

Happiness is In The Air if It Grows (Growing Places are Happier than Shrinking ones)

Monday 24th April, 2023 18:17

Abstract

We study the effect of population change on Subjective WellBeing (SWB) using over 100,000 observations from Behavioral Risk Factor Surveillance System (BRFSS) representative of 392 US counties. SWB correlates higher with population change (.4) than with county level crime (-.25) and income (.2). The relative ecological strong effect size holds in regressions controlling for person level and county level predictors of SWB—population change is one of the strongest ecological predictors of SWB. While ecological variables have a smaller effect on individual SWB than person level variables, their total combined population effect is large. After Delken (2008), this is only the second study on the effect of population change of a city/county on its residents' happiness. Such a gap in the literature is remarkable—we call for more research in this area. As in any non-experimental study, results are not causal. And results may not generalize beyond the US population studied.

Keywords

SUBJECTIVE WELLBEING, LIFE SATISFACTION, HAPPINESS, BEHAVIORAL RISK FACTOR SURVEILLANCE SYSTEM (BRFSS), POPULATION CHANGE, SHRINKAGE

Introduction

Urbanization is rampant: world urban population has exploded from 30% to 50% over 1950-2005, and is projected to grow to 70% in 2050 (population.un.org/wup). Yet, some places shrink.

Take for instance two counties that an author of this study has inhabited. Collin TX, a northern suburb of Dallas, has mushroomed sevenfold just over 4 decades, from 150k in 1980 to 1m in 2019. Camden NJ has stayed flat over the same period, while the county seat, city of Camden, has shrunk about 40% from its height of 125k in 1950 to 72k in 2020. Collin TX and Camden NJ tell a story of many other counties in South v North East. Sunny, spacious, and affordable South aka “Sunbelt” often mushrooms at mind boggling pace. Gritty, crowded, and expensive North East aka “Rustbelt” stays flat or shrinks. Many US counties shrink, and are desperate to regain population, even offering \$15,000 to move in (Block 2021). Likewise, largest American cities are not growing or even shrinking recently (Thompson 2019).

Indeed, it appears that happiness is in the air in vibrant fast growing places; and gloom and doom infects shrinking places, or does it? Empirical test is missing.

The relationship between population change and SWB (Subjective WellBeing) is important and interesting for several reasons. Population change is a key demographic and social metric. SWB is a key progress/development

metric as explained in the next “Theory” section. American localities are very dynamic in population size—some counties are exploding by 50%, and some are shrinking by 10% over just several years.

While there is much research on population size and SWB as recently summarized in Okulicz-Kozaryn and Valente (2021), there is only one study on population change and SWB. Google Scholar queries such as “population change and happiness,” “city growth and happiness,” “population growth and happiness,” “population decline and happiness” do not yield relevant literature. If anything, there is a sizable literature on shrinking city and little of it somewhat relates to quality of life (but not happiness).¹

The only study on population change and SWB is a master thesis written under the direction of a “happiness grandfather,” Ruut Veenhoven (Delken 2008). The thesis offers a conclusion: “Overall satisfaction with life appears not to be lower in shrinking cities and satisfaction with several domains of life even higher. This is not because inhabitants are unaware of the situation of their city, since they appear to be more concerned about job-chances and crime.” We agree that job-chances and crime are critical for happiness, possibly the most important ecological variables when it comes to place growth or shrinkage. But our study finds that even after controlling for crime and employment, shrinkage is related to lower SWB.

Delken (2008) assumes three scenarios for cities: *growing* $\geq 3\%$, $-3\% < \textit{stable} > 3\%$, and $-3\% < \textit{shrinking}$. An advantage of Delken (2008) over our study is use of multiple domain satisfactions—we only use global life satisfaction. An advantage of our study is structural—the US (studied here) is more dynamic in terms of population than Germany (studied in Delken (2008)).

Hartt (2019) makes a similar point to Delken (2008)—people can live happily in shrinking cities, but Hartt (2019) does not use SWB measure but proxies. Hollander (2011) argues similarly: cities can shrink successfully, enjoy “smart decline”: shrinkage does not always mean decline in quality of life.

Indeed, shrinkage in population offers some opportunities for growth, e.g., in terms of urban gardens/agriculture, which do offer multiple benefits (Jackson 2012, Lima and Eischeid 2017). Urban gardens/agriculture are not feasible in economically successful places such as Manhattan or San Francisco, but viable in poor places such as Philadelphia or Detroit. And there is an useful and intriguing concept of Urban Spontaneous Vegetation (USV).² USV has no financial cost, but plenty of authenticity, and it is always appropriate to the site conditions (Kühn 2006).

To summarize this necessarily brief literature review: there is some research related to the population change-SWB nexus, but only one study, Delken (2008), uses SWB measure.

One other study that uses SWB measure has to be discounted as flawed. Similarly to our study, Glaeser et al. (2016) uses BRFSS data and finds a positive effect of population growth on SWB. There are, however, critical problems with Glaeser et al. (2016): it cherry-picks only certain urban areas and drops from the data smaller counties without any clear reason.³ In addition, the analyses in Glaeser et al. (2016) are oversaturated with many controls. Specifically, by adding state fixed effects, which correlate with population size and change, the relationship flips from negative to positive on urbanicity.

Several other studies are somewhat related to the present study, but fundamentally their approaches are disjoint. Park et al. (2021) offers a novel approach using Twitter data, but the research is conducted in one city only. We

¹The terms ‘quality of life’ and ‘happiness’ are defined for instance in Okulicz-Kozaryn and Valente (2019).

²USV colonizes large areas in and around cities, considered low economic value or dereliction, but can contribute valuable ecosystem services. USV may have equal or higher indicator values for habitat provisioning (plant species diversity, invertebrate abundance and taxonomic diversity) and indicators of climatic regulatory services than the other habitats (Robinson and Lundholm 2012).

³Notably, there seems to be a pattern—for instance Glaeser (2011) drops developed countries from the sample so that much of it contains African countries. A case is made that urban places are happier, while in fact they are not (Okulicz-Kozaryn and Valente 2021), with exception of very poor countries such as those in Africa—and these are the very cases that Glaeser retains in his sample.

note that data from social media holds much promise for the future research. Chen et al. (2019) finds that shrinking or as they term “hollowing” rural areas are not less happy, however, the study uses Chinese data—China has unique population change and migration patterns. Goetzke and Islam (2017) and Barreira et al. (2019) argue that unhappiness predicts population decline or happiness predicts population growth. We think that population changes are mostly due to other factors than happiness, and it is rather decline or growth that leads to unhappiness or happiness, not the other way round. People could move out from a shrinking city because they are unhappy about the deteriorating quality of life there, but still such unhappiness is caused by those factors that are the main causes of the shrinkage. For instance, people could be both unhappy and moving out because of the scarcity of jobs and higher crime rates in their shrinking cities. Still, a proper evaluation of the direction of causality is left for future research, perhaps a natural experiment research design.

Theory

Already in 70s SWB has been proposed as a measure of social/human progress/development (Gurin et al. 1960, Campbell et al. 1976, Campbell 1981, Easterlin 1973, 1974). But the idea has not spread widely until 00s (Diener 2009, Stiglitz et al. 2009). While SWB is now a widely accepted measure of social/human progress/development at country/societal/global level, it is still mostly overlooked at lower level of aggregation—at local/municipal/community level—with only a handful of recent studies (Okulicz-Kozaryn 2016, Cloutier and Pfeiffer 2017, Pfeiffer and Cloutier 2016, Mouratidis and Yiannakou 2022, Mouratidis 2021, 2020, 2018, 2017, Martínez and Short 2020). Our present research adds a study at local/county level.

