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UNHAPPY CITIES

Edward L. Glaeser
Joshua D. Gottlieb
Oren Ziv

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ABSTRACT

There are persistent differences in self-reported subjective well-being across U.S. metropolitan areas, and residents of declining cities appear less happy than other Americans. Newer residents of these cities appear to be as unhappy as longer term residents, and yet some people continue to move to these areas. While the historical data on happiness are limited, the available facts suggest that cities that are now declining were also unhappy in their more prosperous past. One interpretation of these facts is that individuals do not aim to maximize self-reported well-being, or happiness, as measured in surveys, and they willingly endure less happiness in exchange for higher incomes or lower housing costs. In this view, subjective well-being is better viewed as one of many arguments of the utility function, rather than the utility function itself, and individuals make trade-offs among competing objectives, including but not limited to happiness.

Edward L. Glaeser
Department of Economics
315A Littauer Center
Harvard University
Cambridge, MA 02138
and NBER
eglaeser@harvard.edu

Joshua D. Gottlieb
Vancouver School of Economics
University of British Columbia
#997 - 1873 East Mall
Vancouver, BC V6T 1Z1
Canada
and NBER
joshua.gottlieb@ubc.ca

Oren Ziv
Harvard University
oziv@nber.org

According to the Behavioral Risk Factor Surveillance System (BRFSS), only 35.9 percent of the residents of the Gary, Indiana metropolitan area report themselves as very satisfied with their lives, as opposed to 45.7 percent across the United States as a whole. Self-reported unhappiness is high in other declining cities, and this tendency persists even when we control for income, race and other personal characteristics. Why are the residents of some cities persistently less happy? Given that they are, why do people choose to live in unhappy places?

The presence of significant differences in self-reported well-being across places within the United States poses something of a challenge for the reigning paradigm of urban economics—the concept of a spatial equilibrium. This central idea—proposed by Alonso (1962), Muth (1964), Rosen (1976) and Roback (1982)—assumes that wages and prices adjust so that in equilibrium there are no arbitrage opportunities across space. In equilibrium, individuals cannot improve their overall utility levels by migrating within the U.S.

There are two ways to reconcile differences in self-reported well-being with the notion of a spatial equilibrium. First, subjective well-being (SWB) may not be equivalent to the economist's concept of utility. Under this view, agents make decisions in order to jointly maximize expected future happiness and other objectives. Compensating differences in other dimensions offset persistent spatial differences in happiness. Second, the observed differences in subjective well-being may not reflect the permanent life-long well-being for otherwise identical people. The unhappiness might be transitory or explained by unobserved individual heterogeneity, especially if some areas attract people who are disproportionately prone to be more or less happy.

In Section I of this paper, we follow the work of Oswald and Wu (2011) and use BRFSS to measure subjective well-being across the United States. We extend their work by calculating SWB at finer geographic levels, adjusting for observable individual differences, and correcting for sampling error. We find significant, although not huge, differences across metropolitan areas both with and without controlling for state fixed effects. After correcting for sampling noise, we find that the cross-city standard deviation of happiness is about 6 percent of a standard deviation of individual happiness. This is approximately the difference in subjective well-being between the sexes, or between high school graduates and those with some college. This difference is roughly the order of magnitude caused by a one standard deviation decline in neighborhood poverty (Ludwig et al., 2012). We also find that this variation persists when we control for a rich battery of individual controls, including employment status and income.

One primary concern is whether these differences are caused by unobserved heterogeneity, either in human capital or in propensity towards happiness. To address this worry, we turn to the panel data in the National Survey of Families and Households (NSFH). Using this panel, we can estimate area-level happiness by looking at individuals who move across metropolitan areas between the survey's first wave (1987-1988) and second wave (1992-1994). Differences in happiness persist, even when we control for individual fixed effects. The correlation between area level estimates with and without individual level fixed effects is 0.69. This leads us to believe that much of the difference in happiness across space reflects more than the selection of unhappy people into unhappy places.

We next document that area-level happiness is essentially uncorrelated with many area attributes. For example, metropolitan area population and housing values are orthogonal to subjective well-being in the BRFSS. Like Florida et al. (2013), we find that area-level education is positively associated with subjective well-being, but we find that this effect vanishes when we control for individual-level education. If more educated individuals only became educated because of the education level of the area, then it can be fairly said that these places have made them happier. But if they would have been educated regardless of place, then the happiness of more educated areas should be interpreted as differential selection.

In Section II, we document the one robust fact that emerges clearly from multiple data sets: places with lower levels of population and income growth are less happy (Glaeser and Redlick, 2009). Lucas (2013) also finds higher rates of migration to counties with higher subjective well-being in the BRFSS, arguing that the migration patterns are consistent with a spatial equilibrium with happiness as a measure of utility. We find the relationship persists for quite long periods (from 1950 to 2000). Moreover, we find the strongest effect at the left tail of SWB. It is not that high-growth places are particularly happy, but rather that very low-growth areas are particularly unhappy. It is possible that people flee areas that produce unhappiness, but the long time periods involved make it hard to believe that these well-being differences are transitory.

We show that the connection between low well-being and decline persists when we control for a bevy of individual controls, including education and income, and even when we control for state fixed effects. This fact appears in the NSFH and General Social Survey (GSS) as well as the BRFSS. In the NSFH, the effect does not persist in the general individual fixed effects estimation, but it re-emerges when we limit our sample to cities with more than 250 respondents across both waves. None of these results speak to whether unhappiness is causing decline or whether decline is causing unhappiness.

Section II also notes three other facts about urban decline and unhappiness. First, while Oswald and Wu (2010) document the relationship between state-level happiness and amenities, we find that the connection between unhappiness and decline in the BRFSS does not reflect the role of urban disamenities associated with decline, such as crime, coldness and inequality. Second, both the GSS and the NSFH allow us to examine movers, and we find that the connection between urban decline and low levels of SWB is just as strong among recent migrants as among longer term residents. This latter fact leans against the interpretation that happiness was *ex ante* identical across areas, but that some areas experienced negative shocks, people were stuck in those areas and their happiness fell accordingly.

Third, we ask whether the unhappiness of declining cities is a new phenomenon, perhaps caused by decline, or represents a more historic tendency. The General Social Survey enables us to look back as far as the early 1970s, and these data suggest that the connection between decline and unhappiness was stronger in the past than it is today. We also have Gallup surveys from the 1940s that show a significant connection between unhappiness and city population during those years, although that connection is not stronger in states that experienced more urban decline. These facts lead us to suspect that the connection with unhappiness and urban decline more likely reflects long-standing attributes of these cities rather than a causal effect of the decline itself.

In Section III, we propose a framework that incorporates spatial differences in SWB into the spatial equilibrium framework. Following writers as diverse as Epictetus, de Mandeville, Irving Fisher and Gary Becker, we assume that happiness, or life satisfaction, is desirable—but far from equivalent to utility. We have objectives in life other than being satisfied, and we may knowingly make choices that reduce happiness, such as exposing ourselves to a more competitive environment, if those choices further other aims (Luttmer, 2007; Benjamin et al., 2011). According to the spatial equilibrium logic, urban unhappiness must be offset by some other urban amenity, such as higher real incomes.

In our model, happiness is generated through experiences, which can be improved by spending money, and happiness is but one ingredient in the utility function. Individuals have other objectives, which we refer to as achievements, such as raising a family. These are also produced with a combination of money and time. The model suggests that the connection between money and happiness may significantly understate the connection between money and utility, because a higher opportunity cost of time causes individuals to engage in less happiness-generating leisure. In a spatial equilibrium, higher wages are compensated shifts, typically offset by higher real estate prices, so higher area wages could easily be associated with lower happiness levels even if utility levels are equalized across space.

In Section IV, we examine whether individuals in declining or otherwise unhappy places are being compensated for their unhappiness. In the 1940 Census, residents of declining cities were receiving significantly higher incomes. A one standard deviation drop in population growth post 1950 was associated with $222 more in income ($3,655 in current dollars), which is more than ten percent of average income. Presumably, high labor costs were one reason why businesses left these areas. One interpretation of these results is that the industrial cities were less happy in 1940, but their residents were being compensated with earnings that could achieve other ends, such as nurturing a family.

The data also shows that housing prices in 1940 were higher in areas that subsequently declined, yet there are essentially no housing quality controls in that early data. As such, while it is possible that some of the high earnings in declining cities were eaten away by higher housing rents, it is also possible that these rents were actually compensation for better housing quality.

When we turn to 2000 Census data, we find that the unhappy, declining cities are no longer receiving higher wages. Wages are essentially uncorrelated with our growth variable in the more modern data. But decline is correlated with house prices and rents. In 1940, the residents of unhappy, declining places seem to have been compensated with higher incomes. In 2000, the residents of those same cities seem to have been compensated with lower housing costs.

We have also examined the direct correlation between our area level happiness measure and area-level rents and incomes, as in Oswald and Wu (2011). We do find some evidence that residents of happy cities pay higher rents, suggesting some form of offset for the added level of happiness. The results are certainly compatible with the view that individuals trade other objectives against happiness when they are choosing where to live. Section V concludes.

I. Unhappiness Across Cities

In this section, we briefly document five stylized facts about urban happiness, primarily in the U.S., but also abroad. We then discuss the connection between unhappiness and decline in Section II.

Throughout this paper, we follow the literature in measuring happiness using self-reported survey data on subjective well-being (SWB). Our primary data source is a large national survey, the Behavioral Risk Factor Surveillance System (BRFSS) conducted by the Centers for Disease Control and Prevention (CDC), which asks individuals to report on their own life satisfaction using a discrete response scale.

Since 2005, CDC has asked all respondents “In general, how satisfied are you with your life?” Respondents were given four possible categories: very satisfied, satisfied, dissatisfied, and very dissatisfied. In each year between 2005 and 2010, around 300,000 subjects answer this question, along with all of the demographic variables listed below. We recognize that satisfaction may strictly differ from happiness, but we will use the terms interchangeably.

The distribution of answers in this sample is shown in Panel A of Table 1. Across these five years, 45.6% of individuals responded that they were “very satisfied” with their life, while 48.7% responded that they were “satisfied”, 4.6% responded that they were “unsatisfied” with their life and slightly over 1.1% reported being “very dissatisfied”. These numbers are very consistent between years. This question has been the focus of much of the previous literature on the economics of happiness.

In all of the work that follows, we recode these answers so that 4 indicates “very satisfied” and 1 indicates “very dissatisfied.” We then rescale the answers linearly so that they have a mean of 0 and standard deviation of 1.[1] Because BRFSS data report the county in which the respondent lives, we are able to link respondents to metropolitan areas.

This measure has several problems, even before considering whether this corresponds to the economic concept of "utility." First, respondents may have different interpretations of the scale used to code responses, or different reference points for life satisfaction. A life situation that one person may consider to be very satisfactory, may be merely satisfactory to another. To the extent that this leads to systematically different responses across respondents, it could confound this variable's interpretation.

To address this issue, we estimate metropolitan area j happiness as the MSA j fixed effect in the following model:

$$(1) \qquad y_{ijt} = \alpha + X_{ijt}\beta + \gamma_t + u_j + \epsilon_{ij}$$

We estimate equation (1) at the individual level, so i indexes individual respondents, j indexes areas, and t indexes the survey wave. In this regression, y_{ijt} represents individual subjective well-being (or SWB), X_{ijt} is a matrix of individual controls, u_j is a metropolitan area fixed effect, γ_t is a year fixed effect, and ϵ_{ij} is an uncorrelated error term. The individual controls include survey month, sex, a polynomial in age, eight race dummies, six marital status dummies, four educational attainment dummies, and variables representing various information about the children in the household.[2]

Second, respondents undoubtedly have a large degree of variability in their happiness at the moment they answer the survey. Because we only have responses from a small fraction of residents in each area (around 0.1%), this variability is likely to cause noisy estimates of area-level SWB. To account for this, we next measure area-level happiness using random effects instead of fixed effects. We estimate the following model, in which coefficients in bold type are considered to be fixed, while the others are random effects:[3]

$$(2) \qquad y_{ijt} = \boldsymbol{\alpha} + X_{ijt}\boldsymbol{\beta} + \boldsymbol{\gamma_t} + u_j + \epsilon_{ij}$$

We consider the demographic characteristics to have a fixed relationship with individual happiness, and allow for random metropolitan area effects as well as an individual error term.

[1] The Data Appendix discusses the issues that arise from the discrete nature of the answers and why we do not think they are a problem, as well as other details of our estimation.
[2] See the Data Appendix for more details.
[3] So one might prefer to call this a "mixed effects" model as opposed to a pure "random effects" model.

This model enables us to compute a number of useful quantities. It allows us to calculate an estimate of the underlying variance of metropolitan area effects (σ_u^2). For each area, we can also determine the best estimate $\hat{u}_j$ of that area's u_j. We refer to these estimates as the metropolitan area's *adjusted life satisfaction*. We use them extensively in subsequent analysis as our estimate of the area's contribution to individual happiness.[4]

Finally, since BRFSS has only asked about life satisfaction since 2005, we have a very limited ability to address time-series variation in happiness. We will thus augment it with other data sources introduced below. We first turn to five sets of facts about life satisfaction across space.

1. Are There Significant Differences in Life Satisfaction across Space?

We first address whether there is a meaningful difference in happiness levels across geographic areas, both before controlling for individual demographic characteristics and after including these controls. We answer this question in multiple ways. First, we run the fixed effects regression (1) and perform an F-test of the joint significance of the metropolitan area fixed effects. Second, we determine whether the estimated variance of metropolitan area random effects in regression (2), σ_u^2, is significantly different from zero. Third, we perform a likelihood ratio test of the fixed effects model (2) against a constrained model in which the random effects are removed (we force $u_j = 0$ for all j).

We run each of these tests on a model with no demographic controls, and with the full set of demographic controls shown in Appendix Table 1. In both cases, all three tests strongly reject the null hypothesis that metropolitan area effects are irrelevant, and all with $p < 0.0001$.

Our next task is to quantify the differences across regions. We do so using two different measures from the random effects estimates in (2). First, σ_u^2 provides an estimate of the variance across the full population of metropolitan and non-metropolitan areas. Second, the empirical variance of the adjusted life satisfaction values, $Var(\hat{u}_j)$, quantifies the dispersion of estimates in the sample of areas where we are able to compute happiness.

In the unadjusted random effects model (where X_{ijt} is empty so we have no demographic estimates $\boldsymbol{\beta}$), we find $\sigma_u = 0.063 \pm 0.004$ and $sd(\hat{u}_j) = 0.058$. Since all of our analyses use measures of SWB rescaled to have zero mean and unit variance across individuals, the variation across geographic regions is around 6% of the individual-level variation in happiness.

[4] Our calculation of these adjusted life satisfaction measures $\hat{u}_j$ recognizes the problem of potentially large sampling variation when measuring SWB in a survey. We therefore calculate the best linear unbiased predictor (BLUP) based on our MSA-level random effects from (2), following the method of Bates and Pinheiro (1998) as implemented in Stata.

These numbers shrink by about one-quarter, to $\sigma_u = 0.047 \pm 0.003$ and $sd(\hat{u}_j) = 0.042$, when we include the demographic controls in model (2). The distribution of these adjusted life satisfaction estimates is shown in Figure 1.

To get a better sense of what this means quantitatively, we can compare it to the estimates of the impact of other characteristics on individual SWB. Moving across one standard deviation in geographic areas has an impact one-third as large as the difference between being a high school graduate or not graduating, or 1.8 times the estimated male-female gap. Based on column 3 in Appendix Table 1, which includes 8 income bins in addition to the basic demographic covariates, the difference between earning \$35,000-\$50,000 (category 6) and \$50,000-\$75,000 (category 7) is around 0.11, or roughly two metropolitan area standard deviations, $2\sigma_u$.

The values of our local happiness estimates themselves are shown visually in Figure 2. This map shows adjusted life satisfaction estimated at the MSA and rural area level after controlling for individual demographics. The map shows a band of less happy areas in parts of the Midwest and the Appalachian states, stretching from Missouri in the west and Alabama in the south well into Pennsylvania and even New Jersey in the east. New York City, Detroit, and much of California also have lower SWB than the happiest areas, which are concentrated in the West, Upper Midwest, and rural areas in the South. Appendix Table 2 shows specific values for a handful of metropolitan and non-metropolitan regions, including the highest and lowest values that we estimate.

In Figure 3, we adjust for employment status and income. Income depends on numerous individual choices, including where to live and possibly including one's happiness level. So we have to interpret area-level happiness estimates that result from this estimation much more cautiously, and as measures only of that part of area-level happiness that is orthogonal to productivity. Keeping this in mind, we show these estimates in Figure 3. This map shows unhappiness much more strongly concentrated in wealthier, urban areas along with the Rust Belt. Because we have now eliminated any happiness component coming through the urban areas' higher incomes—by controlling for their effect on the respondents' income—the map does not mean that they are less happy than other locales. Instead, only the part of area-specific happiness that does not come through income appears to be negative in these regions.

