51**
% Persons with disability, aged >64 years	.41	.05	−.43**
Cause of death[b]			
All causes	826.91	101.81	−.30**
Accidents	38.47	11.77	−.09
Alzheimer's disease	22.54	8.23	.30**
Cerebrovascular diseases	53.21	10.75	−.02
Chronic liver disease and cirrhosis	9.41	3.01	−.26**
Chronic lower respiratory disease	44.63	11.19	−.03
Diabetes mellitus	25.55	7.92	−.29**
Heart disease	220.48	40.12	−.42**
Homicide	5.58	4.99	−.41**
Hypertension	7.12	2.93	−.20**
Influenza	20.15	5.11	−.15**
Malignant neoplasms (cancer)	189.75	20.57	−.24**
Nephritis, nephrotic syndrome and nephrosis	13.24	4.98	−.21**
Parkinson's disease	6.47	1.80	.42**
Septicemia	11.20	5.71	−.22**
Suicide	11.79	3.77	.04

* $p < .05$, ** $p < .01$

[a] Number of unhealthy days over 30 days period

[b] Age adjusted rates per 100,000

correlate moderately with life satisfaction. Similarly, disability rates correlate negatively, and these correlations are strong at the county level during the period of life when disability is most likely to affect work outcomes (between the ages of 21 and 64). Table 5 also shows the correlations between aggregated life satisfaction and death rates for the top 15 causes of death in the United States. Notably, all-cause mortality correlates moderately with life satisfaction, but the pattern of correlations varies across the different causes. For example, counties with high rates of death due to heart disease tend to report lower levels of life satisfaction, with effect sizes that are moderate to strong. However, rates of death from other causes tend to correlate more moderately.

Interestingly, there are some cases—most notably with Alzheimer's Disease and Parkinson's Disease—where correlations are positive. However, these correlations can be understood by examining the links between rates of death and overall life expectancy. For most causes of death, the correlation with life expectancy is negative—higher rates of death are strongly associated with lower life expectancy, with most correlations falling between −.84 for heart disease to −.49 for chronic lower respiratory disease. However, for Parkinson's Disease, the association with life expectancy is reversed ($r = .43$). Higher rates of death by Parkinson's Disease are associated with higher life expectancies, likely

Table 6 Correlations between regional characteristics and life satisfaction for counties

	Mean	SD	Correlation
Population[a]	12.40	1.16	−.20**
Population density[a]	5.83	1.60	−.27**
Commute	24.63	4.99	−.14**

* $p < .05$, ** $p < .01$

[a] Variable was log-transformed before analysis

because Parkinson's Disease is prone to strike those who live to an older age and hence did not die from one of the other causes. The association between life expectancy and Alzheimer's Disease ($r = -.12$), while not positive, is much smaller than the association between life expectancy and the other causes of death listed in this table, which makes a similar explanation likely.

Finally, note the small to moderate positive correlation between average life satisfaction and suicide rates. For many reasons, a negative correlation would be expected. Indeed, this could be seen as one possible test of the validity of the aggregate life satisfaction measure. However, this association must be considered in the context of what is known about the correlates of suicide rates. For instance, at the county level, the correlation between suicide rates and population density is −.59, even though low population densities are associated with higher life satisfaction. Thus, factors beyond overall well-being, such as social integration, may be a more important determinant of whether or not the most unhappy people within a region actually commit suicide when distraught.

The final set of variables we examined focused on the links between regional life satisfaction and the size and density of the region. These results are presented in Table 6. As the correlations in this table show, larger and denser regions typically have lower levels of life satisfaction. It is also the case that regions in which commutes are long have residents who tend to be less satisfied with life. Once population and population density are controlled, however, the association with commuting drops to −.02.