There are several theories explaining mechanisms of SWB. None of the SWB theories (Brickman et al. 1978, Veenhoven and Ehrhardt 1995, Michalos 1985, Carver and Scheier 1990) explains well why population growth or decline would change SWB. Livability theory may be somewhat explanatory (p. 3645 Veenhoven 2014) (replace ‘societies’ with ‘counties’ or ‘places’):

Societies are systems for meeting human needs, but not all societies do that job equally well. Consequently, people are not equally happy in all societies.

Improvement of the fit between social institutions and human needs will result in greater happiness.

Growing places may better satisfy human needs—that’s why they are growing, and places that fail to satisfy may be shrinking—people vote with their feet. There may be more resources available and even more coming if there is growth, and hence a better/more positive outlook for the future. And the opposite may be true if a place is shrinking. Population growth or shrinkage is not only about present conditions but also about outlook, prospects, and direction of change.

The theory that may explain the mechanism between population change and SWB is the so-called “tunnel effect.” Humans think that whatever is happening around, whether things are getting better or worse, will eventually happen to them as well:

Suppose that I drive through a two-lane tunnel, both lanes going in the same direction, and run into a serious traffic jam. No car moves in either lane as far as I can see (which is not very far). I am in the left lane and feel dejected. After a while the cars in the right lane begin to move. Naturally my spirits lift considerably, for I know the jam has been broken and that my lane’s turn to move will surely

come at any moment now. Even though I still sit still, I feel much better off than before because of the expectation that I shall soon be on the move. (Hirschman, quoted in Ravallion and Lokshin 2000, p. 88)

Population growth/decline seems to be related to opportunities/jobs, safety/crime, and so forth, at least prospects or perceptions of those. Hence, if a place grows, there are positive connotations. If it shrinks, it's negative.

In a sense, tunnel effect is related to Multiple Discrepancies Theory (MDT) (Michalos 1985). If by comparison the area is doing well (growing as opposed to shrinking), then a person by association is thinking to be doing better as well, and is happier. In general, doing better than others produces SWB—neighbors are negatives (Luttmer 2005), and others' misfortune may be a source of one's bliss ("Schadenfreude").

Data and Method

All person level data come from the 2005-2010 Behavioral Risk Factor Surveillance System (BRFSS) at cdc.gov/brfss. We use the SMART (Selected Metropolitan/Micropolitan Area Risk Trends) version of BRFSS that is representative of counties.

All county level data come from the Inter-university Consortium for Political and Social Research: County Characteristics, 2000-2007 at [doi:10.3886/ICPSR20660.v2](https://doi.org/10.3886/ICPSR20660.v2). As most county level control variables are for 2000-2005, regression analyses of person level SWB use 2005 BRFSS only. Descriptive statistics at county level only use full 2005-2010 BRFSS collapsed by county.⁴ While we only have 392 counties in 2005-2010 BRFSS, 13% of about 3,000 US counties, there is a good representation across the country including the largest coastal cities, smaller cities, suburbs, exurbs, and rural counties. All 51 states are in the data, but most have fewer than 10 counties represented here, and several have only one or two counties. Small NJ has almost all of its 21 counties represented. And by far most counties in this dataset are from FL, over 40. All counties along with observations on key variables are listed in supplementary material at https://colab.research.google.com/drive/1fFzDc73LbGAC-G6_I58FV1fH691NAs7_?usp=sharing.

The SWB item reads "In general, how satisfied are you with your life?": 1 "very dissatisfied" 2 "dissatisfied" 3 "satisfied" 4 "very satisfied"—over 90 percent of respondents were either satisfied or very satisfied with their lives. Table 1 provides definitions of the variables used in our analysis.

⁴In addition, in the supplementary analyses we use census data for 1990-00 and 2000-10 population growth.

Table 1: Variable definitions.

name	description
swb	"In general, how satisfied are you with your life?"
person-level variables (cdc.gov/brfss):	
income	"Is your annual household income from all sources:"
married or member of an un-married couple	"marital status; Are you:"
unemployed	"Are you currently: Out of work"
age	age
age squared	age squared
White	White
education level	"What is the highest grade or year of school you completed?"
soc/emo support	"How often do you get the social and emotional support you need? "
general health	"Would you say that in general your health is" 1 (poor) - 5 (excellent)
county-level variables (doi:10.3886/ICPSR20660.v2):	
crime rate index	"Index crime rate (per 100,000 persons), 2004"
persistent poverty [0/1]	"20 percent or more of residents were poor as measured by each of the last 4 censuses, 1970, 1980, 1990, and 2000"
% Black	"percent Black, 2005"
low education [0/1]	"25 percent or more of residents 25-64 years old had neither a high school diploma nor GED in 2000."
housing stress [0/1]	"30 percent or more of households had one or more of these housing conditions in 2000: lacked complete plumbing, lacked complete kitchen, paid 30 percent or more of income for owner costs or rent, or had more than 1 person per room."
low employment [0/1]	"Less than 65 percent of residents 21-64 years old were employed in 2000."
population loss [0/1]	"Number of residents declined both between the 1980 and 1990 censuses and between the 1990 and 2000 censuses."
pers. inc. (USD 1,000)/cap	"per capita personal income (USD 1,000), 2005"
population percent change 2000-2005	from county characteristics ICPSR file
population	"census 2000 total resident population"
population density per sq mile, 05-09 * 1,000,000	population density

We follow Okulicz-Kozaryn and Mazelis (2016) in terms of controls. Notable controls include person level `unemployed` and county level `low employment` and `crime rate index`⁵—these variables not only predict SWB but also correlate with population change.

We use a standard OLS regression with clustered standard errors on county with BRFSS sampling weights to account for oversampling. We treat the 4-step happiness variable as continuous. Ordinal happiness can be treated as a continuous variable (Ferrer-i-Carbonell and Frijters 2004).⁶ In fact, the OLS has become the default method in happiness research and its results are found to be very similar to the discrete models that treat the happiness variable as an ordinal variable (Ferrer-i-Carbonell and Frijters 2004, Blanchflower and Oswald 2011, Sorensen 2020).

Results

First, we provide broad descriptive statistics at county level using county level data and means of person level BRFSS variables collapsed over 2005-2010 to county level. Over just 5 years from 2000 to 2005 several counties

⁵For computation see SOM.

⁶We used the following Stata command: `regress <happiness> <person-level variables> <county-level variables> [pw=_cntywt] , robust cluster(<county>)`.

shrank by about 5% and a handful grew by more than 10%.⁷

Table 2 shows correlations. Among ecological (county-level) variables, remarkably, SWB’s very strongest correlation is with population change, >50% stronger than correlation with crime and about twice of the correlation with income. This is the key, and unexpected finding of this research. While positive and weak to moderate correlation was expected, such large magnitude as compared to other variables was unexpected.⁸ The bivariate relationship will hold in multivariate regressions of SWB on county and person level predictors.