A third potential problem with these results is that they may reflect differences in the ways in which states implement the BRFSS. Unlike many surveys, the BRFSS is not centrally administered. Instead, individual state agencies perform the surveys. We cannot be sure of what biases may be created through this decentralized implementation, but it is at least possible that state-level implementation has caused some of the variance that we see in the data.

To address this possibility we re-estimate model (2) controlling for state fixed effects. Since there are a relatively few number of metropolitan areas in many states, we will not use these state-corrected area fixed effects in general. Still, it is important to note the reduction in variance that occurs when we look only at the within-state variance. The standard deviation of $\hat{u}_j$ falls from 0.043 to 0.017 when we control for state fixed effects as well as demographic controls. The variance is significantly reduced, but these effects remain statistically distinct from zero. As such, we conclude that metropolitan differences would persist, even if all the state-level variation reflected only state-level differences in implementing the BRFSS.

This evidence does not rule out the possibility that these differences reflect unobserved individual characteristics. One approach to unobserved heterogeneity is to estimate metropolitan area fixed effects controlling for individual fixed effects. This requires us to use a panel, rather than a repeated cross-section, which forces us to move from the very large BRFSS to the much smaller National Survey of Families and Households (NSFH). The NSFH is a probability sample survey of 13,017 respondents in 9,643 households plus an oversampling of minority and single-family households and households with step-children. The NSFH is a longitudinal study with three waves, the first between 1987 and 1988, the second between 1992 and 1994, and the third wave between 2001 and 2002 (Sweet and Bumpass 1996; Sweet, Bumpass, and Call 1988; Trull and Famularo 1994).

We use data from the first two waves of the NSFH. In both waves, the data contains information on family and personal characteristics of individuals and on individual subjective well-being. In particular, the NSFH asks: “First taking things all together, how would you say things are these days?” Respondents may choose to respond on a 1 to 7 scale, 1 being very unhappy and 7 being very happy. The summary statistics from this survey are shown in Panels B and C of Table 1.[5]

We will later use this measure to examine whether the link between area attributes and well-being is stronger for recent migrants or long-term residents. Here, we restrict our attention to the heterogeneity in subjective well-being across space.

We first estimate adjusted life satisfaction for the merged sample of NSFH waves 1 and 2. The variance of these estimates is 0.0007, roughly in line with the estimates from the BRFSS. The raw variation of metropolitan area fixed effects is larger in the NSFH, but the variance correction is also much larger because the sample size is so much smaller.

We then estimate a PMSA fixed effect variable using the two waves including individual level fixed effects. The correlation between these estimates and the estimates without the individual fixed effects is 0.69. The variance of the PMSA fixed effect with individual fixed effects is 0.64. We conclude from these results that there appears to be significant variation in subjective well-being across space, even when we control for unobservable individual-level heterogeneity by using individual fixed effect estimates.

[5] See the Data Appendix for further details on our use of the NSFH and some issues that arise with identifying movers.

2. Do Metropolitan Area Differences in Subjective Well-Being Persist?

Having established the existence of spatial differences in happiness and estimated their magnitude, we now want to see how they evolve over time. Hypotheses about the temporal pattern of spatial SWB could range from a completely permanent local characteristic (for instance, Honolulu has gorgeous weather and is on the beach, which always makes its residents happy) to a long-term shock common to area-level residents (e.g., the economy in Detroit was poor and declining during our sample period, making its residents unsatisfied), to an extremely transitory common shock caused by the weather or local sports outcomes.

We first test the stability of area effects in two ways. First, we run versions of regression (2) separately for each year, so without year fixed effects:

$$(3) \qquad y_{ij} = \boldsymbol{\alpha}^{(\boldsymbol{t})} + X_{ij}\boldsymbol{\beta}^{(\boldsymbol{t})} + u_j^{(t)} + \epsilon_{ij}$$

We then compare the adjusted life satisfaction estimates across different years ($\hat{u}_j^{(t)}$versus $\hat{u}_j^{(t')}$for $t' \neq t$). Our second method is to augment regression (2) by adding an area-year random effect, v_{jt} to the random effects regression:

$$(4) \qquad y_{ijt} = \boldsymbol{\alpha} + X_{ijt}\boldsymbol{\beta} + \boldsymbol{\gamma}_t + u_j + v_{jt} + \epsilon_{ij}$$

This model estimates the time-invariant area effect, u_j and the time-varying area effect v_{jt} simultaneously. We can test the statistical impact of each of these effects separately, and quantify the importance of permanent and transitory area effects. For this analysis, we use the sample of respondents in the 177 MSAs with at least 200 respondents in all years of our sample.

These tests reveal very clearly that the permanent effects are far more important than the transitory components. When estimating equation (4) without demographic controls, we find $\sigma_u = 0.064 \pm 0.004$ while $\sigma_v = 0.018 \pm 0.002$. Thus there is a statistically significant transitory component, but it varies by 70% less than the permanent area component, and its standard deviation is around 2% of the individual-level standard deviation.[6]

Another way to see this variation is to relate adjusted life satisfaction from regression (3) in one year to that in another year. Using the measures adjusted for demographic controls from 2005 $\left(\hat{u}_j^{(2005)}\right)$ and from 2009 $\left(\hat{u}_j^{(2009)}\right)$, we find an extremely strong positive relationship, with a correlation of 0.48. Thus one quarter of the variation in adjusted life satisfaction is driven by permanent metropolitan area level shocks, and the rest by transitory shocks and estimation error.

[6] Results are similar when demographic controls are included.

Although we have adjusted for the effect of sampling error in computing adjusted life satisfaction, we should expect to see a correlation less than one if our correction is imperfect. Hence the random effects results discussed in the previous paragraph give the more accurate assessment of the relative importance of permanent and transitory components to well-being.

3. *Is Urbanization Associated with Happiness or Unhappiness?*

One natural question is whether happiness increases or diminishes in large cities. Cities have often been seen as entities that create financial wealth, but diminish other types of well-being. We first test this hypothesis by examining the correlation between adjusted life satisfaction and the logarithm of metropolitan area population. If we use the 2010 population, we find a weak positive correlation of 0.07. As metropolitan area population increases by one log point, SWB increases by 0.003 standard deviations and the effect is quite imprecise. We will later show that in an individual level regression, there is also no significant relationship between area level population and self-reported well-being, holding individual level characteristics constant.

Using past population levels, instead of current population levels, we find a positive correlation with population in 2000 and 1990 and a negative correlation with population levels before that point. The relationship between recent levels of SWB and metropolitan area population before 1960 becomes significantly negative. While larger cities today do not evince significantly lower levels of unhappiness, residents of cities that were large in the past do seem to be less happy. We return to this topic later, when we discuss the connection between SWB and population growth.

Following Stevenson and Wolfers (2008), we now briefly turn to worldwide data. Using the World Values Survey, we estimate subjected well-being in rural and urban areas in 39 countries throughout the world. Across the entire sample, we find that the urban happiness is on average higher than rural happiness. This effect is, however, driven primarily by poorer countries.

Figure 4 shows the correlation between the logarithm of per capita GDP in the country in 2007 and the rural-urban gap in subjective well-being. The coefficient is significantly negative and the R^2 is 0.2. In poorer countries, which often have cities that seem particularly hellish, the residents of cities say that they are significantly happier than the residents of rural areas. It is perhaps unsurprising that the developing world is urbanizing so rapidly, as urban residents appear to be both far better paid and happier.

4. *Is Unhappiness Related to Suicide?*

While self-reported well-being provides one measure of satisfaction with one's life, suicide provides a second, perhaps more tangible, piece of evidence on human misery. It is well known that unhappiness predicts suicide at the individual level (e.g. Koivumaa-Honkanenet al. 2003), but the relationship at the aggregate level is far less clear (Daly and Wilson, 2007). As Daly and Wilson argue, suicide may provide a revealed preference of life satisfaction. If happiness and utility were synonymous, we might expect to see a tight link between suicide and SWB at the aggregate as well as the individual level.

We have assembled suicide rates across metropolitan areas using the CDC's National Suicide Statistics data. These rates also differ significantly across metropolitan areas, but they do not correlate well with subjective well-being. Indeed, the raw correlation between these measures and the SWB measure is -0.06, meaning the areas with lower levels of subjective well-being also have lower levels of suicide.

One explanation for this weak correlation is that suicide relates to the bottom tail of the life satisfaction distribution, whereas our measures give much weight to middle of the distribution. To address, this issue we measure only the share of respondents who say their life satisfaction is in the bottom category ("Very Unhappy"). The weak correlation between this variable and suicide rates is shown in Figure 5, which corroborates Daly and Wilson's earlier findings in this area.

New York City may be the prime example of the mismatch between SWB and suicide. New York is particularly notable for both its low suicide rates and its low subjective well-being. We do not think that this implies that subjective well-being is without value as a measure, but rather that it is likely an incomplete and imperfect measure of economists' conception of utility. The economic analysis of suicide (e.g. Becker, 1983) almost always suggests that suicide reflects low utility levels, and yet high suicide rates do not appear in metropolitan areas where SWB appears to be low.

There are many reasons why the aggregate relationship between suicide and subjective well-being is weak, including measurement error. One interpretation is that these local differences tell us little, because they are shaped by local reporting norms rather than real differences in life satisfaction. A second interpretation is that the link between SWB and the economists' concept of utility is far from perfect.

5. Unhappiness and Urban Characteristics

We now turn to area-level correlates of self-reported well-being. Most area level attributes are relatively uncorrelated with subjective well-being, at least once we control for individual level education.

Table 2 presents these facts using area characteristics as of the year 2000. We use the year 2000 both because it predates our well-being data and because it is the last year with a comprehensive census. Our core specification includes a bevy of individual attributes that have been found to correlate with happiness, including education, age, race and family status. We do not include income or employment controls as these represent outcomes that may be caused by an area's economic success. Education and marital status may themselves be determined by the urban environment, and we include regressions both with and without those controls. All regressions cluster the standard errors at the area-year level and include year and month fixed effects.

Our first regression shows the relationship between the population size of the metropolitan area and self-reported well-being. When we do not control for education and marital status, the statistical relationship is small and statistically indistinct from zero. When we include these more endogenous controls, the relationship becomes more negative and statistically significant.

In the third regression, we control for the share of the adult population in the area with a college degree. Using the fixed effects estimated without controlling for individual level education, this variable is strongly positive. Using the fixed effects estimated conditional on these controls, the variable's estimated effect drops by two-thirds and it becomes statistically indistinct from zero. Regressions (5) and (6) examine the share of the adult population with a college degree. The picture is much the same as with the other education variable. The coefficient is large and statistically significant when we control only for area level attributes but not when we control for area-level education. These regressions can be interpreted as suggesting that area level education boosts self-reported well-being by increasing individual educational attainment, or that area level education has no independent effect.

Regressions (7) and (8) examine racial segregation, as measured by a standard dissimilarity index. In this case, we also interact segregation with a dummy variable that takes on a value of one if the individual is black. Both with and without individual controls, segregation is negatively associated with well-being and this effect is approximately twice as large for African-Americas as for whites.

Regressions (9) and (10) are our most fully saturated specifications. In these we control for all of the metropolitan area variables, and the full set of individual level controls. We also interact segregation with all of the race categories. In regression ten, we add state fixed effects.

Regression nine shows results that are similar to the other specifications. Share of the population with a college degree has a positive effect on self-reported happiness, although share of the population with a high school degree has a negative relationship. Segregation continues to have a negative connection to self-reported well-being, and this effect is much stronger for African-Americans. In this specification, housing value has a somewhat surprisingly negative but insignificant effect on subjective well-being.

Column ten includes state fixed effects and is our most complete specification. As many states have only one metropolitan area, this reduces our effective sample and eliminates any variation that represents larger regional trends. In this specification, the positive effect of college education remains, and the effect of high school graduates becomes positive. Housing values now have a negative, significant, relationship with happiness, while segregation is insignificant.

Putting together these results, we draw two tentative conclusions. There is some possibility that individuals report higher levels of well-being in more educated areas, although this is true only when we include a full range of area controls, or when we fail to control for individual level education. Segregation is associated with lower levels of subjective well-being, but only when we don't control for state fixed effects. Overall, these results do not suggest a robust series of correlations between urban attributes and SWB.

II. Unhappiness and Urban Decline

We now turn to the particularly striking correlation between urban unhappiness and decline (Glaeser and Redlick, 2009, Lucas, 2013). We first examine linear specifications and then allow the impact of population growth on subjective well-being to have a piecewise linear shape. We will focus on changes in the logarithms of population and median household income between 1950 and 2000. We first focus on the BRFSS and then turn to the NSFH and the GSS, which enable us to look at movers and estimate equations with individual fixed effects.

Linear Effects of Population Growth and Income

Table 3 presents our first set of results on the correlation between SWB and urban change. The first three regressions show results for population change. The next three regressions show results for income change. The final two regressions show results for both variables together and include other area-level controls.

The first regression shows the relationship between population change and self-reported well-being controlling for individual attributes. The coefficient of 0.087 implies that a 1 log point increase in population growth is associated with a one-twelfth of a standard deviation increase in self-reported well-being. The second regression controls for the more endogenous individual characteristics. The coefficient on population change remains statistically significant, but it falls in magnitude by about one-third. The third regression controls for state fixed effects. In this case, the coefficient falls to about one-third of its value in the first regression, although it retains statistical significance.

Regressions four through six look at income change instead of population change. In a sense, this is the local version of the classic Easterlin (1974) work on income change and happiness. Regression four shows a strong positive relationship between income growth and self-reported well-being. The coefficient is somewhat larger than that on population growth, but since the variation of income growth is smaller, the impact of a one-standard deviation change in income growth is actually smaller than the impact of a one-standard deviation change in population growth.

In regression 5, we add our controls for more endogenous individual attributes. As in the case of population change, the estimated coefficient falls by about one-third. In regression 6, we add state level controls. As before, the coefficient drops by another fifty percent, but it does remain statistically significant.

Regressions seven and eight include both variables and other area level controls. In regression seven, both change variables remain statistically significant. The coefficients are modest but continue to suggest that growth is associated with positive levels of well-being. The only of the other controls that is statistically distinct from zero is segregation, which remains negative.

In regression eight, we also include state fixed effects. Because BRFSS is administered at the state level and there could be important differences in the survey's implementation, we would like to adjust for any such differences. State fixed effects accomplish that. On the other hand, the fixed effects may be over-controlling in important ways, because they eliminate regional variation from our estimates. Our map of adjusted happiness (Figure 2) shows clear regional patterns, and the state fixed effects partial out that variation and more. With this caveat, column 8 shows the same regression as column 7, but adding state fixed effects. These fixed effects eliminate the otherwise robust relationship between urban growth and subjective well-being. But unfortunately they do not tell us whether this reflects different modes of implementing the BRFSS or is simply because the bulk of geographic differences in subjective well-being are regional in nature.

As we will see in the next sub-section, it turns out that the growth-happiness relationship is driven by the lower end of the city growth distribution. This part of the relationship remains extremely robust to state fixed effects, reducing the importance of distinguishing between columns 7 and 8 of Table 3.

The Non-Linear Relationship between Unhappiness and Population Growth

Figure 6 shows the correlation between population growth and adjusted life satisfaction. As the figure makes clear, the effect is much stronger at the lower end of the population change distribution. Low levels of happiness are particularly common in areas that are declining in population, but higher levels of happiness are not especially prevalent in areas where population is growing rapidly.

There are several hypotheses that could explain this non-linearity. For example, if decline is actually causing unhappiness—rather than merely being correlated with it—it might be that decline itself creates urban stresses, relative to stasis, but that urban growth doesn't particularly alleviate those stresses. Declining cities, such as Detroit, often find it difficult to cover the costs of their historic footprint and infrastructure. Decline may be particularly associated with crumbling social or physical infrastructure. It could also be that happiness is caused by other attributes that cause decline, but that among growing cities, the differences come mainly from differences in housing supply and economic productivity, which perhaps have little impact on happiness.

Whatever the cause, the non-linear relationship is obvious in the data. Table 4 shows the connection between SWB and urban growth in the BRFSS, where we have allowed the break in the slope to occur at a value of 0.75, the median for our sample of metropolitan areas. The first regression shows that controlling for exogenous demographic controls, the coefficient on growth, when growth is below the median is 0.214, meaning that a 0.5 change in log population growth is associated with a 0.1 standard deviation increase in SWB. The result is extremely significant and remains so in the second regression, where we include the endogenous demographic controls. In this second regression, the coefficient drops to 0.134, meaning that a 0.5 change in log population growth is associated with a 0.065 standard deviation increase in SWB. This is roughly equivalent to one standard deviation of the metropolitan area fixed effects, and roughly equivalent to the difference in SWB between high school graduates and individuals who have some college education.

