Geographic Disparities in Health and Health Care

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Abstract

Where you live affects how long you live; one landmark study showed 5.3 years lower life expectancy for a male in Gary Indiana compared to New York City, even after adjusting for income. In this paper, I first reconsider the evidence on the wide regional disparities in mortality rates and whether they are associated with corresponding regional differences in health behaviors or health care quality. Some health behaviors and health care quality measures are better at predicting overall mortality than others; just smoking rates and risky drug prescribing together explain 83 percent of overall variation in regional mortality across 306 Hospital Referral Regions. More worrisome are the trends in mortality, in particular those arising from "deaths of despair." I document these changes during 2000-14, finding that in some areas, deaths arising from substance abuse have risen rapidly, while in other parts of the country, it's an increase in alcohol-related deaths; in still others it's rates of self-harm. Taken as a whole, these secular trends have led since 2000 to a 41 percent increase in geographic disparities in mortality – a *divergence* rather than convergence in mortality across U.S. regions.

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I. Introduction

By now it is well understood that where you live affects how long you live. In a landmark study, Chetty et al. (2016) compared life expectancy at age 40 across U.S. regions but adjusted for lifetime income using tax return data. Their principle finding was a remarkable large difference in life expectancy by income. But a secondary and important finding was the extent to which life expectancy, even after adjusting for income, varied across regions, particularly among lower income groups. For people in the bottom income quartiles; a woman living in New York City could expect to live 3.3 years longer (5.3 years for a man) than their counterpart with similar income in Gary Indiana.[1] The authors considered a variety of factors for why such differences existed, but aside from a modest income-based association with health behaviors, little appeared to explain such differences.[2]

There is also an emerging literature on the impact of "place," broadly defined, on health. Social epidemiologists have understood the importance of neighborhood effects for many years; Messer et al. (2006) for example used a principle components approach using multiple measures of socio-economic and health behaviors to create a "deprivation index" applied to granular geographic areas, while Montez and Berkman (2014) noted differential patterns across regions of the rise in the education-mortality gradient. More recently, studies of people who move from healthy to unhealthy areas (or conversely) suggest that even over a short period of time, "place" affects mortality rates. For example, Deryugina et al. (2018) found that subsequent mortality

[1] The authors did not adjust income for differences in living expenses, making the comparison even more noteworthy as the cost of living in New York City is higher than in Gary.

[2] Earlier work also found large differences across the U.S. by race and geography, and race/geography interactions; see Murray et al., 2006.

rates of people moved from New Orleans following Hurricane Katrina converged in part to the general health levels of where they moved. Similarly, Finkelstein et al. (2019) find the role of place to be important in explaining health of movers. The puzzle that remains is to understand what exactly does "place" mean in terms of factors affecting health? It's certainly not genetics or something intrinsic to the individual (since we find these differences even for movers), but it could relate health care quality, *changes* in individual health behavior (e.g., moving to an area where few smoke could affect one's own smoking behavior), or some other social or environmental feature of the region, such as a lack of social capital or community despair.

This paper therefore reconsiders some of the basic evidence on regional disparities in health. While I cannot resolve the association between place and health outcomes, I draw on existing literature, as well as new analysis of regional data, to establish several empirical patterns that can potentially inform public health and economic efforts to reduce such disparities. My regional analysis takes a 30,000 foot view of health disparities by use of the 306 Hospital Referral Regions (HRRs) in the United States, and thus does not address the much larger literature on racial, economic, and ethnic differences at the individual level, or more granular geographic measures of "place" at (e.g.) the Census Block level (Chen et al., 2006).

I first document (as others have) the large cross-sectional variation in regional age-standardized mortality rates and Behavioral Risk Factor Surveillance System (BRFSS) measures of health behaviors for all ages; these are based on data from the Institute for Health Metrics and Evaluation (IHME).[3] It is well understood that at the individual level, health behaviors are critically important in explain longevity, but at the regional level, many such measures do a

[3] The IHME estimates use empirical Bayes approaches to impute smaller county measures by shrinking the individual estimates towards "similar" counties based on income, education, and rural/urban characteristics; I discuss potential biases arising from this imputation in the Methods Section below.

surprisingly poor job; binge drinking is *negatively* associated with mortality. While regional income matters, the most important predictor appears to be smoking, which alone explains 67 percent of the regional variation in mortality. It is unlikely that smoking alone is causal, but instead captures a variety of other health challenges such as low education, poor employment opportunities, and mental health issues (Cutler et al. 2011; Drope et al., 2018). Nonetheless, regional smoking behavior appears to be a sentinel predictor of high mortality rates.

It is well understood that health care utilization varies across the United States as well; both Medicare and commercial (under-65 privately insured) health care utilization exhibit remarkable regional variation, of which only a part can be attributed to health status or prices (Skinner, 2012; Cooper et al., 2018).[4] I consider 2 measures of health utilization, one high-quality (statin prescriptions for Medicare patients with diabetes) and the other low-quality (the use of risky drugs for Medicare patients). While the high-quality measure is statistically significant, only risky drug prescribing is associated with regional differences in mortality. Indeed, just two measures (smoking and risky drug prescribing) predict 83 percent of regional variation in mortality; conditional on these two factors, income is no longer important.

There is also evidence that these geographic patterns of health are very much in flux. The evidence from Fenelon (2013) on the emergence of high-mortality "hot spots" in the South, Dwyer-Lindgren et al.'s (2016) finding that disease-specific patterns of mortality across U.S. counties are evolving rapidly, Cunningham et al.'s (2017) documentation of a narrowing of black-white mortality rates since 1999, and especially Case and Deaton's (2015, 2017) research

[4] Both Sutherland et al. (2008) using standard adjustments for income, race, and self-reported health, and Finkelstein et al. (2016) who study people who move, find roughly 35% differences in regional utilization between the lowest and highest quintiles of health care intensity.

on rising mortality among non-Hispanic whites because of "deaths of despair," all point to a fundamental restructuring of how place affects health outcomes.

