UNHAPPY CITIES

by

Edward L. Glaeser
Harvard University and NBER

Joshua D. Gottlieb
University of British Columbia

and

Oren Ziv[*]
Harvard University

February 21, 2014

Abstract

There are persistent differences in self-reported subjective well-being across the United States, and, in particular, the residents of declining cities report less happiness than other Americans. Although this unhappiness is at least as strong among new residents of such places as long-term residents, some people continue to move to these areas. These areas also seem to have been less happy historically during the era in which these now-declining cities prospered. These patterns are compatible with the view that individuals do not aim to maximize self-reported well-being, or happiness, and that subjective well-being is better viewed as only one part of the utility function. In the past the residents of now declining places were compensated financially for their unhappiness, but it is less clear what draws migrants to these unhappy places today.

---

[*] Glaeser: eglaeser@harvard.edu, Gottlieb: Joshua.Gottlieb@ubc.ca, Ziv: orenziv@fas.harvard.edu. We are grateful to David Albouy, Ori Heffetz, Jacob Leshno, Carolin Pflueger, Kelly Shue, Doug Staiger, Dave Zhao, and especially Erzo Luttmer for valuable comments and assistance. Glaeser and Gottlieb acknowledge support from the Taubman Center for State and Local Government. Gottlieb acknowledges support from the Social Sciences and Humanities Research Council of Canada, the Institute for Humane Studies and the National Institutes on Aging via grant number T32-AG000186-23 to the National Bureau of Economic Research.

I. Introduction

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 nation 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? Migrants come to these areas and they also report less happiness. 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 guiding framework—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 that this idea can coexist with persistent differences in self-reported well-being. First, subjective well-being (SWB) may not be equivalent to the economist's concept of utility, in which case, the residents of unhappy places must receive some other form of compensation. Second, these differences might reflect unobserved individual heterogeneity, so that some areas attract people who are disproportionately prone to be more or less happy.

In Section II of this paper, we follow Oswald and Wu (2007) and use the BRFSS to measure subjective well-being across the United States. We find significant, although not huge, differences across metropolitan areas. Correcting for the natural heterogeneity that occurs due to sampling error, 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 individuals with some college. We also find that this variation persists when we control for a rich battery of individual controls, including income.

One primary concern about these differences is that they are caused by unobserved heterogeneity, either in human capital or just individual propensity towards happiness. To address this worry, we turn to the panel data in the National Survey of Families and Households (NSFH). As such, we can estimate area-level happiness by looking at individuals who move 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, and the correlation between area level estimates with and without individual level fixed effects is 0.69. This fact leads us to believe that at least some of the differences in happiness across space reflect more than the selection of unhappy people into unhappy places.

In Section II, we also document that area level happiness is essentially uncorrelated with many area-level 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 the education of an area is positively associated with subjective well-being. However, 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 suggesting the impact of differential selection.

In Section III, 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.[1] High growth places are not particularly happy, but very low growth areas are particularly unhappy. This connection 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. These results, of course, do not speak to whether unhappiness is causing decline or whether decline is causing unhappiness.

Section III documents two other facts about urban decline and unhappiness. First, 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 got hit with negative shocks, and happiness fell accordingly.

In Section IV, 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, 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.

We assume that happiness is generated through experiences, which can be improved by spending money, and that happiness is but one ingredient in the utility function. We also assume that individuals also have other objectives, which we refer to as achievements, which are also

[1] Glaeser and Redlick (2007) document this using the General Social Survey.

produced through a combination of money and time, such as raising a family. 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.

Section V then returns to the empirics and first asks 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 this data suggests 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 is more likely to reflect the long-standing attributes of these cities rather than decline itself.

If declining cities were unhappy in the past, then presumably their residents were receiving some form of compensation for their unhappiness. In 1940, the residents of cities that subsequently declined were receiving higher wages and paying only slightly higher rents. A one standard deviation drop in population growth after 1950 was associated with $222 more in income ($3,655 in current dollars), which is more than ten percent of average income. Presumably, that is one reason why businesses left these areas. It is also true that current happiness is strongly correlated with lower wages in 1940. 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.

When we turn to 2000 Census data, we still find that happiness is associated with lower wages, holding individual characteristics constant. There is little correlation with rents or housing values. As such, overall, it seems like there is some process of compensation for dwelling in unhappy areas. Yet areas experiencing low population growth from 1950 to 2000 don’t seem to have wages that are high enough or rents that are low enough to offset unhappiness. Given the strong connection between low prices and urban decline that have been documented elsewhere (Glaeser and Gyourko, 2005), it remains possible that lower housing costs explain part of the puzzle.

If these results are taken at face value, then to accept a 0.4 standard deviation drop in happiness (about the gap between a high school dropout and college graduate), individuals require $27,000 per year in extra income in 2000, and $15,000 in 1940, assuming that unhappiness is the same in the two periods. Section VI concludes that if the spatial equilibrium is to be reconciled with the unhappiness of declining places, however, another source of compensation for dissatisfaction must be found, or it must be confirmed that these places have disproportionately attracted people who are prone to lower levels of SWB.

.

II. 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 III.

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 2009, around 300,000 subjects answered 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.[2] Because BRFSS data reported 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

[2] 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.

that this leads to systematically different responses across respondents, it could confound interpretation of these averages.

To address this issue, we estimate metropolitan area happiness using the following fixed effects 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 (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.[3]

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:[4]

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

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.

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 linear unbiased predictor (BLUP) $\hat{u}_j$ of that area's u_j by correcting for the sampling error involved in estimating the fixed effects We use these BLUPs in subsequent analysis as our estimate of the area's association with individual happiness.

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

---

[3] See the Data Appendix for more details.
[4] Thus this is more properly a "mixed effects" model as opposed to a pure "random effects" model, because we allow for a fixed static impact of year and demographics. We estimate it in Stata 11.1 with the xtmixed command.

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 Table 2. 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 BLUPs, $Var(\hat{u}_j)$, 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 analysis uses measures of SWB rescaled to have zero mean and unit variance across individuals, this means that the variation across geographic regions is around 6% of the individual-level variation in happiness.

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 BLUPs 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 Table 2, 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 the BLUPs 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.

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 what biases may be created through this decentralized implementation, but at least it is possible that state-level implementation has caused some of the variance that we see in the data.

To address this possibility we re-estimate the BLUPs controlling for state fixed effects. As 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 Appendix Table 1.

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.

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").[5] 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.

We first estimate BLUPs for the merged sample of NSFH1 and NSFH2. 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 some 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.

[5] 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.

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.

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

Having established the existence of spatial differences in happiness, and learned something about their magnitude, we next want to see how they evolve over time. The full range of hypotheses about the temporal evolution of spatial SWB is reasonable; it 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, such as the weather or local sports team victories.

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 BLUPs across different years ($\hat{u}_j^{(t)}$versus $\hat{u}_j^{(t\prime)}$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 allows for a time-invariant area effect, u_j, as well as the time-varying area effect, v_{jt}. 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 in Figure 4. This graph plots the BLUPs from regression (3) for 2009 $\left(\hat{u}_j^{(2009)}\right)$ against the BLUPs for 2005 $\left(\hat{u}_j^{(2005)}\right)$. In each case, the BLUPs are taken

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

from a model including demographic controls. There is an extremely strong positive relationship, with a correlation of 0.48. Thus, one quarter of the variation in the BLUPs is driven by permanent metropolitan area level shocks, and the rest by transitory shocks and estimation error. As the BLUPs are shaped, in part, by sampling error, even though their variance has been diminished by correcting for that error, we should expect to see a correlation that was less than one even if the heterogeneity was permanent. The 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 cause other types of well-being to diminish. We first test this hypothesis by examining the correlation between the demographically adjusted BLUP variable 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. Later, we will 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 5 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-Honkanan et 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" to 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 the middle part 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 6, 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 surely a highly imperfect measure of what economists' refer to as 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, which we find more congenial, is just that the link between SWB and the economists' concept of utility is far from perfect.

5. Unhappiness and Urban Characteristics

We now turn to the 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 our result 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. As discussed earlier, when we do not control for education and marital status, the statistical relationship is small and statistically indistinct from zero. When we do include these more endogenous controls, the relationship becomes more negative and becomes slightly 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 five and six 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 seven and eight 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 nine and ten represent the 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 allow segregation to be interacted with all of the race categories. In regression ten, we also allow for state-level 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 effect. In essence, these results suggest that education inequality is associated with higher self-reported well-being. 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 effect on subjective well-being.