Table 2: Cross-correlation table

Variables	population percent change 2000-2005	crime rate index	% Black	housing stress	low employment	population loss	pers. inc. (USD 1,000)/cap	swb
population percent change 2000-2005	1.00							
crime rate index	-0.17	1.00						
% Black	-0.21	0.48	1.00					
housing stress	0.04	0.20	0.10	1.00				
low employment	0.09	0.04	0.03	0.18	1.00			
population loss	-0.27	0.18	0.27	-0.01	0.05	1.00		
pers. inc. (USD 1,000)/cap	-0.18	-0.17	0.00	0.05	-0.27	-0.04	1.00	
swb	0.39	-0.25	-0.24	-0.13	-0.18	-0.29	0.22	1.00

Nb. obs. : 376

The scatterplot between population change and SWB is shown in figure 1. There are geographic patterns circled in the graph. For instance, at bottom-left there is a cluster of large North-Eastern cities, at top-right there is a cluster of Southern counties, and three happiest counties in this sample are either in the West or North. Again, shrinkage does not always mean decline in all other areas (Hartt 2019, Delken 2008, Hollander 2011), and so we find outliers as shown in figure 1 at top-left, yet most places fit the pattern that the more growth, the more SWB.

⁷Full county-level and auxiliary descriptive statistics (not shown here) are available at https://colab.research.google.com/drive/1fFzDc73LbGAC-G6_I58FV1fH691NAs7_?usp=sharing. Over 10 years, 1990-2000 or 2000-2010, several counties shrank by >30% and several grew by >50%.

⁸Population growth correlates significantly with several variables. Notably, in growing counties there is little less crime. Also, poorer counties tend to grow faster. While correlation between population change and SWB is remarkably high, the absolute differences on SWB are small. SWB ranges only between 3.2-3.6 on 1-4 scale.

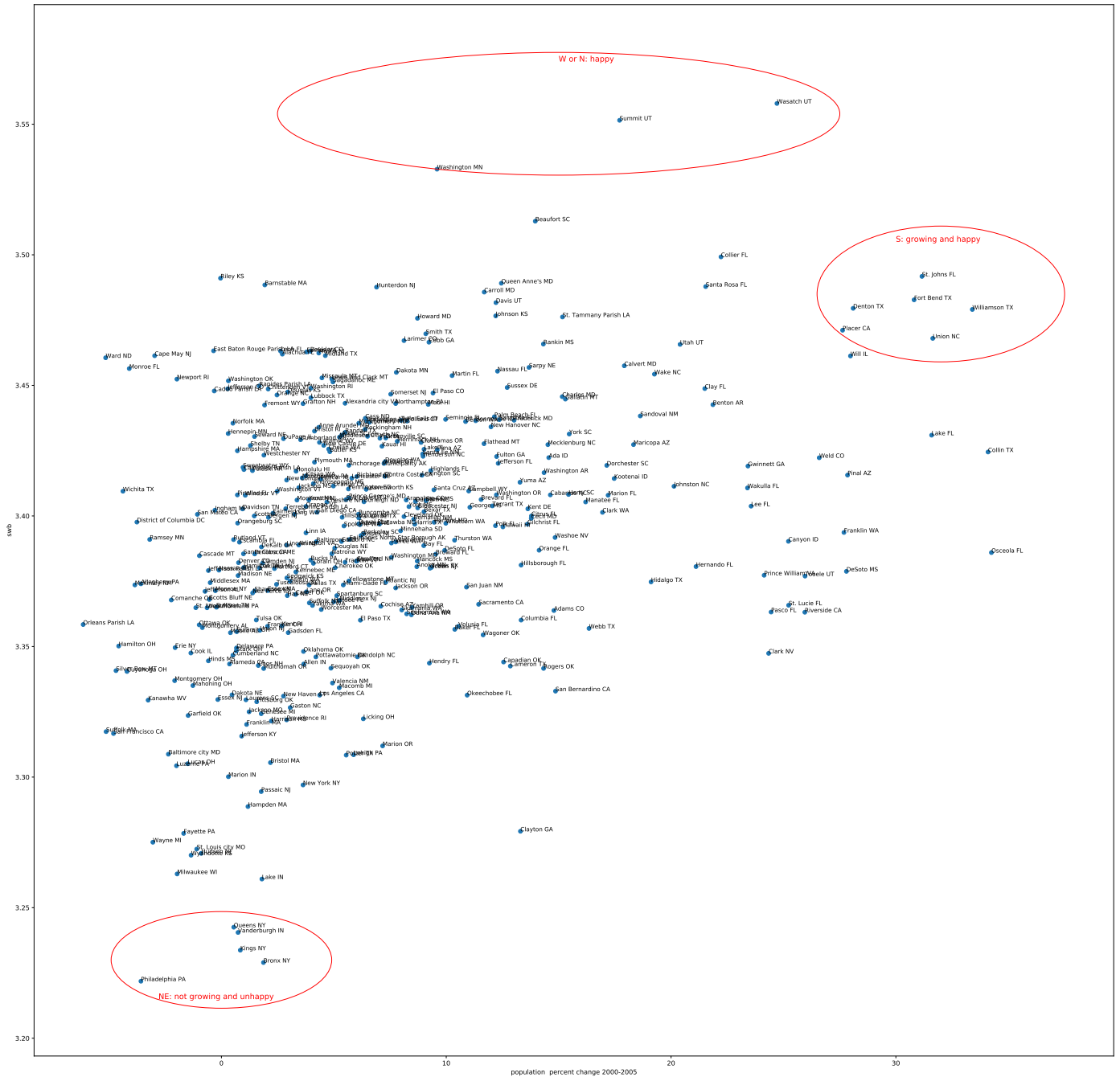
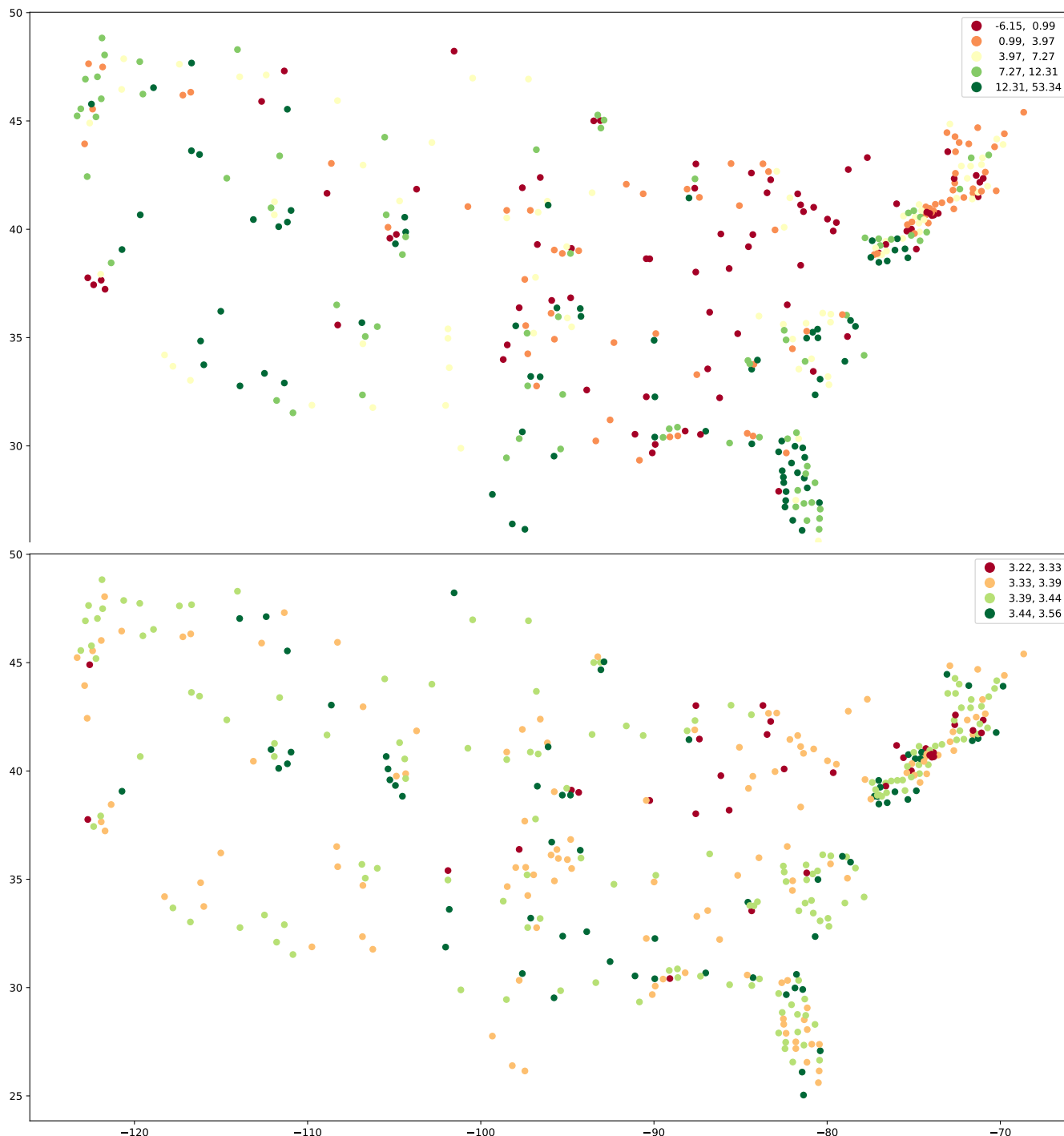