Using county data aggregated up to the HRR level, I consider changes over time in mortality aggregated to the HRR level by cause of death between 2000-2014, a period associated with a fundamental break in mortality trends as first noted by Case and Deaton (2015). These trends cannot be easily explained by economic factors during the same period (Case and Deaton, 2017; Ruhm, 2019). I show that the areas most affected by rising rates of drug overdoses are different from those most affected by deaths due to alcohol abuse, and different still from the regions most affected by rising rates of self-harm, suggesting that social collapse may have very different effects on specific health behaviors depending on whether one lives in Kentucky (opioids) or West Texas (alcohol).

Finally, one might ask whether regional mortality patterns have converged (because of narrowing racial mortality gaps) or diverged over time because of the localization of deaths of despair.[5] I find a remarkable divergence in mortality: In just 15 years, the standard deviation in (log) mortality has widened by 41 percent. Clearly understanding the role of "place" in health outcomes is becoming increasingly important as it accounts for an ever-larger fraction of inequality in U.S. health outcomes.

II. Data and Methods

The U.S. is split into 306 Hospital Referral Regions (HRRs) originally created by the Dartmouth Atlas research group based on the migration patterns of Medicare patients seeking

[5] Becker et al. (2005) found considerable convergence in longevity around the world. For the U.S., Jena et al. (2010) find convergence in life expectancy up to 1980 (as measured by the Gini Coefficient) but then a slight widening of inequality in life expectancy between 1980 and 2000.

inpatient care.[6] Thus HRRs cross state and county lines, for example when patients follow the interstate highways to receive care. Unlike Metropolitan Statistical Areas, HRRs have the advantage of covering all of the U.S. including rural areas (except very sparsely populated areas such as northwest Maine near the Canadian border). And while the regions were not drawn explicitly to capture differences in health behaviors or health status, they are ideally suited to capturing place-based health care effects.[7] Alternative approaches to characterizing regions based on county-level measures; Chetty et al. (2016) use Commuting Zones (N = 741), which represent counties matched based on economic activity, while Case and Deaton have created Coumas, which are a combination of counties and Public Use Microdata Areas (PUMAs), of which there are more than 1,000. Because of potential issues with small sample sizes, particularly with regard to the precision of BRFSS estimates, I chose HRRs, which in terms of sample sizes (306 HRRs) are somewhere between Coumas and Commuting Zones, and states.

While data on health care spending and quality is available at the HRR level, I aggregate up from county-level data for both morbidity and mortality data. Unfortunately, even publicly available county level data is problematic; the Behavioral Risk Factor Surveillance System (BRFSS) health behaviors survey has ceased reporting county data since 2011, and even for earlier years only larger counties reported data; a similar problem exists for specific cause-of-death mortality data. For this reason, I use IHME publicly available data on health behaviors (drawn from BRFSS) and on cause-specific age-standardized mortality (Dwyer-Lindgren et al., 2016); these data currently are available only through 2014. On average, there are about 10

[6] Using 1992-93 data, the Dartmouth Atlas project team first mapped zip codes to Hospital Service Areas or HSAs (all of which at the time had at least one hospital) based on where patients sought their care; these HSAs were then mapped into Hospital Referral Regions (HRR), larger regions (N = 306) where there was a

[7] Case and Deaton (2015, 2017) use

counties per HRR; these are aggregated up to HRR levels using the Missouri Census Data Aggregator (MABLE) with 2010 Census population weights.[8]

The IHME research group estimated county-level estimates using a Bayesian mixed-effects spatial model that for small counties shrinks the estimates towards the predicted value based on median income, race, ethnicity, the high school graduation rate, and density; for large counties there is presumably little need for shrinkage. The IHME researchers have devoted considerable effort to categorizing cause of death including methods for removing "garbage" or non-informative cause of death measures (Dwyer-Lindgren et al., 2016).[9]

One might be concerned about using the IHME data to make inferences about a specific county's mortality rate or smoking rate, given the imputation approach. But since HRRs tend to be quite large relative to county size, and HRRs generally include several larger counties, it is more like providing an optimally estimated missing (county) value for the HRR when calculating weighted averages across counties.[10]

III. Results

A. Cross-sectional Variation in Health and Health Care

Figure 1 provides a map of HRR-level mortality rates across regions in 2014. There are strong spatial patterns, with mortality rates ranging by a factor of 2-to-1, with San Mateo County

[8] http://mcdc.missouri.edu/applications/geocorr2014.html

[9] I use age-standardized mortality rates rather than life-expectancy rates; while the two are obviously closely related, life-expectancy adds an additional weight that scales up mortality for younger people more than for older people with fewer remaining life years.

[10] A potentially more serious concern arises with the imputation methods leading to biases statistical analysis; if two variables are each derived from imputed county data that relies on the same variables such as income and education, then the imputation could mechanically impart a correlation even there isn't one in the true data. The use of HRR-level data will minimize that relative to county data (since the larger counties that weigh more heavily in HRR data will also be less "shrunken" towards the predicted level); as well, as I show below, many of the BRFSS data exhibits zero or even negative correlations, suggesting that this mechanism does not impart large biases.

CA (age-standardized rate of 542 per 100,000) just half of the rate in Florence, South Carolina (1088 per 100,000).[11] As has been shown in previous studies, the highest mortality region is concentrated in Southern states such as Mississippi and Louisiana, as well as Oklahoma and Northern Texas.

What might explain such differences? I consider two broad categories below, health behaviors and health care quality.[12] While it is well understood that health behaviors such as smoking and drinking are major contributors to individual-level mortality rates, one can still ask whether regional variations in such behaviors are also associated with higher overall mortality. As it turns out, the regional correlations between some health behaviors are not consistent with the epidemiological evidence; binge drinking exhibits a *negative* and significant correlation both in bivariate and multiple regressions (that is, more binge drinking is associated with lower mortality); this illustrates the potential biases resulting from the "ecological fallacy" of estimating an individual correlation from aggregated data.[13]

I find that the strongest predictor of regional mortality appears to be the fraction of people in the population who are smoking. Figure 2 shows the simple bivariate correlation between smoking (in 2011, the most recent year in my sample) and 2014 mortality rates. There is a remarkably strong correlation, with an R^2 of 0.67 in a bivariate regression. Not surprisingly,

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[11] Recall that these measures do not adjust for differences in race or ethnicity, and thus capture more than just the impact of "place."