Including state fixed effects represents our most complete specification. As many of the 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 negative effect of high school graduates switches to being positive. Housing values continue to have a negative impact on earnings. Segregation now becomes 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 do not control for state fixed effects. Overall, these results do not suggest a robust series of correlations between urban attributes and SWB.

III. Unhappiness and Urban Decline

We now turn to the particularly striking correlation between urban unhappiness and decline (Glaeser and Redlick, 2007). 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 suggests 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 focus on income change instead of population change. In a sense, this is the local version of the classic Easterlin (1973) 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 the coefficient 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 five, we add in our controls for more endogenous individual attributes. As in the case of population change, the estimated coefficient falls by about one-third. In regression six, 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 one of the other controls that is statistically distinct from zero is segregation, which remains negative. In regression eight, we include state-level fixed effects, which causes the results to lose significance and magnitude.

Overall, there is a robust positive associated between urban growth and subjective well-being. This relationship is robust to other area level controls and a rich array of individual attributes. However, this result is not robust to including state-level fixed effects, which can be interpreted as suggesting that these findings may reflect different modes of implementing the BRFSS or that the bulk of the well-being differences are essentially regional in nature.

The Non-Linear Relationship between Unhappiness and Population Growth

Figure 7 shows the correlation between population growth and self-reported well-being using the BLUP adjusted for demographic controls. As the figure makes clear, the effect is much stronger at the lower end of the population change distribution. Low levels of unhappiness 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.

While there are several hypotheses that could explain this non-linearity, we do not embrace any particular theory. 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 does not 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 a one standard deviation difference in 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 three, 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 these economic outcomes. In this case, the coefficient falls to 0.111. 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.

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 will address two issues using the NSFH. 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 period between the first and second waves is small (under five years), which 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 somewhat different and the controls are not exactly the same. 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 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 fifth regression, we include only areas that had at least 250 respondents in the NSFH, 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 leave us with no certain conclusion, and regression four leaves open the interpretation that unobserved heterogeneity drives the results. But the result from regression five makes it also quite possible to conclude that there are differences between growing and declining cities even after controlling for individual fixed effects.

One view of declining cities is that their residents were hit by a series of negative shocks. Their expected happiness may have been the same as residents of other places, but because these places were unlucky, their residents are unhappy *ex post*. The alternative view is that these areas are in an equilibrium where something else compensates for the unhappiness. We test this alternative view now by looking at whether the impact of urban decline on welfare is larger for movers or stayers.

In the NSFH, we do this by interacting the population growth variables with an indicator variable that takes on a value of one if the individual has moved between the first wave and the second wave. Since moving is only found between the two waves, we also interact the growth spline with an indicator for observations in the second wave. These results are inconclusive. We find no significant interaction, which certainly does not imply that the impact of decline on happiness is limited only to long term residents.

Table 6 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 estimate the spline again controlling for exogenous individual attributes, this time in the GSS. We again find a strong positive relationship between growth and happiness below the mean. The second regression again includes endogenous attributes, 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 changed 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 only to longer term residents. We will discuss the remainder of this Table in Section VI.

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

In Table 7, 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, this represents 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 possibly 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 different measures of local pollution levels, but none of them correlates 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 previous research (Alesina, DiTella, and MacCulloch, 2004) finds that happiness decreases with inequality, especially in Europe, we find a slight positive relationship between happiness and inequality across metropolitan areas within the U.S. 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 the correlation between inequality and unhappiness in the General Social Survey is quite strong (Glaeser, Resseger, and Tobio, 2010).

In the sixth regression, we see that including all of the variables reduces the coefficient on decline to 0.156 from 0.21. 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 here have little impact on the estimated coefficient.

IV. Why Does Happiness Differ Across Space?

If self-reported happiness has any equivalence to the economists' 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 have less human capital, of various forms, than residents of growing cities, and as such, they would have lower levels of life-satisfaction or utility in any metropolitan area. Yet there were persistent differences across space, even when we examined only movers and allowed for individual fixed effects. Our results control for a bevy of individual characteristics. Furthermore, controlling for added metropolitan area level variables, including the percent with college degrees or 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]

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 significantly lower than in growing areas, even if the marginal happiness levels are the same.

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 did 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 in 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).

Is Happiness a Measure of Utility?

While admitting that the preceding facts are open to multiple interpretations, we will focus on one particular interpretation: individuals maximize neither happiness nor life satisfaction, and for the right reward are willing to sacrifice both. According to that view, individuals in less happy areas are foregoing well-being in order to gain some other advantage. This view does not suggest that SWB or happiness are meaningless concepts. Surely both sensations are desirable. But we consider the view that 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 important. 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 is claiming that happiness is both the positive and normative determinant of behavior, and he greatly influenced subsequent

[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.

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 significantly, 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.

More modern researchers on happiness have also often conflated happiness with utility (Alesina, DiTella, and McCulloch, 2004) or at least social welfare (Easterlin, 1974). 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) notes 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."

[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.

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 measures how well people have achieved their goals.

Yet, upon reflection, this view seems barely more tenable than the view that happiness should miraculously match 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—will lead to less satisfaction later in life. Why should we believe that a person could select a course, despite recognizing that it will lead to less satisfaction, and still be choosing his preferred path and, hence, maximizing utility?

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 is not 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 formal 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 V.

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 (2007). 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 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 then becomes 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 $h(s_h) = h_0$ 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

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

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 rents 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, 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 $h_0(w\hat{t}_w + y_0)^\gamma$.

Notice that 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) implies that:

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

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

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

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

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. Rents are rising with productivity and 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.

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.

V. Unhappiness and Urban Decline

The definition of declining cities is that they were more populous in the past than they are today. A critical question in interpreting the relationship between unhappiness and decline is whether it reflects the impact of decline itself, or that America's cities were historically places 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 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 historically located in the city because it had natural advantages, such as access to waterways that made up for the loss in happiness. Over time these attributes become less important, and capital left to lower wage locales while labor left to population areas that were more pleasant.

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). 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 (1973) 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.

In this section, we first turn to historic data. We test whether large cities were in fact unhappier in the past using Gallup Surveys from the 1940s. We also examine whether the correlation between urban decline (over the entire 1950-2000 period) and unhappiness is increasing or decreasing between the 1970s and today using the General Social Survey. In the second part of this section, we turn to wage and rent data and test whether workers were receiving compensation for their unhappiness either in 1940 or in 2000.

Is the Unhappiness of Declining Cities New or Old?

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 back only to the early 1970s. The Gallup samples are small, do not include metropolitan area identifiers, and contain only limited numbers 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, which we do using the General Social Survey in the last three regressions of Table 6. 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 four, 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 do not seem compatible with the view that unhappiness has grown following decades of decline.

Regression five of Table 6 includes controls for the endogenous demographics, while the overall negative relationship weakens the time period 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 appendix) are not precisely the same as the other SWB surveys and, as such, 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 8 shows only the dummy variables for each regression, as none of the interactions are statistically significant. This is partially because the Gallup sample seems to include 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.

Taken together, these results are far from definitive, but they do not suggest that urban unhappiness is entirely 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 associated with living in smaller cities in the past.

These results correspond with the results that we get looking at the BLUPs. The correlation between the logarithm of metropolitan area population and self-reported happiness is weakly positive in 2010. The correlation between the modern happiness outcome and the logarithm of area population in 1950 is strongly negative.

Evidence on Income and Rents in 1940 and 2000

We now turn to the question of compensation. Are the residents of unhappy or declining cities receiving higher returns for their wages either now or in the past? We begin with income, and in both 1940 and 2000, we report five separate specifications in Table 9. In all specifications, we look at total earnings for males aged between 25 and 55. We include a full battery of controls for age, race, and education. We show results for the logarithm of income and for the level of income, but when we examine income levels, we use median regressions.

Our first two specifications examine the population growth spline and earnings in 1940. The first regression shows as population growth increases by .5, the logarithm of wages are lower in 1940 by .072. We do not mean to imply causality in this regression. The wages precede the growth and high wages may have caused 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 looking at the level of income, and we find that as population growth increases by .5, among the slow growing metropolitan areas, per capita incomes are 69 dollars less, which is 1,148 dollars in 2013 dollars.

Our next two specifications replace population change with the BLUP estimate of life satisfaction from the modern BRFSS. Again, this is a somewhat tenuous exercise as we are asking whether workers in 1940 received higher wages for inhabiting cities that are less happy today. That is, however, what we find. In regression three, we find that as the BRFSS measure increases by .05, the logarithm of wages falls by .055. In regression four, we find that as the BRFSS measure increases by .05, the levels of wages falls by 66.2 which is 1,102 dollars in 2013 dollars.