In regression 3, we include controls for income and employment status. While we recognize endogeneity of these outcomes with respect to local labor market conditions, we still think it is worthwhile knowing whether the connection between urban decline and unhappiness disappears when we control for them. In this case, the coefficient falls to 0.101. In regression four, we control for health status (including both a general question about overall health status and a question about days spent ill over the past year). The coefficient falls to 0.097 and remains quite statistically significant. In our last specification, we add state fixed effects, but exclude the health and income questions, and estimate a coefficient of 0.078. Appendix Table 3 demonstrates that the relationship in this final column is robust to numerous other functional forms for the non-linearity.

In all cases, the coefficient is robust statistically and the magnitudes remain quite similar. While it is certainly true that controlling for education and family status significantly reduces the estimate coefficient, other individual controls change the coefficient only slightly. We believe that this suggests that this effect is less likely to reflect unobserved heterogeneity, but to address that issue we turn to the NSFH.

Urban Decline and Unhappiness with Movers and Stayers

We now ask whether the unhappiness of declining cities appears to be limited to longer term residents and whether these results remain when we control for individual fixed effects. Table 5 shows our results using the NSFH.

In its first two waves, the NSFH is a clean panel that can in principle enable us to look at SWB for people who move between areas. Unfortunately, the third wave of the NSFH does not have geographic identifiers and that prevents us from examining movers. We address two issues using these data. First, we examine the impact of decline on SWB using individual fixed effects, so our identification comes from individuals who move across areas. Second, we focus on the second wave and examine whether decline has smaller or larger effects for individuals who have moved since the first wave. Two significant challenges with the NSFH are that the samples are small and the time between the first and second waves is small (under five years). This means that the number of movers is smaller still.

The first regression shows the effect of the population growth spline with exogenous demographic controls. The coefficient is 0.14, somewhat smaller than in the BRFSS, but the question is different and the controls are not identical. In the second regression, we add endogenous demographic controls and find an estimate of 0.108, which is similar in magnitude to the BRFSS. The third regression adds income and employment controls, and the coefficient actually rises to 0.121. In those years, incomes were higher rather than lower in declining cities.

In the fourth regression, we look only at observations in the second wave of the NSFH, so that we can estimate whether the coefficient on decline is different for individuals who moved into the metropolitan area between the first and second wave. The coefficient on decline for stayers is roughly the same as the coefficients in the first three regressions. The interaction between the decline measure and being a mover is negative, meaning that decline is less strongly associated with unhappiness for the movers. However, while the interaction is not small, it is not distinct from zero. It is difficult to conclude much from this regression.

In the fifth regression, we include individual fixed effects and the correlation with urban decline vanishes. After examining a figure looking at the correlation between the area happiness fixed effects and growth, we noticed that there were a number of extremely small cities which had movers with strikingly large changes in subjective well-being.

In the sixth regression, we include only areas that had at least 250 respondents across two NSFH waves, which perhaps increases our confidence that this sample reflects a random sample of the city. In this case, we find the same non-linearity as we did previously, although both the standard error and the coefficients have increased. The fragility of these results leaves us with no certain conclusion, and regression four leaves open the interpretation that unobserved heterogeneity drives the results. But the result from regression five also makes it quite possible to conclude that there are differences between growing and declining cities even after controlling for individual fixed effects.

One possible explanation for the relationship between decline and unhappiness is selective migration. Individuals who leave declining cities may be happier than their neighbors, or growing cities may attract individuals who are happier than the population as a whole. The panel nature of the NSFH allows us to test this hypothesis. In Table 6, we focus on the 1513 individuals in our sample who moved MSAs between waves 1 and 2.

Columns one and two use the entire NSFH sample, in order to test whether individual and PMSA characteristics in wave 1 predict whether an individual moves between waves 1 and 2. Both columns control for subjective well-being in wave 1, the PSMA population growth spline of an individual's wave 1 PMSA, our standard set of exogenous and endogenous individual controls as well as income in wave 1. In column one, the upper part of the population growth spline is positively predictive of mover status, reflecting the high degree of population churn in the upper tail of growing cities. Subjective well-being in wave 1 is not predictive of whether an individual will move between waves 1 and 2.

Column two adds an interaction between individual wave 1 subjective well-being and the population growth spline. Subjective well-being is now marginally positive and significant. Critically, the interaction between the lower spline and subjective well-being is negative and significant. Happier people are less likely to leave declining cities, relative to rising cities. Put another way, we can reject the hypothesis that the happiest individuals are selectively moving out of declining areas.

In columns three and four, we test for the hypothesis that happier migrants select growing cities. We focus on the 935 movers in our sample for which we have data on PMSA population for waves 1 and 2. In column three, we use our set of exogenous controls, wave 1 individual subjective well-being, and wave 1 PMSA population growth spline. In column four, we add controls for wave 1 endogenous individual characteristics and income. Although we cannot reject a positive relationship between wave 1 subjective well-being and wave 2 PMSA population growth, we find no evidence for selection of individuals with higher subjective well-being into growing cities.

Finally, columns five and six analogously assess whether happier migrants select happier cities using data from all 1513 movers in the NSFH. In this specification, we also find little connection between wave 1 "happiness" for movers and choosing, conditional upon moving, to relocate to a happier locale. In Column six, we add controls for endogenous characteristics and income in wave 1. The positive relationship between wave 1 and wage 2 subjective well-being decreases in size and continues to be insignificant. The data does not support the hypothesis that unhappy migrants move to declining or unhappy cities, but the results are not strong enough to reject the possibility of selective migration.

Table 7 now turns to a different data set, the General Social Survey (GSS). The public version of the GSS contains state name and city level population. These two variables enable us to predict the population decline in the area with a fairly high degree of accuracy for the overwhelming majority of data points.

In regression one we again estimate the spline controlling for exogenous individual attributes, this time in the GSS. We continue to find a strong positive relationship between growth and happiness for the areas where growth rates are below the sample median. The second regression adds additional (potential endogenous) controls, such as income and family size, and the coefficient declines only slightly. The third regression interacts these variables with an indicator variable denoting whether the individual has moved across metropolitan areas since age 16. The interaction between this variable and population decline is negative, but very close to zero. In this larger sample, we see little evidence suggesting that the unhappiness associated with urban decline is limited to longer term residents.

Can Urban Disamenities Explain the Correlation between Unhappiness and Urban Decline?

In Table 8, we ask whether observable urban disamenities can explain the correlation between unhappiness and urban decline. We return to our core BRFSS specification, with exogenous but not endogenous individual controls, and include correlates of decline one at a time to test whether these variables reduce the coefficient on urban decline. While none of these estimates can be taken as being causal, they represent a rough pass at judging whether the correlation between decline and happiness merely represents the correlation between decline and some other more important variable.

Our first control is January temperature. The correlation between warm weather and metropolitan growth is well known (Glaeser and Tobio, 2009), and it is certainly possible that tough winters are depressing. While Oswald and Wu (2010) find that climate has a significant relationship with self-reported happiness, we find no connection in our specification once we have controlled for population growth non-linearly. Moreover, this control does little to the estimated coefficient on population decline.

Our second climate variable is precipitation, measured in annual inches of rain. Again, as the second regression in the table shows, this variable has little correlation with SWB in our data and does little to the coefficient on decline. The third variable we test is the log of the number of serious crimes per capita, and again it has little significance and only moderately reduces the estimated coefficient. Some of this change reflects the slightly smaller sample of metropolitan areas for which we have crime data. While being victimized may certainly make someone unhappy, it seems quite possible that crime is sufficiently concentrated in certain population subgroups that it has little impact on average happiness.

The fourth variable captures pollution, which might well be higher in America's erstwhile industrial heartland. We have tried many difference measures of local pollution levels, but none of them correlate well with happiness. Regression four shows total particulates (mean of 10 micron particulate matter, from 2000) and it has little correlation with happiness and does little to change the connection between SWB and urban decline.

Our fifth variable is the Gini coefficient, which measures income inequality as of the year 2000. While Alesina, Di Tella and MacCulloch (2004) find that happiness decreases with inequality, especially in Europe, we find a slight positive relationship between happiness and inequality across U.S. metropolitan areas. Moreover, controlling for inequality does little to change the estimated impact of population decline on unhappiness. The weak connection between inequality and SWB in the BRFSS is somewhat odd, because it is quite strong in the General Social Survey (Glaeser, Resseger and Tobio, 2010).

In the sixth regression, we see that including all of the variables reduces the coefficient on the decline from 0.21 to 0.156. Adding the endogenous demographic controls causes the coefficient to drop further to 0.08. This coefficient should be compared with the Table 3 coefficient of 0.134, which is the effect of decline on happiness without these other amenity controls, but with endogenous demographics. Finally, in the last regression, we include state fixed effects, which changes the coefficients on some of the area amenity controls but have little impact on population growth coefficients.

Is the Unhappiness of Declining Cities New or Old?

Historical data can help us assess whether the relationship between unhappiness and decline reflects the impact of decline itself, or whether these now declining cities were historically defined more by productivity than by pleasure. According to the first view, Detroit was once a place of happiness as well as prosperity, but as the prosperity declined, and the social problems increased, unhappiness spread. According to the second view, Detroit was unhappy even during its heyday, but historically, its residents were well compensated for their joylessness. Capital and labor were historically located in the city because it had natural advantages, such as access to waterways that made up for the loss in happiness.

The era of comprehensive urban happiness measures really only began ten years ago with the BRFSS. The NSFH goes back twenty years, but even that is a relatively short historical window. To investigate the more distant past, we turn to two data sets the General Social Survey (or GSS) and Gallup polls from the 1940s. The GSS has the advantage of allowing relatively comprehensive personal controls, but it dates only back to the early 1970s. The Gallup samples are small, do not include metropolitan area identifiers, and contain only limited number of personal controls.

Our approach is to estimate the impact of area-level population change and then to examine how this effect changes over the decades. We do this using the General Social Survey in the last three regressions of Table 7. We again estimate a spline for population growth, but we interact the coefficients on that spline with indicator variables that represent each decade. The population growth is defined over the entire 1950-2000 period, but the interactions allow the connection between decline and happiness to differ across the decades.

In Regression 4, we control for standard demographic variables and a year trend variable. As the regression shows, the interaction is strongly negative after the 1970s, meaning that the correlation between unhappiness and decline has decreased over time. Indeed, by the 2000s, the connection has disappeared entirely, which is of course, not what we observed in the BRFSS.

This shows that the cities that are declining over the entire period were unhappier in the 1970s, relative to other areas, than they were after 2000. These results are compatible with the view that unhappiness caused the decline or that declining cities have long-standing attributes associated with unhappiness, but they seem don't seem compatible with the view that unhappiness has grown following decades of decline.

Regression five of Table 7 includes controls for the endogenous demographics. While the overall negative relationship weakens, the time pattern is unchanged. The sixth regression includes controls for income and unemployment. Again, the basic time pattern remains clear. Declining cities were even unhappier in the past than they are today.

We now turn to our Gallup poll results. These results use three polls from the 1940s. The questions asked (detailed in the Data Appendix) are not precisely the same as the other SWB surveys, so magnitudes may not be easy to compare. Nonetheless, this survey provides us with our only window onto the more distant past. The Gallup poll provides us with two area-level pieces of information that we use in our regressions. We know the broad city-size categories inhabited by the residents. We also use the state. We use the information both by estimating a basic city-size effect and interacting city size with a dummy variable indicating whether the metropolitan areas in the state had population or income growth below the median level in the overall sample.

We have four regressions in our sample. The first regression shows the basic effect of city size. Residents of cities with more than 500,000 inhabitants were about four percent less likely to say that they were less happy in the 1940s. This supports the idea that big cities during this era had lower levels of subjective well-being.

In regression two, we add a low population growth dummy and interact city size with this dummy. In regression three we do the same with a low income growth dummy, and in regression four we use a low temperature dummy. The results are deeply inconclusive. Table 9 shows only the dummy variables for each regression, as none of the interactions are statistically significant. This is partially because the Gallup sample includes very few people in the sunbelt metropolises that grew over the next decades. Yet overall, larger cities (as opposed to larger metropolitan areas), did typically decline dramatically between 1950 and 2000. In all four regressions, residents of cities with more than 500,000 inhabitants were four to six percent less likely to say they were happy in the 1940s. The results of these regressions coincide with the fact that eight of the ten largest U.S. cities in 1950 lost at least one-fourth of their population over the next 50 years. We believe that these Gallup results again support the view that the large cities of the 1940s, which typically did decline, were also places marked by somewhat lower happiness levels.

These results are hardly definitive, but taken together they suggest that urban unhappiness is not exclusively recent. The GSS shows larger results in the past than in the present. The Gallup results show little connection between happiness and urban growth, but they do support the idea that happiness was lower in large cities in the 1940s, and most of those cities have subsequently declined.

These results correspond to results we can see in the BRFSS estimates. The correlation between the logarithm of metropolitan area population in 2010 and adjusted life satisfaction is 0.03. The correlation between that same happiness outcome and the log of area population in 1950 is -0.28.

III. Why Does Happiness Differ Across Space?

If self-reported happiness has any equivalence to the economist's concept of utility, then modestly enduring differences in self-reported life satisfaction seem to challenge the view that migration and the free operation of housing markets ensure that utility levels are equalized across space. Alternatively, if there are persistent differences in subjective well-being for identical people across space and a spatial equilibrium does hold, then this would imply that subjective well-being is just not equivalent to the economists' conception of utility.

Perhaps the differences that we measured above may not really represent differences in subjective well-being among otherwise identical human beings. The residents of declining cities may have less marketable skills, of various forms, than residents of growing cities, and as such, they would naturally earn less and have lower levels of life-satisfaction or utility in any metropolitan area. Yet our results control for a bevy of individual characteristics and controlling for added metropolitan area level variables, including the percent with college degrees or the share of the population that is white, only modestly reduces the relationship between decline and self-reported life satisfaction. The estimated relationship actually increases in magnitude if we restrict our samples to metropolitan areas with relatively similar levels of college graduates.[7] Finally, while the individual fixed effects results on urban decline were inconclusive outside of the larger cities, there are still significant differences in SWB across cities when we control for individual fixed effects.

It is also possible that individuals on the margin of moving across areas receive the same welfare, but that infra-marginal individuals differ in their average level of well-being across space. Yet for this view to be correct, we would need an explanation of why the average infra-marginal welfare in declining areas is significant lower than in growing areas, even if the marginal happiness levels are the same.

[7] The coefficient when our happiness variable is regressed on the change in population between 1950 and 2000 is 0.023. When we control for share of the population with college degrees and percent white, the coefficient drops to 0.02. When we restrict our sample to metropolitan areas in which twenty-to-thirty percent of adults have college degrees, then the coefficient rises to 0.031.

Another interpretation is that when equivalent individuals *made* location decisions, their expected happiness *was* equal across space, but *ex post* some migrants have fared worse than others, either because they were bad at projecting the happiness that different places bring, or because some areas have received particularly adverse shocks. According to this view, *ex post* welfare differs across space, even though *ex ante* welfare does not. But if this view is correct, then the connection between urban decline and unhappiness should exist primarily for longer term residents of the area, such as people who are unlikely enough to be born in metropolitan areas in decline, not recent migrants. Yet as we have discussed, the connection between unhappiness and urban decline is stronger for individuals who chose to come to the area as adults than for individuals who were born into the area. Moreover, given the well-advertised urban problems of many declining cities such as Detroit, it is hard to imagine that migrants are all that surprised—although it is certainly true that there are general problems in forecasting happiness (Gilbert, 2006; Kahneman and Krueger, 2006).

Is Happiness a Measure of Utility?

While admitting that the preceding facts are open to multiple interpretations, we focus on one particular interpretation: individuals maximize neither happiness nor life satisfaction, and for the right reward, are willing to sacrifice both. According to this view, individuals in less happy areas are foregoing well-being in order to gain some other advantage. This view does not suggest that SWB and happiness are meaningless concepts. Surely a sense of well-being is desirable. But we consider the view where their meaning has little in common with the economists' conception of utility, which is merely a representation of choice. In standard microeconomic theory, an outcome yields higher utility if and only if it is preferred.