4 Discussion

An important question for research on subjective well-being is whether the measures that exist can provide useful information about a population's well-being. After reviewing evidence regarding the judgmental processes that underlie reports of well-being, Schwarz and Strack (1999) suggested that the existing research might lead some to believe that "there is little to be learned from global self-reports of well-being… [W]hat is being assessed, and how, seems too context dependent to provide reliable information about a population's well-being" (p. 80). Elsewhere, we and others have argued that such measures can be useful to assess population levels (e.g., Diener et al. 2009; Diener and Seligman 2004), and more and more evidence has emerged suggesting that this is true (Oswald and Wu 2010; Rentfrow et al. 2009). The current study attempted to further our understanding of these issues by examining the within-nation correlates of regional levels of life satisfaction.

The first major contribution of this work is to confirm that regional variance in well-being does exist, that it is reliable and that it correlates in robust and consistent ways with theoretically meaningful predictors. Our preliminary analyses showed that regional life satisfaction ratings were reliable across the 4 years of assessment, with year-to-year stabilities as high as .66. Such stabilities are only possible if a substantial amount of true score variance exists in the aggregated measures. Thus, these preliminary results demonstrate that broad surveys can provide reliable assessments of the life satisfaction of regional populations and that these assessments are quite stable over time.

More importantly, however, the pattern of correlations provides evidence for the validity of the aggregate measures. If objective characteristics of communities—including unemployment, poverty rates, average education and rates of marriage—consistently predict the average life satisfaction of those communities, then this suggests that the subjective ratings of well-being themselves correspond to real differences, rather than to differences in response styles. Thus, these results provide important information about the practical utility of well-being measures in regard to their role in policy decisions (Diener et al. 2009).

Importantly, specific correlates were not always those that have emerged most consistently from existing individual or national analyses, demonstrating that work at the regional level has the potential to provide valuable new knowledge about subjective well-being. For instance, one of the strongest correlates to emerge from these analyses was the average educational attainment of the region. Notably, educational achievement was also one of the strongest correlates found in Rentfrow et al.'s (2009) study. These results are interesting because they are quite different from those at the individual level, where education has typically been characterized as a relatively weak predictor of individual well-being. This cross-level discrepancy means that the aggregate-level effect does not result from the cumulative benefit that highly educated individuals receive from their education. In other words, it does not appear that education makes individuals happier, in turn leading to greater aggregate happiness for regions with more well educated individuals. Instead, in regions with high levels of education, the population as a whole is happier, even though the educated individuals themselves are not happier than the less educated residents. Of course, this correlational finding cannot determine whether having a highly educated population affects their well-being, as education could easily be an indicator of some other underlying cause. Importantly, it is clear that the education effect is not due to underlying differences in income, as the effect holds even when income is controlled.

Beyond income, additional indicators correlated with average life satisfaction. For instance, the correlation with poverty level was $-.46$ at the county level, and the correlation with unemployment was moderate. Although housing prices (which index both affluence and cost of living) were not robustly associated with aggregate life satisfaction, housing price indexes that focused more on cost of living did. The percentages of people spending more than 35% of their income on their mortgages or rent correlated negatively with well-being. Together, these results suggest that economic hardship (in the form of high levels of poverty, low levels of employment, or high cost of living) tend to be associated with aggregate life satisfaction, even though the association with median income is not strong.

Our knowledge of well-being is further expanded by showing that effects found at the individual or national level replicate at the within-nation regional level. For instance, subjective ratings of health often correlate moderately with life satisfaction and other measures of well-being (Diener et al. 1999). Although these effects can often be smaller than objective ratings of health, recent research shows that specific health conditions can be strongly associated with life satisfaction (Lucas and Donnellan 2007). In the current study, robust correlations became apparent across a wide variety of indicators of health.

Whether self-reports of health, risk factors for poor health (i.e., obesity), rates of disability or rates of death from specific causes were examined, consistent, moderate to strong correlations emerged. Importantly, the various measures complement each other in desirable ways. Self-reports of health reflect a broad range of health conditions that may not be captured by other more specific indicators. Yet they also share method variance with the life satisfaction ratings, which makes them suspect. However, the fact that correlations were replicated across both broad subjective measures and specific objective measures gives support to the idea that there are robust associations between self-reports of life satisfaction and the health of the population.