[12] There are also differences across regions by race and ethnicity; I find in unreported results that the association between the population share that is African-American and mortality is largely mediated by differences in health behaviors and low quality care.

[13] In the ecological fallacy problem, aggregating individual behavior to (e.g.) the state level can lead to incorrect inferences. The classic example (which may or may not still be valid) is that states voting Republican were more likely to have low average incomes, but at the individual level, there was a positive association between income and voting Republican.

healthy regions such as Contra Costa County in California have low rates of both smoking and mortality, in contrast to Huntington West Virgina, with very high rates of both. More interesting are the regions where the correlation is less clear; retirement communities in Florida such as Fort Meyers have lower mortality conditional on smoking, likely reflecting the greater importance of non-smoking retirees (who have a strong impact on mortality rates) compared to native and younger Floridians with higher smoking rates. Conversely, Utah exhibits very lower rates of smoking and lower mortality rates in contrast to Las Vegas, thus (once again) confirming Victor Fuch's (2011) observation that health behaviors can easily explain the higher mortality rates in Nevada compared to Utah.[14] That said, in 2014 the mortality rates in Utah are not far below those in Las Vegas.

Can any of these health variations be explained by the quality or quantity of health care? Figure 3 shows the corresponding regional variation in price-age-race-sex-adjusted Medicare spending in 2014, demonstrating the same kind of two-to-one variation in weighted utilization rates as for mortality, although in the case of Medicare spending, the highest utilization regions are McAllen Texas and Miami. Yet the two maps (Figure 1 and Figure 3) look quite similar, with high rates of both health care spending and mortality in the South, although this apparent correlation tells us little about the importance of health care in explaining mortality; instead it could be that people who are sick, and at high risk of dying, require more spending than those who are eating carefully and avoiding smoking. More reliable measures of regional variation in spending, one using detailed risk adjustment including patient self-reported health (Sutherland et al., 2009), and the other measuring utilization of Medicare movers (Finkelstein et al., 2016) both

[14] That said, it is surprising that the mortality rates in Provo and Las Vegas aren't more different.

suggest a difference in health care intensity (conditional on health) of about 35% between the lowest and highest quintiles of health care intensity.

For this reason, I consider two measures of health care utilization. First, statin prescribing for Medicare patients diagnosed with diabetes (2010) is well understood to be beneficial; this estimate at the HRR level is taken from Morden and Munson (2013) for 2010 data. Second, I use a measure of poor quality; risky prescribing for elderly Medicare enrollees for treatments such as skeletal muscle relaxants, long-acting benzodiazepines and highly sedating antihistamines (Morden and Munson, 2013). I focus on these two measures because there is little need for risk-adjustment; one should particularly encourage the use of statins, and avoid high-risk medications, for sicker patients.[15] Figure 4a (Statins) and 4b (High-Risk Prescribing) demonstrate a very different geographic pattern of use.

I consider a multivariate approach to consider what factors best predict 2014 age-standardized mortality; variables are summarized in Table 1 and the regression results presented in Table 2. First, I include just two variables; smoking and risky prescribing (Column 1); just these two alone explain 83.5 percent of the variation in mortality across regions. Again, the estimated coefficients should not be interpreted as a causal effect; like smoking, risky prescribing may as well reflect patient demand, but unlike smoking, risky prescribing must be enabled by the physician signing a prescription. While log income is itself highly correlated with mortality on a bivariate basis (the coefficient is -330, with a t-statistic of 21), Column (2) demonstrates that conditional on smoking and risky prescribing, income is no longer predictive of mortality. In Column (3), I add statin prescribing rates and obesity; both significant and in the expected

[15] One might be concerned about adherence issues for statins, but less so for risky prescribing.

direction, and raising the R^2 marginally to 0.852. Finally, adding binge drinking leads to a counter-intuitive negative coefficient (Column 4), but adds little to predictive power.

B. Patterns of Changes in Cause-Specific Mortality Rates 2000-2014

In two influential studies, Case and Deaton (2015, 2017) demonstrated the importance of "deaths of despair" from factors such as drinking, drug overdose, and suicides in explaining the rise since the beginning of the century in mortality rates for white non-Hispanic individuals in their late middle-age, with most of the increase explained by people with lower educational attainment. Because my data draws on overall mortality rates, including the elderly (and range only through 2014), all regions experience a decline in overall mortality, but some more than others: For the 5th percentile HRR, mortality fell by 0.5 percent annually, while for the 95th percentile HRR, mortality declined by 2.0 percent, consistent with trends prior to 2000. The geographic areas most affected by the slowdown in mortality (in the darker purple) are broadly consistent with those found in the Case and Deaton (2017) study; essentially the East Coast continues to improve, while the Midwest and South experience the greatest stagnation in mortality rate improvements (Figure 5; Appendix A.1 and A.2 by sex).

The specific cases of death, also drawn from the IHME database, shows geographic variability as well; regions in Kentucky, Ohio, New Mexico, and New Hampshire were strongly affected by the rise in opioid deaths, while the largest increases in deaths related to cirrhosis of the liver and related diseases were in West Texas (and in New Mexico); deaths related to self-harm were even further West in mountain states. While there may have been a common sense of social or economic collapse across these regions, residents responded in quite different ways across the country.