In regression five, we instrument for the BLUP by using January temperature, July temperature and precipitation. This approach has its problems, for these variables may well have a direct impact on earnings. Nonetheless, in the spirit of robustness, we include these results (when looking at the logarithm of income) and find a coefficient of -1.3, implying a .05 increase in the BLUP reduced log earnings by .065.

The next five regressions reproduce these specifications looking at the 2000 Census. As regressions six and seven show, population growth is no longer strongly associated with lower wages today. Detroit may have had high wages in 1940, but it does no longer. As such, it is hard to think that higher wages are the compensation for lower levels of happiness.

In regression eight, however, we do find that areas with higher levels of happiness—again measured with the same demographically corrected BLUP have lower wages. A .05 standard deviation increase in area happiness is offset by .0257 in lower log income. This is one measure of individuals' willingness to sacrifice happiness for cash.

The last regression reproduces these results using our three geographic instruments. Again, there are significantly higher wages paid to people who live in unhappier locales, with a .05 increase in area happiness offset by a .092 decline in log income.

Rosen (1976) taught us to focus on the combination of prices and housing costs to infer amenity levels in the spatial equilibrium. As such, we have also reproduced these exact two tables when the outcomes of interest are housing values (Appendix Table 2) and rents (Appendix Table 3).

We have confined these tables to the Appendix because none of these key coefficients of interest are significant. As such, they add little to our understanding of this puzzle.

VI. 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 a suggestion 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 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 maximizes 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 wages presumably as compensation for their misery.

Declining cities seem also to have been unhappy during the past, but in 1940, the cities that did decline earned outsized incomes and paid little in higher rents. The industrial cities of the Midwest may have reported lower happiness levels, but their residents were getting richer as a result. As transportation technology freed industry from the Great Lakes and the coal mines, we should not be surprised that people left less pleasant locations, but there remains a puzzle. Today, the residents of cities that declined are not receiving higher wages and they do not seem to be paying lower rents either. We leave the quest of understanding how this constitutes an equilibrium to future work.

VII. References

Albouy, David (2008). "Are Big Cities Really Bad Places to Live? Improving Quality-of-Life Estimates Across Cities." National Bureau of Economic Research Working Paper No. 14472, November.

Becker, Gary S. and Luis Rayo (2008). "Comments on 'Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox'." *Brookings Papers on Economic Activity* (1):88-95, Spring

Benjamin, Daniel J., Ori Heffetz, Miles S. Kimball, and Alex Rees-Jones (2011). "What Do You Think Would Make You Happier? What Do You Think You Would Choose?" *American Economic Review* 102(5): 2083-2110, August.

Centers for Disease Control and Prevention (CDC) (2005-2009). *Behavioral Risk Factor Surveillance System Survey Data and Questionnaire*. Atlanta: Department of Health and Human Services, CDC. Available online at http://www.cdc.gov/brfss/.

Clark, Andrew E. and Andrew J. Oswald (1994). "Unhappiness and Unemployment." *The Economic Journal* 104(424):648-659, May.

Di Tella, Rafael, Robert J. MacCulloch, and Andrew J. Oswald (2001). "Preferences Over Inflation and Unemployment: Evidence from Surveys of Happiness." *American Economic Review* 91(1):335-341, March.

Gilbert, Daniel (2006). *Stumbling on Happiness*. New York: Knopf.

Glaeser, Edward L. and Joshua D. Gottlieb (2008). "The Economics of Place-Making Policies." *Brookings Papers on Economic Activity* (1): 155-239, Spring.

Glaeser, Edward L. and David C. Mare (2001). "Cities and Skills." *Journal of Labor Economics* 19(2): 316-342, April.

Glaeser, Edward L. and Kristina Tobio (2008). "The Rise of the Sunbelt." *Southern Economic Journal* 474(3): 610-643, January.

Glenn, Norval D. and Charles N. Weaver (1979): "A Note on Family Situation and Global Happiness." *Social Forces* 57(3): 960-967.

Helliwell, John F. and Robert D. Putnam (2004), "The Social Context of Well-Being." *Philosophical Transactions of the Royal Society of London B* 359(1449): 1435-1446, September.

Internal Revenue Service (IRS) (2006-2008). *U.S. Population Migration Data*. Washington, D.C.: IRS, Statistics of Income Division. Available online at http://www.irs.gov/taxstats/.

Luttmer, Erzo F.P. (2005). "Neighbors as Negatives: Relative Earnings and Well-Being." *Quarterly Journal of Economics* 120(3): 963-1002, August.

Mandeville, Bernard (1714). *The Fable of the Bees: Or, Private Vices, Publick Benefits*. London: Roberts.

Minnesota Population Center (2004). *National Historical Geographic Information System: Pre-release Version 0.1*. Minneapolis, Minn.: University of Minnesota. Available online at http://www.nhgis.org/.

Oswald, Andrew J. and Stephen Wu (2010). "Objective Confirmation of Subjective Measures of Human Well-Being: Evidence from the U.S.A." *Science* 327(5965): 576-579.

Rappaport, Jordan and Jeffrey Sachs (2003). "The United States as a Coastal Nation." *Journal of Economic Growth* 8(1): 5-46, March.

Sacks, Daniel W., Betsey Stevenson, and Justin Wolfers (2010). "Subjective Well-Being, Income, Economic Development, and Growth." National Bureau of Economic Research Working Paper No. 16441, October.

Stevenson, Betsey and Justin Wolfers (2008). "Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox." *Brookings Papers on Economic Activity* (1): 1-87, Spring.

Stevenson, Betsey and Justin Wolfers (2009). "The Paradox of Declining Female Happiness." *American Economic Journal: Economic Policy* 1(2):190-225, August.

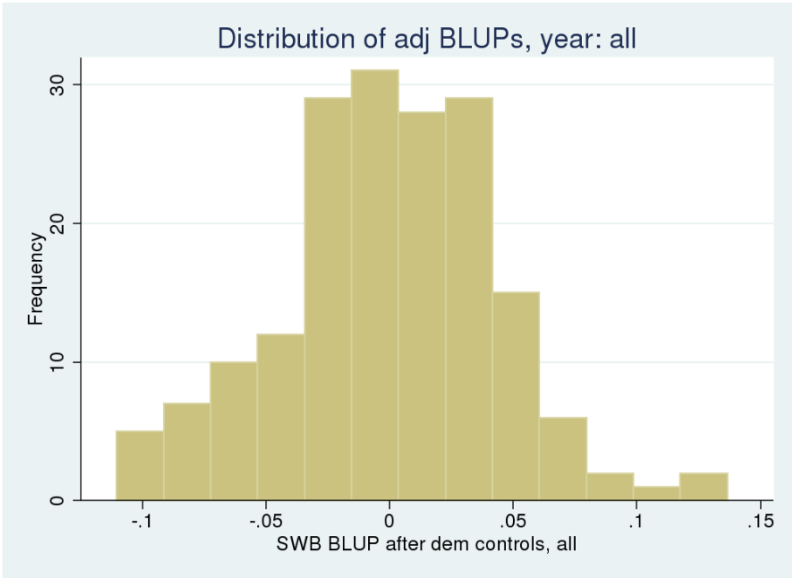
Sweet, James A, Larry L. Bumpass, and Vaughn Call (1988). "The Design and Content of The National Survey of Families and Households." National Survey of Families and Households Working Paper No. 1.

Sweet, James A and Larry L. Bumpass (1996). "The National Survey of Families and Households – Waves 1 and 2: Data Description and Documentation." Center for Demography and Ecology, University of Wisconsin-Madison (http://www.ssc.wisc.edu/nsfh/home.htm).

Stevenson , Betsey and Justin Wolfers (2008). "Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox," *Brookings Papers on Economic Activity, Economic Studies Program*, The Brookings Institution, 39(1): 1-102.

