The Geography of Desperation in America:
Labor Force Participation, Mobility Trends, Place, and Well-being

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There is much to be troubled about in the state of America today. We boast booming stock markets and record low levels of unemployment, yet significant sectors of our society are dying prematurely from preventable deaths (deaths of despair) and almost 20% of prime aged males are out of the labor force.[1] Americans have higher levels of well-being inequality and report more pain on average than countries of comparable and even lower levels of income.[2] There are other signs of decline, ranging from falling levels of civic trust to viscerally divided politics.

These trends have already received significant scholarly attention. Yet we provide a different perspective by tracking the reported well-being and ill-being of individuals and places. We find large differences in these trends across education levels, races, and places. Desperation – and the associated trends in premature mortality – are concentrated among the less than college educated and are much higher among poor whites than poor minorities, who remain optimistic about their futures. The trends are also geographically dispersed, with racially and economically diverse urban and coastal places much more optimistic and with much lower incidences of premature mortality (on average). Both death and desperation are higher in the heartland and in particular in areas that were previously hubs for the manufacturing and mining jobs which have long since disappeared.

Our earlier work shows that the geographic patterns in lack of hope, worry, reported pain, reliance on disability insurance, and deaths of despair are remarkably consistent across these places. Monnat and Brown (2017) find that counties with higher levels of poverty, obesity, deaths due to drugs, alcohol, and suicide, more non-Hispanic whites, individuals on disability or other safety nets, and smokers were the same places where Trump "over-performed" in terms of predicted votes 2016.[3]

In this paper, we supplement what we know about these race and place-based trends with new research on the role of inter-generational mobility, prime aged individuals out in the labor force, and rural and micropolitan versus urban differences. We explore how patterns across these cohorts, races, and places associate with the worrisome trends in lack of hope and premature death. We also add in new indicators which assess financial, social, purpose, and community level well-being.

A related issue is why there is less geographic mobility today – e.g. people moving to economic opportunities - than there was before. Internal migration rates have trended steadily downward over the past 25 years and are now lower than at any time in the post-war period. There are many reasons for this, ranging from high housing costs in the economically vibrant urban areas – and potential skill mismatches for low-skilled workers – to the collapse of the housing market during the financial crisis and the inability

[1] Graham, Laffan, Pinto (2018).
[2] Blanchflower and Oswald (2019).
[3] Graham and Pinto (2018); Monnat and Brown (2018).

of many home owners to sell their homes or foreclose on their mortgages.[4] While there is no consensus on the extent to which this trend is a driver of the decline in labor force participation, recent research suggests that the trend is longer term and structural, rather than simply a feature of the financial crisis, although the latter may have exacerbated it.[5]

There are other reasons for the decline in geographic mobility that are more difficult to observe or measure. Some of these are likely linked to the downward trend in intergenerational mobility during the same period. Cultural and normative differences across places – which seemed to have increased over time along with increasing economic divisions – can make it difficult for some to assimilate in other places and regions. There is also selection bias in terms of those who choose to leave home to seek opportunity and those who stay behind. The latter cohort may be less likely to have the skills that enable them to move. While we cannot answer these complex questions at this juncture, some of our findings are suggestive.

In this paper, we first review the associations that we have discovered between low well-being and the deaths of despair across races and places more generally. We focus on the ill-being of prime aged males out of the labor force – a particularly troubled group, and how the trends for this cohort differ across gender and race. We then explore additional links between intergenerational and geographic mobility and well-being, using county level data from Raj Chetty and his team and our metrics of individual well-being from the U.S. Gallup daily data. Finally, we explore how some of our main findings differ across metropolitan, micropolitan, and rural areas.[6] In all of these, we explore differential patterns in financial, social, purpose, and community level well-being. We hope that better understanding the large differences in well-being and resilience that we find across cohorts, races, and places can help in crafting solutions to our crisis of desperation and premature mortality.

Background

Our earlier work established consistent trends in well-being/ill-being and premature mortality across individuals, races, and places. For our well-being metrics, we used the 2010-2015 Gallup data for the U.S., a continuing survey that interviews a nationally representative sample of 500-1000 respondents each day, and includes a range of questions about health and well-being, in addition to socio-economic and demographic traits.[7] For the mortality data, we use the CDC compressed mortality data set for county level deaths from suicide, drug and alcohol poisoning, and indeterminate causes for respondents aged 35-64.

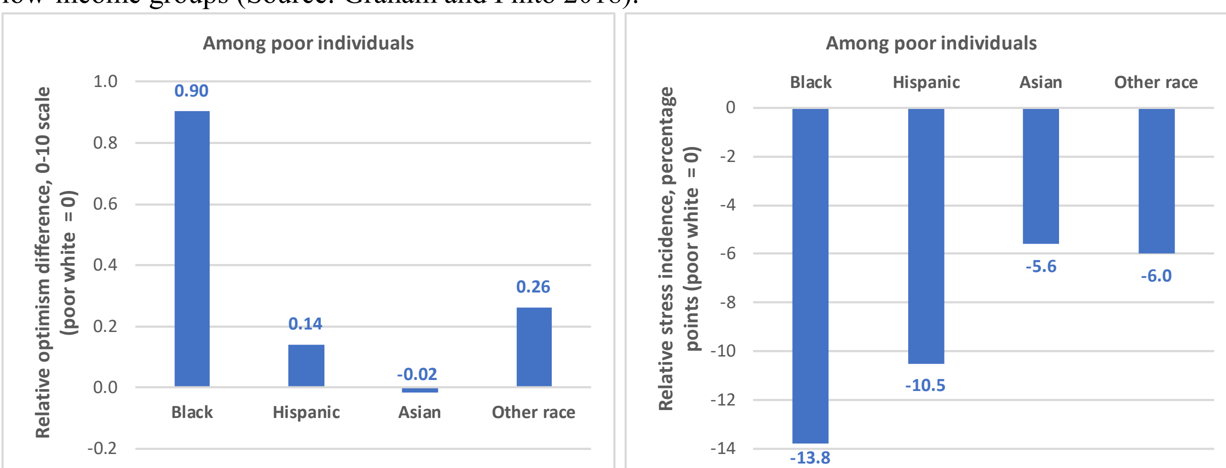
[4] Recent research finds that those respondents who are most likely to move are willing to foreclose on their mortgages as long as they have a job to move to (Demyanyk et al. 2017).
[5] See Dao, Furceri, and Loungani (2017) on moving rates, and Abraham and Kearney (2018) for a broader review in the context of labor force participation.
[6] The Office of Management and Budget defines a Metropolitan Statistical Area as having "*at least one urbanized area of 50,000 or more population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties*"; Micropolitan Statistical Areas are defined in the same way, except that they "*have at least one urban cluster of at least 10,000 but less than 50,000 population*" (OMB Bulletin No. 18-04).
[7] Graham is a Senior Scientist at Gallup and in that capacity receives access to the data. See Graham and Pinto (2018).

At the level of individuals, we find that respondents with higher levels of optimism (assessed by a question asking how their life satisfaction in five years will rank on the 11-point Cantril ladder) and lower levels of worry (reported for the previous day) are less likely to be in a county with high levels of premature mortality. We also find that places (both MSA's and counties) with higher levels of optimism and lower levels of worry are less likely to have a prevalence of these deaths.

Our findings on well-being and ill-being across different groups are in line with the concentration of the "deaths of despair" among less than college educated whites, with blacks and Hispanics having much lower rates. They also accord with recent research that finds that blacks and Hispanics are less likely to report depression or to commit suicide than whites - a difference that may be explained by different cultural norms and acquired resilience, as well as to different trends in aspirations and relative status.[8]

Our findings match patterns in well-being to the mortality trends. We find remarkably large gaps in both optimism and stress and worry across these groups. Poor blacks are by far the most optimistic group compared to poor whites: they are 0.9 points higher on the 0-10 scale (0.43 standard deviations). Poor blacks are also 14 percentage points (0.28 standard deviations) less likely to report stress the previous day half as likely as poor whites to report stress in the previous day, while poor Hispanics fall somewhere in the middle. While blacks and Hispanics are in general more optimistic than whites, the gaps are less pronounced at higher levels of income (Figure 1).

Figure 1: Differential optimism and stress associated with different race groups (relative to white), within low-income groups (Source: Graham and Pinto 2018).



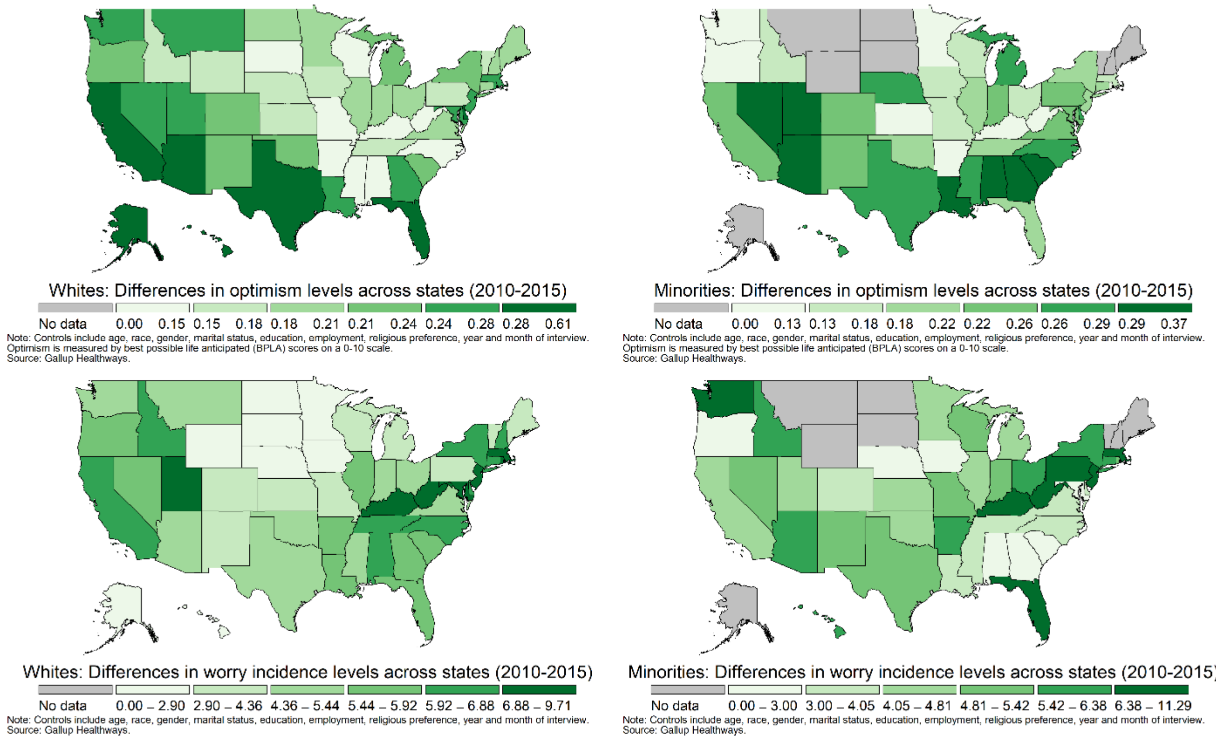
These patterns play out at the aggregate level as well. Places (MSA's and counties) that have a higher percentage of black and Hispanic respondents have higher levels of optimism and lower levels of stress; lower levels of smoking and higher levels of exercise; and fewer deaths of despair. Not surprisingly, these places tend to be urban and to have more vibrant economies, while those that are predominantly white and with higher levels of deaths tend to be in the heartland in places with declining employment opportunities.