Similarly, existing individual level results were replicated with variables indexing the rates of marriage in the population. However, the results were primarily found using rates of marriage and widowhood; correlations with divorce rates and percentages of people who were unmarried tended to be weaker. If these effects were simply due to the individual level effects, we might expect them to map more closely on the individual level results, with stronger correlations for rates of divorce. This partial correspondence leads to questions about other factors that might be associated with marriage rates that might indicate regional levels of subjective well-being.

The correlates from our study that overlapped with Rentfrow et al.'s (2009) analysis of state level differences sometimes diverged in important ways. Notably, Rentfrow et al. found strong evidence for a link between greater inclusiveness and higher well-being. The variables that were selected as indicators of this construct—including the number of immigrants, the number of homosexuals and the rates of "bohemians" in the region—all correlated positively with average well-being. In our study, however, correlations with related variables were smaller, and sometimes in the opposite direction. This suggests that the measures included in the Gallup-Healthways study and those assessed by the CDC differ in important ways, and future research that uses well-being at the population level must look closely at these psychometric characteristics so future discrepancies can be understood.

Finally, regional analyses allow for important new advances in the understanding of well-being constructs by opening up a set of new variables that can be examined. Intuition suggests that people choose specific regions based on the characteristics of those regions—some may believe that they will be happier in a small town; others may thrive on the fast-paced lifestyle found in a city (Schkade and Kahneman 1998). These intuitions suggest that characteristics of the region matter, yet these variables have rarely been studied. The results from the current study show that the correlations with population size and population density (along with the average length of the commute) tend to be moderate to strong. On average, counties that are smaller and less dense have more satisfied populations. Importantly, these may have significant applied implications. If future work can identify the specific characteristics of large and small areas that are most strongly linked with well-being, then city planning and other policy decisions can be made to emulate the characteristics of flourishing areas.

5 Limitations

The primary limitation of this study is one shared by most work that relies on existing data from large, population-based surveys —the measures are short and not all constructs that would be desirable to have information about were assessed (see Trzesniewski et al. 2010, for a review). However, this is a necessary trade-off to conduct this kind of work. Very few region level analyses have been conducted precisely because such large sample sizes are needed, and the cost of adding questions is quite high when sample sizes range into the millions.

Furthermore, concerns about the potentially low reliability of the measure are mitigated by these large samples. When aggregating over all respondents within a county, random measurement error is averaged out, just as it would be by averaging across multiple items within a single individual. Of course, there are other problems with single-item measures like the one used in this study (Martinez-Martin 2010; Dollinger and Malmquist 2009). For instance, one item may not be able to capture the breadth of the construct of interest. However, life satisfaction is a relatively narrow construct that is probably well suited to assessment by short measures. As evidence, the specific items that are typically included on multiple item scales are often just slight rewordings of the same general statement.

Finally, the biggest limitation is that these correlational data cannot determine whether the robust predictors that we identified have any causal impact on regional well-being, and this information is essential for guiding policy decisions. However, initial correlational work like that presented in this paper provides important evidence that regional differences in well-being exist. As governments pay more attention to these data, it becomes more and more likely that additional measures will be assessed. With more data, designs that are more sophisticated can be used. For instance, the BRFSS already has four waves of data available, and, if life satisfaction continues to be assessed, then longitudinal analyses can be conducted at the aggregate level. When combined with information about policy changes in different regions, stronger statements can be made about the role that specific factors have in regional well-being. The work presented in this paper provides an important first step in using well-being measures for policy decisions.

6 Summary

An increasing number of psychologists and economists have called for a greater focus on systematic assessments of well-being among broad populations. If differences in well-being exist, and this variance is linked to objective circumstances, then these data can be used to guide policy decisions and improve the well-being of citizens. For progress to be made towards these goals, evidence must show that measures of regional well-being are reliable and valid. The current study shows that across the county level, regional measures of life satisfaction are reliable and linked to important predictors including poverty, unemployment, educational achievement, population size and density and various indicators of health.

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