The debate over whether individuals either do or should maximize happiness or SWB is ancient and intellectually rich. Bentham (1789) famously wrote that "Nature has placed mankind under the governance of two sovereign masters, *pain* and *pleasure.* It is for them alone to point out what we ought to do, as well as to determine what we shall do." Bentham's claim is that happiness is both the positive and normative determinant of behavior. He greatly influenced subsequent 19th century economists such as John Stuart Mill, who wrote, "The creed which accepts as the foundation of morals, Utility, or the Greatest Happiness Principle, holds that actions are right in proportion as they tend to promote happiness, wrong as they tend to produce the reverse of happiness."

These economists are reflecting a far more ancient philosophical tradition. Socrates' student Aristippus founded the Cyrenaic School, which taught a strongly hedonistic philosophy, emphasizing pleasure as life's central goal. The later Epicureans shared some of these views, although Epicurus thought that pleasure was achieved by simple modesty rather than riotous living. In his letter to Menoeceus, Epicurus writes "When we say, then, that pleasure is the end and aim, we do not mean the pleasures of the prodigal or the pleasures of sensuality."[8] Giants of medieval philosophy, including Augustine and Aquinas, also accepted that human beings pursued happiness above all, but taught that true happiness is to be found by following God's will.

Some modern researchers on happiness, though certainly not all, have also often conflated happiness with utility (Alesina, Di Tella and MacCulloch, 2004) or at least social welfare (Easterlin, 1995).[9] Yet it is quite possible to believe that happiness is interesting and important, without accepting the equivalence. There is also an equally ancient and distinguished philosophical tradition that strongly rejects the notion that individuals either do or should maximize happiness.

While the Epicureans believed strongly in maximizing pleasure and minimizing pain, the Stoics certainly did not. About 1900 years ago, Epictetus wrote "What is our nature? To be free, noble, self-respecting….We must subordinate pleasure to these principles, to minister to them as a servant." Epictetus is at least making the normative claim that there are other goals—freedom, nobility, self-respect—that distinctly trump happiness. Kant, similarly, argued that morality called us to try to be worthy of happiness, but that happiness itself did not automatically flow from the morality that should be humanity's ultimate goal.

For at least a century, mainstream economists have moved away from equating utility with happiness. Fisher (1892) wrote "It is not necessary for [the economist] to take sides with those who wrangle to prove or disprove that pleasure and pain alone determine conduct." Stigler (1950) noted that "the one changing element in the general knowledge was the growing skepticism of hedonism in academic circles." More recently, Becker and Rayo (2008) wrote, "These examples suggest an alternative interpretation of the happiness data, namely, that happiness is a commodity in the utility function in the same way that owning a car and being healthy are."

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[8] In the Nichomachean Ethics, Aristotle urged the pursuit of "Eudaimonia", which has been translated as happiness. For example, Browne (1889) translates Aristotle as writing "Happiness, then, appears something perfect and self-sufficient, being the end of all human actions." Other scholars, however, contend that the word, which combines the roots of good and spirit, should be not be seen as equivalent to happiness.

[9] Alesina et al. (2014, p. 2010) explicitly state that they "measure 'utility' in terms of survey answers about 'happiness'." They elaborate in footnote 7 that they, and in their view much of the literature on economics of happiness, aim to measure "*experienced* utility, a concept that emphasizes the pleasures derived from consumption". They view these survey responses, in certain circumstances, as "reasonable substitutes to observing individual choices" (footnote 7, p. 2012). Many other prominent papers in this literature implicitly posit such an equivalence, such as Easterlin (1995, p. 36). Easterlin writes, "Formally, this model corresponds to a model of interdependent preferences in which each individual's utility or subjective well-being varies directly with his or her own income and inversely with the average income of others."

Of course the literature has also considered many subtle points about the appropriate conception of subjective well-being. For example, Kahneman and Thaler (1991) and Kahneman and Krueger (2006) distinguish between decision utility and experienced utility. We certainly do not claim to introduce a novel distinction here. Our contribution, in part, is to use the decision-utility maximization embodied in spatial equilibrium to put more structure on the theoretical and empirical relationships between choices and subjective well-being.

Perhaps the most obvious piece of evidence supporting Becker and Rayo's interpretation is the fact that parents of small children typically report unusually low levels of happiness or life satisfaction (Baumeister, 1991). If happiness were equivalent to utility, then presumably this relationship should act as a great deterrent against the survival of the species. Yet in Becker and Rayo's formulation, this negative relationship is no puzzle at all, as parents receive ample compensation in the form of progeny, for their suffering.

Some suggest that in its very wording, life satisfaction should capture all the elements of utility. While it seems wildly implausible to hope that maximizing utility should automatically mean maximizing joy or happiness, it is more conceivable that individuals answer the question about life satisfaction in such a way that actually ranks their preferred outcomes, as does a utility function. In this case, an individual who has received a more preferred outcome will report a higher level of life satisfaction. Hence utility and subjective well-being become one and the same, even though they are not themselves the ultimate desiderata, because they act as a thermometer which measure how well people have achieved their goals.

Yet, upon reflection, this view seems barely more tenable than the view that happiness should miraculously map into with human preferences. An individual may choose a more competitive environment with more opportunity to shape the world, and yet know that this world will – by opening up opportunities and inviting comparisons with high achievers—lead to less satisfaction later in life. A utility-maximizing person could select a Ph.D. program, or a city, despite recognizing that it will leads to less satisfaction.

Among all members of the classical economic tradition, Bernard de Mandeville, may be the most powerful proponent of the view that human beings should not maximize happiness, especially not in location choice. In *The Fable of the Bees*, he writes "To be happy is to be pleas'd, and the less Notion a Man has of a better way of Living, the more content he'll be with his own… the greater a Man's Knowledge and Experience is in the World, the more exquisite the Delicacy of his Taste, and the more consummate Judge he is of things in general, certainly the more difficult it will be to please him….But when a Man enjoys himself, Laughs and Sings, and in his Gesture and Behaviour shews me all the tokens of Content and Satisfaction, I pronounce him happy, and have nothing to do with his Wit or Capacity." Clearly, de Mandeville thinks little of happiness. When he writes "ask'd where I thought it was most probable that Men might enjoy true Happiness, I would prefer a small peaceable Society, in which Men, neither envy'd nor esteem'd by Neighbours, should be contented to live upon the Natural Product of the Spot they inhabit, to a vast Multitude abounding in Wealth and Power," he is not espousing such places, but arguing that it is perfectly sensible to choose busier, but less happy, locales.

We do not mean to suggest that happiness isn't desirable, and for that reason, if the spatial equilibrium logic of Rosen (1976) and Roback (1979) is correct, then there must be some sort of compensation offsetting the unhappiness of declining cities. Individuals must be receiving some other benefit, such as higher real wages, that offset the costs of lower life-satisfaction.

Otherwise, it would be hard to understand why individuals remain in unhappy cities. We formalize these issues in the model that follows.

Happiness and Utility

To formalize this discussion, we begin with a general framework meant to capture the difference between happiness and utility. We then adapt our structure to deal with cities and urban decline, which requires considerably more assumptions about structure and ultimately even functional forms. This latter section puts forward the model that will be taken to the data in Section IV.

In Becker (1966), individuals maximize a function $U(\cdot)$ defined over a vector of objectives $\tilde{Z}$, where each element in that vector Z_i is a function of time spent (t_i) and spending (s_i). One possible approach is to assume that life satisfaction is defined over an alternative function $H(\cdot)$ of those same objectives, but that approach provides little guidance for modeling or testable implications.

We assume that subjective well-being represents an alternative function $W(\cdot)$ over the same set of objectives. It may be that welfare is a function of well-being and other objectives, or that well-being is simply a slightly different function of exactly the same inputs that guide utility. In the first case, utility can be described as $U\left(W\left(\tilde{Z}\right), \tilde{Z}_{NH}\right)$, where $\tilde{Z}_{NH}$ refers to those objectives that enter into utility directly, such as child-rearing, as well as possibly also impacting well-being.

We will approach well-being and utility as reflecting a combination of experiences and achievements. Well-being or happiness, will be conceived as experience-based utility, following Bentham (1789) and Kahneman and Krueger (2006). Individuals care about experienced utility, but they also care about achievements, which can also be produced with time and money. We lose little generality by assuming at this point that there is a single achievement, which is produced with achievement-specific time denoted t_A and achievement-specific spending s_A. Individual earnings are the product of wages and time spent working wt_w and unearned income y_0, which includes the fixed cost of housing.

Both time spent working and time pursuing the alternative achievement convey experienced utility per unit time of t_w and t_A respectively. The remainder of hedonic time generates well-being equal to $h(s_h)t_h$, where s_h reflects the total amount of spending on these activities. The term $h(s_h)t_h$ is meant to be an aggregate of all other time, and even includes sleeping.

The individual's problem can thus be written as maximizing:

(5) $U(h_w t_w + h_a t_a + h(s_h)t_h, Z(s_a, t_a))$

subject to the time budget constraint $t_w + t_a + t_h = 1$ (we have normalized the total time available to equal one) and the cash budget constraint $wt_w + y_0 = s_h + s_a$. The two budget constraints can be combined to create a single total budget constraint of $w + y_0 = w(t_a + t_h) + s_a + s_h$.

In this model, as in almost all economic models, more income is preferred to less, and translates into higher levels of utility. Yet the link between happiness and wages is less clear. If, for example, $Z(\cdot)$ is produced entirely with earnings, then as long as the uncompensated wage elasticity is positive, happiness diminishes with wages even though utility increases. If $h(s_h) = h_0$ is independent of income, then the derivative of happiness with respect to the wage equals $(h_0 - h_w)$ times the derivative of t_h with respect to the wage, which equals

(6) $\frac{\partial t_h}{\partial w} = \frac{-wZ'(s_a)U_Z + (1-t_h)Z'(s_a)\left((h_0-h_w)U_{HZ} - wZ'(s_a)U_{ZZ}\right)}{-(U_{HH}(h_0-h_w)^2 - 2(h_0-h_w)wZ'(s_a)U_{HZ} + (wZ'(s_a))^2U_{ZZ})}$

Across space, the impact of income on happiness may be even more negative. Suppose that amenities are constant across space, and that utility levels are unchanged with changes in wages; $\frac{\partial y_0}{\partial w} = -(1 - It_0)$: the change in housing costs exactly offsets the change in earnings. If this is the case, then in the case discussed above, where spending does not impact the hedonic flow of time, then $\frac{\partial t_h}{\partial w} = \frac{-wZ'(s_a)U_Z}{-(U_{HH}(h_0-h_w)^2 - 2(h_0-h_w)wZ'(s_a)U_{HZ} + (wZ'(s_a))^2U_{ZZ})} < 0$, so happiness is always lower in higher wage cities. Since the impact of area level wages is a compensated, rather than an uncompensated change in wages, it will invariably cause an increase in hours worked and a decrease in time spent in household production.

We now turn to the spatial equilibrium, where we assume that $h_w = h_a = 0$. We also assume a Cobb-Douglas utility function, with a weight of α on happiness, and power functions for producing the other goods, and that $Z(s_a, t_a) = z_0(s_a)^z(t_a)^{1-z}$, where z_0 is a city-specific production shifter. We assume that time spent at work is fixed at $\hat{t}_w$ but that time can still be allocated between leisure and the other achievement. Further, $h(w\hat{t}_w + y_0) = h_0(w\hat{t}_w + y_0)^\gamma$, where h_0 is a city-specific amenity. Given these assumptions, then indirect utility is proportional to $(h_0)^\alpha(z_0)^{1-\alpha}(w\hat{t}_w + y_0)^{\alpha\gamma+(1-\alpha)z}$ and happiness is proportional to $h_0(w\hat{t}_w + y_0)^\gamma$.

The Cobb-Douglas welfare function generates a happiness-income tradeoff of $\frac{d\log(Happiness)}{d\log(Income)} = -\frac{1-\alpha}{\alpha}$. This tradeoff is a distinct concept from the derivative of happiness with respect to the wage (assuming unearned income is negligible), which equals γ.

We have two options here, choosing fixed or flexible working time, but the simpler functional forms come with fixed hours. In that case, the spatial equilibrium condition can be written as:

(7) $w\hat{t}_w + y_0 = k_0 h_0^{-\frac{\alpha}{\alpha\gamma+(1-\alpha)z}} z_0^{-\frac{1-\alpha}{\alpha\gamma+(1-\alpha)z}}$.

The values of h_0 and z_0 are determined both by natural amenities, such as climate, and amenities tied to public services, such as safety. Declining areas could well have lower levels of quality of life both because they are in relatively cold areas of the U.S. and because a reduced level of spending leads to lower levels of public amenities.

An urban equilibrium involves three separate equations. The first is the spatial equilibrium curve for consumers in which welfare—but not happiness—must equal a constant reservation utility across space. The second condition is that firm profits are equalized across space. The third condition is that the cost of housing equals the cost of supplying homes.

We assume a linear housing supply curve, so that the flow cost of housing in a city, denoted *r*, is $r = c_0 + c_1 \log(N_t) + c_2 \log(N_t/N_{t-1})$, where N_t reflects the population in the place, and we assume that $y_0 = -r$. This can be generated by an assumption that houses are created with a Cobb-Douglas utility function using traded and non-traded capital, where non-traded capital is in fixed supply. In principle, c_0, c_1 and c_2 might all vary across areas.

Finally, we have linear labor demand so that $w\hat{t}_w = A - B\log(N_t)$. This can be generated by assuming that there are a fixed number of firms with Cobb-Douglas production functions and two types of labor, one of which is traded and the other is not (Glaeser, 2007). Again, *A* and *B* might differ across metropolitan areas.

Using the housing supply curve, labor demand curve, and taking logs of equation (7) yields:

$$(8) \qquad log(N_t) = \frac{1}{B+c_1+c_2}\left(A - c_0 + c_2 Log(N_{t-1}) - k_0 h_0^{-\frac{\alpha}{\alpha\gamma+(1-\alpha)z}} z_0^{-\frac{1-\alpha}{\alpha\gamma+(1-\alpha)z}}\right)$$

$$(9) \qquad w\hat{t}_w = \frac{1}{B+c_1+c_2}\left((c_1+c_2)A + Bc_0 - \mathrm{B}c_2\log(N_{t-1}) + Bk_0 h_0^{-\frac{\alpha\gamma}{\alpha\gamma+(1-\alpha)z}} z_0^{-\frac{1-\alpha}{\alpha\gamma+(1-\alpha)z}}\right)$$

$$(10) \qquad r = \frac{1}{B+c_1+c_2}\left((c_1+c_2)\left(A - k_0 h_0^{-\frac{\alpha}{\alpha\gamma+(1-\alpha)z}} z_0^{-\frac{1-\alpha}{\alpha\gamma+(1-\alpha)z}}\right) + B\left(c_0 - c_2\log(N_{t-1})\right)\right)$$

$$(11) \qquad \log(Happiness) = \log\left(k_0^{\gamma}(1-\hat{t}_w)\right) + \frac{(1-\alpha)z}{\alpha\gamma+(1-\alpha)z}\log(h_0) - \frac{(1-\alpha)\gamma}{\alpha\gamma+(1-\alpha)z}\log(z_0).$$

Population is increasing with productivity, decreasing with the cost of providing housing and increasing with the two amenity variables. Income is rising with productivity and the costs of supply housing and falling with the two amenity variables. Housing rents increase with productivity, with the cost of housing and with the two amenity variables. Happiness is rising with the happiness-related amenity and declining with the non-happiness related amenity. This becomes a four equation system for empirical work, where the impacts of local variables can be traced through these four distinct outcomes.

In this formulation, happiness is a measure of local amenities—and local amenities only—because population and housing prices adjust to shifts in local demand and construction costs.

The spatial equilibrium requires that gaps in real income end up being proportional to happiness, holding as such happiness should be declining in real income. The slope is predicted to equal $\frac{(1-\alpha)z}{\alpha}$ on real income, which equals $\frac{(1-\alpha)}{\alpha}$—the basic happiness income tradeoff—times z—the elasticity of the non-happiness related component of welfare with respect to earnings.

We can also use the spatial indifference condition and find that happiness is proportional to $(z_0)^{\frac{\alpha-1}{\alpha}}(w\hat{t}_w + y_0)^{\frac{\alpha-1}{\alpha}z}$, meaning that holding z_0 constant, we should expect to find that richer places are less happy, and holding income constant, we should expect to find happier places deficient in some other desirable (non-happiness related) amenity. The unhappiness of declining cities, therefore, needs to be compensated either with higher real incomes or with some other asset.

IV. Are Individuals Compensated for Unhappiness?

In this section, we do not implement the four equation empirical estimation section discussed above, but rather restrict ourselves to a simpler empirical approach inspired by the theory. We will test whether individuals in declining, or unhappy, cities are being compensated for their misery by either lower housing costs or higher wages.