C. Have Regional Disparities Gotten Worse?

Since Barro and Sal-i-Martin (1992), there has been an interest in macroeconomic models of convergence. More recently, Becker et al. (2005) documented the importance of convergence in life expectancy along with income, finding that a combined measure capturing the value of improved lifespan implied a marked convergence across countries in full economic income. By the same token, the patterns of mortality change shown in Figure 5 could imply either convergence or divergence in regional health inequality. To consider this question, I first consider σ-convergence; the standard deviation of log-mortality (unweighted by HRR-level population) increased from .102 to .143, or a (log) increase of 0.41. The coefficient of log 1999 mortality on the log change in mortality between 2014 and 2000, 0.33 (t-statistic 11.9) similarly points to a distinct lack of β-convergence, a pattern that can be seen quite clearly in Figure 7. Note that the regions with the lowest initial level of mortality per 100,000 people (on the horizontal axis) are far more likely to have experienced the greatest gains; the coastal affluent cities such as San Francisco, Manhattan, and even the Bronx experienced rapid declines in mortality compared to the far more sluggish improvements in Jonesboro, Arkansas, and (surprisingly) Harlingen and McAllen, Texas.[16] I acknowledge that some of the declines in mortality among regions like San Francisco and Manhattan may also be the consequence of selective migration; as rents have risen since 2000, poorer (and sicker) patients could have moved out. Thus migration patterns may have contributed to some (but not all) of the increase in regional health inequality.

[16] New Orleans likely experienced unusually rapid improvement in mortality because of the displacement of poorer neighborhoods.

IV. Discussion and Conclusion

In this paper, I have taken a first look at a surprisingly neglected issue in economics – regional disparities in health outcomes, and in particular the two-to-one differences in mortality rates across large regions of the United States. Not surprisingly, health behaviors matter in explaining such differences, but not all health behaviors are equal: The largest sentinel prediction of higher regional mortality rates is the fraction of people who smoke. While smoking does have clear detrimental health effects, it is likely that smoking is symptomatic of other health-related issues in the community such as low education, poor employment opportunities, and mental health issues (Drope et al., 2018).[17] Cutler et al. (2011) found similar results; as the fraction of people smoking declined over time, smoking behavior became more predictive of adverse health outcomes.

Another sentinel measure that predicts regional mortality is the rate of high-risk prescribing by physicians. This regression coefficient is surely not causal, as this represented a fairly small fraction of physician decisions – statin prescribing for diabetics in the Medicare population. And the evidence from other studies is not strongly suggestive that overall spending (as shown in Figure 3) should be strongly negatively associated with mortality outcomes. For example, while Doyle et al. (2015) found a generally positive association between spending and health outcome for acute emergency-room care, in a subsequent study, they find essentially no association between total spending and survival in the longer (one-year) term owing to the adverse effects of excessive post-acute care (Doyle et al., 2017). Their finding, that some types of treatments are far more effective than others, was supported by a more recent study using regional fixed-effects that found some health inputs (e.g., primary stenting for heart attack

[17] In ongoing work I am also considering other measures of health (and environmental) behaviors.

patients) have a beneficial impact on survival, while other types of spending, such as home health care, have no effect (Likosky et al., 2018). And while it is well established that risky prescribing does have adverse health effects, it should be acknowledged that these patterns of behavior could be symptomatic of a dysfunctional health care system coupled with community distress.

More problematic is the rising degree of regional inequality in mortality rates; the standard deviation of log mortality across the 306 Hospital Referral Regions is estimated to have increased by 0.41 (e.g., more than 40 percent) during the period 2000-14. In part this is arising from large variations in the regional impact of specific deaths of despair; the patterns of growth in drug-related deaths may reflect the ability of illegal opioid distributors targeting specific rural markets based more on lack of competition than demand *per se* (Case and Deaton, 2017; Quinones, 2015), while rising rates of alcohol-related deaths may relate to longer-term economic and social malaise.

There are several limitations to this exploratory work. The first is the incompleteness of the data, and the necessity to match different (but nearly adjacent) years because of data limitations. The second is the limitations of coefficients estimated at an aggregated that are unlikely to provide a reliable guide to the micro-level or causal impact of a particular health input. Finally, using regression analysis at the aggregate level to distinguish among factors such as health care, health, and other environmental and social factors is difficult, given how interrelated such factors are. Social breakdown, health behaviors such as diabetes and obesity, health care access, and income are all likely to be interrelated (Everson et al., 2002).

An earlier literature has emphasized the importance of considering health as well as income in evaluating converge and economic progress (Becker et al., 2005). Between 1840 and

1980, there was rapid economic convergence across states (Barro and Sali-i-Martin, 1990), but since then, convergence has slowed or in years leading up to the Great Recession, even stopped (Ganong and Shoag, 2017). Thus considering regional disparities in well-being more generally – presumably capturing economic, mortality, and morbidity measures – could paint a concerning picture of rising inequality since 2000. One might be more concerned were regions where mortality was rising the more rapidly were also those experiencing economic declines, but the current empirical evidence suggests that economic and health trends are not closely related (Case and Deaton, 2017; Ruhm, 2019).

Future research will include efforts to explain why some regions experienced large declines, and others did not. However, in earlier periods of time, Cutler et al. (2011) did not find that find that changes in health behaviors could explain changes in mortality over time. Thus there is likely to remain a puzzling role of "place" in determining morbidity and mortality which has become increasingly important in the United States, and is worthy of attention in economics as well as in public health.

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Table 1: Summary Statistics (N = 306)

	e(mean)	e(sd)	e(min)	e(max)
Mortality (2014)	819.1855	116.2036	541.8167	1087.824
Mortality (2000)	950.6824	96.36195	725.2344	1209.271
Log Mortality Difference	-.1538766	.058907	-.3505406	-.0378456
Smoking Rate (2011)	.2224997	.0369554	.1013	.2991
High-Risk Drugs (2010)	.2678889	.065156	.14	.43
Log Income (2010)	10.83467	.2249095	10.32301	11.63019
Statin Prescribing (2010)	.7116765	.0365135	.604	.805
Obesity (2011)	.3608826	.0373849	.2350473	.471615
Binge Drinking (2012)	.1847502	.0395624	.0015767	.3109058