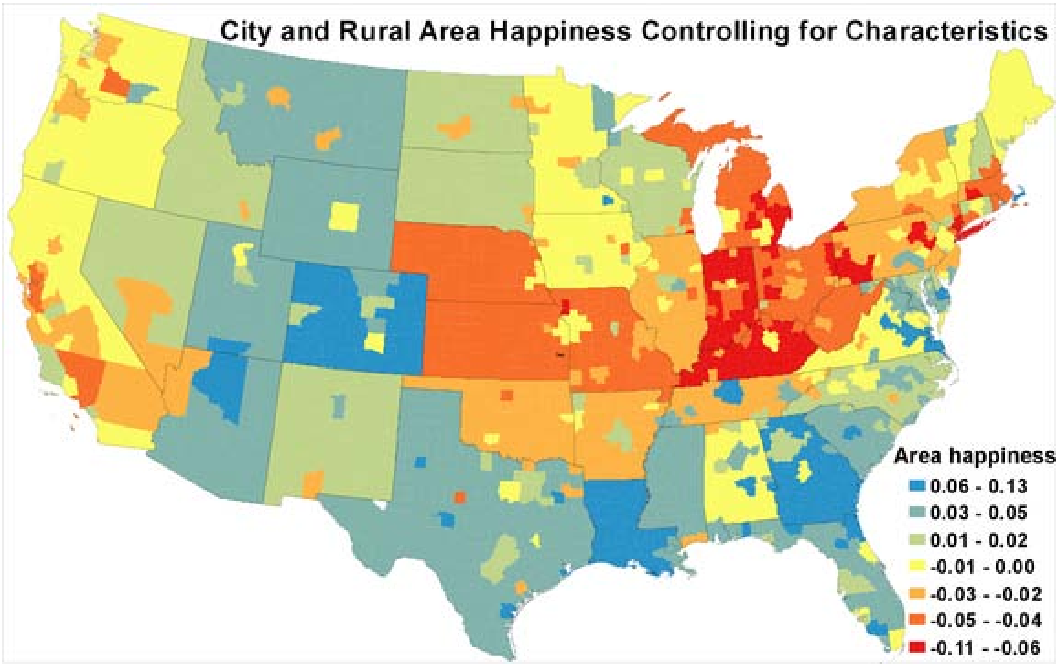
Trull, Elaine and Lisa Famularo (1996), "National Survey of Families and Households: Field Report." Philadelphia: Temple University Institute for Survey Research. Available online at ftp://elaine.ssc.wisc.edu/pub/nsfh/cmapp_n.001.

Figure 1: Distribution of BLUPs



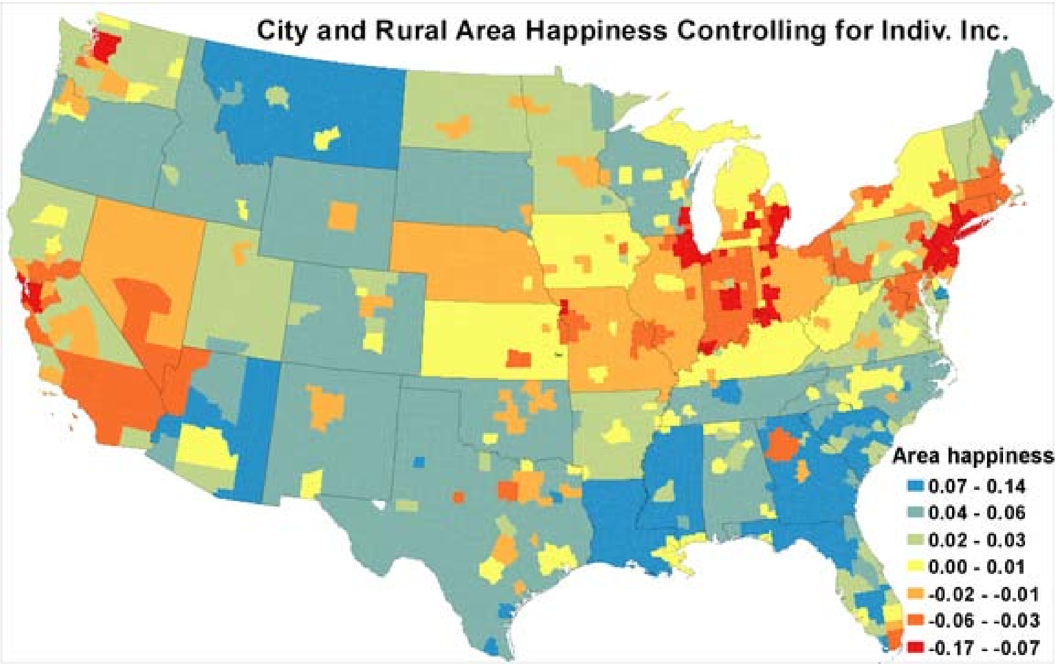
Source: This figure shows the Best Linear Unbiased Predictors (BLUPs) of metropolitan area relationships with individual life satisfaction after controlling for demographic covariates in a mixed effects model. Data are from CDC (2005-2009).

Figure 2: Estimated Metropolitan and Rural Area Happiness BLUP



Source: This figure shows the Best Linear Unbiased Predictors (BLUPs) of metropolitan area relationships with individual 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 Happiness BLUP

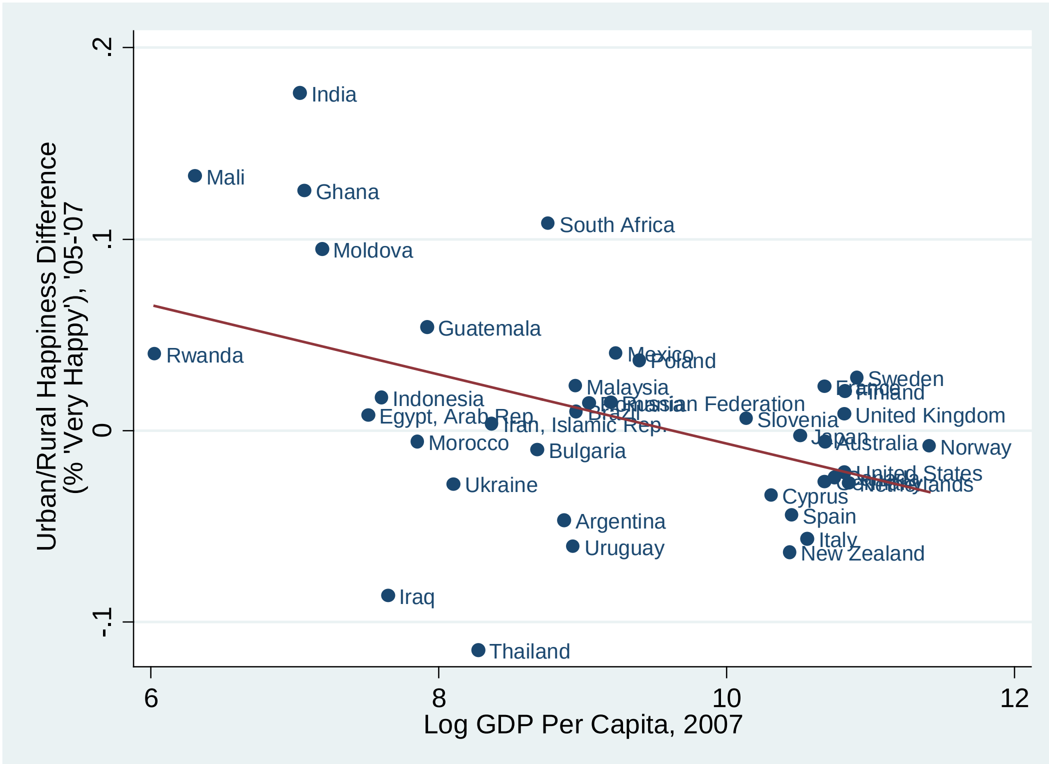


Source: This figure shows the Best Linear Unbiased Predictors (BLUPs) of metropolitan area relationships with individual life satisfaction after controlling for demographic covariates and individual income in a mixed effects model. Data are from CDC (2005-2009).

Figure 4: Correlation of BLUPs over time

Source: This figure shows the Best Linear Unbiased Predictors (BLUPs) of metropolitan area relationships with individual life satisfaction after controlling for demographic covariates in a mixed effects model. Data are from CDC (2005, 2010).

