Geographic Disparities in Health and Health Care

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A House Divided: Geographic Disparities in 21st-Century America
4 October 2019
Motivation

• Increasing interest in geographic disparities in health outcomes (e.g., Chetty et al., 2016; Case & Deaton, 2017)

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• Macro question: Since 2000 has there been convergence (or divergence) in the geographic distribution of health?
Methods

• Choice of region: Hospital Referral Regions, or HRRs (N = 306)
  • *State* sample size too small: N = 51
  • *Coumas* combine counties, (N ~1000) or *commuting zones* (N ~ 740); larger samples, but precision of measures more challenging
  • *HRRs* cut through counties, reflect travel patterns to hospitals
Example: Evansville Indiana Hospital Referral Region

Source: Dartmouth Atlas Project
Methods

• Choice of region: Hospital Referral Regions (N = 306)

• Institute for Health Metrics and Evaluation (U. Washington) provide county data on mortality and health behaviors
  • For smaller counties: Random effects estimator “shrinks” county-level data towards county-specific predicted means by income, education, rurality
  • Concern: Smaller counties almost entirely based on prediction
  • Aggregated up to HRR using MABLE
Geocorr 2014: Geographic Correspondence Engine

Rev. 9/10/2016 with Census 2010 (and later) geography

This application accesses the MABLE geographic database to generate custom correlation lists as reports and/or files. Click on the help icons (helpl) for detailed info on any section of this form. Please note that processing time may be several minutes for large areas or multiple states.

Help | Examples | What's new | Other Geocorr versions

**INPUT OPTIONS**

Select the state(s) to process: ☐
Methods

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• Institute for Health Metrics and Evaluation (U. Washington) provide county data on mortality and health behaviors
• Dartmouth Atlas data (various years)
• Census data (income)

https://www.dartmouthatlas.org/
Age-Standardized Mortality per 100,000 by HRR, 2014

Source: Vital Statistics, IHME
Correlation between Smoking and Mortality, by HRR

\[ \rho = 0.82 \]
Smoking is More a Sentinel Marker than a Causal One

• Causal estimates << HRR-level coefficient
• Changes in smoking don’t seem to predict changes in mortality (Cutler et al., 2011)
• Smoking associated with other poor health behaviors
Does Health Care Quality Predict Regional Variation in Mortality?

2014 Price-Adjusted Spending by Hospital Referral Region (HRR)
High-Quality Care: Percent of Diabetics Age 65-74 Filling at least 1 Statin Prescription, 2010

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

Examples include skeletal muscle relaxants, long-acting benzodiazepines and highly sedating antihistamines

Regression Analysis Explaining Mortality per 100,000 (N = 306 HRRs)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smoking Rate (2011)</td>
<td>1838.4</td>
<td>1787.2</td>
<td>1629.3</td>
</tr>
<tr>
<td></td>
<td>(21.80)</td>
<td>(16.41)</td>
<td>(14.99)</td>
</tr>
<tr>
<td>Risky Prescribing (2010)</td>
<td>839.9</td>
<td>743.0</td>
<td>644.4</td>
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<tr>
<td></td>
<td>(17.56)</td>
<td>(13.34)</td>
<td>(11.36)</td>
</tr>
<tr>
<td>Log Income</td>
<td></td>
<td>-20.7</td>
<td>22.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.08)</td>
<td>(1.13)</td>
</tr>
<tr>
<td>Fraction Black</td>
<td></td>
<td>144.0</td>
<td>111.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.63)</td>
<td>(2.83)</td>
</tr>
<tr>
<td>Statin Prescribing (2010)</td>
<td></td>
<td></td>
<td>-266.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-3.18)</td>
</tr>
<tr>
<td>Obesity Rate (2011)</td>
<td></td>
<td></td>
<td>502.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.59)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.8351</td>
<td>0.8421</td>
<td>0.8561</td>
</tr>
</tbody>
</table>
### Male Mortality Rates by Age and Cause, Ages 25 to 54, 1980 to 2016

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Heart disease</td>
<td>121</td>
<td>64</td>
<td>53</td>
<td>-3.2%</td>
<td>-1.2%</td>
</tr>
<tr>
<td>Cancer</td>
<td>82</td>
<td>58</td>
<td>42</td>
<td>-1.8%</td>
<td>-2.0%</td>
</tr>
<tr>
<td>Accidents</td>
<td>65</td>
<td>48</td>
<td>76</td>
<td>-1.4%</td>
<td>+2.9%</td>
</tr>
<tr>
<td>Suicides</td>
<td>24</td>
<td>22</td>
<td>27</td>
<td>-0.4%</td>
<td>+1.5%</td>
</tr>
<tr>
<td>Homicides</td>
<td>25</td>
<td>11</td>
<td>14</td>
<td>-3.9%</td>
<td>+1.2%</td>
</tr>
<tr>
<td>HIV/AIDS</td>
<td>0</td>
<td>15</td>
<td>4</td>
<td>-</td>
<td>-8.3%</td>
</tr>
<tr>
<td>All other</td>
<td>105</td>
<td>94</td>
<td>91</td>
<td>-0.5%</td>
<td>-0.2%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>421</td>
<td>312</td>
<td>307</td>
<td>-1.5%</td>
<td>-0.1%</td>
</tr>
</tbody>
</table>

(Source: C. Coile & M. Duggan, JEP 2019)
Change Between 2000 and 2014 in Age-Standardized Mortality
Change in Mortality from Mental and Substance Abuse Disorders, 2000-2014
Change in Mortality from Cirrhosis and other Liver Disorders, 2000-2014
Change in Mortality from Self-Harm, 2000-2014
### Sigma Convergence?

<table>
<thead>
<tr>
<th>Year</th>
<th>Standard Deviation of Log Mortality (N = 306)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>.101</td>
</tr>
<tr>
<td>2014</td>
<td>.143</td>
</tr>
</tbody>
</table>
Association Between Log Mortality (1999) and Change in Log Mortality (2000-14) by HRR


- AR- JONESBORO
- CA- SAN FRANCISCO
- CA- SAN MATEO CO.
- LA- NEW ORLEANS
- NV- LAS VEGAS
- NY- BRONX
- NY- MANHATTAN
- TX- HARLINGEN
- TX- MCALLEN

Graph showing the relationship between log mortality in 1999 and change in log mortality from 2000 to 2014 for various HRRs.
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• *More research is required*...