Figure 1: Note: this is a hi-res image that necessarily uses a small font so that labels are readable—zoom 2x to 10x. Ellipses mark patterns: NE: not growing and unhappy (except one IN county (Midwest)); S: growing and happy (except one IL county (Midwest)); W or N: happy. Also do note that in general around the regions marked with ellipses, there are many more counties from the same region. Notably at lower-left: Wayne MI that houses Detroit; and Suffolk MA that houses Boston. Right above the bottom-left ellipse, there is Hudson NJ (slightly hidden behind St Louis city MO), and Passaic NJ, both just outside of NYC and part of New York metro. New York NY (Manhattan) is right next to Passaic NJ. At upper-right, there are multiple Southern counties, mostly FL. Douglas CO and Flagler FL grew by 42 and 53 percent and are not shown in the graph. All counties along with values on key variables are shown at https://colab.research.google.com/drive/1fFzDc73LbGAC-G6_I58FV1fH691NAs7_?usp=sharing.

Figure 2 shows thematic maps. Again, as in figure 1, the North East and Midwest mostly stay flat or shrink and are unhappy. The South mostly grows and is happy, and the North and West are happy as well.

Figure 2: Thematic maps across counties. Population percent change 2000-2005 (quantiles) in 1st panel and SWB (natural breaks) in 2nd panel. X and Y axes are labeled with latitude and longitude. Points are not labeled with county names for readability, but all counties along with values on key variables are shown at https://colab.research.google.com/drive/1fFzDc73LbGAC-G6_I58FV1fH691NAs7_?usp=sharing.



Next, we move to regressions of SWB on population percent change 2000-2005 and person/county level controls using person level 2005 BRFSS data and county level data.

We start with a simple bivariate model in column a0. The effect of population change is cut by almost half in model a1 that controls for person level predictors of SWB. This is expected as SWB is mostly a function of person

level characteristics, but what is remarkable and unexpected is that sequential addition of county level controls in subsequent columns does not attenuate the estimate on population change. Remarkably, in full model a4 the effect size of population change is almost twice larger than that of crime, and also substantially larger than the effect of county level income. Results using population change 2000-2010 are similar (see Supplementary Online Material (SOM)). Results using 1990-2000 population change (also in SOM) are weaker, as expected, as that time period is further away from 2005 BRFSS data, but still the effects are significant and the effect of 1990-2000 population change is similar to the effect of crime and county level income.

	a0	a1	a2	a3	a4
population percent change 2000-2005	0.036***	0.022***	0.019***	0.022***	0.022***
income		0.086***	0.088***	0.087***	0.086***
married or member of an unmarried couple		0.106***	0.107***	0.107***	0.107***
unemployed		-0.058***	-0.058***	-0.058***	-0.057***
age		-0.200***	-0.209***	-0.210***	-0.209***
age squared		0.290***	0.300***	0.301***	0.300***
White		-0.043***	-0.043***	-0.042***	-0.043***
education level		-0.014+	-0.019*	-0.019*	-0.019*
soc/emo support		0.316***	0.315***	0.315***	0.315***
general health		0.226***	0.229***	0.229***	0.228***
crime rate index			0.016**	0.018**	0.014*
persistent poverty			0.002	0.004	0.003
% Black			-0.017**	-0.013*	-0.006
low education				0.013	0.022
housing stress				-0.006	-0.001
low employment				-0.011	-0.009
population loss				-0.003	-0.003
pers. inc. (USD 1,000)/cap				0.007	0.017**
population density per sq mile, 05-09 * 1,000,000					-0.022**
population					-0.009
N	163656	138453	132677	131657	131657
+ 0.10 * 0.05 ** 0.01 *** 0.001					

Table 3: OLS beta (fully standardized) regressions of SWB on **population percent change 2000-2005**. Note that standardization does not allow robust cluster options—the standardized coefficients are useful for comparison, but their standard errors do not account for heteroscedascity and clustering at county level—however, the differences are negligible—see SOM for models with clustered standard errors (and without beta option). Note: only BRFSS 2005 data are used as most of the county level controls are available for 2000-2005. All regressions use BRFSS-SMART county weight variable “_cntywt.”

Discussion and Future Research

We started with a hypothesis that population growth has a smell of happiness—happiness is in the air—and population loss or shrinkage reeks of gloom and doom. Our results mostly agree, caveat being that about a fifth or so of observations do not fit the pattern well as shown in the scatterplot and maps earlier.

A noteworthy result is the strength of the relationship—SWB correlates higher with population change than with county level crime and income—and the stronger effect sizes hold in regressions controlling for person level and county level predictors of SWB. Yet, the absolute effect of population change, as those of other ecological variables, is small—10 percent increase in population leads to very little additional happiness, about .01 or .02 increase on 1-4 SWB scale. But this is not an effect to be disregarded for at least two reasons. First, population change is one of the strongest predictors among ecological variables (ecological variables have small effects on SWB as expected—most SWB is explained by genes (Schnittker 2008) and person level predictors (Veenhoven 2014)). Second, the population change of a county has a small effect on a single person living there, but population change does not affect a single person—typically there are hundreds of thousands of people in a county. An effect of .01 or .02 for everyone is equivalent to an effect of 1 or 2 for 1 person out of 100. Hence, if a county of 100k grows (or shrinks) by 10% the human wellbeing effect is as if 1,000 people became happier by 1 or 2 on 1-4 scale, say from ‘dissatisfied’ to ‘satisfied’ or ‘very satisfied.’