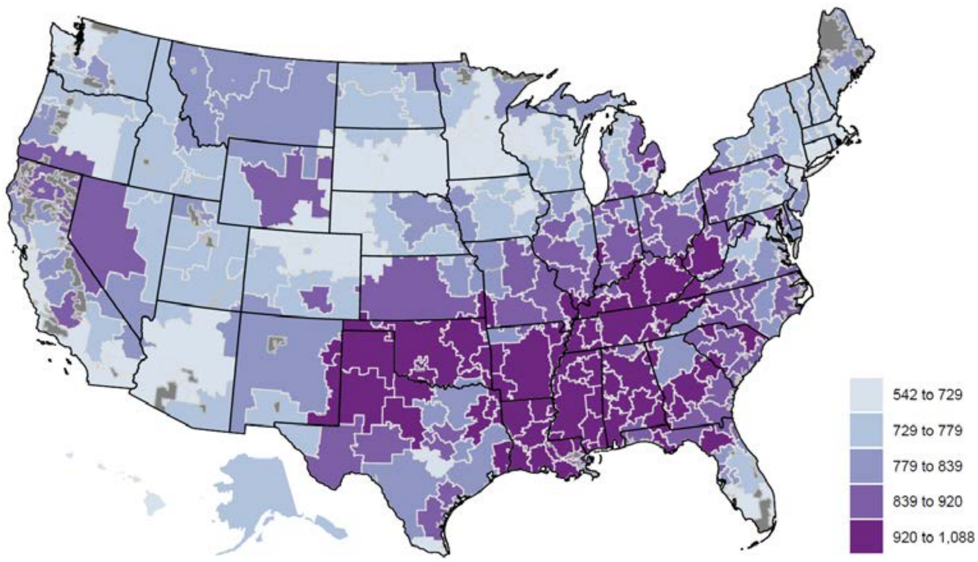
Table 2: Regression Coefficients

(Dependent Variable: Mortality per 100,000 in 2014)

	(1)	(2)	(3)	(4)
Smoking Rate	1838.4	1818.5	1634.2	1677.8
	(21.80)	(16.42)	(14.87)	(15.62)
Risky Prescribing	839.9	835.4	706.8	525.8
	(17.56)	(16.54)	(13.37)	(7.87)
Log Income		-5.3	37.8	34.1
		(-0.28)	(1.94)	(1.80)
Statin Prescribing			-247.0	-222.7
			(-2.92)	(-2.70)
Obesity Rate			577.2	655.8
			(5.38)	(6.19)
Binge Drinking				-368.2
				(-4.25)
Constant	185.2	247.7	-176.1	-74.6
	(10.94)	(1.09)	(-0.75)	(-0.33)
Observations	306	306	306	306
R-squared	0.8351	0.8351	0.8522	0.8606

t statistics in parentheses

Figure 1: Mortality Rate per 100,000, Age Standardized, by Hospital Referral Region: 2014



Source: Author's calculation using IHME mortality data by county converted to HRR using the U.S. Census MABLE crosswalk (weighted by 2010 population).

Figure 2: Correlation between mortality and smoking by HRR, 2014

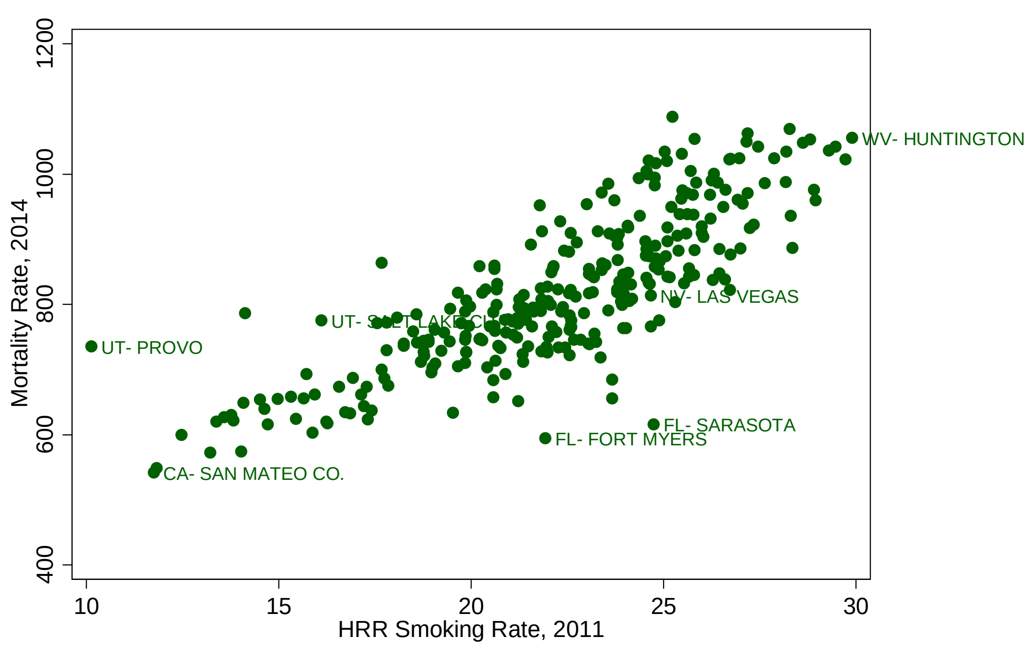


Figure 3: Price-Adjusted Medicare Expenditures in the Fee-for-Service Medicare Population by HRR: 2014