In an earlier exploration, we found that there is a distinct if less well understood role of place.[9] We explored how optimism, stress, worry, and reported pain differed for minorities versus whites across U.S.

[8] See Case and Deaton (2015, 2017) on the patterns for deaths of despair, and Assari and Lankari (2016) for differences across racial cohorts.
[9] Graham and Pinto, 2018.

states. Controlling for objective indicators such as health, education, and unemployment rates (but not income), we found that minorities tended to be most optimistic and least worried in the southeastern cluster of states, where there is a concentration of African American culture and churches, and the southwestern cluster, where there is a large concentration of Hispanics. While these places do not have good objective conditions (and the former have a history of racism and segregation), we seem to be picking up cultural and other place specific factors once we control for these conditions. On the other hand, the optimism of whites displays very different geographic patterns (Figure 2). Trends in stress and reported pain (not shown here) display relatively more similar geographic patterns across races.

Figure 2: The geography of life optimism and worry in the U.S. (Source: Graham and Pinto 2018).



Our findings on the association between patterns in well-being/ill-being and those in the deaths of despair – and on the differential levels of hope and resilience between whites and minorities – are relatively new. Yet the relationship between well-being and better outcomes is not. Based on panel data for Russia for 1995-2000, Graham et al. (2004) wrote the first economics paper showing that individuals with higher levels of life satisfaction in a first period earned more income and had better health a second one. This accorded with the findings in some psychological studies based on much smaller samples around the same time. Since then, others have confirmed such linkages, based on sibling studies and experimental work, among other approaches.[10] Well-being matters to long-term outcomes, while lack of it – and desperation in particular – seems to play a role in premature mortality.

In a separate paper, we explored the relationship between optimism and longevity, based on longitudinal data in the Panel Study of Income Dynamics.[11] We found that respondents born between

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[10] DeNeve and Oswald, 2012; Diener and Chan (2011).
[11] O'Connor and Graham, 2018. Stevenson and Wolfers (2009), meanwhile, find a paradox of declining female happiness around the same time, but that is distinct from trends in optimism, and the trend reversed in recent years.

1935 and 1945 who reported to be optimistic in their twenties were more likely than those who did not to be alive in 2015. Investments in education were a reinforcing channel. Women and blacks became more optimistic over time, beginning in the 1970's when gender and civil rights improved. In contrast, the one group that experienced drops in optimism around the same time were less than college educated white males, not coincidentally when the decline in manufacturing began. These trends suggest that had we been regularly tracking well-being metrics over time, as the governments in the U.K., Canada, and New Zealand, among others, have begun to do, we might have picked up on our crisis of desperation before rising mortality rates sounded the alarm bells.

Related to this, exploratory survey work among low income young adults in Latin America shows that those who have hope and aspirations for the future are more likely to invest in their education and health, and less likely to engage in risky behaviors than are less optimistic respondents.[12] Most of the optimistic, high-achieving respondents have experienced at least one negative shock in the past, suggesting resilience in addition to hope. While this research is in its early stages, it is yet another example of how well-being – and hope for the future in particular – matters to future outcomes. Given the widespread despair in the U.S. today, it seems important to better understand the roots of hope - and how or if it can be restored - in populations and places where it has been lost. The role of place and community is an important but not well understood part of the story.

Data

The main data source for this paper, as in the previous work summarized above, is the Gallup Healthways (GH) survey, a cross-sectional nationally representative survey that is collected daily for adult individuals across the U.S.

Our key outcome of interest is well-being, in its multiple dimensions. We take advantage of the broad well-being focus of the GH survey to consider a wide range of indicators that we combine into 11 different indices. We utilize measures focusing on two distinct dimensions of SWB that are well established in the literature – evaluative and hedonic. The former relates to how people think about and assess their lives; we use both current and expected life satisfaction questions, defined on a 0-10 integer scale that is ordered from worst to best possible life. The latter dimension captures how individuals experience their daily lives; this includes both positive (having felt enjoyment, happiness, smiled or laughed in the previous day) and negative affect (having felt stress, worry, anger, or sadness in the previous day), all defined in binary terms.

In addition to these standard well-being metrics, we also include indices for purpose, community well-being, financial well-being, perceptions about the economy, social well-being, and three separate ones for different dimensions of health/physical well-being. All the indices are constructed by adding the components that are part of them. For instance, if someone reported both stress, worry, anger, and sadness, that respondent would have a negative affect index of 4 – the maximum for that particular index, since it only has 4 components. To make interpretation and comparability of results more straightforward, we standardize each of the indices, allowing us to interpret our regression results in standard deviations of the corresponding index.

Gallup Well-Being Indices:

[12] Graham and Ruiz-Pozuelo, 2018.

Evaluative well-being index: "compared to the best possible life you can imagine, on a ladder scale where 10 is the best possible life you can imagine and 0 is the worst possible life you can imagine, how satisfied are you with your life today?"; on the same ladder, where do you expect your life satisfaction to be in five years?"

Negative affect index: "did you experience worry frequently yesterday" yes or no; the same phrasing and binary response choices for: stress, anger, and sadness, respectively

Positive affect index: "did you experience happiness frequently yesterday" – yes or no; the same phrasing and binary response choices for: enjoyment, smiling, or laughing

Purpose well-being: I like what I do every day (agree/disagree); same phrasing and binary response choices for: learn or do something interesting every day; use my strengths to do what I do best every day; leader in my life makes me enthusiastic about the future; reached most of my goals in the past 12 months

Community well-being: are you satisfied with the city/area where you live – agree/disagree; the city/area where you live is the best place for you (agree/disagree); same answers for: house/apartment is ideal for you/your family; can't imagine a better community; proud of your community/area where you live; always feel safe/secure; recognition/help improve city/area past 12 months

Financial well-being: did not lack money to buy food (past 12 months); did not lack money for health care (12 ms); enough money to do everything you want to do (agree/disagree); worried about money (past 7 days) (disagree/agree); satisfied with standard of living compared to ppl spend time with (agree/disagree)

Economic perceptions: economic conditions today are good/excellent (agree/disagree); economic conditions are getting better (agree/disagree)

Social well-being: someone always encourages you to be health (agree/disagree); family/friends give you positive energy every day (agree/disagree); relationship with partner stronger than ever (agree/disagree); always make time for vacation/trips with friends/fam (agree/disagree)

Health index 1: did not experience physical pain yesterday (yes/no); no poor health days in previous 30 (yes/no); did not have heart problems preventing doing things people your age normally do (yes/no); health self-assessment is in general excellent/very good (yes/no); physical health is near perfect (agree/dis); doc would say I do great job managing health (agree/disagree); always feel good about my physical appearance (agree/disagree)

Health index 2: at least one day with 30+ mins of exercise in past 7 days (yes/no); no restrictions on the amount of exercise you do (yes/no); did you eat healthy all day yesterday (yes/no); at least one day with 5+ servings of fruits and vegetables in past 7 days (yes/no); not obese (yes/no); felt active and productive every day (agree/dis); little pleasure/interest in doing things last two weeks (not at all/yes); never uses drugs (or prescription meds) which affect mood/help you relax (yes/no); does not smoke (yes/no); zero alcoholic drinks in a typical week (yes/no);

Health index 3: have never been told by physician/nurse you have high blood pressure (yes/no); same question phrasing/answers for: cholesterol; diabetes; depression; heart attack; asthma; cancer

GH also covers a wide range of socio-demographic and economic details. In addition to income, household size, education, marital status, and religious preference, we also have information on the respondents' age, race, gender, labor market status, and county of residence. Depending on the specification, one or more of these latter characteristics will be our key independent variables. The labor market categories present in GH are as follows: self-employed, employed full-time, employed part-time, underemployed (employed part-time but wanting full-time), and out of the labor force. This labor market variable can then be interacted with age, gender, or race, as we explore different types of heterogeneities in well-being across labor market status. In our main specifications, we use Gallup data and focus on the 2010-16 period. For this period, Gallup provides us with a repeated cross section of approximately 1.6 million U.S. adults.

Finally, for the work on mobility, we supplement the GH with county level data on relative mobility, absolute mobility, percentage of children who live at the same address as their parents, and percentage who live in one of their childhood Census tracts in adulthood made available by Raj Chetty and the Opportunity Insights Project.[13] When doing so, we also add in other county-level controls:, mean household income, Gini coefficient, top income share, poverty rate, unemployment rate, labor force participation rate, deaths of despair as defined by Case and Deaton (2015), total population, and share of non-white population.[14]

Empirical methodology and Results

We explore three separate demographic and cohort well-being trends in relation to place:

a) Heterogeneities by labor market status, across different age, gender, and race groups, with a particular focus on those who are out of the labor force.

b) Well-being differences across counties with different levels of intergenerational mobility (absolute and relative) and geographic mobility (different shares of population living in parents' home and living in childhood census tracts).

c) Heterogeneities by county type – from those belonging to the larger metropolitan areas to suburban to smaller rural ones.

Prime Age Males Out of the Labor Force

Prime age males out of the labor force (OLF) are a particularly worrisome group. Prime age labor force participation has been declining over the past two decades, but has become a question of particular concern for several reasons. One is the extent to which the trend seems to be secular rather than cyclical,

[13] See https://opportunityinsights.org/data/.
[14] Respectively, there were obtained through the American Community Survey, the Economic Policy Institute, the US Census Bureau Small Area Income and Poverty Estimates, the Bureau of Labor Statistics Local Area Unemployment Statistics , National Center for Health Statistics, US Census Bureau, and the Survey of Epidemiology and End Results (accessed through NBER).

and another is the extent to which declining labor force participation and the opioid crisis have become intertwined.[15]

In 2016, 19% of 25 to 54-year-olds (men and women) were OLF. Forty percent of the prime aged OLF population is made up of less than high school educated women, most of whom are caregivers for the elderly or for children. The rest of the OLF – both men and women – have dropped out of the labor force for other reasons, mainly related to disability, with other common motives being pursuing further education and retirement). OLF women are more likely to live with spouses, while men are more likely to live with their parents. Within prime age men OLF, 35% are white, 32% are black, and 29% are Hispanic. Three-quarters of the OLF live in households with earned income, while 11% have no earnings and rely on social safety net benefits; 1.3 million report no income at all. Forty-five percent (3.3 million) of households with OLF males are in the bottom income quintile, while 28% (4.6 million) of households with OLF women are. In contrast, 2 million women OLF and half a million men OLF are in households in the top income quintile, presumably living with a wealthy spouse.[16] Despite the mixed range of incomes for OLF men, black OLF men are consistently more likely to be below the poverty line and to have less own income to rely on than white ones; they also receive less income from disability benefits.[17] Reliance on SSDI rose from 1% to 3% of prime age men from 1967 to 2014, while the labor force participation rate fell by 7.5% during the same time, showing that while disability is part of the story, it is not all of it.

Prime age men – as opposed to women – tend to have a lack of attachment to either family or purposeful activity and disproportionate levels of addiction to opioids, which is a barrier to labor force re-entry. They report more pain than most other groups. Fifty-three percent of OLF men report pain the previous day compared to 30% of employed men, and 44% report to take pain medication compared to 20% of employed men. Only 34% of prime aged women OLF report to be on pain medication. Prime aged males are also more likely to live in counties with higher rates of opioid prescription, places that also tend to suffer from manufacturing decline. Time-use surveys show that leisure time and video games account for 20-45% of the decline in working hours for men OLF, while women are more likely to be involved in care-giving activities.[18] The lack of purposeful activity of these men, meanwhile, shows up in very low levels of reported well-being and in objective health, as we discuss below.