This approach begins with a simple view of America's changing urban system. We initially built cities in places where firms had a productive advantage because of proximity to waterways and coalmines. Moreover, we also built those cities in ways that favored productivity rather than pleasure. Over time, declining transport costs enabled capital and labor to flee low amenity places (Glaeser and Kohlhase, 2006) and move to "consumer cities" endowed with higher amenity levels (Glaeser, Kolko and Saiz, 2001). An increasingly wealthy population also built new cities that were more oriented towards consumer well-being.

Within the context of the model, this can be understood as a change in the covariance between productivity and the amenity parameters. In early 20th century America, productivity may have been higher in lower amenity places but in late 20th century America, that negative covariance disappeared. As a result, population growth was faster in places that had higher amenities initially and lower levels of productivity.

This argument provides a slightly different interpretation of the Easterlin (1974) result, at least insofar as it applies to America's metropolitan areas. In the early part of the 20th century, a city needed to be unpleasant to be productive. In the late 20th century, it did not. Since technological change favored pleasant, happier locales, it seemed as if happiness was tied to income growth, even if it was ultimately driven by the local environment.

We now turn to the question of compensation. Since no one would presumably have built an intrinsically unhappy city unless it is more productive, we first look at income levels in 1940. We test whether the declining cities, which seem also to have been unhappy in the past, paid higher wages in 1940. We also look at housing rents and prices during that year, but housing quality controls are so weak, we are wary of putting too much weight on those results. We then turn to 2000 to test whether either wages or rents are compensating the residents of unhappy declining cities. Finally, we look at whether rents or incomes seem to be directly compensating for happiness in the 2000 Census.

Census Results for 1940

Table 10 provides our results for 1940. We begin with three regressions for income, in which we look at total earnings for males aged between 25 and 55. We include a full battery of controls for age, race and education. The first regression shows that as population growth increases by 0.1 log points, for the cities with population growth below the median, wages drop by 0.014 log points. Cities that would subsequently decline were very well paid in 1940. We do not mean to imply causality with this regression. The wages precede the decline and may have caused the decline. We mean instead to suggest that the residents of cities that declined after 1950, and that are unhappy today, were relatively well compensated in 1940.

The second regression repeats this exercise controlling for city size today. In this column, we simply include an indicator variable that takes on a value of one if the population of the metropolitan area is greater than five million. The coefficient on population is quite large, and it causes the coefficient on population growth below the median to decline to -0.1. The strong positive coefficient on large population size is also quite compatible with the compensation hypothesis, for the Gallup data show that people who live in extremely large cities were dramatically less happy in the 1940s.

As a third exercise, we also instrument for population growth using climate variables, including January and July temperatures and precipitation. The coefficient on population decline is largely unchanged from the second regression. We see this regression as more of a specification check, but it does seem to support the idea that the declining areas were built in ways and in areas that were not particularly prone to create happiness, but which were highly productive.

Regressions (4) and (5) in Table 10 provides results for housing prices and rents. In both cases, the declining cities also have higher housing costs. These higher costs would mean lower real incomes in these areas which should eat away some of the compensation received for living in less happy places. However, we are wary of drawing much from these regressions since we are not really able to control for housing quality in these regressions. As such, the results could just be showing that the residents of industrial cities in 1940 had substantially better housing than the residents of the Sunbelt in those years.

Census Results for 2000

Table 11 shows results from the 2000 Census. The first four regressions show results for income and there is no significant correlation with urban decline. The first specification includes only individual controls; the second specification includes the indicator variable for extremely large metropolitan areas. The third regression reduces the weight on observations from larger cities in the regressions, so that the results are not disproportionately dominated by two or three extremely large metropolitan areas. The fourth regression includes both the indicator dummy and the weights. All regressions paint a similar picture: declining metropolitan areas are not particularly well or poorly paid relative to the U.S. as a whole.

The next set of regressions show results for housing values. In this case, the first regression shows a coefficient of 0.13 which is not distinct from zero. However, this low coefficient appears to be driven primarily by New York City, which has extremely high housing values and relatively low growth rates. In the second regression, we control for large population size, which strongly influences housing values. With this control, we estimate a coefficient of 0.3 on population growth below the median. This implies that a 0.1 log decrease in population growth between 1950 and 2000 is associated with housing values that are 0.03 log points lower. The last two regressions find quite similar coefficient when we include the metropolitan population weights or include both the weights and the population control.

In the last four regressions of this table, this pattern reappears. With no controls and no weighting, there is no correlation between decline and weights. With either a large city dummy or population weights or both, the coefficient becomes significant and the elasticity ranges from 0.2 to 0.3. As such, the residents of declining cities may be less happy, but they are being at least modestly compensated for lower levels of happiness with lower housing costs.

In Table 12, we look directly at the correlation between happiness, housing rents and area incomes. We have again controlled for individual attributes, but distinct issues with this specification remain. If the spatial equilibrium is imperfect, then a temporary shock to local income should make people happier not unhappy. As such, we may not see the negative relationship between happiness and real incomes that is predicted by the model.

The happiness variable is not particularly correlated with area income, and the sign changes across the specifications.[10] One interpretation of this is that while people need higher real incomes to put up unhappy places, when people have higher real incomes they are happier. The offset between these two forces creates the near zero coefficients. The second set of regressions examine housing values, again the results are close to zero although they tend to be weakly positive.

The last set of results examines the connection between happiness and rental costs. While the coefficient in regression (9) is negative, the subsequent regressions are strongly positive. Again, New York is particularly important in these regressions and in driving the negative coefficient in

[10] Glaeser and Gottlieb (2008) present GSS data that also show a low correlation between happiness and income in the cross-section of cities.

the first regression. It is a large city with high rents and low self-reported happiness. When we control for being in a big city, or if we reduce the weight on observations for particularly large cities, the coefficient on the happiness measure ranges from 0.53 to 0.66. A 0.1 standard deviation increase in area level happiness is associated with a 0.06 log point increase in area rents.

This relationship is shown in Figure 7 which collapses the data to the metropolitan area level, but excludes California (which has much higher rents). The positive relationship is generally visible, but a small number of cities with higher rents and lower levels of self-reported happiness can be seen in the upper left hand corner of the graph. These are the large metropolitan areas of the east coast, such as New York and Boston. These places also tend to pay high wages, which is presumably how their residents are being compensated for lower levels of happiness.

In sum, this Table suggests that higher wages compensated for the unhappiness of cities that were large and productive in the 1940s, but would subsequently decline. The population decline has not offset the unhappiness, but is associated with lower housing costs that could partly compensate for the lower reported well-being in such places. This tradeoff is consistent with a model in which happiness is one argument in utility, but harder to reconcile with views that emphasize happiness as equivalent to utility, or as individuals' ultimate objective.

V. Conclusion

In this paper, we have documented significant differences in self-reported well-being across American cities that persist, even when we control for endogenous and exogenous demographics and even when we control for individual fixed effects. These facts are not reliably correlated with many area level attributes, but they do seem to be connected with urban decline across at least three large data sets. We do not interpret this correlation as suggesting that population decline causes unhappiness. Indeed, cities that have declined also seem to have been unhappy in the past, which suggests that a better interpretation might be that these areas were always unhappy—and that was one reason why they declined.

Differences in happiness and subjective well-being across space weakly support the view that the desires for happiness and life satisfaction do not uniquely drive human ambitions. If we choose only that which maximized our happiness, then individuals would presumably move to happier places until the point where rising rents and congestion eliminated the joys of that locale. An alternative view is that humans are quite understandably willing to sacrifice both happiness and life satisfaction if the price is right. This viewpoint rationalizes the well-known tendency of parents to report lower levels of happiness and life satisfaction. Indeed, the residents of unhappier metropolitan areas today do receive higher real wages—presumably as compensation for their misery.

Declining cities seem also to have been unhappy during the past, but in 1940, the cities that were prone to future decline earned outsized incomes, both nominal and real. The industrial cities of the Midwest may have reported lower happiness levels, but their residents were getting richer as a result. As transportation cost declines freed industry from the Great Lakes and the Coal Mines, we shouldn't be surprised that people left less pleasant locations. Today, the residents of cities that declined aren't receiving higher nominal wages, but they do seem to be paying lower rents. As such, the unhappiness of America's declining cities may have been compensated with higher incomes in the past and lower housing costs today.

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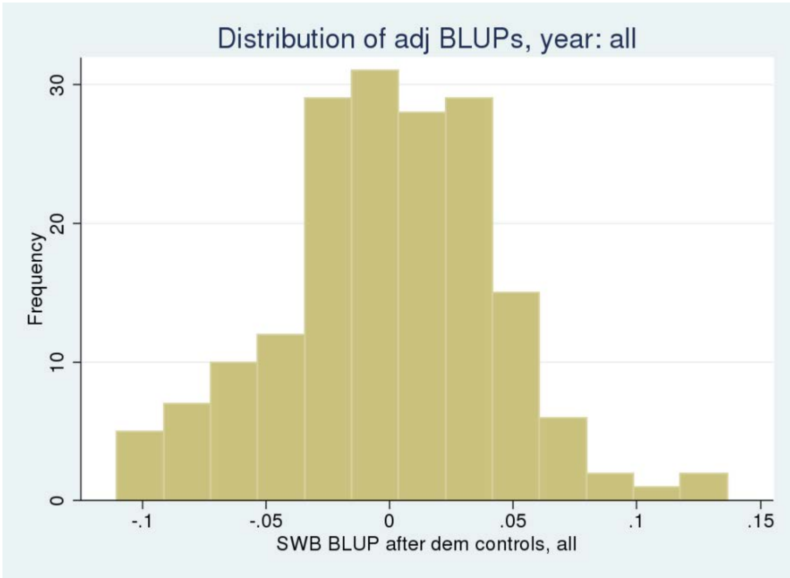
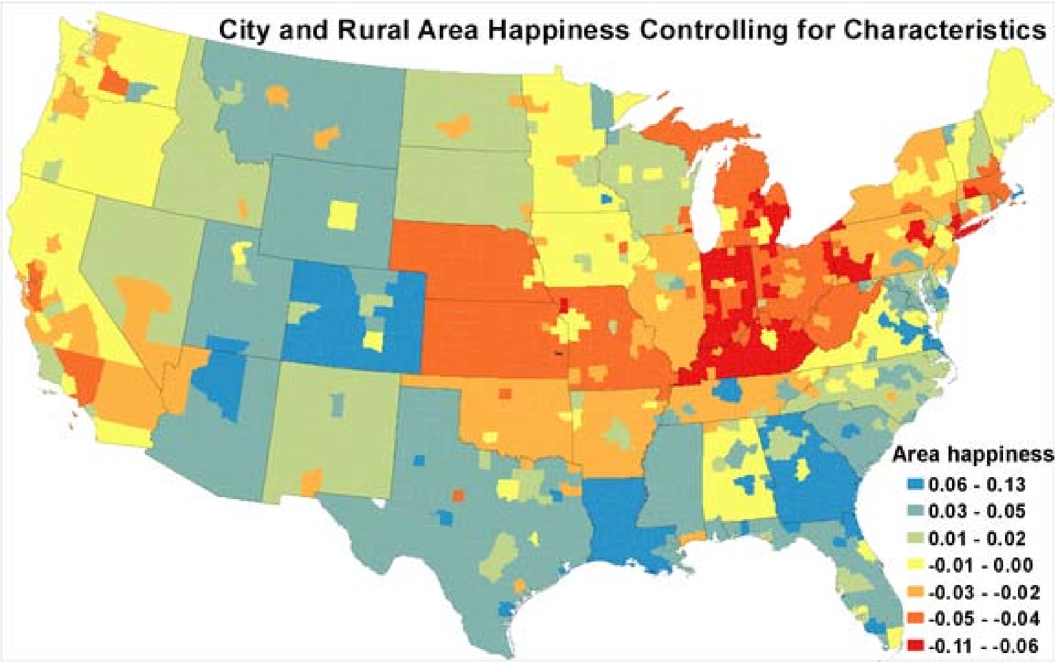
Figure 1: Distribution of Adjusted Life Satisfaction



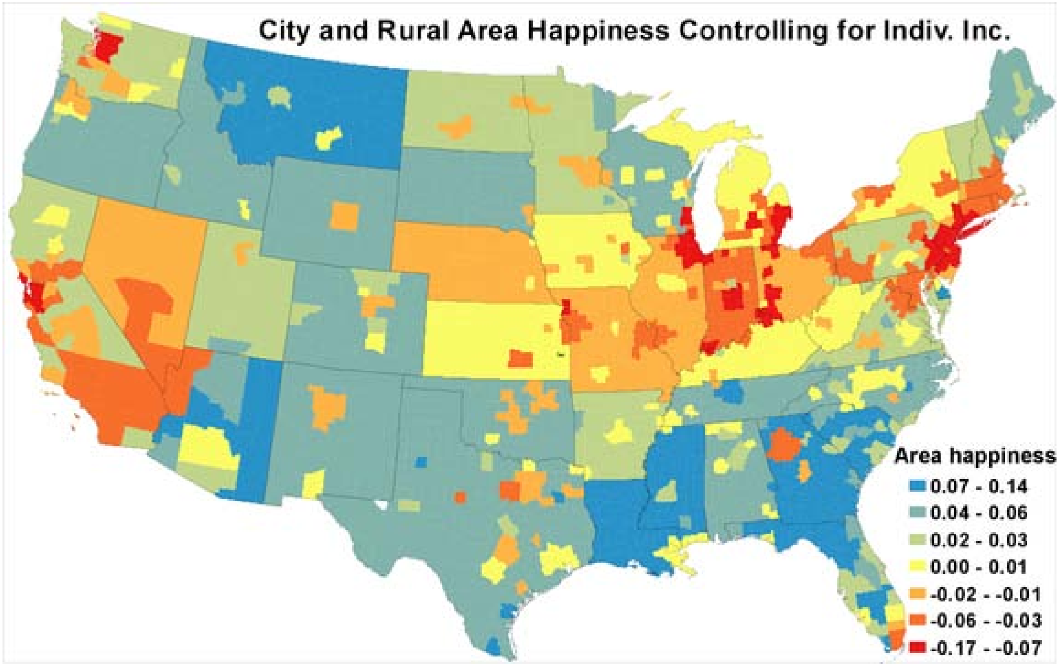
Source: This figure shows the distribution of metropolitan area adjusted life satisfaction after controlling for demographic covariates in a mixed effects model. Data are from CDC (2005-2009).

Figure 2: Estimated Metropolitan and Rural Area Adjusted Happiness



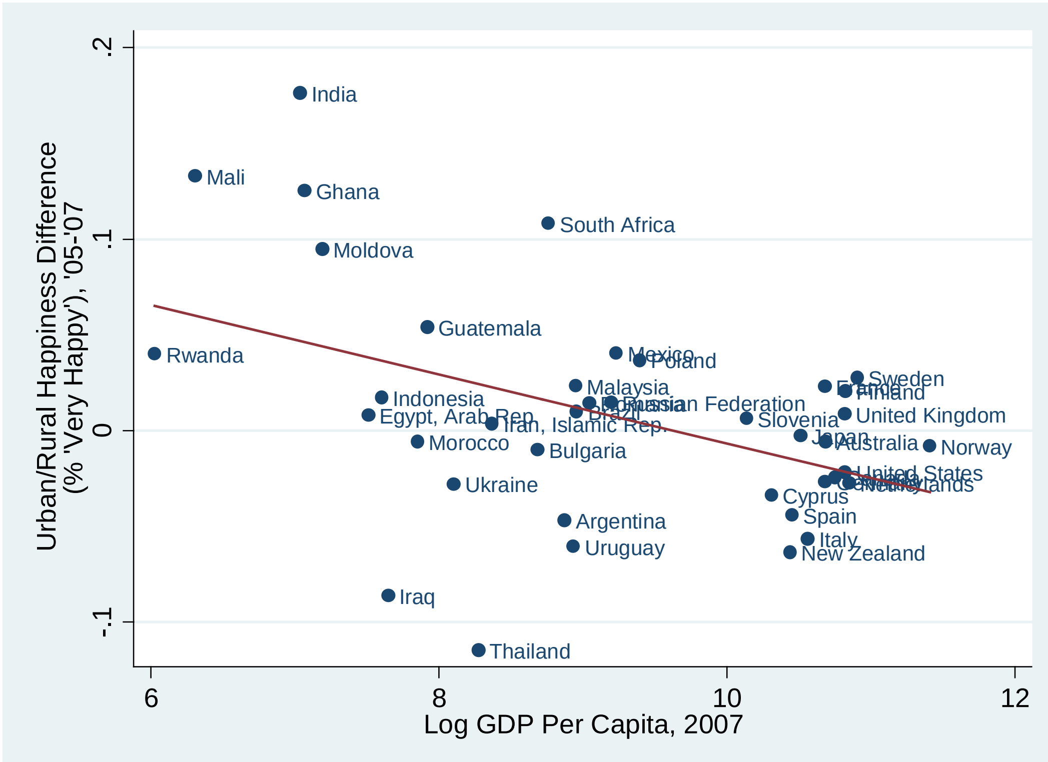
Source: This figure shows each metropolitan and rural area's adjusted life satisfaction, after controlling for demographic covariates in a mixed effects model. Data are from CDC (2005-2009).