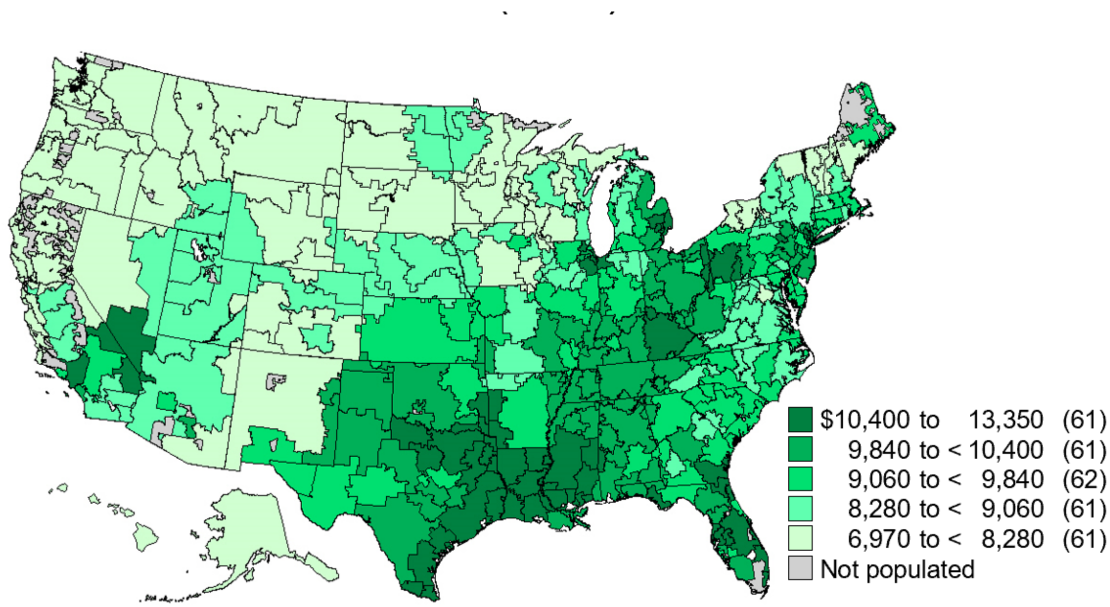
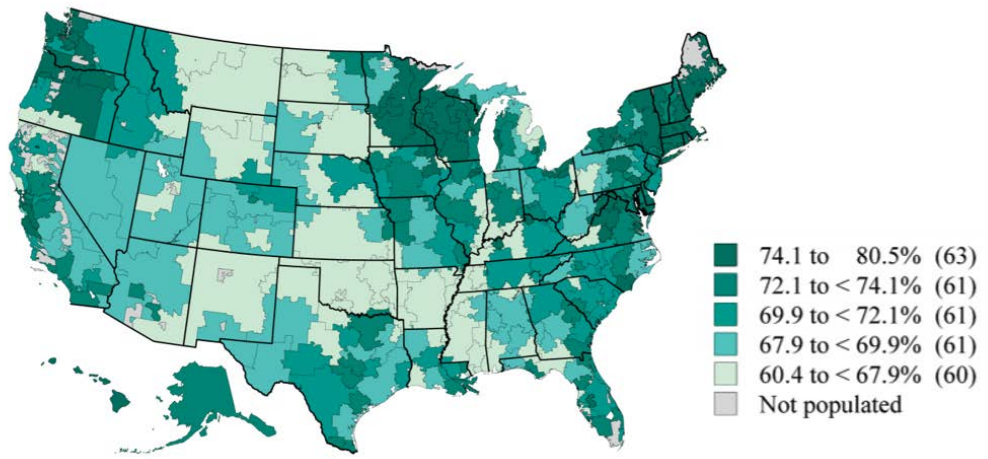
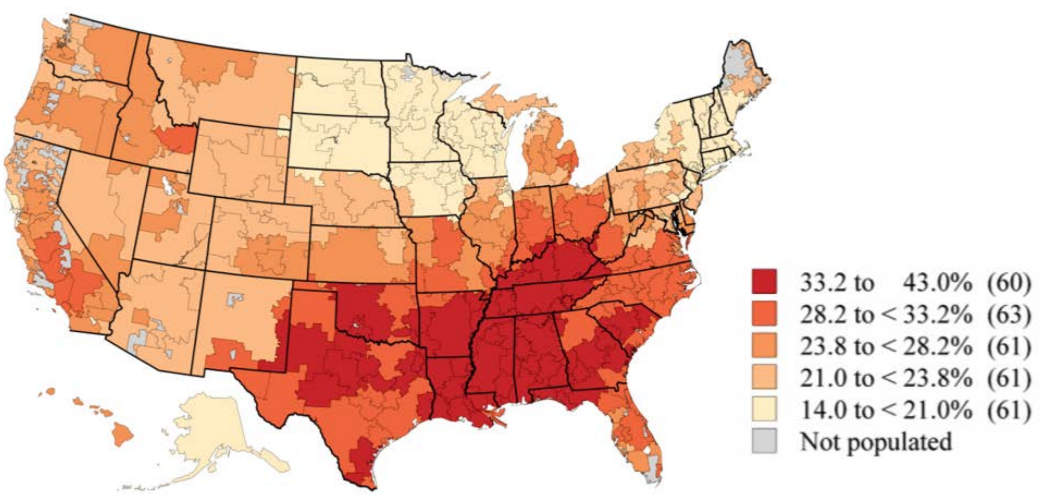


Figure 4a: High-Quality Care: Percent of Diabetics Age 65-74 Filling at least One Statin Prescription, 2010



Source: N. Morden and J. Munson, The Dartmouth Atlas of Prescription Medicare Drug Use, 2013.

Figure 4b: Low-Quality Care: Percent Filling at Least One High-Risk Medication Prescription, 2010



Source: N. Morden and J. Munson (eds.) The Dartmouth Atlas of Prescription Medicare Drug Use, 2013. Examples include skeletal muscle relaxants, long-acting benzodiazepines and highly sedating antihistamines