In recent work on prime age males out of the labor force, we compared the subjective well-being of those in the U.S. with their full-time employed counterparts at home, as well as in the European Union, Latin America, and North African and the Middle East. We first looked at how prime-age males *within* the U.S. compared with their employed and unemployed counter-parts, and then how they compared with prime aged males OLF in these other three regions.[19] Our findings were rather stark.

Our analysis was based on the Gallup World Poll, which also collects a wide range of demographic and socioeconomic data, and covers 162 countries around the world. The sample size per country – generally about 1000 respondents – is much smaller than that of GH for the U.S..

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[15] See, among others, Aaronson et al. (2014); Krueger (2017); and Blanchflower (2019). There has been a slight increase in labor force participation for this group in the past few years, but we do not yet have the matching well-being data to include these trends in our analysis.
[16] Schanzenbach et al. (2017).
[17] Hispanics fall somewhere in between the two on most of these indicators. Binder and Bound (2019).
[18] Krueger (2017).
[19] Pinto and Graham, 2019; Graham and Pinto, 2019.

The first comparison refers to the well-being of those in different employment categories *within* each region. The second comparison explores differences in the 'absolute' levels of well-being of that group across regions. *Within* the U.S., we find that the OLF (males between the ages of 25 and 54 who are not seeking employment) are a particularly miserable group compared to both their employed and unemployed counterparts. Their life satisfaction is low and optimism for the future is much lower than that of the unemployed, as well as more likely to have been angry and sad the day before. *Across* regions, the U.S. OLF have lower life satisfaction than the OLF in the EU and Latin America, lower optimism than those in Latin America, and higher incidence of negative affect (as measured by worry, stress, anger, and sadness) than the OLF in the other regions.

The distinct findings for the U.S. may be partly due to the strongly held norm of individual effort and to the lack of support for collective safety nets, both of which contribute to more stigma for the OLF than for those in other regions. In addition, marriage rates and civic or religious participation – both of which tend to be associated with higher levels of well-being - have also fallen significantly more for the U.S. working class—in part related to labor force drop-out – relative to the college educated since the 1970's.[20] Another related explanation is that it is quite common for prime aged men – and women - in Latin America and the Middle East to work at least some time in the informal sector. As such they are considered out of the formal labor force, even though they may still be quite active. In contrast, in both the U.S. and the EU, formal labor markets predominate, and the expectation of having stable and respected jobs is (or was) much higher. This is particularly the case for non-Hispanic whites in the U.S.

Here we use the GH to follow up on that work an allow for a substantially more detailed look into the U.S. This exercise is similar to Krueger (2017), but GH gives us the advantage of having a substantially larger sample, allowing us to look into a broader set of dimensions, and also controlling for other characteristics that are relevant for well-being. The empirical specification we use as a starting point, in order to look into the well-being across labor market status is formalized by Equation (1) below:

(1) $SWB_{ict} = \alpha_0 + \sum_{j=1}^{6} \beta_j * LMstatus_{j,ict} + \delta_1 * (X_{ict}) + \pi_c + \tau_t + \varepsilon_{ict}$

SWB represents each of the 11 well-being indices described in the previous section for individual i, from county c, in year t. $LMstatus$ is our key variable of interest and represents one of the six categories previously described (full-time employment is used as the reference/omitted category). Therefore, our key parameters of interest are the set of β_j. X is a vector containing the other individual-level socio-demographic controls – age group, gender, race, type of county where respondent lives, marital status, educational level, pre-tax household income group, household size, preferred religion, as well as controls for the month and days of week where the interview took place. π_c and τ_t represent country and year fixed effects, respectively.

We are particularly interested in race and gender heterogeneities across labor market status. In those instances, we modify Equation (1) slightly to be able to focus explicitly on those interactions, as Equation (2) formalizes for the gender interactions.

(2) $SWB_{ict} = \alpha_0 + \sum_{j=1}^{6} \beta_j * LMstatus_{j,ict} + \gamma_1 * Female_{ict} + \sum_{j=1}^{6} \theta_j * LMstatus_{j,ict} * Female_{ict} + \delta_1 * (X_{ict}) + \pi_c + \tau_t + \varepsilon_{ict}$

[20] Sawhill, 2018; Brookings-AEI Opportunity Report, 2019.

SWB, $LMstatus$, π_c, and τ_t represent the same as in (1). $Female$ is the binary indicator for gender (with male being the reference/omitted category) and $LMstatus * Female$ is the interaction term. Therefore, our key parameters of interest are β_j, γ_1, and θ_j. X is again a vector containing the same individual-level socio-demographic controls as before (except for gender). For the interactions between labor market status and race, we use an analogous specification to (2), but with race instead of gender.

Table 1 below shows our estimates from the implementation of Equation (1), using the full 2010-2016 GH sample, and highlighting the result for both unemployed and OLF categories (the reference category corresponds to those who are employed full-time). The regression, as all others in this paper, uses the national-level sampling weights from GH and was run as an OLS model.

First, we see that being unemployed is associated with the largest well-being reductions across most dimensions and by substantial magnitudes – depending on the indicator, between 0.11 and 0.44 standard deviations.

Second, when looking at those who are OLF, it is clear that prime age respondents are typically worse off than both their younger and older counter-parts across every nearly every dimension, suggesting a particular state of overall ill-being. It is noteworthy that prime age OLF respondents report much worse health than those who are unemployed, suggesting that their labor force dropout may be related to objective health conditions.

Third, the OLF youth report higher well-being that the other OLF groups, being much closer to the well-being of those who are employed full-time that with the unemployed, generally consistent with Krueger's (2017) results for that group; it is also intuitively expected, because for part of that group the reason for not being in the labor force is likely voluntary and relates to still being in school; given their human capital investment, one would expect their life evaluation, future outlook, daily experiences, and overall well-being in other dimensions to significantly exceed that of other OLF groups whose absence is mainly due to lack of (real or perceived) work opportunities.

Table 1: Labor market status and well-being in the US, 2010-2016 (full sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Evaluative well-being index	Negative affect index	Positive affect index	Purpose well-being index	Community well-being index	Financial well-being index	Economy perceptions index	Social well-being index	Health well-being index 1 (self-assessment)	Health well-being index 2 (behaviors)	Health well-being index 3 (diseases)
Out of the workforce prime-age (25-54)	-0.110***	0.227***	-0.236***	-0.328***	-0.088***	-0.111***	-0.038***	-0.116***	-0.506***	-0.346***	0.409***
	(0.005)	(0.007)	(0.006)	(0.008)	(0.008)	(0.008)	(0.005)	(0.007)	(0.012)	(0.013)	(0.008)
Out of the workforce youth (< 25)	-0.016**	0.016*	-0.015**	-0.128***	0.027*	0.080***	0.048***	-0.074***	-0.109***	0.036**	0.064***
	(0.007)	(0.010)	(0.008)	(0.016)	(0.016)	(0.014)	(0.010)	(0.015)	(0.013)	(0.015)	(0.005)
Out of the workforce older (> 54)	-0.106***	0.084***	-0.140***	-0.269***	-0.021***	0.012**	0.005	-0.087***	-0.478***	-0.293***	0.415***
	(0.004)	(0.005)	(0.004)	(0.007)	(0.006)	(0.006)	(0.004)	(0.006)	(0.007)	(0.007)	(0.004)
Unemployed	-0.206***	0.286***	-0.137***	-0.435***	-0.190***	-0.384***	-0.104***	-0.190***	-0.226***	-0.188***	0.156***
	(0.005)	(0.006)	(0.005)	(0.011)	(0.011)	(0.010)	(0.006)	(0.010)	(0.010)	(0.011)	(0.004)
Observations	1558271	1278586	1615002	483507	482777	482830	1113224	481753	480194	453301	1614662
R-squared	0.111	0.081	0.055	0.094	0.122	0.247	0.084	0.101	0.140	0.111	0.239

Robust clustered (at the county-level) standard errors in parentheses.
*** p<0.01; ** p<0.05; * p<0.1
Note: Controls for remaining labor market status (employed full-time is the omitted category) are included. Additionally, controls for age group, gender, race, marital status, educational level, pre-tax household income, household size, preferred religion, as well as fixed effects for day of week when the interview took place, month of interview, year, and county of residence, are also included.

Table 1 also makes clear that, when comparing the groups in this way, the reported ill-being of the unemployed clearly exceeds that of the OLF. Nevertheless, as observed earlier, there are some differences across gender in the reasons for dropping out of the labor force, which may also be related to different well-being levels. We investigate that possibility by restricting the sample to only the prime-age respondents and using specification (2), interacting gender and labor market status – Table 2 below illustrates the results we obtain.

The second and third rows of Table 2, corresponding to prime age males who are unemployed and OLF, respectively, displays higher magnitudes than those of the same categories in Table 1, suggesting that prime age males in those situations are particularly unhappy. Within prime age male respondents, the gap between the unemployed and the OLF is now also smaller, as expected if the reasons for dropping out from the labor force differ across genders. These results reflect a broader world-wide pattern in which women are typically happier than men, except in places where gender rights are very unequal.[21]

The first row in Table 2 shows that full-time employed women report clearly higher evaluative and hedonic well-being than full-time employed men; across the remaining indices, the picture is somewhat more mixed, with higher purpose, community, and social well-being, but lower financial well-being and expectations about the economy. Relative to the respondents employed full-time, the well-being differences across gender are even greater among the unemployed and especially among those who are OLF. As in Krueger (2017), prime age women OLF are significantly less unhappy – in terms of both evaluative and experienced well-being – than males in the same situation[22], possibly because the incidence of reasons for labor force dropout are different across genders; one might expect that someone who drops out to spend more time with family will likely have a better life evaluation and daily experience that someone forced to do so because of health reasons or for having given up the search for a job with. The gender differences extend into other dimensions as well: while prime age OLF women have markedly lower purpose, community, and financial well-being than full-time employed women, that is smaller than the one between full-time employed men and OLF men.

[21] A note of caution, though, is that women and men may have different response scales, with the bias being greater in places where women have worse rights and do not feel comfortable reporting to be unhappy. See Graham and Chattopadhyay (2013) and Montgomery (2017). In the U.S., Stevenson and Wolfers (2009) find that women are generally happier than men, but that trend decreased over time, at least up until the late 1980's.

[22] Krueger (2017) finds that, while among prime age women those employed and those OLF report relatively similar levels of well-being, those who are OLF still report lower life satisfaction scores and higher incidences of pain and sadness. Additionally, those women who report to be out of the labor force due to reasons other than "home responsibilities" report lower levels of well-being than other OLF women.