This is only the 2nd study on county/city population growth/shrinkage. There is some related research to the population growth-SWB nexus, but only one study, Delken (2008), uses SWB measure. Such a gap in the literature is remarkable.

We do not necessarily contradict the shrinkage literature (e.g., Delken 2008, Hartt 2019, Hollander 2011) arguing that shrinkage does not mean low QOL. We find that while in general shrinkage results in lower SWB, there are many outliers to this pattern as shown in figure 1. Still, those outliers are an exception, not the rule, and hence, the calls for so-called “smart shrinkage” (Audirac 2018, Grossmann et al. 2013, Hirt and Beauregard 2021) could be reevaluated. The general finding is that shrinkage leads to unhappiness. Such unhappiness can arguably lead to further shrinkage in a vicious circle.

In addition to the main goal of this study, i.e., an investigation of an overlooked relationship between population change and SWB, our study can contribute to the ongoing debate on urban shrinkage.

“Smart shrinkage” may work, but still most people want to live in places that provide jobs and a safe living environment. Our research note does not aim to evaluate policy tools used to revitalize localities or to make policy recommendations. But we argue that subjective indicators of wellbeing should be considered and used to complement other objective measures in the policy deliberations around revitalization of shrinking cities. The key policy implication is for local governments, NGOs, and communities to pay attention to shrinkage/growth and associated SWB. The two are related as the present study shows, and while many national governments and world development scholars use SWB, local policy making and scholarship mostly overlooks SWB. And even if one doesn’t care much about SWB in itself, SWB is still a useful metric as it affects multiple other outcomes of interest such as voting—for instance unhappiness predicts Trump victory (Ward et al. 2021)—for a database of SWB findings see <https://worlddatabaseofhappiness.eur.nl>.

Future research could use a case study research design to find out about the causal mechanisms between shrinkage and SWB. Importantly, data at a finer resolution than county would serve as an important robustness check—counties are large and demographic processes within a county are far from being uniform. Ideally a study should be conducted at a level of municipality or census tract. While such data representative of multiple cities does not exist for the US, there may be local data available for single city and representative of its neighborhoods, such as in Cali (Martínez and Short 2020), Oslo Mouratidis and Yiannakou (2022), Mouratidis (2017), and Toronto Helliwell et al. (2018).

Abbreviations

- Behavioral Risk Factor Surveillance System (BRFSS)
- Multiple Discrepancies Theory (MDT)
- Non-Governmental Organization (NGO)
- SMART (Selected Metropolitan/Micropolitan Area Risk Trends)
- Subjective WellBeing (SWB)
- Supplementary Online Material (SOM)
- Urban Spontaneous Vegetation (USV)

Declarations

- Availability of data and material: only free publicly available data used; code available as python notebook online; other code as stata dofile available upon request

- Competing interests: none
- Funding: none
- Authors' contributions:
 Conceptualization: aok, be
 Methodology aok
 Software aok
 Validation aok
 Formal analysis aok
 Investigation aok
 Resources aok
 Data Curation aok
 Writing - Original Draft aok, be
 Writing - Review & Editing aok, be, emz
 Visualization aok
 Supervision aok
- Acknowledgments: none

References

- AUDIRAC, I. (2018): “Shrinking cities: An unfit term for American urban policy?” *Cities*, 75, 12–19.
- BARREIRA, A. P., L. C. NUNES, M. H. GUIMARÃES, AND T. PANAGOPOULOS (2019): “Satisfied but thinking about leaving: The reasons behind residential satisfaction and residential attractiveness in shrinking Portuguese cities,” *International Journal of Urban Sciences*, 23, 67–87.
- BLANCHFLOWER, D. G. AND A. J. OSWALD (2011): “International happiness: A new view on the measure of performance,” *The Academy of Management Perspectives*, 25, 6–22.
- BLOCK, D. (2021): “Move to Berrien County, Michigan, for the Beaches—And the \$15,000. Some of America’s shrinking towns are trying to lure remote workers with cash. It’s not going so great.” *The Atlantic*.
- BRICKMAN, P., D. COATES, AND R. JANOFF-BUMAN (1978): “Lottery winners and accident victims: Is happiness relative?” *Journal of Personality and Social Psychology*, 36, 917–927.
- CAMPBELL, A. (1981): *The sense of well-being in America: Recent patterns and trends*, McGraw-Hill Companies.
- CAMPBELL, A., P. E. CONVERSE, AND W. L. RODGERS (1976): *The quality of American life: perceptions, evaluations, and satisfactions*, Russell Sage Foundation, New York NY.
- CARVER, C. S. AND M. F. SCHEIER (1990): “Origins and functions of positive and negative affect: a control-process view.” *Psychological review*, 97, 19.
- CHEN, Q., M. DELGADO, AND H. FANG (2019): “Does rural population hollowing bring a loss in happiness,” *ageconsearch.umn.edu*.
- CLOUTIER, S. AND D. PFEIFFER (2017): “Happiness: An Alternative Objective for Sustainable Community Development,” in *Handbook of Community Well-Being Research*, springer, 85–96.

- DELKEN, E. (2008): “Happiness in shrinking cities in Germany,” *Journal of Happiness Studies*, 9, 213–218.
- DIENER, E. (2009): *Well-being for public policy*, Oxford University Press, New York NY.
- EASTERLIN, R. A. (1973): “Does money buy happiness?” *The public interest*, 30, 3.
- (1974): “Does Economic Growth Improve the Human Lot?” in *Nations and households in economic growth: Essays in honor of Moses Abramovitz*, ed. by P. A. David and M. W. Reder, New York: Academic Press, Inc., vol. 89, 98–125.
- FERRER-I-CARBONELL, A. AND P. FRIJTERS (2004): “How Important is Methodology for the Estimates of the Determinants of Happiness?” *Economic Journal*, 114, 641–659.
- GLAESER, E. (2011): *Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier*, Penguin Press, New York NY.
- GLAESER, E. L., J. D. GOTTLIEB, AND O. ZIV (2016): “Unhappy Cities,” *Journal of Labor Economics*, 34, S129–S182.
- GOETZKE, F. AND S. ISLAM (2017): “Testing for spatial equilibrium using happiness data,” *Journal of Regional Science*, 57, 199–217.
- GROSSMANN, K., M. BONTJE, A. HAASE, AND V. MYKHENKO (2013): “Shrinking cities: Notes for the further research agenda,” *Cities*, 35, 221–225.
- GURIN, G., J. VEROFF, AND S. FELD (1960): *Americans view their mental health: A nationwide interview survey.*, Basic Books, New York NY.
- HARTT, M. (2019): “The prevalence of prosperous shrinking cities,” *Annals of the American Association of Geographers*, 109, 1651–1670.
- HELLIWELL, J. F., H. SHIPLETT, AND C. P. BARRINGTON-LEIGH (2018): “How Happy are Your Neighbours? Variation in Life Satisfaction among 1200 Canadian Neighbourhoods and Communities,” Tech. rep., National Bureau of Economic Research.
- HIRT, S. AND R. BEAUREGARD (2021): “Must shrinking cities be distressed cities? A historical and conceptual critique,” *International Planning Studies*, 26, 1–13.
- HOLLANDER, J. B. (2011): “Can a city successfully shrink? Evidence from survey data on neighborhood quality,” *Urban Affairs Review*, 47, 129–141.
- JACKSON, K. L. (2012): “Urban Agriculture and Critical Environmental Justice: A Case Study of Gardens and Growers in Philadelphia and Camden,” *Rutgers-Camden Doctoral Dissertation*.
- KÜHN, N. (2006): “Intentions for the unintentional: Spontaneous vegetation as the basis for innovative planting design in urban areas,” *Journal of landscape Architecture*, 1, 46–53.
- LIMA, M. F. AND M. R. EISCHEID (2017): “Shrinking cities: rethinking landscape in depopulating urban contexts,”