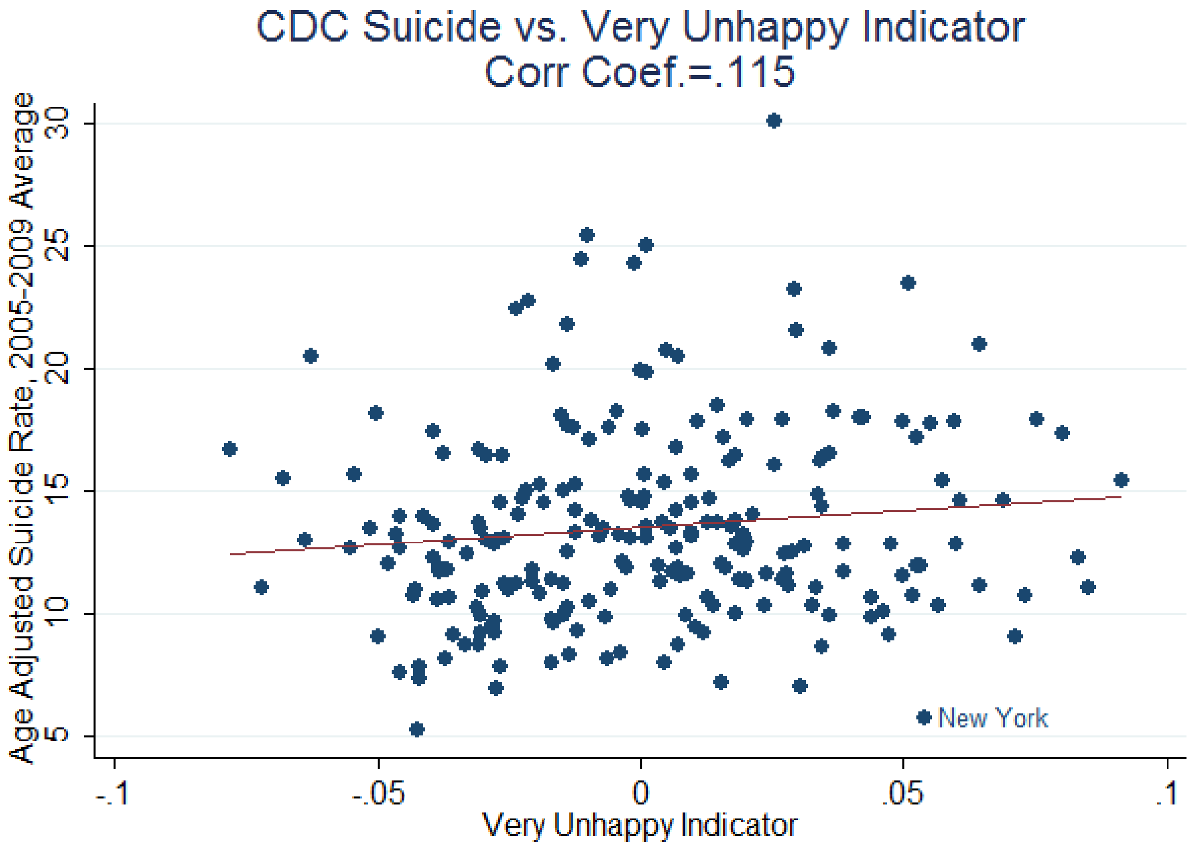
Figure 5: Urban-Rural Happiness Gradient vs. GDP Across Countries



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

Source: World Values Survey and World Bank

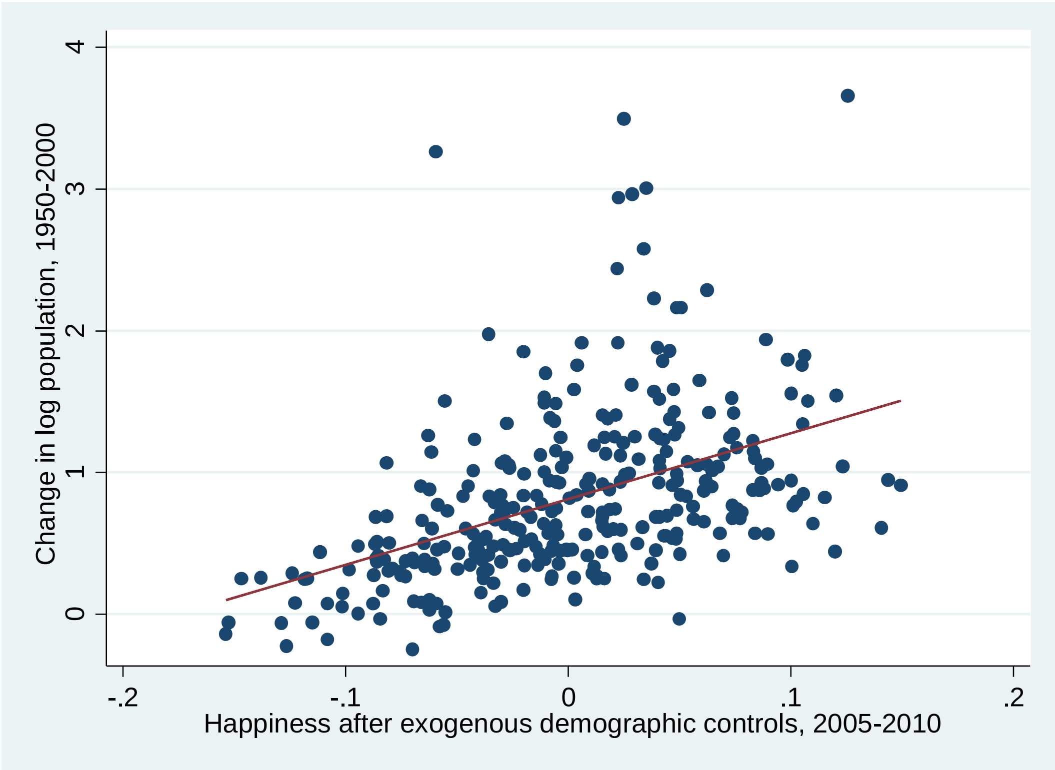
Figure 6



"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 6, which corroborates Daly and Wilson's earlier findings in this area."

Source: Behavioral Risk Factor Surveillance System Survey (CDC, 2005-2009) and National Suicide Statistics (CDC).

Figure 7: Population Decline and Subjective Well-Being



Source: This figure shows the Best Linear Unbiased Predictors (BLUPs) of metropolitan area relationships with individual life satisfaction, after controlling for other demographic covariates in a mixed effects model, against MSA population change from 1950 to 2000. Data are from CDC (2005-2010).

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)
VARIABLES					**Self-Reported Well-Being**					
Log Population, 2000	-0.00662	-0.00845**							-0.00727**	-0.00172
	(0.00518)	(0.00331)							(0.00339)	(0.00278)
% BA Grad, 2000			0.330***	0.0977					0.273***	0.0444
			(0.0965)	(0.0690)					(0.0857)	(0.0320)
% HS Grad, 2000					0.421***	0.0716			-0.232*	0.158***
					(0.137)	(0.104)			(0.129)	(0.0560)
Segregation Index, 2000							-0.160***	-0.130***	-0.103***	-0.0179
							(0.0343)	(0.0225)	(0.0314)	(0.0259)
Segregation x Black							-0.263***	-0.144***	-0.131***	-0.0634*
							(0.0470)	(0.0411)	(0.0356)	(0.0340)
Segregation x Asian									0.0708	0.0901*
									(0.0770)	(0.0479)
Segregation x HPI									-0.0326	-0.0482
									(0.106)	(0.106)
Segregation x Other									0.213***	0.228***
									(0.0654)	(0.0701)
Segregation x AIAN									-0.0629	-0.0568
									(0.0621)	(0.0589)
Segregation x Multiracial									-0.149***	-0.141
									(0.0273)	
Segregation x Hispanic									-0.213	-0.390
									(0.274)	(0.251)
Exogenous Controls (Age, Gender, Race)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous Controls (Education, Martial Status, Family Size)	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StateFE	No	No	No	No	No	No	No	No	No	No
Constant	-1.855***	2.172***	-1.970***	2.027***	-2.213***	1.991***	-1.769***	2.164***	2.356***	2.023***
	(0.297)	(0.280)	(0.268)	(0.266)	(0.276)	(0.270)	(0.289)	(0.264)	(0.251)	(0.264)
Observations	1,185,403	1,185,403	1,185,403	1,185,403	1,185,403	1,185,403	1,134,245	1,134,245	1,134,245	1,134,245
R-squared	0.007	0.076	0.008	0.076	0.008	0.076	0.008	0.076	0.076	0.078

Souces: Behavioral Risk Factor Surveillance System Survey (CDC), U.S. Census and Glaeser and Vigdor (2001)
Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3
Happiness and Urban Change, BRFSS

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				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)
Exogenous Controls (Age, Gender, Race)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous Controls (Education, Martial Status, Family Size)	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No	No	Yes	No	Yes
Constant	-1.824***	2.102***	2.185***	-2.500***	1.702***	2.067***	2.096***	1.965***
	(0.266)	(0.265)	(0.256)	(0.296)	(0.284)	(0.273)	(0.288)	(0.270)
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-squared	0.008	0.076	0.078	0.008	0.077	0.078	0.077	0.078