Table 2: Gender well-being heterogeneities across labor market status in the US, 2010-2016 (prime-age sample)

Variables	(1) Evaluative well-being index	(2) Negative affect index	(3) Positive affect index	(4) Purpose well-being index	(5) Community well-being index	(6) Financial well-being index	(7) Economy perceptions index	(8) Social well-being index	(9) Health well-being index 1 (self-assessment)	(10) Health well-being index 2 (behaviors)	(11) Health well-being index 3 (diseases)
Female	0.170***	0.086***	0.043***	0.137***	0.079***	-0.037***	-0.050***	0.072***	-0.026***	0.090***	0.003
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.003)
Unemployed	-0.272***	0.368***	-0.179***	-0.519***	-0.233***	-0.468***	-0.109***	-0.209***	-0.238***	-0.231***	0.114***
	(0.011)	(0.012)	(0.012)	(0.021)	(0.021)	(0.020)	(0.011)	(0.020)	(0.020)	(0.020)	(0.009)
Out of the workforce	-0.226***	0.317***	-0.322***	-0.396***	-0.122***	-0.202***	-0.045***	-0.139***	-0.632***	-0.434***	0.473***
	(0.009)	(0.010)	(0.009)	(0.013)	(0.013)	(0.012)	(0.008)	(0.013)	(0.017)	(0.016)	(0.009)
(Female) X (Unemployed)	0.120***	-0.055***	0.038**	0.073***	0.026	0.080***	-0.001	0.012	-0.031	0.030	0.086***
	(0.014)	(0.018)	(0.015)	(0.028)	(0.030)	(0.027)	(0.015)	(0.028)	(0.027)	(0.028)	(0.012)
(Female) X (Out of the workforce)	0.157***	-0.122***	0.119***	0.074***	0.041**	0.118***	0.005	0.016	0.182***	0.141***	-0.102***
	(0.010)	(0.013)	(0.010)	(0.016)	(0.017)	(0.016)	(0.010)	(0.016)	(0.016)	(0.018)	(0.010)
Observations	634168	512949	645596	189877	188869	189528	444030	189352	188513	178219	645450
R-squared	0.114	0.079	0.062	0.114	0.115	0.252	0.093	0.110	0.162	0.141	0.143

Robust clustered (at the county-level) standard errors in parentheses.
*** p<0.01; ** p<0.05; * p<0.1
Note: Controls for remaining labor market status (employed full-time is the omitted category) are included. Additionally, controls for age group, race, marital status, educational level, pre-tax household income, household size, preferred religion, as well as fixed effects for day of week when the interview took place, month of interview, year, and county of residence, are also included.

Finally, we limit the sample to prime age males and focus on race heterogeneities in well-being across labor market status and find important differences.[23] While in relative terms there are more black males OLF than there are white ones, black prime aged males have higher evaluative well-being, driven by both higher happiness and more optimism, than white ones, as do Hispanic males OLF.[24] This finding is suggestive of the more general pattern of optimism and resilience among minorities compared to whites in the U.S. Some of this may be due to cultural and community and other unobservable differences across races, but it is possible some may also be due to objective trends. While levels of education and marriage rates are still higher for whites *on average*, less educated whites experienced lower gains in education, and greater declines in marriage rates than did minorities over the past few decades.[25]

Related to this, the gaps in black-white life satisfaction and optimism are much smaller in the better employment categories, such as full or part time employment, than they are for the OLF. The same pattern holds for Hispanics. Within prime age males, the stigma of being OLF – and, to a lesser extent, unemployed – seems to be felt particularly acutely by whites, perhaps because of the strong individual effort norm that traditionally paid off well for white males, while other groups faced higher discrimination in the labor market than they do today.

[23] For conciseness and due to their larger sample size, we focus specifically on non-Hispanic whites, Blacks, and Hispanics.
[24] While the same pattern of decline in labor force participation holds within all sub-groups, blacks experienced larger declines than whites at all age levels. This is especially true among high school drop outs, where black participation rates tumbled by 30–40 percentage points (Binder and Bound 2019).
[25] Coile and Duggan (2019).

Table 3: Race well-being heterogeneities across labor market status in the US, 2010-2016 (prime-age male sample)

Variables	(1) Evaluative well-being index	(2) Negative affect index	(3) Positive affect index	(4) Purpose well-being index	(5) Community well-being index	(6) Financial well-being index	(7) Economy perceptions index	(8) Social well-being index	(9) Health well-being index 1 (self-assessment)	(10) Health well-being index 2 (behaviors)	(11) Health well-being index 3 (diseases)
Black	0.208***	-0.212***	0.053***	0.014	-0.066***	-0.078***	0.451***	0.040**	0.200***	0.053***	-0.016**
	(0.009)	(0.010)	(0.009)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.014)	(0.015)	(0.008)
Hispanic	0.165***	-0.158***	0.111***	0.293***	0.280***	0.118***	0.343***	0.173***	0.165***	0.269***	-0.075***
	(0.009)	(0.010)	(0.007)	(0.014)	(0.015)	(0.013)	(0.013)	(0.015)	(0.011)	(0.015)	(0.007)
Unemployed	-0.331***	0.392***	-0.213***	-0.628***	-0.288***	-0.544***	-0.099***	-0.219***	-0.329***	-0.324***	0.164***
	(0.013)	(0.015)	(0.015)	(0.025)	(0.028)	(0.024)	(0.012)	(0.026)	(0.025)	(0.025)	(0.011)
Out of the workforce	-0.308***	0.387***	-0.395***	-0.510***	-0.190***	-0.275***	-0.059***	-0.193***	-0.775***	-0.568***	0.584***
	(0.011)	(0.012)	(0.012)	(0.017)	(0.017)	(0.016)	(0.010)	(0.017)	(0.020)	(0.019)	(0.011)
(Black) X (Unemployed)	0.204***	-0.027	0.034	0.273***	0.127**	0.126***	-0.116***	0.058	0.170***	0.129**	0.002
	(0.030)	(0.033)	(0.036)	(0.053)	(0.056)	(0.047)	(0.033)	(0.054)	(0.050)	(0.051)	(0.024)
(Black) X (Out of the workforce)	0.285***	-0.078***	0.107***	0.243***	0.156***	0.146***	-0.028	0.161***	0.160***	0.173***	-0.054**
	(0.024)	(0.027)	(0.025)	(0.036)	(0.039)	(0.031)	(0.023)	(0.036)	(0.039)	(0.037)	(0.025)
(Hispanic) X (Unemployed)	0.123***	0.095**	-0.017	0.210***	0.040	0.158***	-0.039	-0.001	0.123**	0.116**	0.020
	(0.030)	(0.038)	(0.030)	(0.052)	(0.056)	(0.049)	(0.031)	(0.052)	(0.050)	(0.054)	(0.025)
(Hispanic) X (Out of the workforce)	0.179***	-0.039	0.090***	0.216***	0.096***	0.107***	-0.003	0.096***	0.318***	0.242***	-0.169***
	(0.024)	(0.035)	(0.028)	(0.034)	(0.035)	(0.033)	(0.022)	(0.034)	(0.038)	(0.039)	(0.025)
Observations	337748	271636	343776	103914	103339	103619	238317	103664	103044	98900	343677
R-squared	0.125	0.081	0.067	0.128	0.122	0.253	0.109	0.131	0.172	0.143	0.141

Robust clustered (at the county-level) standard errors in parentheses
*** p<0.01; ** p<0.05; * p<0.1
Note: Controls for remaining labor market status (employed full-time is the omitted category) are included. Additionally, controls for age group, marital status, educational level, pre-tax household income, household size, preferred religion, as well as fixed effects for day of week when the interview took place, month of interview, year, and county of residence, are also included.

The evaluative well-being of OLF and unemployed whites is roughly at the same low levels. The unemployed have lower life satisfaction than the OLF but higher optimism. Both groups have similarly high levels of negative affect, and lower levels of positive affect (compared to other employment/racial groups). A possible explanation is that the unemployed are still looking for a job and have some hope for the future, while the OLF have, for the most part, given up. The OLF have by far the worst health indicators of any groups, suggesting that at least some of the OLF have dropped out of the labor force *due* to poor health, rather than the other way around. Indeed, our results are in lined with Krueger's (2017) showing that 44% of prime aged males OLF reported to be taking pain medication, which is twice the rate of unemployed men. This trend is part of the increased consumption of opioids among this cohort and helps explain their lower likelihood of becoming re-employed and higher likelihood of becoming addicted to opioids and other drugs.[26]

In this instance unemployed blacks and Hispanics have lower optimism levels than their OLF counterparts of the same race, but still higher levels of optimism than their white counterparts. Unemployed minorities still have to deal with discrimination in the labor market – and are more likely to be underemployed than whites – which might explain the lower levels of optimism for those still seeking jobs, while the OLF may have simply given up and have raw optimism as a coping tool.[27]

[26] The suppliers of opioids targeted these cohorts and the places that they lived at the height of the push to sell them. Satel (2019) notes, though, that from the perspective of clinical psychiatry, any level of supply is more likely to create addicts in populations with a higher propensity to addiction. The lack of attention to the very low levels of well-being among this population seems to be a part of this story.

[27] Nunn et al. (2019).

When we look across race on purpose, community, financial, and social well-being, we again find that blacks and Hispanics typically score higher than whites. The gap is again biggest for those who are in inferior labor market status – the OLF and the unemployed – compared to the full-time employed. Black OLF males score much higher across the board on the indicators in the purpose index than do white OLF males. On community, like full-time employed blacks, black OLF males score lower on safety and security, but higher on the indicators that assess their desire to make their community better and the extent to which they get recognition for doing so. These findings highlight the remarkable levels of resilience among blacks living in precarious circumstances compared to their white counterparts.[28]

The geographic distribution of prime aged males OLF in part reflects the broader geography of desperation, with the pattern of low well-being markers and high levels of deaths of despair concentrated primarily (not only) in rural and suburban places in the heartland of the country, where manufacturing jobs used to be a stronghold but have declined in number and in quality. And beyond the trends in manufacturing, prime aged OLF males are more likely to reside in counties with higher prevalence of opioid prescriptions (both higher levels and increasing trends over time from 1999-2016), inter-twining the problems of depressed labor force participation and opioid addiction.[29]

Inter-generational and Geographic Mobility and Well-Being: Happy Peasants and Frustrated Achievers?

A key issue in the U.S. today is the extent to which the American Dream – the idea that there are opportunities available and that those individuals who work hard get ahead – is still widely shared today. That dream was a reality for many Americans for decades, with the U.S. having a reputation for high intergenerational mobility rates, and most parents expecting that their children would live better than they did.

Yet that reality has changed over time. The World Bank's Index of Economic Opportunity shows that intergenerational mobility in the U.S. is lower than in most OECD countries, roughly comparable with that of Spain and Portugal (Brunori, Ferreira, and Portugal, 2013). Chetty et al. (2016) find that while 90% of children born in the 1950's attained higher levels of income than their parents, only 50% of those born in the 1980's live better than their parents did. Those drops in mobility have occurred at all parts of the distribution. Yet they are starkest for the middle classes and for those living in industrial midwestern states, such as Illinois and Michigan. They attribute the declines to lower rates of growth and to greater inequality in the distribution of that growth.

Public perceptions, long tolerant of inequality due to the strong belief in the prospects of upward mobility, have since caught up. Alesina et al. (2004) found that there was an overall negative association of inequality with reported happiness in Europe – particularly for the poor, but the only cohort who were made unhappy by inequality in the U.S. were left leaning rich people. Yet, in 2016, a Pew survey found that 62% of Americans thought their children would live worse than they do. In contrast, in Latin America, only 13% of Chileans and 38% of Argentines (the regional pessimists) think that their children will live worse than they do (Reeves, 2014; for an overall review of comparative inequality and mobility trends between the U.S. and other countries, see Graham, 2017).

[28] An important caveat, though, is selection bias in the sample of young African American men, who are over-represented in the incarcerated population and therefore obviously not present in our data.
[29] Krueger (2017).