Figure 5: Change between 2000-2014 in Age-Standardized Mortality by HRR

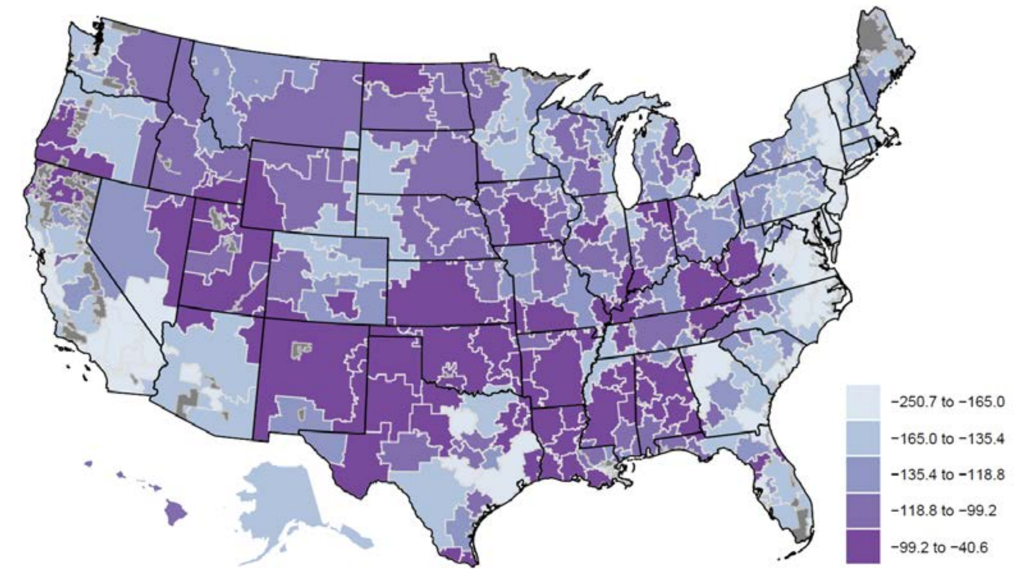


Figure 6a: Change between 2000-2014 in Age-Standardized Mortality for Mental and Substance-Abuse Disorders, by HRR

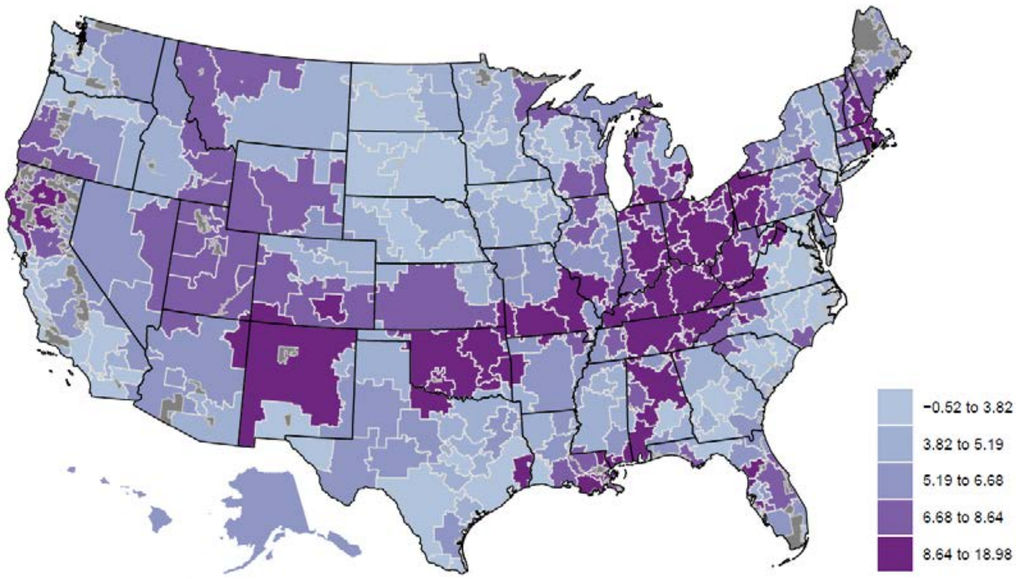


Figure 6b: Change between 2000-2014 in Age-Standardized Mortality for Cirrhosis and Other Chronic Liver Conditions, by HRR

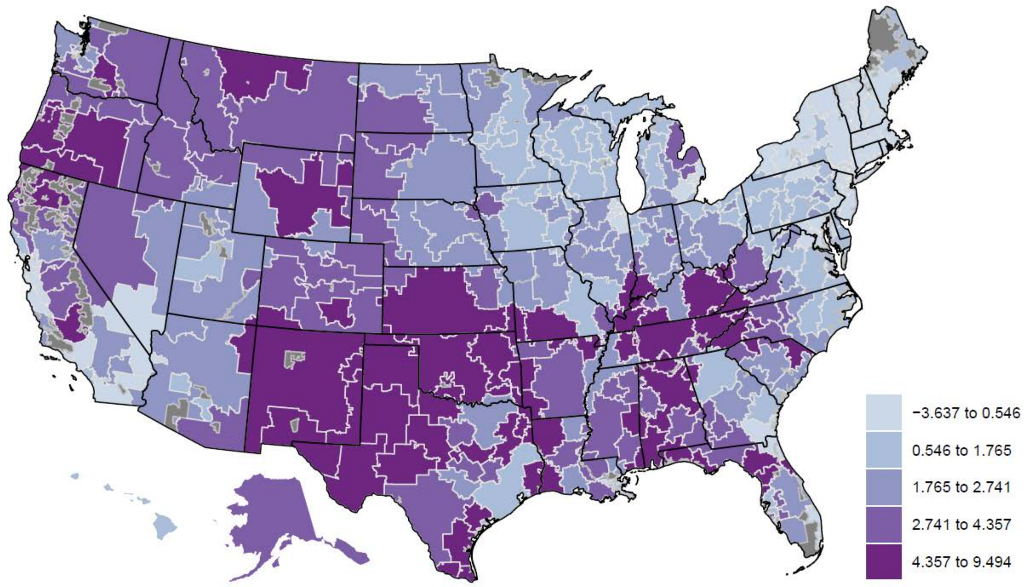


Figure 6c: Change between 2000-2014 in Age-Standardized Mortality for Self-Harm, by HRR