Souces: Behavioral Risk Factor Surveillance System Survey (CDC), U.S. Census and Glaeser and Vigdor (2001)
Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4
Happiness and Urban Population Growth Differences, BRFSS

VARIABLES	(1)	(2)	(3)	(4)	(5)
	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)
Exogenous Controls (Age, Gender, Race)	Yes	Yes	Yes	Yes	Yes
Endogenous Controls (Education, Martial Status, Family Size)	No	Yes	Yes	Yes	Yes
Employment and Income Variables	No	No	Yes	Yes	No
Health Controls	No	No	No	Yes	No
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	No	Yes
Constant	-1.835***	2.082***	-0.467*	-0.0646	2.144***
	(0.255)	(0.260)	(0.270)	(0.185)	(0.255)
Observations	1,182,563	1,182,563	1,182,563	1,164,203	1,182,563
R-squared	0.009	0.077	0.125	0.185	0.078

Souces: Behavioral Risk Factor Surveillance System Survey (CDC) and U.S. Census.
Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 5
Happiness, Urban Decline and Mobility, NSFH

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Self-Reported Well-Being				
Change in log population (below median) 1950-2000	0.141***	0.108***	0.121***	-0.0392	1.092*
	(0.0362)	(0.0337)	(0.0337)	(0.215)	(0.631)
Change in log population (above median) 1950-2000	-0.0574***	-0.0506***	-0.0565***	-0.0122	-0.766
	(0.0160)	(0.0188)	(0.0192)	(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)
Log Household Income			0.0958***	0.0587**	0.970***
			(0.00569)	(0.0255)	(0.692)
Age Controls	Yes	Yes	Yes	Yes	Yes
Exogenous Controls (Gender, Race)	Yes	Yes	Yes	No	No
Endogenous Controls (Education, Marital Status, Family Size)	No	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	No	Yes	Yes
Constant	-1.102	-0.0766	-2.112	-2.415	-3.468
	(0.896)	(1.267)	(2.156)	(3.028)	(4.222)
Observations	17,019	17,019	14,625	14,625	6,989
R-squared	0.010	0.048	0.053	0.709	0.684

Souces: National Survey of Families and Households and U.S. Census.
Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 6
Happiness Regressions Using the General Social Survey

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Reported Happiness (1=unhappy, 2=somewhat happy, 3=happy)					
Population Spline 1 - Below Median Income Growth	0.214***	0.205***	0.222***	0.521***	0.485***	0.459***
	(0.0527)	(0.0596)	(0.0818)	(0.104)	(0.113)	(0.113)
Population Spline 2 - Above Median Income Growth	-0.0295	0.00245	-0.0382	-0.0961	-0.0819	-0.0752
	(0.0438)	(0.0469)	(0.0658)	(0.0768)	(0.0853)	(0.0803)
*Pop Spline 1 * Move*			-0.0355			
			(0.118)			
*Pop Spline 2 * Move*			0.0543			
			(0.0780)			
Moved=1			0.0378			
			(0.0555)			
*Pop Spline 1 * 1980 Decade Dummy*				-0.287**	-0.296**	-0.277**
				(0.134)	(0.123)	(0.122)
*Pop Spline 1 * 1990 Decade Dummy*				-0.372***	-0.451***	-0.421***
				(0.121)	(0.0992)	(0.0952)
*Pop Spline 1 * 2000 Decade Dummy*				-0.556***	-0.446**	-0.440***
				(0.144)	(0.169)	(0.159)
*Pop Spline 1 * 2010 Decade Dummy*				-0.510***	-0.344	-0.298
				(0.172)	(0.225)	(0.214)
*Pop Spline 2 * 1980 Decade Dummy*				0.130	0.134	0.128
				(0.103)	(0.103)	(0.0969)
*Pop Spline 2 * 1990 Decade Dummy*				0.0398	0.113	0.111
				(0.0978)	(0.128)	(0.118)
*Pop Spline 2 * 2000 Decade Dummy*				0.0107	0.0116	0.00589
				(0.0795)	(0.110)	(0.106)
*Pop Spline 2 * 2010 Decade Dummy*				0.188**	0.161	0.180
Exogenous controls (gender, race, age)	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous controls (education, family size, marital status)	No	Yes	Yes	No	Yes	Yes
Income and Employment Indicators	No	Yes	Yes	No	No	Yes
Constant	0.813	5.429*	5.331*	2.462	14.09*	12.96
	(2.769)	(2.774)	(2.805)	(6.216)	(7.956)	(8.006)
Observations	9,995	7,541	7,541	9,995	7,541	7,541
R-squared	0.021	0.051	0.051	0.024	0.040	0.054

Notes: Standard errors clustered at MSA level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable z-scored. All regressions include a year trend. Regressions (5)-(6) include decade dummies.
Sources: GSS and U.S. Census

Table 7
Self-Reported Well-Being and Disamenities

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Self-Reported Well-Being							
Population Spline 1 (Below Median Population Growth, 1950-2000)	0.210***	0.215***	0.177***	0.213***	0.224***	0.156***	0.0863***	0.0830***
	(0.0177)	(0.0183)	(0.0241)	(0.0188)	(0.0214)	(0.0310)	(0.0218)	(0.0317)
Population Spline 2 (Above Median Population Growth, 1950-2000)	0.00115	0.00547	0.0363*	0.00250	0.00445	0.0231	0.0134	0.0164
	(0.0141)	(0.0124)	(0.0218)	(0.0135)	(0.0130)	(0.0301)	(0.0200)	(0.0135)
Average January Temperature	0.000262					0.00153**	0.00177***	-0.00281***
	(0.000440)					(0.000773)	(0.000488)	(0.000966)
Precipitation		0.000402				0.000117	-0.000146	0.00190***
		(0.000278)				(0.000579)	(0.000386)	(0.000491)
Log of Crime			0.00451			0.00457	0.00258	0.0115
			(0.00963)			(0.0103)	(0.00625)	(0.00770)
Pollution				0.000265		0.000171	0.000487	-3.81e-05
				(0.000704)		(0.00124)	(0.000839)	(0.00165)
Gini Coefficient, 2000					0.0957	-0.0538	0.325	0.863
Exogenous Controls (age, race, gender)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous Baseline Controls (educ., marital status)	No	No	No	No	No	No	Yes	Yes
State FE	No	No	No	No	No	No	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.849***	-1.876***	-2.067***	-1.830***	-1.842***	-1.951***	1.924***	1.860***
	(0.264)	(0.261)	(0.273)	(0.269)	(0.287)	(0.564)	(0.404)	(0.342)
Observations	1,182,563	1,182,563	328,379	931,580	1,126,257	261,987	261,987	261,987
R-squared	0.009	0.009	0.009	0.010	0.009	0.010	0.078	0.079

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)
Sources: Behavioral Risk Factor Surveillance System Survey (CDC) and U.S. Census.

Table 8
Happiness in the 1940s

	(1)	(2)	(3)	(4)
VARIABLES		Happiness (Happy=1, Unhappy=0)		
population dummy==Farm Pop	0.0255***	0.0179	0.00760	0.000815
	(0.00923)	(0.0138)	(0.0141)	(0.0181)
population dummy==Towns under 2,500	0.00977	-0.00555	0.0123	-0.00284
	(0.00835)	(0.0104)	(0.0122)	(0.0187)
population dummy==10,000 to 100,000	0.00526	-0.0149	-0.00717	-0.0125
	(0.00795)	(0.0120)	(0.0128)	(0.0105)
population dummy==100,000 to 500,000	-0.00441	-0.0310	-0.00685	-0.0280
	(0.0132)	(0.0186)	(0.0205)	(0.0249)
population dummy==500,000 and over	-0.0412***	-0.0502***	-0.0497***	-0.0599***
	(0.00819)	(0.00907)	(0.0150)	(0.0117)
Population Growth 1950-2000 Lower than Mean		-0.0186		
		(0.0148)		
Income Growth 1950-2000 Lower than Mean			0.0124	
			(0.0157)	
1 if Jan Temp<35 Degrees Fahrenheit				0.00910
				(0.0191)
Constant	0.816***	0.826***	0.827***	0.831***
	(0.0254)	(0.0263)	(0.0265)	(0.0288)
Observations	10,809	10,809	10,809	10,809
R-squared	0.027	0.029	0.029	0.028

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Sources: Gallup Polls #1946-0369, #1947-0399, #1948-0418 and #1948-0425; Census Data.

Notes: SE clustered at the state level. Dummy dropped: size=2500 to 10000. All regressions include controls for demographic variables (age, race, gender, schooling), regions, and a year trend variable. 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 35F dummy interactions .