Indeed, lack of confidence that hard work will pay off – and more generally lack of hope for the future - is an important factor underlying the desperation in the U.S. today. The gap between believing hard work will get you ahead between the poor and the rich in the U.S. is, remarkably, twenty times greater than it is in Latin America (on average). The rich and the poor are equally likely to say that hard work will get you ahead in Latin America. In contrast, the poor in the U.S. are much less likely to answer affirmatively to this question than are the poor in Latin America, while the rich in the U.S. are more likely to answer it affirmatively than are the Latin American rich.[30]

Here, we explored the linkages between our range of subjective well-being indicators some place-based characteristics data at the county level that is made available by the Opportunity Insights Project. In particular, we use their data on absolute and relative mobility, the share of individuals living with their parents, the share of individuals living in one of their childhood census tracts, and teenage birth rates. The measure of absolute mobility is the expected rank of children whose parents were at percentile 25 in the national income distribution. As such, an increase in the value of this variable reflects higher mobility. Relative mobility is measured as the slope from an OLS regression of child rank on parents' rank. In this instance, a *decrease* in the value of this variable implies *more* mobility. Our empirical specification is again fairly straightforward, as formalized in equation (3):

$$(3)\quad SWB_{ict} = \alpha_0 + \beta_1 * W_{ct} + \delta_1 * (X_{ict}) + \varepsilon_{ict}$$

SWB represent the same set of well-being outcomes as in Equation (1). W is the vector of county-level variables we are using. This includes the ones mentioned in the paragraph above, as well as controls for mean household income, inequality, poverty, unemployment, labor force participation, mortality, population size, and share of non-whites, as referenced in the previous section.

In the first specification, X includes only a limited set of typically more exogenous controls: age, gender, race, day of the week and month of the interview, year, and state of residence. In the second one, we include a full battery of controls, adding labor market status, household income bracket, education, marital status, and religious preference.

Generally, we find support for a pattern that we have previously found which we call "happy peasants and frustrated achievers."[31] Our first basic - and unsurprising - finding is that the (log) county level mortality rate is negatively correlated with life satisfaction, future life satisfaction (optimism), and positive affect; and positively correlated with negative affect. It is negatively correlated with purpose, community well-being, social well-being, and financial well-being and economic perceptions. It is negatively correlated with health self-assessments and healthy behaviors, and positively correlated with being diagnosed with the diseases included in the index, such as diabetes and heart disease. In contrast, the log population rate is negatively correlated with life satisfaction but positively correlated with optimism for the future, positively correlated with stress and worry, and negatively correlated with daily happiness. Both of these findings hold with and without the full battery of controls.

The percentage of non-Hispanic whites is negatively correlated with life satisfaction, optimism, and positive affect, and positively correlated with negative affect. It is negatively correlated with purpose,

[30] The poor are defined as being in the bottom quintile of the income distribution in the Gallup World Poll for each place, while the rich are in the top quintile. For detail, see Graham (2017).
[31] Graham and Pettinato, 2002.

financial well-being and economic perceptions, and social well-being. Like the mortality rate it is also negatively correlated with health indices and positively correlated with disease diagnoses. Community well-being is the one dimension that is *positively* correlated with a higher percentage of non-Hispanic white respondents. When we add in all controls in addition to the exogenous ones, though, the coefficients on life satisfaction, optimism, and affect become insignificant.

Table 4 – Well-being and absolute mobility, exogenous controls only (2014-2015)

Variables	(1) Evaluative well-being index	(2) Negative affect index	(3) Positive affect index	(4) Purpose well-being index	(5) Community well-being index	(6) Financial well-being index	(7) Economy perceptions index	(8) Social well-being index	(9) Health well-being index 1 (self-assessment)	(10) Health well-being index 2 (behaviors)	(11) Health well-being index 3 (diseases)
Log(Abs mobility: Expected rank of children whose parents are at P25)	-0.131**	0.051	-0.068	0.005	0.148	0.002	-0.296***	0.014	-0.021	0.028	-0.036
	(0.059)	(0.058)	(0.057)	(0.057)	(0.097)	(0.056)	(0.068)	(0.058)	(0.059)	(0.062)	(0.058)
Log(% who live in one of their childhood Census tracts in adulthood)	-0.082***	0.061***	-0.015	-0.005	0.119***	-0.105***	-0.128***	-0.024	-0.050**	-0.046*	0.084***
	(0.025)	(0.023)	(0.024)	(0.024)	(0.033)	(0.024)	(0.027)	(0.023)	(0.023)	(0.026)	(0.023)
Log(% of children who live at the same address as their parents in 2015)	-0.013	0.099***	-0.073***	-0.102***	-0.077**	-0.083***	0.069**	-0.047**	-0.046*	-0.046*	0.024
	(0.026)	(0.024)	(0.025)	(0.025)	(0.035)	(0.026)	(0.029)	(0.024)	(0.024)	(0.024)	(0.024)
Log(Teenage Birth Rate)	-0.014	-0.061***	0.009	0.036**	-0.043*	0.007	-0.094***	-0.006	-0.008	-0.030*	0.033**
	(0.017)	(0.016)	(0.015)	(0.015)	(0.025)	(0.016)	(0.019)	(0.015)	(0.016)	(0.017)	(0.016)
Log(Gini coeficient (0-100)	-0.031	0.190**	-0.133	-0.154*	0.156	-0.001	0.079	0.013	0.095	-0.041	0.053
	(0.098)	(0.089)	(0.090)	(0.091)	(0.131)	(0.096)	(0.102)	(0.092)	(0.094)	(0.098)	(0.091)
Log(Top 10% income share (0-100)	0.111***	-0.020	0.028	0.108***	0.145**	0.007	0.133***	-0.014	0.126***	0.098**	-0.153***
	(0.043)	(0.038)	(0.039)	(0.040)	(0.058)	(0.042)	(0.044)	(0.039)	(0.041)	(0.045)	(0.038)
Log(Mean household income)	0.184***	-0.099***	0.106***	0.165***	0.015	0.314***	0.164***	0.162***	0.158***	0.158***	-0.090**
	(0.035)	(0.038)	(0.039)	(0.040)	(0.054)	(0.036)	(0.041)	(0.037)	(0.039)	(0.038)	(0.042)
Log(Case-Deaton composite mortality rate, ages 35-64 (per 100,000))	000))"	-0.042**	0.006	-0.003	-0.011**	-0.001	-0.018***	-0.014***	-0.012**	-0.003	-0.008
	(0.010)	(0.010)	(0.010)	(0.009)	(0.013)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Log(Total population)	-0.006	0.001	-0.001	-0.011***	-0.017***	-0.005	-0.007	-0.003	-0.002	-0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Log(White non-Hispanic share of population (0-100%))	-0.054***	0.030**	-0.035**	-0.054***	0.063***	-0.076***	-0.089***	-0.031***	-0.096***	-0.080***	0.071***
	(0.015)	(0.013)	(0.014)	(0.014)	(0.024)	(0.017)	(0.013)	(0.011)	(0.013)	(0.013)	(0.014)
Log(Poverty rate (0-100%))	-0.005	0.060***	-0.033	-0.006	-0.124***	0.004	0.049*	-0.009	-0.061**	-0.042	0.039
	(0.024)	(0.023)	(0.024)	(0.025)	(0.035)	(0.024)	(0.028)	(0.024)	(0.026)	(0.025)	(0.024)
Log(Unemployment rate (0-100%))	-0.053**	-0.017	-0.032	-0.009	-0.108***	-0.068***	-0.132***	0.004	-0.022	-0.036*	-0.016
	(0.021)	(0.021)	(0.020)	(0.020)	(0.035)	(0.020)	(0.025)	(0.018)	(0.021)	(0.022)	(0.020)
Log(Labor force participation rate (0-100%))	-0.083	0.008	-0.009	0.049	0.055	0.014	0.325***	-0.033	0.101**	-0.065	-0.138***
	(0.054)	(0.045)	(0.044)	(0.043)	(0.070)	(0.054)	(0.062)	(0.045)	(0.051)	(0.051)	(0.043)
Observations	312748	322215	320566	318797	318223	318212	318585	317590	316406	297980	320153
R-squared	0.037	0.037	0.015	0.014	0.069	0.071	0.052	0.010	0.029	0.023	0.181

Clustered standard errors (at the county level) in parentheses.
*** p<0.01; ** p<0.05; * p<0.1
Note: All regressions include the controls for age, gender, and race, as well as controls for year, month of interview, day of the week, and state of residence. Sample is restricted to 2014-2015.

For absolute mobility, as above, our first specification includes only exogenous controls: age, gender, and race, and then state and day/month of the interview dummies. With this specification, we find that absolute mobility is negatively correlated with both life satisfaction and optimism, and also negatively correlated with believing that the economy will improve. When we add in the controls for income, education, labor force and marital status, the only significant SWB indicator is economic perceptions, which is negative.

Relative mobility (which is harder to interpret in the tables as a negative coefficient means more mobility/less correlation with your parent's rank within each quintile) has less of clear pattern with our SWB indicators, although those that are significant suggest higher levels of well-being. Relative mobility is positively correlated with community well-being and the health indices, but negatively with disease reports. It is also positively correlated with worry. It seems that moving out of low opportunity places leads to better health and community satisfaction, but also to more worry and higher expectations. The results are essentially the same with and without the full battery of controls.

Table 5 – Well-being and relative mobility, exogenous controls only (2014-2015)