- LUTTMER, E. F. P. (2005): “Neighbors as Negatives: Relative Earnings and Well-Being,” *Quarterly Journal of Economics*, 120, 963–02.
- MARTÍNEZ, L. AND J. R. SHORT (2020): “Life satisfaction in the city,” *Scienze Regionali*, 0–0.
- MICHALOS, A. (1985): “Multiple discrepancies theory (MDT),” *Social Indicators Research*, 16, 347–413.
- MOURATIDIS, K. (2017): “Built environment and social well-being: How does urban form affect social life and personal relationships?” *Cities*, 74, 7–20.
- (2018): “Rethinking how built environments influence subjective well-being: a new conceptual framework,” *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, 11, 24–40.
- (2020): “Neighborhood characteristics, neighborhood satisfaction, and well-being: The links with neighborhood deprivation,” *Land Use Policy*, 99, 104886.
- (2021): “Urban planning and quality of life: A review of pathways linking the built environment to subjective well-being,” *Cities*, 115, 103229.
- MOURATIDIS, K. AND A. YIANNAKOU (2022): “What makes cities livable? Determinants of neighborhood satisfaction and neighborhood happiness in different contexts,” *Land Use Policy*, 112, 105855.
- OKULICZ-KOZARYN, A. (2016): “Happiness Research for Public Policy and Administration,” *Transforming Government: People, Process and Policy*.
- OKULICZ-KOZARYN, A. AND J. M. MAZELIS (2016): “Urbanism and Happiness: A Test of Wirth’s Theory on Urban Life,” *Urban Studies*.
- OKULICZ-KOZARYN, A. AND R. R. VALENTE (2019): “Livability and subjective well-being across European cities,” *Applied Research in Quality of Life*, 14, 197–220.
- (2021): “Urban unhappiness is common,” *Cities*, 103368.
- PARK, Y., M. KIM, J. SHIN, AND M. E. HEIM LAFROMBOIS (2021): “Changing trends in long-term sentiments and neighborhood determinants in a shrinking city,” *Journal of Planning Education and Research*, 0739456X211044215.
- PFEIFFER, D. AND S. CLOUTIER (2016): “Planning for happy neighborhoods,” *Journal of the American Planning Association*, 1–13.
- RAVALLION, M. AND M. LOKSHIN (2000): “Who wants to redistribute? The tunnel effect in 1990s Russia,” *Journal of Public Economics*, 76, 87–104.
- RILEY, C. B., K. I. PERRY, K. ARD, AND M. M. GARDINER (2018): “Asset or liability? Ecological and sociological tradeoffs of urban spontaneous vegetation on vacant land in shrinking cities,” *Sustainability*, 10, 2139.
- ROBINSON, S. L. AND J. T. LUNDHOLM (2012): “Ecosystem services provided by urban spontaneous vegetation,” *Urban Ecosystems*, 15, 545–557.

- SCHNITTKER, J. (2008): “Happiness and Success: Genes, Families, and the Psychological Effects of Socioeconomic Position and Social Support,” *American Journal of Sociology*, 114, S233–S259.
- SORENSEN, J. (2020): “The rural happiness paradox in developed countries,” *social science research*.
- STIGLITZ, J., A. SEN, AND J. FITOUSSI (2009): “Report by the Commission on the measurement of economic performance and social progress,” *Available at www.stiglitz-sen-fitoussi.fr*.
- THOMPSON, D. (2019): “Why Are America’s Three Biggest Metros Shrinking? Why Are America’s Three Biggest Metros Shrinking?” *The Atlantic*.
- VEENHOVEN, R. (2014): “Livability Theory,” *Encyclopedia of Quality of Life and Well-Being Research*, 3645–3647.
- VEENHOVEN, R. AND J. EHRHARDT (1995): “The Cross-National Pattern of Happiness: Test of Predictions Implied in Three Theories of Happiness,” *Social Indicators Research*, 34, 33–68.
- WARD, G., J.-E. DE NEVE, L. H. UNGAR, AND J. C. EICHSTAEDT (2021): “(Un) happiness and voting in US presidential elections.” *Journal of Personality and Social Psychology*, 120, 370.

ONLINE APPENDIX

[note: this section will NOT be a part of the final version of the manuscript, but will be available online instead]

Descriptive statistics

See https://colab.research.google.com/drive/1fFzDc73LbGAC-G6_I58FV1fH691NAs7_?usp=sharing

Urban Spontaneous Vegetation (USV).

USV is visualized in figure 3.

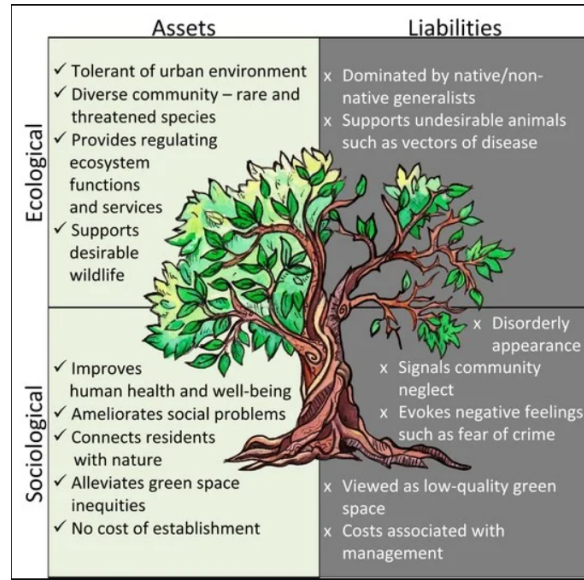


Figure 3: A graphical abstract of Riley et al. (2018).

Robustness Checks: Additional Regression Models

In addition to the variables used earlier, we use here two alternative measures of population change as defined in the table below.