Figure 3: Estimated Metropolitan and Rural Area Adjusted Happiness



Source: This figure shows each metropolitan and rural area's adjusted life satisfaction, after controlling for demographic covariates and individual income in a mixed effects model. Data are from CDC (2005-2009).

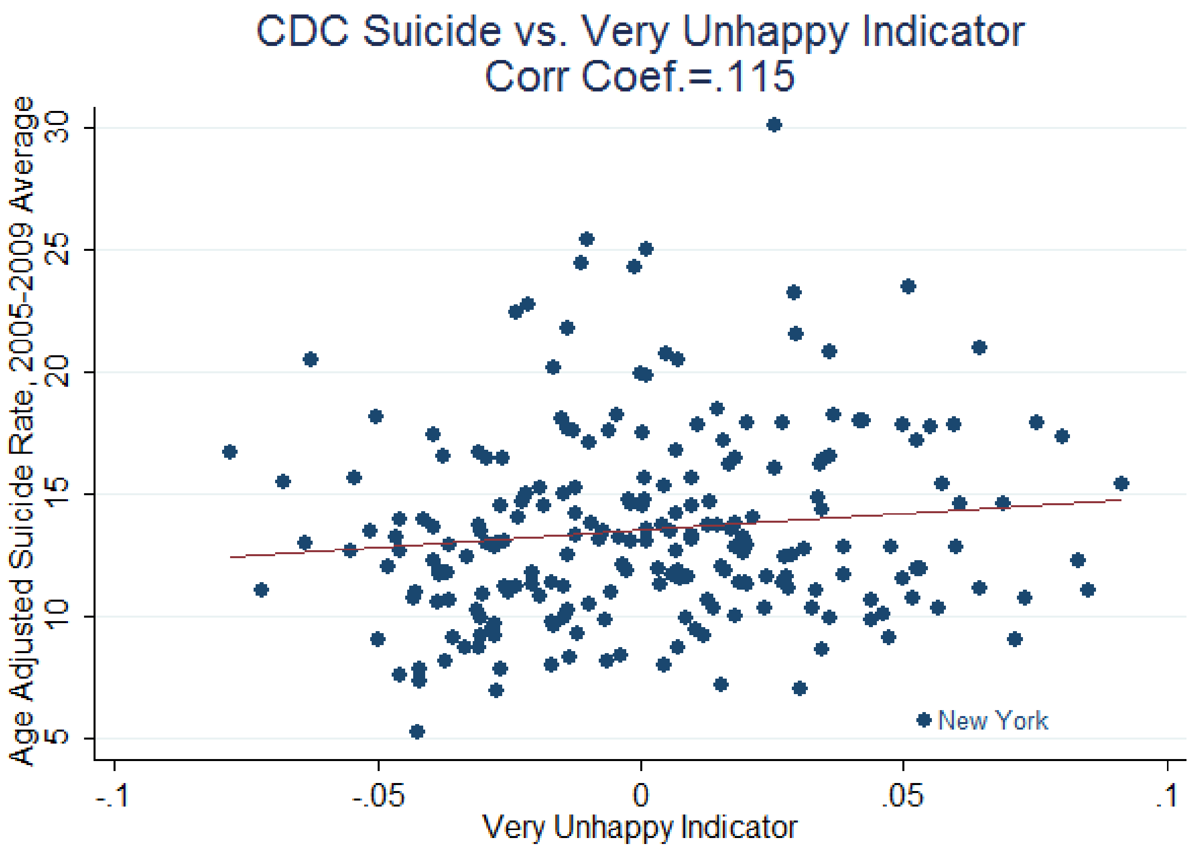
Figure 4: Urban-Rural Happiness Gradient vs. GDP Across Countries



Regression line: y = -0.0181 *Log GDP* + 0.174, N=39, R^2=0.20.

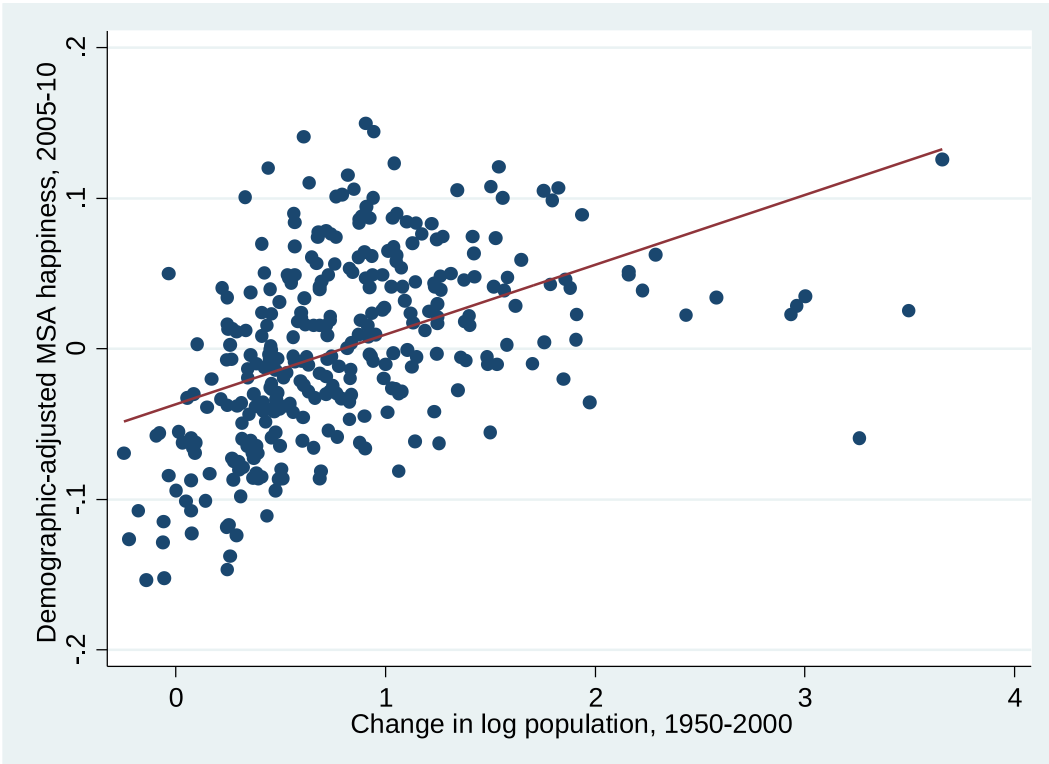
Source: World Values Survey and World Bank

Figure 5



This figure shows the age-adjusted suicide rate for each metropolitan area, against the (normalized) share of inhabitants saying they are "very unhappy." Data are from Behavioral Risk Factor Surveillance System Survey (CDC, 2005-2010) and National Suicide Statistics (CDC).

Figure 6: Population Change and Adjusted Happiness



Source: This figure shows each metropolitan and rural area's adjusted life satisfaction, after controlling for demographic covariates in a mixed effects model, against MSA population change from 1950 to 2000. Data are from CDC (2005-2010).

Figure 7: MSA Rent and Adjusted Happiness

Source: This figure shows each metropolitan and rural area's adjusted life satisfaction, after controlling for demographic covariates in a mixed effects model, against adjusted housing rent from the Census (the median of each MSA's residuals from regressing rent on housing characteristics). Data are from CDC (2005-2010) and Ruggles et al. (2010).

Table 1: Distribution of responses to life satisfaction questions

Panel A: BRFSS life satisfaction question, 2005-2009

Answer:	Number of respondents:
Very satisfied	717,779
Somewhat satisfied	766,374
Somewhat unsatisfied	72,258
Very unsatisfied	17,950
Total sample size:	1,574,361

Panel B: NSFH life satisfaction question, wave 1 (1987-1988)

Answer:	Number of respondents:
1-Very unhappy	244
2	206
3	522
4	1,894
5	2,667
6	3,073
7-Very happy	2,723
Total sample size:	11,329

Panel C: NSFH life satisfaction question, wave 2 (1992-1994)

Answer:	Number of respondents:
1-Very unhappy	153
2	145
3	438
4	1,271
5	2,253
6	2,370
7-Very happy	1,874
Total sample size:	8,504

Source: Panel A: Behavioral Risk Factor Surveillance System Survey (CDC, 2005-2009). Panel B: Sweet, Bumpass and Call (1988). Panel C: Sweet and Bumpass (1996).

Table 2

Happiness Levels Across Space, BRFSS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:					**Self-Reported Well-Being**					
Log Population, 2000	-0.0066	-0.0085**							-0.00325	0.000921
	(0.00577)	(0.00371)							(0.00463)	(0.00334)
% BA Grad, 2000			0.330***	0.0977					0.394***	0.185***
			(0.108)	(0.0768)					(0.114)	(0.0624)
% HS Grad, 2000					0.421***	0.0716			-0.276**	0.0893
					(0.151)	(0.116)			(0.125)	(0.0833)
Segregation Index, 2000							-0.160***	-0.130***	-0.130***	-0.0323
							(0.0379)	(0.0250)	(0.0342)	(0.0326)
Segregation x Black							-0.263***	-0.144***	-0.113**	-0.0573
							(0.0507)	(0.0482)	(0.0440)	(0.0387)
Segregation x Asian									0.0506	0.0872
									(0.0882)	(0.0582)
Segregation x HPI									-0.0370	-0.0488
									(0.151)	(0.154)
Segregation x Other									0.217**	0.230**
									(0.101)	(0.101)
Segregation x AIAN									-0.0695	-0.0576
									(0.0832)	(0.0822)
Segregation x Multiracial									-0.160***	-0.140***
									(0.0618)	(0.0527)
Segregation x Hispanic									-0.0549	-0.252
									(0.247)	(0.205)
Log Median House Value									-0.0398	-0.0447***
									(0.0258)	(0.0114)
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes
State Fixed Effects	No	No	No	No	No	No	No	No	No	Yes
Observations (Thousands)	1,185	1,185	1,185	1,185	1,185	1,185	1,134	1,134	1,134	1,134
R^2	0.007	0.076	0.008	0.076	0.008	0.076	0.008	0.076	0.076	0.078

Sources: Authors' regressions on microdata from the Behavioral Risk Factor Surveillance System Survey (CDC), U.S. Census (Ruggles et al., 2010), and Glaeser and Vigdor (2001).
Notes: All regressions control for year fixed effects, month fixed effects, age, race, and sex. "Additional controls" include education, marital status, and family size. Standard errors in parentheses are clustered at the MSA level (*** p<0.01, ** p<0.05, * p<0.1).

Table 3
Happiness and Urban Change, BRFSS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:				**Self-Reported Well-Being**				
Change in Log Population, 1950-2000	0.0635***	0.0412***	0.0174***				0.0270***	0.00312
	(0.0146)	(0.00925)	(0.00649)				(0.0104)	(0.00710)
Change in Log Income, 1950-2000				0.185***	0.119***	0.0586***	0.0597**	0.0301
				(0.0295)	(0.0192)	(0.0156)	(0.0298)	(0.0216)
% BA Grad, 2000							0.124	-0.0260
							(0.113)	(0.0406)
% HS Grad, 2000							-0.170	0.185***
							(0.140)	(0.0706)
Segregation Index, 2000							-0.0930***	-0.0484***
							(0.0230)	(0.0180)
Additional Controls	No	Yes	Yes	No	Yes	Yes	Yes	Yes
State Fixed Effects	No	No	Yes	No	No	Yes	No	Yes
Observations	1,182,563	1,182,563	1,182,563	1,166,056	1,166,056	1,166,056	1,114,898	1,114,898
R^2	0.008	0.076	0.078	0.008	0.077	0.078	0.077	0.078

Source: Authors' regressions on microdata from the Behavioral Risk Factor Surveillance System Survey (CDC), U.S. Census (Ruggles et al., 2010), and Glaeser and Vigdor (2001).

Notes: All regressions control for year fixed effects, month fixed effects, age, race, and sex. "Additional controls" include education, marital status, and family size. Standard errors in parentheses are two-way clustered (Cameron, Gelbach and Miller, 2011) at both the MSA and year levels (*** p<0.01, ** p<0.05, * p<0.1).

Table 4
Happiness and Urban Population Growth Differences, BRFSS

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			**Self-Reported Well-Being**		
Change in log population (below median) 1950-2000	0.214***	0.134***	0.101***	0.0972***	0.0781***
	(0.0186)	(0.0146)	(0.0174)	(0.0180)	(0.0127)
Change in log population (above median) 1950-2000	0.00409	0.00503	0.00929	0.00771	-0.00443
	(0.0127)	(0.00795)	(0.00711)	(0.00642)	(0.00564)
Additional Controls	No	Yes	Yes	Yes	Yes
Employment and Income Controls	No	No	Yes	Yes	No
Health Controls	No	No	No	Yes	No
State Fixed Effects	No	No	No	No	Yes
Observations	1,182,563	1,182,563	1,182,563	1,164,203	1,182,563
R^2	0.009	0.077	0.125	0.185	0.078

Source: Authors' regressions on microdata from the Behavioral Risk Factor Surveillance System Survey (CDC) and U.S. Census (Ruggles et al., 2010).
Notes: All regressions control for year fixed effects, month fixed effects, age, race, and sex. "Additional controls" include education, marital status, and family size. Standard errors in parentheses are two-way clustered (Cameron, Gelbach and Miller, 2011) at both the MSA and year levels (*** p<0.01, ** p<0.05, * p<0.1).

Table 5
Happiness, Urban Decline and Mobility, NSFH

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			**Self-Reported Well-Being**			
Change in log population (below median) 1950-2000	0.141***	0.108***	0.121***	0.142**	-0.0392	1.092*
	(0.0362)	(0.0337)	(0.0337)	(0.0702)	(0.215)	(0.631)
Change in log population (above median) 1950-2000	-0.0574***	-0.0506***	-0.0565***	-0.0387	-0.0122	-0.766
	(0.0160)	(0.0188)	(0.0192)	(0.0356)	(0.0677)	(0.508)
Wave 2	-0.0131***	0.0274	0.00919		-0.176	-0.246
	(0.00403)	(0.151)	(0.0528)		(0.167)	(0.315)
Mover				0.0869		
				(0.124)		
Mover x Change in log population (below median) 1950-2000				-0.0851		
				(0.211)		
Mover x Change in log population (above median) 1950-2000				0.0217		
				(0.0681)		
Log Household Income			0.0958***		0.0587**	0.0879***
			(0.00569)		(0.0255)	(0.692)
Additional Controls	No	Yes	Yes	Yes	Yes	Yes
Person Fixed Effects	No	No	No	No	Yes	Yes
Waves	1&2	1&2	1&2	2 only	1&2	1&2
Observations	17,019	17,019	14,625	8,491	14,625	6,989
R^2	0.010	0.048	0.053	0.046	0.709	0.684

Source: Authors' regressions on microdata from the National Survey of Families and Households (Sweet and Bumpass, 1996) and U.S. Census (Ruggles et al., 2010).
Notes: All regressions control for month fixed effects, age, race, and sex. "Additional controls" include education, marital status, and family size. Standard errors in parentheses are clustered at the MSA level (*** p<0.01, ** p<0.05, * p<0.1).

Table 6
Movers and Happiness in NSFH

	(1)	(2)	(3)	(4)	(5)	(5)
Dependent variables:	**Mover status**		**Wave 2 PMSA Growth**		**Wave 2 PMSA SWB**	
Wave 1 Subjective Well-being (SWB)	-0.00137	0.0128*	0.0227	0.0218	0.00227	0.00165
	(0.00352)	(0.00723)	(0.0262)	(0.0279)	(0.00150)	(0.00149)
Change in log population (below median) 1950-2000	0.00942	0.00804	0.580***	0.619***		
	(0.0331)	(0.0333)	(0.176)	(0.178)		
Change in log population (above median) 1950-2000	0.0422***	0.0431***	0.0139	-0.00488		
	(0.0151)	(0.0147)	(0.0988)	(0.0997)		
SWB x Change in log population (below median) 1950-2000		-0.0327**				
		(0.0160)				
SWB x Change in log population (above median) 1950-2000		0.0152				
		(0.0119)				
Wave 1 PMSA adjusted life satisfaction (below median)					0.170***	0.152**
					(0.0598)	(0.0583)
Wave 1 PMSA adjusted life satisfaction (above median)					0.118	0.108
					(0.112)	(0.117)
Log Household Income	-0.0123**	-0.0124**		-0.00476		-0.00353**
	(0.00537)	(0.00537)		(0.0332)		(0.00171)
Additional Controls	Yes	Yes	No	Yes	No	Yes
Observations	8,528	8,528	935	935	1,513	1,513
R^2	0.066	0.066	0.093	0.113	0.039	0.062

Source: Authors' regressions on microdata from the National Survey of Families and Households (Sweet and Bumpass, 1996) and U.S. Census (Ruggles et al., 2010).
Notes: All regressions control for month fixed effects, age, race, and sex. "Additional controls" include education, marital status, and family size. Standard errors in parentheses are robust to heteroskedasticity (*** p<0.01, ** p<0.05, * p<0.1).