Variables	(1) Evaluative well-being index	(2) Negative affect index	(3) Positive affect index	(4) Purpose well-being index	(5) Community well-being index	(6) Financial well-being index	(7) Economy perceptions index	(8) Social well-being index	(9) Health well-being index 1 (self-assessment)	(10) Health well-being index 2 (behaviors)	(11) Health well-being index 3 (diseases)
Log(Rel mobility: Slope from OLS regression of child rank on parent rank)	-0.005	-0.027	0.000	-0.002	-0.194***	-0.025	-0.032	0.000	-0.040*	-0.088***	0.032
	(0.021)	(0.020)	(0.021)	(0.022)	(0.028)	(0.021)	(0.023)	(0.021)	(0.023)	(0.023)	(0.022)
Log(% who live in one of their childhood Census tracts in adulthood)	-0.109***	0.066***	-0.029	-0.004	0.108***	-0.110***	-0.194***	-0.021	-0.062***	-0.058**	0.084***
	(0.022)	(0.021)	(0.022)	(0.021)	(0.030)	(0.023)	(0.025)	(0.020)	(0.021)	(0.023)	(0.021)
Log(% of children who live at the same address as their parents in 2015)	0.005	0.093***	-0.064***	-0.102***	-0.093***	-0.083***	0.110***	-0.049**	-0.043*	-0.048**	0.028
	(0.024)	(0.022)	(0.024)	(0.024)	(0.032)	(0.024)	(0.028)	(0.021)	(0.022)	(0.023)	(0.023)
Log(Teenage Birth Rate)	0.007	-0.062***	0.020	0.036***	-0.017	0.013	-0.042**	-0.008	0.005	-0.012	0.031**
	(0.015)	(0.014)	(0.014)	(0.014)	(0.021)	(0.015)	(0.017)	(0.014)	(0.015)	(0.015)	(0.015)
Log(Gini coeficient (0-100)	0.010	0.184**	-0.113	-0.155*	0.178	0.007	0.176*	0.009	0.115	-0.018	0.053
	(0.096)	(0.088)	(0.091)	(0.091)	(0.126)	(0.095)	(0.103)	(0.090)	(0.093)	(0.096)	(0.090)
Log(Top 10% income share (0-100)	0.108**	-0.020	0.026	0.108***	0.140**	0.006	0.125***	-0.013	0.124***	0.095**	-0.152***
	(0.043)	(0.038)	(0.040)	(0.040)	(0.055)	(0.042)	(0.045)	(0.039)	(0.040)	(0.044)	(0.038)
Log(Mean household income)	0.177***	-0.096***	0.103***	0.165***	0.024	0.314***	0.150***	0.163***	0.158***	0.160***	-0.092**
	(0.035)	(0.036)	(0.039)	(0.040)	(0.051)	(0.036)	(0.041)	(0.037)	(0.041)	(0.041)	(0.044)
Log(Case-Deaton composite mortality rate, ages 35-64 (per 100,000))	-0.035***	0.032***	-0.013	-0.032***	-0.070***	-0.036***	-0.033***	-0.024**	-0.030***	-0.044***	0.022**
	(0.010)	(0.010)	(0.010)	(0.009)	(0.013)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Log(Total population)	-0.007*	0.002	-0.001	-0.011***	-0.014**	-0.005	-0.008	-0.003	-0.002	-0.003	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Log(White non-Hispanic share of population (0-100%))	-0.048***	0.032**	-0.032**	-0.054***	0.087***	-0.072***	-0.072***	-0.031***	-0.089***	-0.068***	0.068***
	(0.015)	(0.013)	(0.014)	(0.014)	(0.023)	(0.017)	(0.014)	(0.012)	(0.014)	(0.013)	(0.015)
Log(Poverty rate (0-100%))	-0.004	0.060***	-0.032	-0.006	-0.120***	0.005	0.051*	-0.009	-0.060**	-0.040	0.038
	(0.024)	(0.022)	(0.024)	(0.025)	(0.035)	(0.024)	(0.028)	(0.024)	(0.026)	(0.026)	(0.024)
Log(Unemployment rate (0-100%))	-0.053**	-0.017	-0.033	-0.009	-0.109***	-0.068***	-0.132***	0.004	-0.022	-0.037*	-0.016
	(0.021)	(0.020)	(0.020)	(0.020)	(0.034)	(0.020)	(0.025)	(0.018)	(0.021)	(0.022)	(0.020)
Log(Labor force participation rate (0-100%))	-0.085	0.007	-0.010	0.050	0.051	0.014	0.318***	-0.032	0.099*	-0.068	-0.138***
	(0.055)	(0.045)	(0.044)	(0.043)	(0.069)	(0.054)	(0.063)	(0.045)	(0.051)	(0.050)	(0.043)
Observations	312748	322215	320566	318797	318223	318212	318585	317590	316406	297980	320153
R-squared	0.037	0.037	0.015	0.014	0.070	0.071	0.052	0.010	0.029	0.023	0.181

Clustered standard errors (at the county level) in parentheses.

*** p<0.01; ** p<0.05; * p<0.1

Note: All regressions include the controls for age, gender, and race, as well as controls for year, month of interview, day of the week, and state of residence. Sample is restricted to 2014-2015.

Our controls for the percentage of people (per county) living in their parents' home or in a childhood census tract, which reflects generally lower levels of mobility, are generally significant. A county's percentage of respondents living in a childhood census tract is negatively correlated with life satisfaction, optimism, economic perceptions, financial well-being, and most health indicators, and positively correlated with negative affect and with disease reports. In contrast, it is positively correlated with community well-being, suggesting that many of these respondents are still content with their communities even though there is less opportunity. Respondents in counties with a high percentage of those who still live in their parents' homes, meanwhile, have negative indicators on all of our SWB variables, with the exception of life satisfaction, optimism, and disease reports, which are insignificant.

The results on the percent of those living in their parents' homes are essentially the same with and without controls. Despite the use of other controls, it is possible that this variable is picking up some of the most negative aspects that are related with hopelessness and lack of economic opportunity and of geographic mobility at the county level. With all controls, the percentage of people living in one of their childhood's census tracts remains associated with higher community well-being, but lower optimism, worse economic expectations, and worse health, and higher negative affect. Given that the share of people living with their parents is accounted for, this variable may reflect the situation of counties that have a substantial number of people who are unlikely to move away, are content with their communities, and are relatively better off.

Table 6 – Well-being and absolute mobility, full controls (2014-2015)

Variables	(1) Evaluative well-being index	(2) Negative affect index	(3) Positive affect index	(4) Purpose well-being index	(5) Community well-being index	(6) Financial well-being index	(7) Economy perceptions index	(8) Social well-being index	(9) Health well-being index 1 (self-assessment)	(10) Health well-being index 2 (behaviors)	(11) Health well-being index 3 (diseases)
Log(Abs mobility: Expected rank of children whose parents are at P25)	-0.094	0.032	-0.046	0.006	0.118	0.079	-0.216***	0.015	0.030	0.062	-0.079
	(0.058)	(0.056)	(0.056)	(0.054)	(0.097)	(0.050)	(0.064)	(0.054)	(0.054)	(0.059)	(0.053)
Log(% who live in one of their childhood Census tracts in adulthood)	-0.043*	0.044**	0.004	0.007	0.126***	-0.035*	-0.082***	-0.011	-0.008	-0.010	0.056***
	(0.024)	(0.022)	(0.023)	(0.022)	(0.033)	(0.021)	(0.026)	(0.022)	(0.021)	(0.024)	(0.021)
Log(% of children who live at the same address as their parents in 2015)	-0.017	0.081***	-0.054**	-0.079***	-0.072**	-0.097***	0.032	-0.028	-0.036*	-0.027	0.013
	(0.025)	(0.023)	(0.024)	(0.023)	(0.035)	(0.022)	(0.027)	(0.023)	(0.021)	(0.023)	(0.022)
Log(Teenage Birth Rate)	0.001	-0.056***	0.017	0.035**	-0.046*	0.021	-0.061***	-0.000	0.005	-0.014	0.020
	(0.016)	(0.015)	(0.015)	(0.014)	(0.024)	(0.014)	(0.018)	(0.015)	(0.015)	(0.015)	(0.015)
Log(Gini coeficient (0-100)	-0.063	0.159*	-0.112	-0.134	0.174	-0.061	-0.014	0.051	0.057	-0.038	0.057
	(0.091)	(0.086)	(0.086)	(0.084)	(0.127)	(0.082)	(0.096)	(0.087)	(0.085)	(0.090)	(0.082)
Log(Top 10% income share (0-100)	0.144***	-0.045	0.059	0.130***	0.160***	0.061*	0.135***	0.022	0.160***	0.115***	-0.173***
	(0.040)	(0.036)	(0.037)	(0.036)	(0.056)	(0.036)	(0.042)	(0.037)	(0.036)	(0.041)	(0.034)
Log(Mean household income)	0.002	-0.031	0.013	0.021	-0.098*	0.041	0.041	0.029	-0.027	-0.017	0.017
	(0.033)	(0.035)	(0.035)	(0.034)	(0.056)	(0.030)	(0.036)	(0.033)	(0.035)	(0.033)	(0.038)
Log(Case-Deaton composite mortality rate, ages 35-64 (per 100,000))	-0.024**	0.028***	-0.008	-0.019**	-0.063***	-0.022**	-0.035***	-0.012	-0.021**	-0.033***	0.018**
	(0.010)	(0.009)	(0.010)	(0.009)	(0.013)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
Log(Total population)	-0.007*	0.004	-0.003	-0.012***	-0.019***	-0.007**	-0.005	-0.004	-0.003	-0.005	0.005
	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)
Log(White non-Hispanic share of population (0-100%))	-0.013	0.010	-0.003	-0.019	0.086***	-0.017	-0.057***	-0.004	-0.039***	-0.027**	0.030**
	(0.015)	(0.013)	(0.013)	(0.012)	(0.024)	(0.014)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)
Log(Poverty rate (0-100%))	0.006	0.032	-0.007	0.007	-0.116***	0.020	0.025	0.015	-0.045*	-0.039*	0.023
	(0.022)	(0.022)	(0.022)	(0.022)	(0.035)	(0.020)	(0.025)	(0.022)	(0.023)	(0.022)	(0.022)
Log(Unemployment rate (0-100%))	-0.031	-0.027	-0.019	0.010	-0.108***	-0.035**	-0.112***	0.007	0.003	-0.003	-0.030*
	(0.020)	(0.019)	(0.019)	(0.018)	(0.035)	(0.017)	(0.023)	(0.017)	(0.020)	(0.020)	(0.018)
Log(Labor force participation rate (0-100%))	-0.090*	0.044	-0.029	0.030	0.067	-0.032	0.277***	-0.011	0.017	-0.094**	-0.061
Observations	312,748	322,215	320,566	318,797	318,223	318,212	318,585	317,590	316,406	297,980	320,153
R-squared	0.108	0.077	0.062	0.087	0.107	0.238	0.078	0.092	0.132	0.103	0.237

Clustered standard errors (at the county level) in parentheses.

*** p<0.01; ** p<0.05; * p<0.1

Note: All regressions include the controls for age, gender, and race, as well as controls for year, month of interview, day of the week, and state of residence. Sample is restricted to 2014-2015.

Table 7 – Well-being and relative mobility, full controls (2014-2015)