Table 4: Variable definitions.

name	description		
population percent change 2000-2010	popGro00	10=100*((census2010pop-pop00)/pop00); from https://www2.census.gov/programs-surveys/popest/datasets/2000-2010/intercensal/county/co-est00int-tot.csv	var census2010pop
population percent change 1990-2000	popGro90	00=100*((pop00-apr1 1990Pop)/apr1 1990Pop); from https://www2.census.gov/programs-surveys/popest/datasets/1980-1990/counties/totals/comp8090.zip	var apr1 1990Pop

Regarding regular OLS (not standardized coefficients)–the effect is small, about .002 or .001 depending on the model so if a place doubled in size (100% increase), SWB would go up by .2 or .1 on 1-4 scale, which is large at county level–as SWB ranges between 3.2 to 3.6 across counties in this sample, but increase of 100% over 5 years is very unlikely; rather something like 10% which would result only in .02 or .01 increase, which is small. Still effect of population change from beta coefficients is much larger than that of crime or that of per capita income.

	a0rc	a1rc	a2rc	a3rc	a4rc
population percent change 2000-2005	0.004***	0.002***	0.002***	0.002***	0.002***
income		0.025***	0.026***	0.026***	0.025***
married or member of an unmarried couple		0.139***	0.140***	0.140***	0.140***
unemployed		-0.168***	-0.167***	-0.167***	-0.166***
age		-0.008***	-0.008***	-0.008***	-0.008***
age squared		0.000***	0.000***	0.000***	0.000***
White		-0.056***	-0.056***	-0.055***	-0.056***
education level		-0.008	-0.011*	-0.011*	-0.011*
soc/emo support		0.185***	0.184***	0.184***	0.184***
general health		0.134***	0.136***	0.135***	0.135***
crime rate index			0.000*	0.000*	0.000*
persistent poverty			0.012	0.025	0.018
% Black			-0.001*	-0.001	-0.000
low education				0.023*	0.041
housing stress				-0.008	-0.002
low employment				-0.028	-0.024
population loss				-0.006	-0.006
pers. inc. (USD 1,000)/cap				0.000	0.001**
population density per sq mile, 05-09 * 1,000,000					-1.436**
population					-0.000
constant	3.352***	2.057***	2.056***	2.037***	2.019***
N	163656	138453	132677	131657	131657
+ 0.10 * 0.05 ** 0.01 *** 0.001; clustered robust std err					

Table 5: OLS (robust cluster) regressions of SWB: population percent change 2000–2005

	b0	b1	b2	b3	b4
population percent change 2000-2010	0.041***	0.022***	0.019***	0.023***	0.023***
income		0.087***	0.088***	0.087***	0.086***
married or member of an unmarried couple		0.106***	0.107***	0.107***	0.107***
unemployed		-0.058***	-0.058***	-0.058***	-0.057***
age		-0.200***	-0.209***	-0.209***	-0.209***
age squared		0.290***	0.300***	0.300***	0.300***
White		-0.044***	-0.043***	-0.042***	-0.043***
education level		-0.015+	-0.020*	-0.020*	-0.019*
soc/emo support		0.316***	0.315***	0.315***	0.315***
general health		0.226***	0.229***	0.229***	0.228***
crime rate index			0.014*	0.014*	0.010+
persistent poverty			0.003	0.005	0.004
% Black			-0.017**	-0.011+	-0.004
low education				0.015	0.021
housing stress				-0.005	-0.000
low employment				-0.015	-0.011
population loss				-0.002	-0.003
pers. inc. (USD 1,000)/cap				0.006	0.016*
population density per sq mile, 05-09 * 1,000,000					-0.021**
population					-0.005
constant	***	***	***	***	***
N	163656	138453	132677	131657	131657
+ 0.10 * 0.05 ** 0.01 *** 0.001					

Table 6: OLS beta (fully standardized) regressions of SWB: population percent change 2000–2010

	b0rc	b1rc	b2rc	b3rc	b4rc
population percent change 2000-2010	0.002***	0.001***	0.001***	0.001***	0.001***
income		0.026***	0.026***	0.026***	0.025***
married or member of an unmarried couple		0.139***	0.140***	0.140***	0.140***
unemployed		-0.168***	-0.167***	-0.167***	-0.166***
age		-0.008***	-0.008***	-0.008***	-0.008***
age squared		0.000***	0.000***	0.000***	0.000***
White		-0.057***	-0.057***	-0.055***	-0.056***
education level		-0.008+	-0.011*	-0.011*	-0.011*
soc/emo support		0.185***	0.184***	0.184***	0.184***
general health		0.134***	0.136***	0.135***	0.135***
crime rate index			0.000+	0.000+	0.000
persistent poverty			0.017	0.031	0.026
% Black			-0.001+	-0.001	-0.000
low education				0.027*	0.038
housing stress				-0.006	-0.000
low employment				-0.038+	-0.028
population loss				-0.005	-0.007
pers. inc. (USD 1,000)/cap				0.000	0.001*
population density per sq mile, 05-09 * 1,000,000					-1.399*
population					-0.000
constant	3.350***	2.058***	2.061***	2.043***	2.025***
N	163656	138453	132677	131657	131657
+ 0.10 * 0.05 ** 0.01 *** 0.001; clustered robust std err					

Table 7: OLS (robust cluster) regressions of SWB: population percent change 2000–2010

	c0	c1	c2	c3	c4
population percent change 1990-2000	0.033***	0.017***	0.012*	0.013**	0.013**
income		0.086***	0.087***	0.087***	0.086***
married or member of an unmarried couple		0.107***	0.108***	0.108***	0.108***
unemployed		-0.059***	-0.058***	-0.058***	-0.058***
age		-0.193***	-0.202***	-0.202***	-0.202***
age squared		0.283***	0.292***	0.293***	0.292***
White		-0.042***	-0.043***	-0.042***	-0.042***
education level		-0.015*	-0.020*	-0.020*	-0.020*
soc/emo support		0.317***	0.316***	0.316***	0.316***
general health		0.226***	0.229***	0.228***	0.228***
crime rate index			0.016**	0.014*	0.012*
persistent poverty			0.002	0.006	0.004
% Black			-0.021***	-0.012*	-0.007
low education				0.010	0.017
housing stress				-0.004	0.000
low employment				-0.017+	-0.012
population loss				-0.006	-0.006
pers. inc. (USD 1,000)/cap				0.002	0.011+
population density per sq mile, 05-09 * 1,000,000					-0.019*
population					-0.006
constant	***	***	***	***	***
N	162958	137885	132109	131089	131089
+ 0.10 * 0.05 ** 0.01 *** 0.001					

Table 8: OLS beta (fully standardized) regressions of SWB: population percent change 1990–2000

	c0rc	c1rc	c2rc	c3rc	c4rc
population percent change 1990-2000	0.001**	0.001**	0.000*	0.001*	0.000*
income		0.025***	0.026***	0.026***	0.025***
married or member of an unmarried couple		0.140***	0.141***	0.141***	0.141***
unemployed		-0.169***	-0.168***	-0.168***	-0.167***
age		-0.007***	-0.008***	-0.008***	-0.008***
age squared		0.000***	0.000***	0.000***	0.000***
White		-0.055***	-0.056***	-0.055***	-0.056***
education level		-0.009+	-0.011*	-0.011*	-0.011*
soc/emo support		0.186***	0.185***	0.185***	0.185***
general health		0.134***	0.136***	0.135***	0.135***
crime rate index			0.000*	0.000+	0.000+
persistent poverty			0.012	0.031	0.022
% Black			-0.001*	-0.001	-0.000
low education				0.019+	0.033
housing stress				-0.005	0.000
low employment				-0.048*	-0.036
population loss				-0.013	-0.014
pers. inc. (USD 1,000)/cap				0.000	0.001
population density per sq mile, 05-09 * 1,000,000					-1.231+
population					-0.000
constant	3.351***	2.051***	2.053***	2.050***	2.032***
N	162958	137885	132109	131089	131089
+ 0.10 * 0.05 ** 0.01 *** 0.001; clustered robust std err					