Table 9
Income and Happiness Regressions, 1940 and 2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			1940					**2000**		
VARIABLES	**Log of Income**	**Income**	**Log of Income**	**Income**	**Log of Income**	**Log of Income**	**Income**	**Log of Income**	**Income**	**Log of Income**
Spline - Below Median Population Growth	-0.144**	-135.9*				-0.0449	-286.8			
	(0.0577)	(70.82)				(0.0517)	(1,912)			
Spline -Above Median Population Growth	-0.0442	-52.79				-0.0146	-496.6			
	(0.0455)	(61.72)				(0.0222)	(769.6)			
swb BLUP after full dem controls, all, nsfe			-1.101***	-1,324***	-1.306***			-0.518**	7,231	-1.883***
			(0.174)	(271.9)	(0.468)			(0.260)	(12,409)	(0.679)
Demographic Controls (age, education, race)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Median Regression	No	Yes	No	Yes	No	No	Yes	No	Yes	No
2SLS (Instrument BLUP with January Temperature, July Temperature, and Precipitation)	No	No	No	No	Yes	No	No	No	No	Yes
Constant	7.111***	1,243***	7.006***	1,135***	6.996***	10.27***	31,580***	10.22***	34,895***	10.20***
	(0.0290)	(30.53)	(0.0142)	(18.72)	(0.0266)	(0.0360)	(1,320)	(0.0189)	(803.6)	(0.0258)
Observations	78,580	78,580	78,580	78,580	78,580	194,655	194,655	194,655	195,447	194,655
R-squared	0.211	0.183	0.216	0.186	0.216	0.223	0.148	0.224	0.137	0.216

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). SE clustered at the MSA level. Sample is employed males aged 25-55 who work full-time and earn more than half the federal minimum wage for a full-time worker. Population weights are used in the non-median regressions.
Source: U.S. Census Microdata

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 (2005-2009) 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.[9] During our sample period of 2005 to 2009, the survey covers all 50 states and Washington, DC.[10] 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.[11] 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

[9] CDC provides weights to adjust for differences in phone line density across areas, but we do not use these weights.
[10] Puerto Rico, Guam and the U.S. Virgin Islands are also included, but we drop the three territories.
[11] 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.[12] 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.[13] We therefore create indicator variables for four age ranges of the randomly selected child, and six categories for the respondent's relationship.[14] 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 4 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

[12] Sacks, Stevenson, and Wolfers's (2010) NBER working paper is the natural citation on income. I don't know whom to cite on sex, age, and race; perhaps Oswald?

[13] 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.

[14] 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. [15] 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 Table 2 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 specifications (not reported), we interact the number or age of children with the respondent's

[15] 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.

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 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 Table 2 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

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

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

Proxying with Mental Health

The BRFSS survey data on life satisfaction are only available for a few recent years, from 2005 through 2009. In order to explore changes in area-level life satisfaction over longer time periods, we have to use a different proxy for subjective well-being in other years. This new proxy is based on the area's reported mental health. Going back to 1993, BRFSS asks respondents to report how many days they were unhappy during the previous month. In the question labeled "MENTHLTH", the survey asks:

> "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?"
>
> 0-30 Number of days

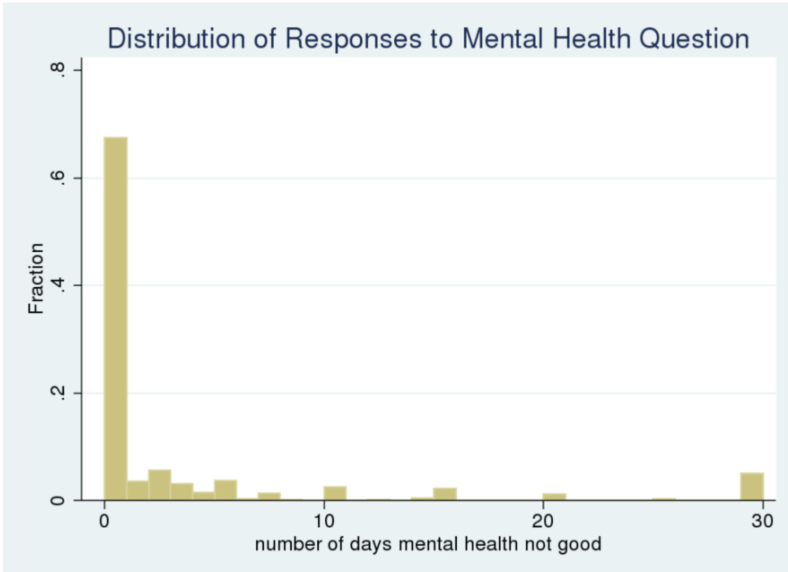
The distribution of responses to this question is shown in Appendix Figure 1. As the Figure shows, the vast majority of individuals report 0 days of depression. Between 2005 and 2009, 68% of respondents reported 0 days of bad mental health, with a generally declining distribution thereafter. Nevertheless, there is some variation in responses. Between 2005 and 2009, 17% report between 1 and 5 days of bad mental health. 4.6% report between 6 and 10 days, about 5.3% report between 11 and 29 days, and 5.2% of individuals report 30 days of bad mental health. Round numbers (5, 10, 15, etc.) generally have significantly more responses than other days. This is especially true at higher numbers. This distribution, like the life satisfaction question, is generally stable between years.

In order to interpret these responses in a manner comparable to the life satisfaction question, we transform these responses based on the empirical relationship between individual answers to the mental health question and the life satisfaction question. Appendix Figure 2 plots the average life satisfaction reported by respondents with each number of days of depression across the five waves of BRFSS data for which both questions are present, 2005-2009. The dots show the simple averages, and the red line shows a smoothed version of these responses. The smoothing is done using an Epanechikov kernel, with a degree 1 polynomial and a rule of thumb bandwidth[16]. There is a clear monotonic relationship, in the direction we would expect. We use this smoothed relationship to transform each year's mental health data onto the scale of life satisfaction answers, which we then normalize as before.

With these data on transformed and normalized mental health, we will be able to extend our analysis back to 1993. To start, Appendix Figure 3 shows the relationship between MSA fixed effects estimated by using the original life satisfaction data in regression (1) and those estimated by putting transformed mental health in regression (1). The two measures of MSA well-being have R^2=0.23.

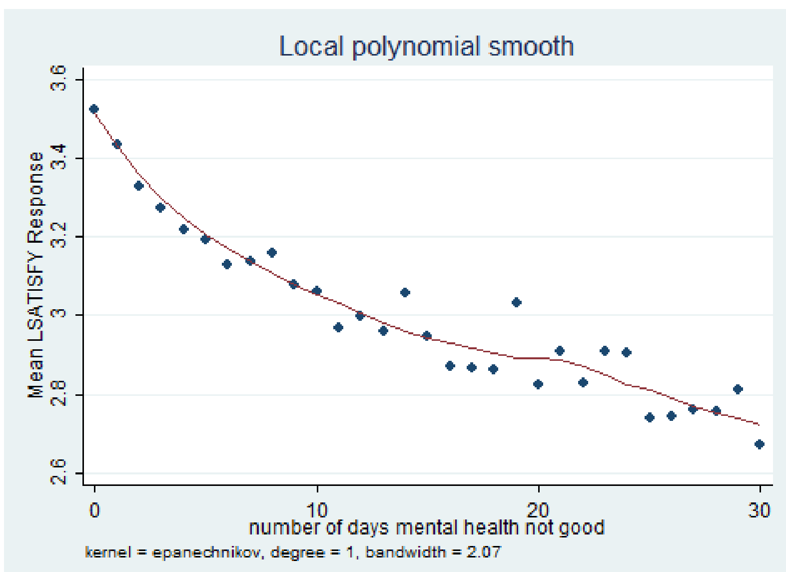
[16] This is implemented using the lpoly command in Stata.