Variables	(1) Evaluative well-being index	(2) Negative affect index	(3) Positive affect index	(4) Purpose well-being index	(5) Community well-being index	(6) Financial well-being index	(7) Economy perceptions index	(8) Social well-being index	(9) Health well-being index 1 (self-assessment)	(10) Health well-being index 2 (behaviors)	(11) Health well-being index 3 (diseases)
Log(Rel mobility: Slope from OLS regression of child rank on parent rank)	-0.000	-0.025	-0.001	-0.007	-0.203***	-0.018	-0.032	-0.008	-0.048**	-0.085***	0.037*
	(0.021)	(0.019)	(0.020)	(0.019)	(0.027)	(0.018)	(0.022)	(0.018)	(0.019)	(0.020)	(0.019)
Log(% who live in one of their childhood Census tracts in adulthood)	-0.061***	0.045**	-0.005	0.007	0.107***	-0.023	-0.132***	-0.010	-0.012	-0.015	0.048**
	(0.021)	(0.020)	(0.021)	(0.019)	(0.030)	(0.019)	(0.025)	(0.020)	(0.019)	(0.022)	(0.019)
Log(% of children who live at the same address as their parents in 2015)	-0.004	0.077***	-0.048**	-0.080***	-0.084***	-0.107***	0.062**	-0.030	-0.039**	-0.033	0.023
	(0.023)	(0.021)	(0.022)	(0.021)	(0.031)	(0.021)	(0.026)	(0.020)	(0.020)	(0.021)	(0.021)
Log(Teenage Birth Rate)	0.015	-0.054***	0.025*	0.036***	-0.013	0.014	-0.021	-0.001	0.012	-0.002	0.023*
	(0.014)	(0.013)	(0.013)	(0.012)	(0.020)	(0.013)	(0.016)	(0.013)	(0.013)	(0.013)	(0.014)
Log(Gini coeficient (0-100)	-0.036	0.159*	-0.098	-0.133	0.209*	-0.077	0.060	0.049	0.064	-0.026	0.067
	(0.090)	(0.085)	(0.086)	(0.084)	(0.122)	(0.081)	(0.096)	(0.086)	(0.083)	(0.088)	(0.082)
Log(Top 10% income share (0-100)	0.142***	-0.045	0.058	0.130***	0.154***	0.062*	0.129***	0.022	0.158***	0.113***	-0.174***
	(0.040)	(0.036)	(0.037)	(0.036)	(0.053)	(0.036)	(0.044)	(0.037)	(0.036)	(0.041)	(0.034)
Log(Mean household income)	-0.002	-0.030	0.011	0.022	-0.090*	0.045	0.031	0.030	-0.025	-0.013	0.013
	(0.033)	(0.034)	(0.035)	(0.034)	(0.051)	(0.030)	(0.037)	(0.033)	(0.036)	(0.036)	(0.040)
Log(Case-Deaton composite mortality rate, ages 35-64 (per 100,000))	-0.023**	0.028***	-0.008	-0.019**	-0.059***	-0.023**	-0.032***	-0.012	-0.020**	-0.031***	0.018**
	(0.010)	(0.009)	(0.010)	(0.009)	(0.012)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Log(Total population)	-0.007**	0.004	-0.003	-0.012***	-0.016**	-0.006*	-0.006	-0.004	-0.002	-0.003	0.004
	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)
Log(White non-Hispanic share of population (0-100%))	-0.009	0.012	-0.001	-0.018	0.111***	-0.018	-0.044***	-0.003	-0.033***	-0.017	0.028**
	(0.015)	(0.013)	(0.014)	(0.012)	(0.023)	(0.015)	(0.013)	(0.012)	(0.011)	(0.011)	(0.013)
Log(Poverty rate (0-100%))	0.007	0.032	-0.007	0.007	-0.111***	0.020	0.027	0.015	-0.044*	-0.037*	0.022
	(0.022)	(0.021)	(0.022)	(0.022)	(0.034)	(0.020)	(0.026)	(0.022)	(0.024)	(0.022)	(0.022)
Log(Unemployment rate (0-100%))	-0.031	-0.027	-0.019	0.010	-0.109***	-0.035**	-0.113***	0.007	0.002	-0.004	-0.030*
	(0.020)	(0.019)	(0.019)	(0.018)	(0.034)	(0.017)	(0.023)	(0.017)	(0.020)	(0.020)	(0.018)
Log(Labor force participation rate (0-100%))	-0.092*	0.043	-0.030	0.030	0.062	-0.031	0.272***	-0.011	0.016	-0.096**	-0.062
	(0.048)	(0.041)	(0.040)	(0.038)	(0.066)	(0.042)	(0.055)	(0.040)	(0.043)	(0.043)	(0.038)
Observations	312,748	322,215	320,566	318,797	318,223	318,212	318,585	317,590	316,406	297,980	320,153
R-squared	0.108	0.077	0.062	0.087	0.108	0.238	0.078	0.092	0.132	0.103	0.237

Clustered standard errors (at the county level) in parentheses.

*** p<0.01; ** p<0.05; * p<0.1

Note: All regressions include the full set of individual-level controls, as well as fixed effects for year, month of interview, day of the week, and state of residence.

Again, since we include both the share living in a childhood census tract and the share who live in parents' home as county-level variables, it is likely that the former is capturing those areas where people stayed in the same areas where they grew up, but fared relatively well compared to those at home. They have likely not had much mobility compared to those who have left, but they are content with the place they live in, even though they are not optimistic about the future or are generally not in good health. Those respondents who are still living with their parents, meanwhile, are simply unhappy and unhealthy.[32]

Metropolitan, Micropolitan, and Rural Area Differences

As a final exercise, we explored how the well-being dimensions varied across county type. Our findings in general confirm our previously established pattern contrasting higher levels of well-being and better economies in urban areas on the coast compared to rural and suburban areas in the heartland, but with some nuances.

Our work on rural and micropolitan areas compared to urban ones departs from a much larger extant literature. Recent research finds that from 2008 to 2017, the rate of employment growth differed markedly across counties, increasing in a nearly monotonic way along the rural-urban continuum. While in rural counties and, to a smaller extent, those in micropolitan statistical areas, the employment rate was negative throughout this period, that was not the case for counties belonging to Metropolitan Statistical Areas (MSAs).[33] Within MSAs themselves, there were clear heterogeneities, with the larger ones seeing substantially larger rates of employment growth. This represented a clear departure from the 2001-2007 period, one in which all county types experienced positive employment growth and more so in smaller MSAs than in the larger ones.

Prior research using data for the U.S. from 2005-2008 (Oswald and Wu, 2011) found that, when controlling for socio-demographic characteristics (but not for income), there was no association between states' regression-adjusted well-being and their GDP. When income was added to the list of controls, well-being was then negatively associated with state GDP, as would be predicted by compensating differentials theory.[34] In particular, the research suggests that richer states offer lower utility from non-income sources, although some differences remain in regression-adjusted well-being across states.

We use a similar approach, yet with a focus on differences across county types. When analyzing county-level heterogeneities and the evidence in favor of compensating differentials, the specification used is again analogous to (1), but now with county-type as the key independent variable of interest, as formalized in Equation (4):

(4) $SWB_{ist} = \alpha_0 + \sum_{j=1}^{6} \beta_j * County\ type_{j,ist} + \delta_1 * (X_{ist}) + \pi_s + \tau_t + \varepsilon_{ist}$

SWB and τ_t represent the same as in (1). $County\ type$ is a variable dividing counties into 6 types, using the same data as Hendrickson et al. (2018)[35]:

[32] When we run the same mobility regressions without the controls for the percent of those living in their parents' census tract and homes, we get some modest differences. Much of the negative subjective well-being is picked up by the coefficient prime age workers out of the labor force, and much of the positive well-being picked up by the coefficients on blacks and Hispanics. Results available on request.

[33] See Hendrickson et al. (2018). We are defining as "rural" the counties that are not part of either metropolitan or micropolitan statistical areas.

[34] Oswald and Wu (2011).

[35] We thank Hendrickson et al. (2018) for sharing their data with us.

(i) to (iii) correspond to those belonging to a MSA with more than 1 million, between 250 thousand and 1 million, and less than 250 thousand people[36], respectively;

(iv) counties in micropolitan statistical areas;

(v) rural counties, adjacent to MSAs; and

(vi) rural counties, non-adjacent to MSAs.

Our key parameters of interest are again the set of coefficients β_j. X is still a vector containing individual-level socio-demographic controls and π_s corresponds to state fixed effects, as in this specification we can no longer use county fixed effects.

Table 8 shows the results we obtain when including only "exogenous" controls that are known to be correlated with reported well-being – age, race, gender, month of interview, day of the week, year, and state of residence.[37] We find sizable and significant differences across different types of counties, with evaluative well-being increasing – driven by both current life satisfaction and life satisfaction expected in the future, but particularly the latter – as we move from rural areas into progressively larger metropolitan ones. While there are no significant differences regarding negative affect, the incidence of positive affect also increases as we move along the rural-metropolitan spectrum.

As we move to larger metro areas, we see that well-being again tends to increase along all of the other dimensions – purpose, financial, economic expectations, and social – except for community-level indicators, where respondents tend to be more satisfied in rural areas. All three indices of health well-being are also worse in rural areas. Overall, even after accounting for the age, gender, and race make-ups of each area, average well-being is considerably higher in metropolitan areas, particularly the larger ones.

Most of these patterns hold, with coefficients of smaller magnitude, even after following Oswald and Wu's (2011) approach and including the remaining non-pecuniary controls (i.e., all except for household income). The main differences are that positive affect, purpose, and one of the health indices now become non-significant, while negative affect is now more associated with large metro areas, driven by higher incidence of stress and anger (Table 9). These results suggest that while larger metro offer lower non-pecuniary utility, but not so low as to eliminate the well-being gaps across county types: even after controlling for non-pecuniary elements, significant differences in well-being across county types within each state remain. While we are not presuming causality, this also suggests that the characteristics people in rural areas are more likely to have are those that are associated with lower levels of happiness, such as less job opportunities or lower education.

Table 8: Well-being across county type in the US, 2010-2016 (only exogenous controls)

[36] 2010 was the base year from which the county types were defined by population was 2010.

[37] State of residence, in particular, is unlikely to be fully exogenous – despite mobility costs, individuals are, at least to some extent, able to choose their state of residence. The results from Table 8, however, do not change meaningfully when excluding that.

Variables	(1) Evaluative well-being index	(2) Negative affect index	(3) Positive affect index	(4) Purpose well-being index	(5) Community well-being index	(6) Financial well-being index	(7) Economy perceptions index	(8) Social well-being index	(9) Health well-being index 1 (self-assessment)	(10) Health well-being index 2 (behaviors)	(11) Health well-being index 3 (diseases)
Large metro (1M+)	0.145***	-0.010	0.041***	0.034**	-0.060***	0.177***	0.236***	0.085***	0.166***	0.097***	-0.109***
	(0.009)	(0.011)	(0.010)	(0.015)	(0.021)	(0.016)	(0.012)	(0.014)	(0.017)	(0.016)	(0.011)
Medium metro (250k to 1M)	0.113***	-0.012	0.038***	0.024	-0.075***	0.122***	0.162***	0.063***	0.101***	0.060***	-0.072***
	(0.009)	(0.011)	(0.009)	(0.015)	(0.020)	(0.016)	(0.012)	(0.014)	(0.016)	(0.015)	(0.011)
Small metro (<250k)	0.078***	-0.003	0.023**	0.030**	-0.063***	0.083***	0.112***	0.053***	0.078***	0.042***	-0.045***
	(0.010)	(0.011)	(0.010)	(0.015)	(0.020)	(0.016)	(0.012)	(0.014)	(0.017)	(0.015)	(0.011)
Micropolitan	0.045***	-0.004	0.011	0.013	-0.050***	0.054***	0.082***	0.037***	0.041**	0.009	-0.024**
	(0.009)	(0.011)	(0.009)	(0.015)	(0.019)	(0.016)	(0.011)	(0.014)	(0.016)	(0.015)	(0.011)
Rural - metro adjacent	0.009	0.006	-0.008	-0.005	-0.005	-0.002	0.032***	0.005	0.009	-0.011	-0.017
	(0.010)	(0.012)	(0.010)	(0.016)	(0.019)	(0.017)	(0.011)	(0.015)	(0.017)	(0.016)	(0.012)
Observations	1558198	1278527	1614927	483502	482773	482827	1113181	481749	480189	453301	1614589
R-squared	0.039	0.035	0.012	0.012	0.059	0.065	0.053	0.008	0.025	0.020	0.179

Robust standard errors, clustered at the county level, in parentheses
*** p<0.01; ** p<0.05; * p<0.1
Note: Controls for age, gender, race, year, month of interview, day of week when the interview took place, and state of residence are also included.