Table 7
Happiness Regressions Using the General Social Survey

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			**Self-Reported Happiness**			
Change in log population (below median) 1950-2000	0.214***	0.205***	0.222***	0.521***	0.485***	0.459***
	(0.0527)	(0.0596)	(0.0818)	(0.104)	(0.113)	(0.113)
Change in log population (above median) 1950-2000	-0.0295	0.00245	-0.0382	-0.0961	-0.0819	-0.0752
	(0.0438)	(0.0469)	(0.0658)	(0.0768)	(0.0853)	(0.0803)
Change in log population (below median) 1950-2000 × Individual moved			-0.0355			
			(0.118)			
Change in log population (above median) 1950-2000 × Individual moved			0.0543			
			(0.0780)			
Moved			0.0378			
			(0.0555)			
Change in log population (below median) 1950-2000 × 1980 Decade Dummy				-0.287**	-0.296**	-0.277**
				(0.134)	(0.123)	(0.122)
Change in log population (below median) 1950-2000 × 1990 Decade Dummy				-0.372***	-0.451***	-0.421***
				(0.121)	(0.0992)	(0.0952)
Change in log population (below median) 1950-2000 × 2000 Decade Dummy				-0.556***	-0.446**	-0.440***
				(0.144)	(0.169)	(0.159)
Change in log population (below median) 1950-2000 × 2010 Decade Dummy				-0.510***	-0.344	-0.298
				(0.172)	(0.225)	(0.214)
Change in log population (above median) 1950-2000 × 1980 Decade Dummy				0.130	0.134	0.128
				(0.103)	(0.103)	(0.0969)
Change in log population (above median) 1950-2000 × 1990 Decade Dummy				0.0398	0.113	0.111
				(0.0978)	(0.128)	(0.118)
Change in log population (above median) 1950-2000 × 2000 Decade Dummy				0.0107	0.0116	0.00589
				(0.0795)	(0.110)	(0.106)
Change in log population (above median) 1950-2000 × 2010 Decade Dummy				0.188**	0.161	0.180
				(0.0928)	(0.134)	(0.134)
Additional controls	No	Yes	Yes	No	Yes	Yes
Income and Employment Controls	No	Yes	Yes	No	No	Yes
Decade Fixed Effects	No	No	No	No	Yes	Yes
Observations	9,995	7,541	7,541	9,995	7,541	7,541
R^2	0.021	0.051	0.051	0.024	0.040	0.054

Source: Authors' regressions on microdata from the General Social Survey (GSS) and U.S. Census (Ruggles et al., 2010).
Notes: All regressions control for a year trend, age, race, and sex. "Additional controls" include education, marital status, and family size. Standard errors in parentheses are clustered at the MSA level (*** p<0.01, ** p<0.05, * p<0.1).

Table 8
Self-Reported Well-Being and Disamenities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:				**Self-Reported Well-Being**				
Change in log population (below median) 1950-2000	0.210*** (0.0193)	0.215*** (0.0194)	0.177*** (0.0238)	0.213*** (0.0192)	0.224*** (0.0214)	0.156*** (0.0344)	0.0863*** (0.0251)	0.0830* (0.0446)
Change in log population (above median) 1950-2000	0.00115 (0.0151)	0.00547 (0.0124)	0.0363* (0.0240)	0.00250 (0.0135)	0.00445 (0.0130)	0.0231 (0.0331)	0.0134 (0.0224)	0.0164 (0.0240)
Average January temperature	0.000262 (0.000459)					0.00153** (0.000780)	0.00177*** (0.000442)	-0.00281** (0.00134)
Precipitation		0.000402 (0.000299)				0.000117 (0.000682)	-0.000146 (0.000480)	0.00190** (0.000840)
Log of Crime			0.00451 (0.0102)			0.00457 (0.0115)	0.00258 (0.00703)	0.0115 (0.00707)
Pollution				0.000265 (0.000782)		0.000171 (0.00140)	0.000487 (0.000955)	-3.81e-05 (0.00107)
Gini coefficient, 2000					0.0957 (0.163)	-0.0538 (0.643)	0.325 (0.420)	0.863*** (0.237)
Additional Controls	No	No	No	No	No	No	Yes	Yes
State Fixed Effects	No	No	No	No	No	No	No	Yes
Observations	1,182,563	1,182,563	328,379	931,580	1,126,257	261,987	261,987	261,987
R^2	0.009	0.009	0.009	0.010	0.009	0.010	0.078	0.079

Source: Authors' regressions on microdata from the Behavioral Risk Factor Surveillance System Survey (CDC) and U.S. Census (Ruggles et al., 2010).
Notes: All regressions control for year fixed effects, month fixed effects, age, race, and sex. "Additional controls" include education, marital status, and family size. Standard errors in parentheses are clustered at the MSA level (*** p<0.01, ** p<0.05, * p<0.1).

Table 9
Happiness in the 1940s

	(1)	(2)	(3)	(4)
Dependent variable:	Happiness			
Population Indicator: Farm Town	0.0611***	0.0478	0.0276	0.00195
	(0.0221)	(0.0301)	(0.0268)	(0.0432)
Population Indicator: Town Under 2,500	0.0234	-0.00112	0.0244	-0.00680
	(0.0200)	(0.0200)	(0.0261)	(0.0447)
Population Indicator: 10,000 to 100,000	0.0126	-0.0227	-0.0233	-0.0299
	(0.0190)	(0.0234)	(0.0271)	(0.0251)
Population Indicator: 100,000 to 500,000	-0.0105	-0.0531	-0.0188	-0.0669
	(0.0315)	(0.0348)	(0.0456)	(0.0596)
Population Indicator: Over 500,000	-0.0984***	-0.0780*	-0.112***	-0.143***
	(0.0196)	(0.0415)	(0.0277)	(0.0280)
Population Growth 1950-2000 Below Mean		-0.0354		
		(0.0341)		
Income Growth 1950-2000 Below Mean			-0.00355	
			(0.0347)	
Mean January Temperature Below 35°F				0.0218
				(0.0458)
Constant	0.101	0.114*	0.141**	0.137*
	(0.0607)	(0.0622)	(0.0623)	(0.0689)
Observations	10,809	10,809	10,809	10,809
R^2	0.027	0.029	0.029	0.028

Source: Authors' regressions on microdata from Gallup Polls #1946-0369, #1947-0399, #1948-0418 and #1948-0425, and U.S. Census (Ruggles et al., 2010).
Notes: Omitted population category is towns from 2,500 to 10,000. All regressions control for age, race, sex, schooling, regions, and a year trend. Regression (2) includes city size dummies and population growth lower than mean dummy interactions. Regression (3) includes city size dummies and population growth lower than mean dummy interactions. Regression (4) includes city size dummies and January temperature lower than 35°F dummy interactions. Standard errors in parentheses are clustered at the state level (*** p<0.01, ** p<0.05, * p<0.1).

Table 10

Income, Housing Value, Rent and Population Growth, 1940

	(1)	(2)	(3)	(4)	(5)
Dependent variables:		**Log Income, 1940**		**Log House Value, 1940**	**Log Rent, 1940**
Population Growth Below Median	-0.144**	-0.104***	-0.102***	-0.219*	-0.294***
	(0.0577)	(0.0324)	(0.0365)	-0.128	(0.103)
Population Growth Above Median	-0.0442	-0.0261	-0.0830	-0.157	-0.0619
	(0.0455)	(0.0404)	(0.0591)	(0.124)	(0.119)
Indicator for MSA with 5+ million population		0.0671***	0.0623***	0.296***	0.376***
		(0.0211)	(0.0212)	(0.0656)	(0.0541)
Two Stage Least Squares	No	No	Yes	No	No
Observations	7,765,625	7,765,625	7,765,625	6,535,037	10,526,639
R^2	0.211	0.215	0.214	0.035	0.095

Source: Authors' regressions on U.S. Census microdata (Ruggles et al., 2010).
Notes: Rent variable is monthly contract rent. The 1940 Census data do not include housing quality information. The sample for income regressions is employed males aged 25-55 who work full-time and earn more than half the federal minimum wage for a full-time worker. All income regressions include age, race, and education controls. The two stage least squares regression instruments with January temperature, July temperature, and precipitation dummy variables. All regressions include household or person weights. Standard errors are clustered at the MSA level (*** p<0.01, ** p<0.05, * p<0.1).

Table 11

Income, Housing Value, Rent and Population Growth, 2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Log Income, 2000				Log House Value, 2000				Log Rent, 2000			
Population Growth Below Median	-0.0366	0.0109	0.0336	0.0460	0.131	0.302**	0.265***	0.306***	-0.00925	0.208**	0.291***	0.321***
	(0.0478)	(0.0533)	(0.0309)	(0.0290)	(0.246)	(0.132)	(0.0771)	(0.0625)	(0.221)	(0.0807)	(0.0614)	(0.0517)
Population Growth Above Median	-0.00517	0.00640	-0.00467	-0.00306	0.0404	0.0953	0.154***	0.161***	0.124**	0.171***	0.172***	0.175***
	(0.0188)	(0.0196)	(0.0130)	(0.0130)	(0.0753)	(0.0579)	(0.0494)	(0.0495)	(0.0622)	(0.0467)	(0.0323)	(0.0323)
Indicator for MSA with 5+ million population		0.0900***		0.161***		0.555***		0.686***		0.387***		0.488***
		(0.0310)		(0.0270)		(0.123)		(0.138)		(0.0514)		(0.0522)
MSA Size Weight	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations (thousands)	30,044	30,044	30,044	30,044	42,914	42,914	42,914	42,914	22,125	22,125	22,125	22,125
R^2	0.215	0.217	0.191	0.193	0.361	0.411	0.425	0.439	0.059	0.108	0.107	0.118

Source: Authors' regressions on U.S. Census microdata (Ruggles et al., 2010).
Notes: Rent variable is monthly contract rent. All housing regressions include controls for housing quality. The sample for income regressions is employed males aged 25-55 who work full-time and earn more than half the federal minimum wage for a full-time worker. All income regressions include age, race, and education controls. All regressions include household or person weights. The "MSA size weight" indicates that observations are reweighted to reflect MSA size differences, but appropriate individual or household weights are maintained within each MSA. Standard errors are clustered at the MSA level (*** p<0.01, ** p<0.05, * p<0.1).

Table 12
Income, Housing Value, Rent and Happiness, 2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables:	Log Income, 2000				Log Housing Value, 2000				Log Rent, 2000			
MSA adjusted life satisfaction	-0.0791	0.154	0.0389	0.0884	-0.607	0.157	0.124	0.292	-0.293	0.659*	0.529**	0.646***
	(0.178)	(0.197)	(0.0922)	(0.0899)	(0.589)	(0.387)	(0.264)	(0.240)	(0.516)	(0.335)	(0.228)	(0.215)
Indicator for MSA with 5+ million population		0.0950***		0.157***		0.489***		0.617***		0.338***		0.440***
		(0.0284)		(0.0242)		(0.134)		(0.144)		(0.0617)		(0.0559)
MSA Size Weight	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations (thousands)	30,044	30,044	30,044	30,044	42,914	42,914	42,914	42,914	22,125	22,125	22,125	22,125
R^2	0.215	0.217	0.191	0.193	0.361	0.400	0.410	0.421	0.053	0.089	0.077	0.086

Source: Authors' regressions on U.S. Census microdata (Ruggles et al., 2010).
Notes: Rent variable is monthly contract rent. All housing regressions include controls for housing quality. The sample for income regressions is employed males aged 25-55 who work full-time and earn more than half the federal minimum wage for a full-time worker. All income regressions include age, race, and education controls. All regressions include household or person weights. The "MSA size weight" indicates that observations are reweighted to reflect MSA size differences, but appropriate individual or household weights are maintained within each MSA. Standard errors are clustered at the MSA level (*** p<0.01, ** p<0.05, * p<0.1).

Data Appendix

BRFSS

Throughout this paper, we follow the literature in measure happiness using self-reported survey data on subjective well-being (SWB). We use a large national survey, the Behavioral Risk Factor Surveillance System (BRFSS), conducted by the Centers for Disease Control and Prevention (CDC), which asks individuals to report on their own life satisfaction using a discrete response scale.

The CDC (2005-2010) has conducted BRFSS surveys annually since 1985, in order to study risk factors for various diseases. This is a large, nationally-representative survey, involving more than 350,000 respondents in over two thousand counties annually.

The BRFSS survey is administered by individual states via telephone interviews. The interviews are collected via computer-assisted phone calls to randomly selected landlines.[11] During our sample period of 2005 to 2009, the survey covers all 50 states and Washington, DC.[12] Individuals report their county to the interviewer, and we drop observations where county is not reported.

Based on the self-reported county, respondents live in 367 metropolitan statistical areas (MSAs) and non-metropolitan regions.[13] When we examine temporal patterns in the data, we restrict the sample to the 177 MSAs with at least 200 respondents in each year.

The life satisfaction question we use has been a part of the BRFSS "core" since 2005. Core questions are asked in every interview with minor exceptions. In 2009, the life satisfaction question was not asked in less than 5% of BRFSS surveys, which is approximately the same percent unasked of similar questions in the survey. This number is slightly lower in other years. Responses to LSATISFY of "refused" and "unsure" are treated as missing responses and dropped from the dataset.

One might be concerned that individual SWB is reported on a discrete scale, with values whose interpretation is not obvious. When we summarize one area's happiness as a linear average of these discrete values, the resulting summary is undoubtedly a noisy and imperfect measure area-level happiness. We cannot solve this problem, but Stevenson and Wolfers (2008) find that more

[11] CDC provides weights to adjust for differences in phone line density across areas, but we do not use these weights.

[12] Puerto Rico, Guam and the U.S. Virgin Islands are also included, but we drop the three territories.

[13] We use the county FIPS code to assign the respondent to a metropolitan area. We use the Office of Management and Budget's definitions of metropolitan areas from 1999 (which correspond to data from the 2000 Census). We use Primary Metropolitan Statistical Areas (PMSAs) rather than Consolidated Metropolitan Statistical Areas (CMSAs), where applicable. We classify respondents in New England, according to their New England Consolidated Metropolitan Statistical Area (NECMA) rather than PMSA or CMSA. We classify all respondents not living in an MSA, PMSA, or NECMA as part of one "non-metropolitan region" for their state (e.g., "non-metropolitan Texas").

sophisticated methods yield results that are extremely highly correlated across countries (correlations are regularly above 0.99) with results from this method.

We standardize each year's data separately, with respect to the overall mean and standard deviation for the survey year in question.

One wave of the BRFSS may actually be administered in two different years (e.g., the 2009 wave interview respondents from January 2009 through January 2010). The year fixed effects γ_t that we estimate represent the survey wave as opposed to the actual year of the interview.

The concern about systematic differences in individual SWB is not merely hypothetical. On the contrary, a large body of research has documented regular patterns based on age, sex, income, life events, and other demographic characteristics.[14] To the extent that people sort across areas based on these same characteristics, this will bias our estimates of area-level happiness.

A small percentage of survey respondents refuse to respond to one or more of the demographic questions asked. The total fraction refusing to answer, unsure of, or not being asked at least one demographic question of interest is about 2.3% in any year. We drop any observation with any such missing demographic information, as well as respondents over 85 years old.

The controls for children's characteristics deserve further elaboration. While the survey nearly always has information about the number of children in the household, more detailed information is available for only one randomly selected child. In most states during most years, the BRFSS asks about the age of one randomly selected child in the household, as well as the respondent's relationship to that child.[15] We therefore create indicator variables for four age ranges of the randomly selected child, and six categories for the respondent's relationship.[16] The omitted group for these questions is respondents with no children. We add a separate dummy variable indicating respondents with children in state-years when no question was asked about a child's age.