Appendix Figure 1: Responses to BRFSS question about days suffering depression



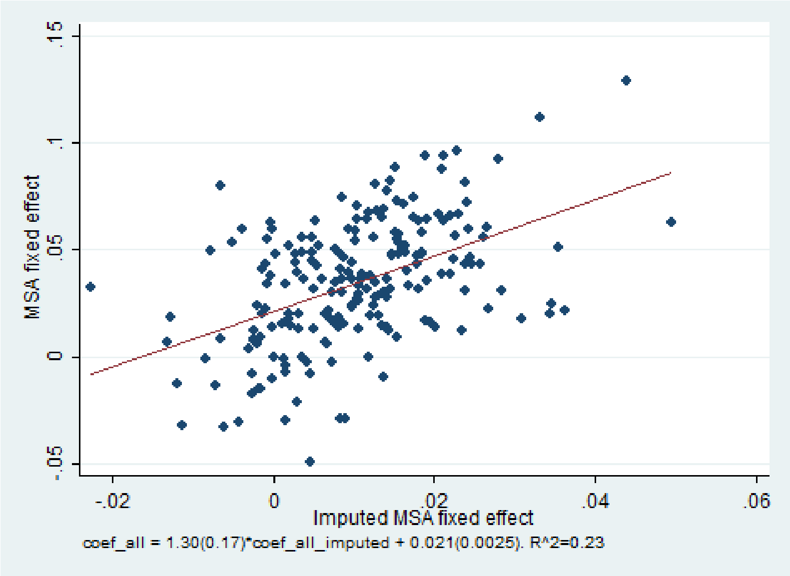
Source: Behavioral Risk Factor Surveillance System Survey (CDC, 2005-2009).

Appendix Figure 2: Relationship between individual responses to mental health question and life satisfaction question in BRFSS



Source: Behavioral Risk Factor Surveillance System Survey (CDC, 2005-2009).

Appendix Figure 3: Relationship between MSA fixed effect for transformed mental health question and life satisfaction question in BRFSS



Source: This figure shows fixed effects of metropolitan area relationships with individual life satisfaction after controlling for demographic covariates, against a similar number estimated with transformed mental health data ("imputed MSA fixed effect"). Data are from CDC (2005-2009).

Appendix Table 1: Selection of metropolitan areas ranked by happiness

Rank:	Metropolitan area:	BLUP after demographic controls:	BLUP controlling for demographics and income:	BLUP without controls:
1	Lafayette, LA	0.127	0.125	0.103
2	Non-metropolitan Hawaii	0.117	0.104	0.054
3	Non-metropolitan Louisiana	0.112	0.144	0.070
4	Shreveport, LA	0.109	0.110	0.081
10	Honolulu, HI	0.084	0.026	0.046
11	Nashville, TN	0.084	0.072	0.060
16	Norfolk, VA	0.073	0.032	0.073
17	Charlottesville, VA	0.073	0.058	0.143
18	Flagstaff, AZ	0.067	0.061	0.107
19	Galveston, TX	0.067	0.063	0.098
20	Tallahassee, FL	0.066	0.068	0.062
27	Naples, FL	0.060	0.028	0.121
32	Anchorage, AK	0.052	0.012	0.050
43	Colorado Springs, CO	0.046	0.030	0.094
50	Washington, DC	0.042	-0.056	0.039
53	West Palm Beach, FL	0.041	-0.004	0.082
54	McAllen, TX	0.041	0.090	-0.007
65	Burlington, VT	0.034	0.016	0.072
72	Raleigh-Durham, NC	0.032	0.007	0.061
87	Non-metropolitan Texas	0.028	0.046	0.006
100	El Paso, TX	0.023	0.040	-0.040
112	Atlanta, GA	0.019	-0.032	0.035
139	Minneapolis-St. Paul, MN	0.011	-0.029	0.059
140	Baltimore, MD	0.011	-0.058	0.023
277	Chicago, IL	-0.026	-0.078	-0.012
288	Las Vegas, NV-AZ	-0.028	-0.050	-0.059
301	Seattle, WA	-0.034	-0.077	0.009
302	San Francisco, CA	-0.035	-0.086	-0.035
304	Boston, MA	-0.035	-0.059	-0.043
306	San Jose, CA	-0.036	-0.107	0.003
307	Vallejo-Fairfield-Napa, CA	-0.036	-0.066	-0.048
309	Los Angeles, CA	-0.037	-0.056	-0.105
348	Nassau-Suffolk, NY	-0.066	-0.144	-0.022
354	Non-metropolitan Indiana	-0.073	-0.045	-0.099
358	Pittsburgh, PA	-0.078	-0.040	-0.111
360	Gary, IN	-0.089	-0.095	-0.185
362	Detroit, MI	-0.090	-0.118	-0.117
364	Toledo, OH	-0.095	-0.079	-0.136
365	South Bend, IN	-0.110	-0.098	-0.142
367	New York, NY	-0.114	-0.174	-0.156

Source: Best Linear Unbiased Predictors (BLUPs) of metropolitan area relationships with individual life satisfaction after controlling for demographic covariates in a mixed effects model. Data are from CDC (2005-2009).

Appendix Table 2
Housing Value Regressions, 1940 and 2000

	1940					2000				
	Log of Housing Value	**Housing Value**	**Log of Housing Value**	**Housing Value**	**Log of Housing Value**	**Log of Housing Value**	**Housing Value**	**Log of Housing Value**	**Housing Value**	**Log of Housing Value**
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Spline - Below Median Population Growth	-0.301	-1,237*				0.124	16,464			
	(0.238)	(744.2)				(0.298)	(54,707)			
Spline - Above Median Population Growth	-0.253*	-1.94e-10				-0.0241	-666.1			
	(0.130)	(295.6)				(0.0983)	(20,062)			
swb BLUP after full dem controls, all, nsfe			-3.600***	-11,360***	-6.360***			-2.106**	-408,535**	-6.798***
			(0.862)	(4,167)	(1.834)			(0.926)	(174,599)	(2.244)
Housing Quality Controls (Built year, type of unit, rooms, bedrooms)	N/A	N/A	N/A	N/A	N/A	Yes	Yes	Yes	Yes	Yes
2SLS (Instrument BLUP with January Temperature, July Temperature, and Precipitation)	No	No	No	No	Yes	No	No	No	No	Yes
Constant	3.363***	29.97***	2.967***	20.71***	2.939***	11.71***	169,380***	11.76***	179,680***	12.30***
	(0.138)	(6.692)	(0.0489)	(0.925)	(0.0666)	(0.195)	(39,306)	(0.0878)	(10,568)	(0.211)
Observations	106,112	106,112	106,112	106,112	106,112	300,676	300,676	300,676	300,676	300,676
R-squared	0.044	0.002	0.103	0.003	0.101	0.339	0.192	0.353	0.204	0.299

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). SE clustered at the MSA level. 1940 Microdata has no building quality variables. 2000 sample drops the lowest end of housing stock (units without plumbing or a kitchen, or with only one room). Household weights are used in the non-median regressions. Regressions (7) and (9) did not converge in the median regression form, so OLS is used.
Source: U.S. Census Microdata

Appendix Table 3
Rent Regressions, 1940 and 2000

	1940					2000				
	Log of Rent	**Rent**	**Log of Rent**	**Rent**	**Log of Rent**	**Log of Rent**	**Rent**	**Log of Rent**	**Rent**	**Log of Rent**
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Spline - Below Median Population Growth	-0.497*	-12.69				0.0108	26.90			
	(0.271)	(12.64)				(0.210)	(121.1)			
Spline - Above Median Population Growth	-0.186	-1.205				0.0721	16.26			
	(0.154)	(4.933)				(0.0684)	(30.06)			
swb BLUP after full dem controls, all, nsfe			-4.387***	-102.6***	-5.011***			-0.860	-464.7	-1.406
			(0.550)	(18.55)	(1.292)			(0.560)	(347.4)	(1.518)
Housing Quality Controls (Built year, type of unit, rooms, bedrooms)	N/A	N/A	N/A	N/A	N/A	Yes	Yes	Yes	Yes	Yes
2SLS (Instrument BLUP with January Temperature, July Temperature, and Precipitation)	No	No	No	No	Yes	No	No	No	No	Yes
Constant	3.363***	29.97***	2.967***	20.71***	2.939***	6.090***	495.6***	6.310***	726.7***	6.421***
	(0.138)	(6.692)	(0.0489)	(0.925)	(0.0666)	(0.177)	(95.51)	(0.170)	(45.92)	(0.0977)
Observations	106,112	106,112	106,112	106,112	106,112	144,708	144,708	144,708	144,708	144,708
R-squared	0.044	0.002	0.103	0.003	0.101	0.058	0.076	0.061	0.086	0.060

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). SE clustered at the MSA level. 1940 Microdata has no building quality variables. 2000 sample drops the lowest end of housing stock (units without plumbing or a kitchen, or with only one room). Household weights are used in the non-median regressions.
Source: U.S. Census Microdata

Appendix Table 4: 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)
Regression includes 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, 2005-2009), against the variables shown, month dummies, BRFSS wave fixed effects and, in some specifications, 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.