Table 9: Well-being across county type in the US, 2010-2016 (no income controls)

Variables	(1) Evaluative well-being index	(2) Negative affect index	(3) Positive affect index	(4) Purpose well-being index	(5) Community well-being index	(6) Financial well-being index	(7) Economy perceptions index	(8) Social well-being index	(9) Health well-being index 1 (self-assessment)	(10) Health well-being index 2 (behaviors)	(11) Health well-being index 3 (diseases)
Large metro (1M+)	0.072***	0.022**	0.001	-0.008	-0.086***	0.063***	0.157***	0.041***	0.066***	0.009	-0.045***
	(0.008)	(0.010)	(0.008)	(0.013)	(0.020)	(0.014)	(0.011)	(0.013)	(0.014)	(0.014)	(0.009)
Medium metro (250k to 1M)	0.064***	0.011	0.010	-0.000	-0.090***	0.045***	0.112***	0.032**	0.039***	0.004	-0.032***
	(0.008)	(0.010)	(0.008)	(0.013)	(0.019)	(0.014)	(0.011)	(0.013)	(0.014)	(0.014)	(0.009)
Small metro (<250k)	0.045***	0.014	0.004	0.015	-0.072***	0.029**	0.078***	0.030**	0.036**	0.003	-0.018*
	(0.008)	(0.010)	(0.008)	(0.013)	(0.019)	(0.014)	(0.011)	(0.013)	(0.014)	(0.014)	(0.009)
Micropolitan	0.027***	0.006	0.001	0.005	-0.054***	0.023	0.063***	0.024*	0.018	-0.011	-0.010
	(0.008)	(0.010)	(0.008)	(0.013)	(0.018)	(0.014)	(0.010)	(0.013)	(0.014)	(0.014)	(0.009)
Rural - metro adjacent	0.006	0.008	-0.009	-0.010	-0.008	-0.013	0.029***	-0.001	0.001	-0.018	-0.014
	(0.009)	(0.011)	(0.009)	(0.015)	(0.018)	(0.015)	(0.010)	(0.014)	(0.015)	(0.015)	(0.010)
Observations	1558198	1278527	1614927	483502	482773	482827	1113181	481749	480189	453301	1614589
R-squared	0.087	0.065	0.044	0.074	0.089	0.163	0.075	0.081	0.114	0.091	0.228

Robust standard errors, clustered at the county level, in parentheses.
*** p<0.01; ** p<0.05; * p<0.1
Note: Controls for age, gender, race, labor market status, marital status, educational level, household size, preferred religion, as well as fixed effects for day of week when the interview took place, month of interview, year, and state of residence, are also included.

Finally, we also add income controls (Table 10). Now, the sign on evaluative well-being further decreases, but remains positive. However, the index itself hides some heterogeneity, as current life satisfaction is now higher in rural areas, although optimism (as proxied by expected future life satisfaction) remains negative. The magnitude of the coefficient on negative affect increased for metro areas, while positive affect became negatively associated with larger metro areas. The coefficient signs for purpose and financial well-being in metro areas also turn negative, while social well-being and one of the health indicators become non-significant. The remaining two health indices (self-assessed health and diseases) remain slightly more favorable in large metro areas, although with a much smaller coefficient.[38]

[38] Because the disease diagnosis question is "have you never been diagnosed with the following diseases", a negative coefficient signifies a lower likelihood of disease incidence in the particular type of county.

Overall, the results from Tables 9 and 10 are also broadly in line with Oswald and Wu's (2011), in that we also reject a null hypothesis of equality of well-being across different areas. However, as with their results, our results are compatible with the notion that higher-income metro areas offer lower non-pecuniary utility, though some well-being differences remain, with higher levels of optimism in larger metro areas being the most important one.

Our results are again suggestive of the happy peasant/frustrated achiever theme, where respondents living in rural areas do not seem particularly worried or stressed, but they have little hope for the future. In contrast, those living in larger urban areas have much higher levels of life satisfaction and optimism about the future, but also higher expectations and more stress. They also are suggestive of recent research on reduced labor market flexibility, which re-enforces the above patterns, as people are more likely to search for jobs within a limited geographic span (which may complement their skill sets as well as where they feel comfortable culturally).[39]

Table 10: Well-being across county type in the US, 2010-2016 (all controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Evaluative well-being index	Negative affect index	Positive affect index	Purpose well-being index	Community well-being index	Financial well-being index	Economy perceptions index	Social well-being index	Health well-being index 1 (self-assessment)	Health well-being index 2 (behaviors)	Health well-being index 3 (diseases)
Large metro (1M+)	0.028***	0.050***	-0.023***	-0.043***	-0.120***	-0.027**	0.143***	0.005	0.023*	-0.022	-0.023**
	(0.008)	(0.010)	(0.008)	(0.013)	(0.020)	(0.013)	(0.011)	(0.013)	(0.014)	(0.014)	(0.009)
Medium metro (250k to 1M)	0.036***	0.030***	-0.007	-0.022*	-0.110***	-0.011	0.103***	0.010	0.012	-0.017	-0.017*
	(0.008)	(0.010)	(0.008)	(0.013)	(0.019)	(0.013)	(0.011)	(0.013)	(0.013)	(0.013)	(0.009)
Small metro (<250k)	0.029***	0.026***	-0.007	0.003	-0.084***	-0.003	0.072***	0.017	0.020	-0.008	-0.009
	(0.008)	(0.010)	(0.008)	(0.013)	(0.019)	(0.014)	(0.011)	(0.013)	(0.014)	(0.014)	(0.009)
Micropolitan	0.016**	0.014	-0.006	-0.005	-0.063***	-0.003	0.059***	0.014	0.005	-0.021	-0.004
	(0.008)	(0.010)	(0.008)	(0.013)	(0.018)	(0.013)	(0.010)	(0.013)	(0.014)	(0.014)	(0.009)
Rural - metro adjacent	0.002	0.011	-0.012	-0.013	-0.010	-0.021	0.027***	-0.004	-0.003	-0.021	-0.012
	(0.009)	(0.010)	(0.009)	(0.014)	(0.018)	(0.014)	(0.010)	(0.014)	(0.014)	(0.015)	(0.010)
Observations	1558198	1278527	1614927	483502	482773	482827	1113181	481749	480189	453301	1614589
R-squared	0.107	0.077	0.052	0.086	0.101	0.239	0.077	0.093	0.132	0.102	0.235

Robust standard errors, clustered at the county level, in parentheses.
*** p<0.01; ** p<0.05; * p<0.1
Note: Controls for age, gender, race, labor market status, marital status, educational level, household size, preferred religion, household income, as well as fixed effects for day of week when the interview took place, month of interview, year, and state of residence, are also included.

Conclusions

The past few years have exposed deep divisions in the United States. Many of these – in our politics, in our civic discourse, and in our vision of what America should be – are a result of a widening gap between those with opportunities and with hope for the future, and those who are falling behind. These divisions are evident in our high levels of income inequality and reduced levels of intergenerational mobility, in the gaps across the rich and poor on indicators ranging from educational outcomes to life expectancy to marriage rates, and, most sadly, in the trends in preventable premature deaths.

[39] Demyank et al. (2017), Manning and Petrongolo (2017). With this geographic specification, meanwhile, we do not find much heterogeneity across races.

In earlier work we tried to tell this story from the perspective of peoples' well-being: hopes for the future, satisfaction with life today, and stress, worry, anger or contentment the previous day. We find deep divisions in well-being across the rich and the poor. But the story is more complex and varies a great deal across race and place. The deepest desperation is among cohorts in the white working class who previously had privileged access to jobs (and places) that guaranteed stable, middle class lives. Rather ironically, African Americans and Hispanics - the cohorts that historically faced high levels of discrimination — retain higher levels of well-being, especially hope for the future.

In this paper, we provide more detail on patterns in these trends across places and people, with a focus on the cohorts with the lowest levels of well-being – and who are most vulnerable to despair and its manifestations in premature mortality. Our previously identified patterns in differential levels of optimism and resilience (including to deaths of despair) across races, still hold – and indeed are attenuated - at the level of labor force participation, mobility, and place.

We find particularly high levels of misery among prime aged males out of the labor force. The differences across races, though, play out the same way, and white OLF males are a particularly troubled cohort compared to black and Hispanic prime aged males OLF; to other labor market groups – including prime aged females OLF; and even to prime aged males OLF in Europe, Latin America, and the Middle East. This pattern also plays out at the level of place, with places in the heartland with declining employment – and higher rates of deaths of despair - having a higher concentration of the population out of the labor force.

We looked at the role of intergenerational and geographic mobility. Our findings are more significant on the latter type of mobility. Still, we find that individuals that live in counties with lower levels of absolute and relative mobility tend to have worse well-being and health indicators, with one important exception. These same respondents are more likely than the average to be satisfied with life today and with their communities, although they are not optimistic about the future. These trends reflect a "happy peasant and frustrated achiever" pattern that we have found in developing economies, where respondents with higher levels of upward mobility have lower levels of life satisfaction today, but higher aspirations for their futures, while those with lower mobility are content today but have lower aspirations.

An important part of the mobility story hinges on peoples' ability and willingness to move to where jobs are. We explored the well-being of individuals living in counties with a higher or lower percentage of respondents who still live in their parents' census tract, and then with those who still live in their parents' homes. The counties with more "stayers" are more likely to be in rural and suburban areas rather than urban ones, and to have less absolute and relative mobility.

Respondents in counties with a high percentage of those still in their parents' census tract tend to be content today and satisfied with their communities, but they are not hopeful for the future and have poor health indicators. Respondents in those countries with a high percentage of respondents who are still living in their parents' homes – who typically have very low levels of mobility and are often OLF – are the most miserable, displaying lower levels of well-being across most dimensions, as well as very poor objective health indicators. Those individuals who are in their parents' census tract have not had much mobility – and certainly not locational mobility – but have done relatively well compared to those who are still with their parents.

When we look across rural and micropolitan areas compared to urban ones, we find that the former have significantly lower levels of well-being across most dimensions (including objective health indicators), with rural areas typically scoring lower than micropolitan ones. One except is community well-being, with these same places tending to have high levels of satisfaction with the community. There is selection bias, as those who have stayed rather than moving to opportunities elsewhere have done so either by choice or because of inability to move. There seem to be many respondents who like where they live despite the absence of opportunities. At the same time those who could not or have not moved away are less likely to have different types of communities as a reference point.

When we divide the sample into whites versus minorities (African Americans and Hispanics), we find that both rural whites and minorities have lower well-being than their urban counterparts. Yet the rural-urban well-being gaps are much larger for whites than they are for minorities, again reflecting the consistent differences in minority vs white well-being. Not surprisingly, then, the percentage of white respondents per community is associated with significantly worse well-being and health indicators and behaviors, although these same respondents have high levels of satisfaction with their communities. In contrast, black respondents – including OLF ones – tend to have high levels of well-being across many dimensions, but *not* with overall community well-being (including, not surprisingly, safety and security). Yet within that index, they score much higher than the average on questions about wanting to make their communities better places and in getting recognition for doing so.

Our regional story reflects the broader patterns that we have found elsewhere: coastal, urban places score much higher on most well-being indicators than do those in the heartland of the country. Respondents in large metropolitan areas have significantly higher levels of overall evaluative well-being – especially hope for the future, but also higher levels of stress and worry, among other things, likely reflecting higher expectations. Those in rural and micropolitan areas are much less optimistic about the future, but are also less stressed and worried, and seem to have lower expectations about their health status, among other things. These results again reflect the happy peasant and frustrated achiever finding that we have found in many other places in the past.

Our story is a nuanced one, with pockets of remarkable levels of hope and resilience among cohorts with a history of discrimination and marginalization, but who are gradually getting ahead and for the most part have faith in an American dream. Yet the most consistent – and worrisome – finding is the high levels of desperation among less than college educated whites – both at the level of the individual and the level of places where they are concentrated – and the strong association with living in those places and the deaths of despair. Much previous work shows that hope matters to health, productivity, and lifespans. While restoring hope among populations where it has been lost is not a topic that is usually the bailiwick of economists, the geography of desperation in America suggests that we must begin to take this issue on.

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