Appendix Table 1 reports the coefficients on the controls in this regression, when run on our full sample of 1,574,361 respondents across five waves of BRFSS. For the most part, these coefficients are consistent with findings in the previous literature, and robust to the inclusion or exclusion of area fixed effects. In column 1, we include only the basic demographic controls discussed above. We find that age has an important influence on subjective well-being, as estimated by a fifth-order polynomial in age. On average men are 0.036 standard deviations less

[14] *e.g.* Sacks, Stevenson, and Wolfers (2010)
[15] The survey is divided into core questions and modules, the latter of which each state individually elects whether to ask in their phone interviews. Individual states sometimes add additional questions on their own. None of the questions we focus on are module or state questions in any year, except for the age of one randomly selected child.
[16] In the 2006 survey, the age of the child is not recorded, but is imputed from the reported birthdate. In 2007, the age is recorded in the BRFSS in months, and we round this down to an integer number of years.

happy than women. There are strongly significant differences across races, with whites reporting the highest average well-being.

The most significant correlates of happiness in column 1 are education level and marital status. Education has one of the largest impacts on individual responses, with a range of nearly half a standard deviation from high school dropouts to college graduates. But bear in mind that this regression does not control for individual-level income, which may mediate this relationship somewhat. Marital status is also extremely important, with married individuals half a standard deviation happier than single or divorced respondents. Those reporting being separated are one-sixth of a standard deviation less happy than singles or divorcees.

Our estimates of the relationship between happiness and the presence of children in the household differ from previous findings. The existing literature has generally found a significant negative association between happiness and having children, especially young children. [17] In the BRFSS data, however, there seems to be a more complex relationship. This regression allows us to compute the connection between a respondent's subjective well-being and the presence of children with various characteristics in the household. To calculate the complete relationship, we need to add the coefficients for the appropriate number of children (one, two, three or more), the age of the randomly selected child (one of four categories, or unknown), and the respondent's relationship to the randomly selected child. For all of these characteristics, the coefficients presented in Appendix Table 1 are expressed relative to the omitted group of respondents with no children in the household.

Parents in a one-child household are, on average, anywhere from 0.01 standard deviations less happy than similar respondents with no child to 0.07 standard deviations happier, depending on the child's age. Older children appear to be associated with less happiness, all else equal, with 11-17-year-olds having a coefficient 0.076 standard deviations below 0-1-year-olds. We find increasingly positive coefficients as the number of children increases, with a bump of 0.04 standard deviations for a second child and a further 0.01 standard deviation gain with a third child or beyond.

These benign or positive relationships between children and happiness disappear if the respondent is the child's guardian but not the biological parent. Grandparents, foster parents, and unspecified other relatives have very strong negative coefficients, which wipe out the (otherwise positive) associations with most categories of number and age of children. In other

[17] The negative relationship between children—especially young children—and parents' happiness is widely accepted in the literature. Di Tella, MacCulloch, and Oswald (2001) report increasingly negative coefficients on life satisfaction in the EuroBarometer as the number of children increases (table A1). This finding dates back at least to Glenn and Weaver (1979), who find the negative coefficient to be largest for children under 5 years old in the General Social Survey (Table 1). The closest finding to ours is Clark and Oswald (1994), who estimate a negative effect of having one child relative to no children, and insignificant negative effects of having two or more children compared with none (Tables 2 and 3). They do not report results controlling for children's ages.

specifications (not reported), we interact the number or age of children with the respondent’s marital status or relationship with the random child. These regressions tend to confirm that the positive correlation between children and respondents’ well-being is concentrated among married couples and respondents who are the child's biological parents, while the other groups tend to have negative associations between the presence of children and their own well being.

Even without these interactions, our data suggest a more complex relationship than that previously found between subjective well-being and the presence and age of children. These correlations are sensitive to the relationship between the children present and the individual in question. Nevertheless, it is unlikely that the inclusion of controls for relationship with the child fully explains the difference between our results and the negative coefficients on children’s presence reported in other papers. The cases of non-parental relationship status are probably not sufficiently prevalent to explain the aggregate negative associations found in other datasets.

Subsequent regressions in Appendix Table 1 add controls for the respondent’s economic situation. In column 2, we add dummies for labor force status. With employed individuals as the omitted group, we find that self-employment is associated with a 0.036 standard deviations more well-being, while the unemployed are 0.44 to 0.57 standard deviations less happy than employed workers. Retirees are 0.02 standard deviations less happy than workers, controlling for age, and those unable to work are 0.7 standard deviations less happy than workers. Including labor force status controls has only a modest impact on the coefficients on other demographics, with the notable exception of the indicator for being black. This dummy reverses signs, from -0.025 in column 1 to 0.01 in column 2.

Column 3 adds controls for reported income categories, in addition to of the previous characteristics. These dummies show that happiness increases monotonically in income, with a range of 0.6 from the omitted category (less than $10,000 per year) to the highest-income category (above $75,000 per year). Because income is correlated with many of the other covariates, its inclusion dramatically shifts some of the coefficients on other variables, including education, unemployment, race and marital status, relative to their levels in column 2.

Aggregate Data

Our aggregate data about the metropolitan and non-metropolitan areas in the country come from various sources. These data mostly come from the National Historical Geographic Information System (Minnesota Population Center, 2004), which compiles data from the U.S. Census. We obtain these data at the county level and consolidate them using the same metropolitan area definitions from 1999 as we use for the BRFSS. We obtain a number of quality of life measurements from Albouy (2008), and geographic data from Rappaport and Sachs (2003).

Data on Movers from the National Survey of Families and Households

To examine the relationship between changes in subjective well-being and changes in geographic location, we need to match the longitudinal NSFH data to geographic data. Because the geographic locations of survey respondents are considered confidential, we can't link individual responses to the names of the counties or PMSAs in which those individuals reside. However, the NSFH provided us with a match between survey respondent case IDs and certain geographic characteristics ("geomerge").[18] For each wave, for each publically available observation, the NSFH provided a corresponding dataset with the observation case ID number and the characteristics of the respondent's county and PMSA. While we can't link individual respondents to named geographic locations, we can link individuals with the relevant characteristics of their counties and PMSAs in each wave. Included in our match are census data on county and PMSA population, education, and income, other geographic amenities like crime statistics and temperature, and the county and PMSA fixed effects on subjective well-being that we estimated previously using the BRFSS.

With the geographic characteristics from both NSFH waves, we are able to isolate the population of NSFH respondents who moved counties or PMSAs. In NSFH2, 2,395 respondents *report* moving cities since NSFH1. Using our matched dataset, we find 1,939 respondents who both answered the question on subjective well-being and have different county characteristics for NSFH1 and NSFH2, denoting a change in the respondent's county of residence. Of that group, we similarly find 1,480 respondents to have moved to a new PMSA.

Our analysis focuses on the relationship between the changes in reported subjective well-being of this population and the changes in the respondents' county and PMSA characteristics. We run regressions of the form

$$(5) \qquad \Delta y_i = \tau + \psi \Delta \hat{u}_i + \varphi \Delta X_i + \varepsilon_i$$

across individuals who move. The coefficient ψ identifies the relationship between changes in area-level happiness and changes in individual happiness, possibly controlling for changes in other covariates (at the area or individual level) between the two observations, captured in ΔX_i.

[18] We are extremely grateful to Larry Bumpass, Jack Solock, Charles Fiss, and the Center for Demography of Health and Aging University of Wisconsin-Madison for generously conducting this geomerge for us and providing us with the data. The use of these geographically merged, but not individually identified data was approved by the Institutional Review Board at the National Bureau of Economic Research.

Historical Gallup Polls

Gallup polls in the 1940s asked:

> "In general, how happy would you say you are – very happy, fairly happy, not very happy, not at all happy?"

We recoded answers as a dummy variable equal to 1 for "very happy" and "fairly happy" responses and 0 for "not very happy" or "not at all happy." The distribution of raw answers is as follows:

Very happy	3,787	39.12%
Fairly happy	5,069	52.37%
Not very happy	708	7.31%
Not at all happy	116	1.20%
Total	9,680	100.00%

Appendix Table 1: Coefficients on demographic characteristics in life satisfaction regression

Variable:	(1) Estimate	(1) Standard error	(2) Estimate	(2) Standard error	(3) Estimate	(3) Standard error
Age / 10	-2.061	(0.149)	-0.995	(0.185)	0.664	(0.183)
Age^2 / 100	0.761	(0.066)	0.266	(0.081)	-0.419	(0.080)
Age^3 / 1,000	-0.150	(0.014)	-0.038	(0.017)	0.092	(0.017)
Age^4 / 10,000	0.015	(0.001)	0.0034	(0.0017)	-0.008	(0.002)
Age^5 / 100,000	-0.0006	(0.0001)	-0.0002	(0.0001)	0.0002	(0.0001)
Male	-0.036	(0.002)	-0.037	(0.002)	-0.060	(0.002)
Black	-0.025	(0.003)	0.010	(0.004)	0.071	(0.004)
Asian	-0.124	(0.006)	-0.130	(0.008)	-0.093	(0.007)
Pacific Islander	-0.016	(0.017)	0.011	(0.020)	0.053	(0.020)
Native American	-0.079	(0.007)	-0.017	(0.008)	0.034	(0.008)
Other race, non-Hispanic	-0.119	(0.010)	-0.093	(0.012)	-0.050	(0.012)
Multiple races	-0.145	(0.006)	-0.103	(0.007)	-0.070	(0.007)
Hispanic	-0.014	(0.004)	-0.012	(0.004)	0.071	(0.004)
Some high school	-0.176	(0.003)	-0.101	(0.004)	-0.040	(0.004)
Some college	0.072	(0.002)	0.054	(0.002)	0.002	(0.002)
College graduate	0.273	(0.002)	0.229	(0.002)	0.096	(0.003)
Married	0.457	(0.003)	0.406	(0.003)	0.266	(0.003)
Divorced	0.003	(0.003)	0.005	(0.004)	0.005	(0.004)
Separated	-0.175	(0.006)	-0.141	(0.007)	-0.136	(0.007)
In unmarried couple	0.166	(0.005)	0.143	(0.006)	0.082	(0.006)
One child < 18 in household	0.016	(0.006)	-0.002	(0.007)	0.004	(0.007)
Two children < 18 in household	0.057	(0.006)	0.032	(0.007)	0.035	(0.007)
Three or more children < 18 in household	0.067	(0.007)	0.041	(0.008)	0.054	(0.007)
Random child < 2 years old	0.052	(0.009)	0.069	(0.010)	0.074	(0.010)
Random child 2-4 years old	-0.020	(0.008)	-0.017	(0.010)	-0.019	(0.010)
Random child 5-10 years old	-0.021	(0.008)	-0.025	(0.009)	-0.031	(0.009)
Random child 11-17 years old	-0.024	(0.007)	-0.032	(0.009)	-0.041	(0.008)
Random child’s age not asked	-0.028	(0.006)	-0.025	(0.007)	-0.028	(0.007)
Respondent is random child’s parent	-0.001	(0.007)	0.001	(0.008)	0.004	(0.008)
Respondent is random child’s grandparent	-0.158	(0.010)	-0.109	(0.013)	-0.101	(0.012)
Respondent is random child’s foster parent	-0.057	(0.017)	-0.030	(0.017)	-0.034	(0.017)
Respondent is random child’s sibling	0.072	(0.013)	0.098	(0.017)	0.013	(0.017)
Respondent is random child’s other relative	-0.077	(0.016)	-0.039	(0.019)	-0.049	(0.019)
Self-employed			0.036	(0.003)	0.046	(0.032)
Unemployed for more than 1 year			-0.574	(0.007)	-0.416	(0.007)
Unemployed for less than 1 year			-0.436	(0.006)	-0.323	(0.006)
Homemaker			-0.005	(0.004)	0.031	(0.004)
Student			-0.028	(0.007)	0.049	(0.007)
Retired			-0.019	(0.003)	0.040	(0.003)
Unable to work			-0.717	(0.004)	-0.543	(0.004)
Income \$10,000-\$15,000					0.047	(0.006)
Income \$15,000-\$20,000					0.117	(0.005)
Income \$20,000-\$25,000					0.169	(0.005)
Income \$25,000-\$35,000					0.247	(0.005)
Income \$35,000-\$50,000					0.346	(0.005)
Income \$50,000-\$75,000					0.454	(0.005)
Income > \$75,000					0.615	(0.005)
Metropolitan and non-metropolitan area fixed effects	Yes		Yes		Yes	
R^2	0.076		0.11		0.13	
Sample size:	1,574,361		1,084,596		1,084,596	

Source: Linear regression of individual responses to life satisfaction question in the Behavioral Risk Factor Surveillance System Survey (CDC, 2005-2010), against the variables shown, month dummies, BRFSS wave fixed effects and dummies for 367 metropolitan statistical areas and non-metropolitan regions. The omitted category of respondent is a single white female with a high school education and no children in the household, and in regressions (2) and (3), employed in the marketplace with income less than \$10,000 per year.

Appendix Table 2: Selection of metropolitan areas ranked by happiness

Rank:	Metropolitan area:	Adjusted happiness (controlling for demographics):	Adjusted happiness (controlling for demographics and income):	Unadjusted happiness:
1	Charlottesville, VA	0.150	0.080	0.150
2	Rochester, MN	0.144	0.089	0.156
3	Lafayette, LA	0.141	0.146	0.117
4	Naples, FL	0.126	0.077	0.144
6	Flagstaff, AZ	0.121	0.071	0.112
7	Shreveport, LA	0.120	0.125	0.089
15	Non-metropolitan Hawaii	0.103	0.109	0.050
16	Galveston, TX	0.103	0.067	0.098
20	Norfolk, VA	0.100	0.069	0.071
22	Honolulu, HI	0.094	0.079	0.042
26	Colorado Springs, CO	0.089	0.049	0.090
29	Washington, DC	0.087	0.044	0.045
31	Raleigh-Durham, NC	0.084	0.040	0.064
41	Tallahassee, FL	0.076	0.052	0.041
43	Atlanta, GA	0.074	0.024	0.043
52	Anchorage, AK	0.069	0.058	0.056
56	Nashville, TN	0.064	0.084	0.054
58	West Palm Beach, FL	0.062	0.034	0.071
70	Minneapolis-St. Paul, MN	0.053	0.022	0.063
77	Burlington, VT	0.049	0.025	0.067
92	Baltimore, MD	0.044	0.016	0.028
108	McAllen, TX	0.039	0.015	-0.027
121	Non-metropolitan Texas	0.029	0.031	0.008
174	San Jose, CA	0.004	-0.045	-0.006
179	Chicago, IL	0.002	-0.028	-0.018
187	Seattle, WA	-0.003	-0.032	0.005
242	San Francisco, CA	-0.027	-0.037	-0.032
250	Nassau-Suffolk, NY	-0.030	-0.067	-0.020
279	Vallejo-Fairfield-Napa, CA	-0.042	-0.050	-0.056
284	Boston, MA	-0.044	-0.032	-0.039
287	Los Angeles, CA	-0.047	-0.035	-0.094
301	Las Vegas, NV-AZ	-0.059	-0.037	-0.065
328	Detroit, MI	-0.080	-0.088	-0.110
350	Non-metropolitan Indiana	-0.104	-0.061	-0.080
353	Gary, IN	-0.111	-0.087	-0.175
355	Pittsburgh, PA	-0.115	-0.071	-0.095
359	New York, NY	-0.123	-0.120	-0.159
364	South Bend, IN	-0.138	-0.104	-0.126
365	Erie, PA	-0.147	-0.103	-0.126
367	Scranton, PA	-0.154	-0.086	-0.126

Source: Each metropolitan and rural area's adjusted life satisfaction is estimated after controlling for demographic covariates in a mixed effects model. Data are from CDC (2005-2010).

Appendix Table 3:
Robustness of Happiness-Population Decline Relationship to Alternative Functional Forms
(Based on Column 5 of Table 4)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			**Self-Reported Well-Being**		
Change in log population (below sample median) 1950-2000	0.0781***				0.0672***
	(0.0127)				(0.0161)
Change in log population (above sample median) 1950-2000	-0.00443				-0.00655
	(0.00564)				(0.00576)
Change in log population (below sample mean) 1950-2000		0.0699***			
		(0.0104)			
Change in log population (above sample median) 1950-2000		-0.00745			
		(0.00561)			
Change in log population, 1950-2000			0.0797***		
			(0.0128)		
Change in log population, 1950-2000, squared			-0.0106***		
			(0.00361)		
Change in log population, 1950-2000, is below sample median				-0.0240***	-0.00767
				(0.00430)	(0.00537)
Observations	1,182,563	1,182,563	1,182,563	1,182,563	1,182,563
R^2	0.078	0.078	0.078	0.078	0.078

Source: Authors' regressions on microdata from the Behavioral Risk Factor Surveillance System Survey (CDC) and U.S. Census (Ruggles et al., 2010).
Notes: All regressions control for state fixed effects, year fixed effects, month fixed effects, age, race, sex, education, marital status, and family size. Standard errors in parentheses are clustered at the MSA-year level (*** p<0.01, ** p<0.05, * p<0.1).