Table 9: OLS (robust cluster) regressions of SWB: population percent change 1990–2000

Logit

We recoded the depended variable to binary 0-1 as follows:

	RECODE of ls (swb)			
swb	0	1	.	Total
very dissatisfied	12,932	0	0	12,932
dissatisfied	53,425	0	0	53,425
satisfied	0	565,730	0	565,730
very satisfied	0	528,005	0	528,005
.	0	0	60,023	60,023
Total	66,357	1,093,735	60,023	1,220,115

	a0	a1	a2	a3	a4
RECODE of ls (swb)					
population percent change 2000-2005	0.020***	0.013***	0.010*	0.012**	0.012**
income		0.121***	0.120***	0.120***	0.119***
married or member of an unmarried couple		0.675***	0.685***	0.684***	0.683***
unemployed		-0.804***	-0.799***	-0.795***	-0.792***
age		-0.046***	-0.046***	-0.046***	-0.046***
age squared		0.001***	0.001***	0.001***	0.001***
White		-0.502***	-0.539***	-0.517***	-0.518***
education level		-0.190***	-0.197***	-0.197***	-0.196***
soc/emo support		0.738***	0.744***	0.744***	0.745***
general health		0.638***	0.656***	0.654***	0.653***
crime rate index			-0.000	0.000	-0.000
persistent poverty			-0.002	0.048	0.045
% Black			-0.005+	-0.003	-0.002
low education				0.187***	0.185+
housing stress				-0.003	0.015
low employment				-0.205+	-0.116
pers. inc. (USD 1,000)/cap				0.003	0.006+
population density per sq mile, 05-09 * 1,000,000					-6.247
population					0.000
N	163656	138453	132677	131657	131657

+ 0.10 * 0.05 ** 0.01 *** 0.001; clustered robust
std err

Table 10: Logistic (robust cluster) regressions of SWB: population percent change 2000-2005

Only urban sample

First dropping counties with less than 100k population (about 10 perc of sample); and second dropping counties with less than 200k population (about 30 perc of sample). Results are similar.

	a0	a1	a2	a3	a4
population percent change 2000-2005	0.036***	0.022***	0.019***	0.022***	0.022***
income		0.086***	0.088***	0.087***	0.086***
married or member of an unmarried couple		0.106***	0.107***	0.107***	0.107***
unemployed		-0.058***	-0.058***	-0.058***	-0.058***
age		-0.201***	-0.210***	-0.211***	-0.211***
age squared		0.291***	0.301***	0.302***	0.301***
White		-0.043***	-0.043***	-0.042***	-0.043***
education level		-0.014+	-0.020*	-0.020*	-0.020*
soc/emo support		0.316***	0.314***	0.314***	0.315***
general health		0.226***	0.229***	0.229***	0.228***
crime rate index			0.016**	0.018**	0.014*
persistent poverty			0.002	0.004	0.003
% Black			-0.017**	-0.012*	-0.005
low education				0.012	0.020
housing stress				-0.006	-0.001
low employment				-0.011	-0.008
population loss				-0.002	-0.003
pers. inc. (USD 1,000)/cap				0.007	0.018**
population density per sq mile, 05-09 * 1,000,000					-0.022**
population					-0.006
N	147193	124208	118858	117838	117838

+ 0.10 * 0.05 ** 0.01 *** 0.001

Table 11: OLS beta (fully standardized) regressions of SWB: population percent change 2000-2005; subsample: counties with more than 100k population size

	a0	a1	a2	a3	a4
population percent change 2000-2005	0.032***	0.021***	0.018**	0.022**	0.022***
income		0.086***	0.088***	0.087***	0.086***
married or member of an unmarried couple		0.106***	0.108***	0.108***	0.107***
unemployed		-0.059***	-0.059***	-0.058***	-0.058***
age		-0.195***	-0.205***	-0.205***	-0.205***
age squared		0.285***	0.296***	0.297***	0.296***
White		-0.044***	-0.043***	-0.043***	-0.043***
education level		-0.015+	-0.020*	-0.020*	-0.020*
soc/emo support		0.315***	0.313***	0.314***	0.314***
general health		0.225***	0.229***	0.228***	0.228***
crime rate index			0.017**	0.020**	0.015**
persistent poverty			0.001	0.004	0.003
% Black			-0.016**	-0.011+	-0.003
low education				0.014	0.019
housing stress				-0.005	0.000
low employment				-0.013	-0.007
population loss				-0.001	-0.002
pers. inc. (USD 1,000)/cap				0.010+	0.022**
population density per sq mile, 05-09 * 1,000,000					-0.024**
population					-0.004
N	119680	101018	95668	95668	95668
+ 0.10 * 0.05 ** 0.01 *** 0.001					

Table 12: OLS beta (fully standardized) regressions of SWB: population percent change 2000–2005; subsample: counties with more than 200k population size

Without population loss control variable

	a0	a1	a2	a3	a4
population percent change 2000-2005	0.036***	0.022***	0.019***	0.022***	0.023***
income		0.086***	0.088***	0.087***	0.086***
married or member of an unmarried couple		0.106***	0.107***	0.107***	0.107***
unemployed		-0.058***	-0.058***	-0.058***	-0.057***
age		-0.200***	-0.209***	-0.210***	-0.209***
age squared		0.290***	0.300***	0.300***	0.300***
White		-0.043***	-0.043***	-0.042***	-0.043***
education level		-0.014+	-0.019*	-0.019*	-0.019*
soc/emo support		0.316***	0.315***	0.315***	0.315***
general health		0.226***	0.229***	0.229***	0.228***
crime rate index			0.016**	0.018**	0.014*
persistent poverty			0.002	0.004	0.003
% Black			-0.017**	-0.013*	-0.007
low education				0.013	0.024+
housing stress				-0.006	-0.001
low employment				-0.011	-0.010
pers. inc. (USD 1,000)/cap				0.007	0.018**
population density per sq mile, 05-09 * 1,000,000					-0.022**
population					-0.010
N	163656	138453	132677	131657	131657
+ 0.10 * 0.05 ** 0.01 *** 0.001					

Table 13: OLS beta (fully standardized) regressions of SWB: population percent change 2000–2005; without population loss variable

Crime Index

Crime index rate variable, like other county level variables, comes from the Inter-university Consortium for Political and Social Research: County Characteristics, 2000-2007 at doi:10.3886/ICPSR20660.v2. The codebook definition is as follows.

CrimeRate04: Index crime rate (per 100,000 persons), 2004

CrimeRate04 = 100,000(IdxCrime04/CrimePop04), rounded to two decimal places.

IdxCrime04 = Total number of index crimes reported to police, 2004

CrimePop04 = County population of agencies reporting crimes, 2004

Source

U.S. Dept. of Justice, Federal Bureau of Investigation. Uniform Crime Reporting Program Data [United States]: County-Level Detailed Arrest and Offense Data, 2004 [Computer file]. ICPSR04466-v1. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [producer and distributor], 2006-07-26. DS4 (Crimes Reported).

The data source has separate records for the formerly independent cities of Clifton Forge and South Boston, Virginia. To maintain compatibility with the current county definitions, the data for Clifton Forge was merged with the data for Alleghany County, Virginia and the data for South Boston was merged with the data for Halifax County, Virginia.