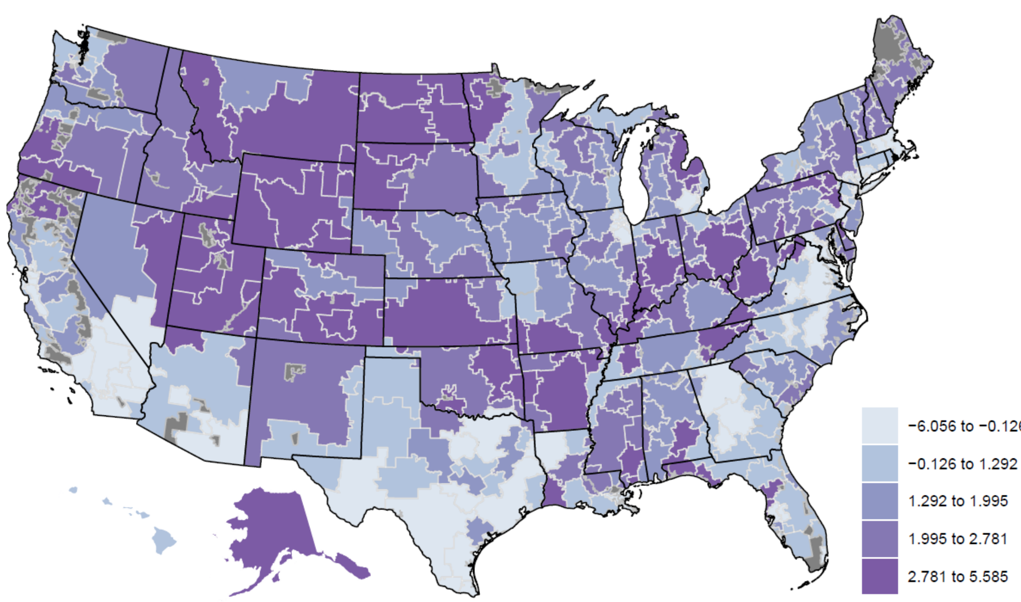
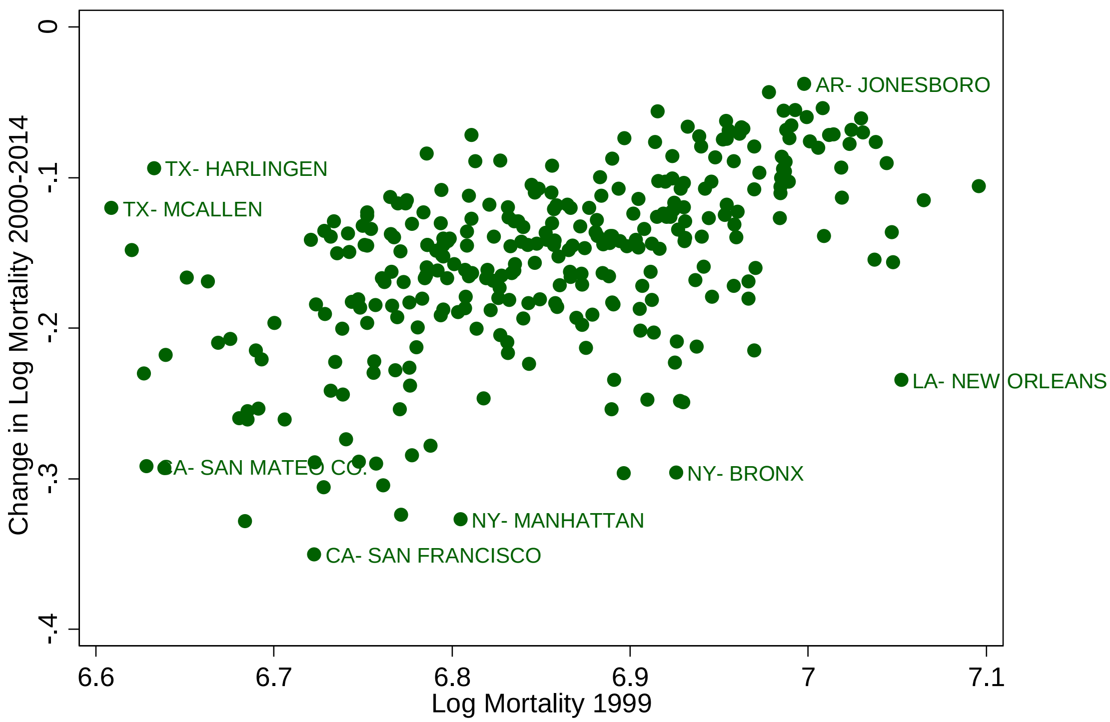
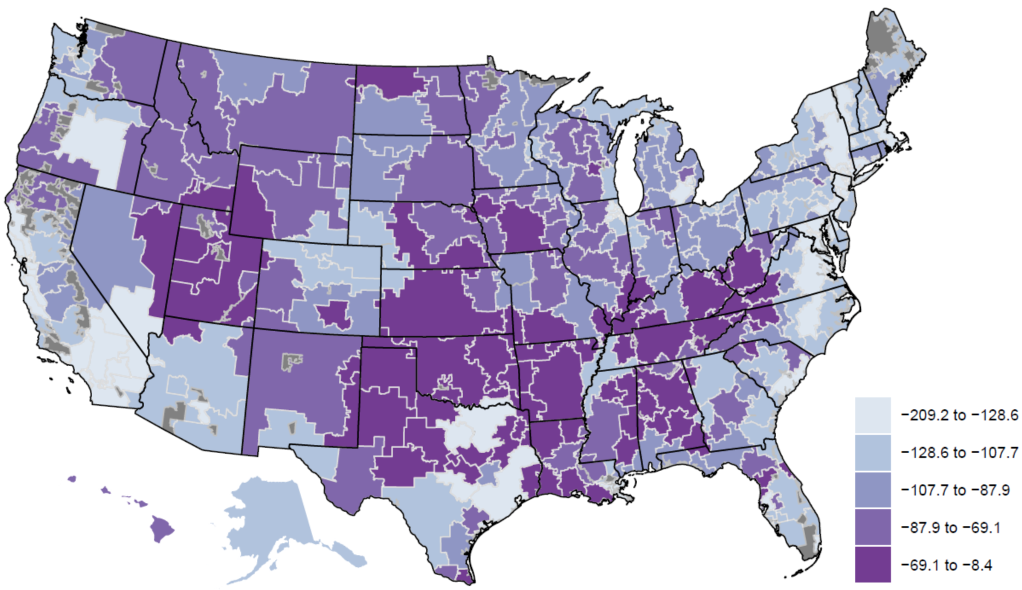


Figure 7: Log Mortality in 1999 and Subsequent Change in Log Mortality, 2000-2014, by HRR



Appendix Figure A.1: Change between 2000-2014 in Age-Standardized Mortality by HRR: Women



Appendix Figure A.2: Change between 2000-2014 in Age-Standardized Mortality by HRR: Men