Mapping Chronic Disease Clusters Using Prescription Data As A Proxy

Authors: Ronald E. Cossman[1], Ph.D; Jeralynn S. Cossman[1], Ph.D; Wesley L. James[1], M.S; Troy Blanchard[1], Ph.D; Richard Thomas[2], Ph.D; Louis Pol[3], Ph.D. and Arthur Cosby[1], Ph.D.
1 Social Science Research Center (SSRC), Mississippi State University
2 University of Tennessee Health Science Center
3 College of Business, University of Nebraska, Omaha

The Problem: Chronic diseases account for more than 70% of all deaths and 60% of health care costs in the United States. These chronic conditions disproportionately affect women, minorities and rural residents, accounting for one-third of potential life lost before age 65. Yet, the U.S. does not have a sub-state chronic disease surveillance system. The inadequate system that we do have is the annual state-level Behavioral Risk Factor Surveillance Survey (BRFSS) and a CDC list of reportable diseases for urban areas. This lack of real time, detailed information on chronic diseases has important implications for public health planning and disease burden intervention. A second problem with our existing surveillance system is that it is based on a sample of the population and extrapolated to the general population. This means that it lacks adequate coverage in important rural areas.

A Solution: We use prescriptions-filled at the county level (2003) as a proxy for the prevalence of chronic illness in the resident population. We use a proprietary prescription database to map the prevalence of mortality causing illnesses: heart disease (the leading cause of death in the country and the subject of this poster), as well as cerebrovascular disease, emphysema, diabetes mellitus and four non-fatal conditions: sinusitis, arthritis, ADHD and pain management. It is reasonable to assume that if individuals are filling prescriptions for heart disease or diabetes medications, they suffer from those illnesses. **This is the first time that chronic illness has been estimated at the county level in the U.S. for non-metro counties.**

Calibrating the Model: We tested correlations between our dataset and the 2000 – 2003, state-level, Behavioral Risk Factor Surveillance Survey (BRFSS) to assess the accuracy of prescription rates as a proxy for chronic illness prevalence. The prescription data were aggregated to the state level to match the BRFSS coverage area and only adults are included in both populations. Statistically significant correlations for the two chronic diseases (stroke and diabetes) ranged from a low .658** (stroke in 2001) to a high of .774** (diabetes in 2001). The correlations for heart disease were .628* (2000, n=14)), .661** (2001, n=20), .709 (2002, n=7) and .614** (2003, n=24). Thus, for heart disease and two other chronic diseases there was a high degree of correlation, although we did not expect 100% correlation. That finding would indicate a perfect correlation between state-level self-reported chronic disease prevalence and prescriptions-filled rates, by individuals.

Map 1: Proportion of People Age 18+ With Coronary Heart Disease, 2003.
This map shows the 24 states that reported heart disease data in 2003. It displays the percent of the adult population who self-reported having been diagnosed by a health professional as having heart disease.

Map 2: Proportion of People Age 18+ with Heart Disease Prescriptions Filled, 2003.
Using the number of heart disease prescriptions filled at the county-level from the year 2003 and dividing this by the resident adults, we calculated a crude prescription-fill rate per 100 residents (99.4% of heart disease prescriptions go to those 18+). Thus the rate is directly comparable to the BRFSS heart disease map. Heart disease drugs were chosen based on the National Disease and Therapeutic Index. The drug classes were Renin Angiotensin Systemic Antagonist, Beta and Alpha blockers and Cholesterol Reducers and Lipotropics. There are three major advantages to this map, compared to the BRFSS map. First, it reports for all counties in the U.S., allowing one to see variation between counties. Second, it reports for rural counties, which have decidedly different rates from urban areas. Finally, the prescription map is based on an actual count, not a sample of the population.

Figures 1 and 2: The categorical distribution of the data is shown. We use quintiles for classes. Note that four counties report more than 50 prescriptions per 100 residents, perhaps the site of prescription distribution centers. However the U.S. average is a more reasonable 10.3% (10.3 prescriptions per 100). Although an arithmetic average has been calculated for prescription rates, from a therapeutic standpoint we do not know what an “average” prescription prevalence rate should be.

Comparing Levels of Heart Disease Deaths and Heart Disease Prescription Rates: Identifying “At-Risk” Populations

We now turn our attention to identifying the potential “at-risk” population. If heart disease death rates are high among the resident population, but the heart disease prescription rate is low, that population may be “at-risk” for untreated heart disease. There are other explanations such as a healthier population, but such conclusions would require additional investigation. To identify the “at-risk” population, we compare the historical heart disease mortality rates to current prescription rates.

Map 3: Crude Heart Disease Mortality 55+ Population, 1998-2003.
We calculated the crude cause-specific mortality rate for the county over a five-year period (1998-2003). We used a five year period to stabilize county-level rates. Since the majority of heart disease deaths occur to those 55 and older (92.3% of all heart disease deaths), we used an age adjustment for mortality, thus improving the precision of the calculated rates. Note that comparing deaths

5 years or less after prescriptions are filled may not be a sufficient lag time. Regrettably, more recent county-level mortality data are not yet available. Since the geographic patterns of mortality rates change very slowly, the close ordering of the morbidity and mortality data was not a serious issue, though it should be kept in mind. We use one standard deviation (S.D.) as the cut-points to classify "high" and "low" rates. Note: These maps display **absolute** crude high and low rates, not relative rates, thus county-to-county comparisons should be made with caution.

Map 4: Crude Heart Disease Rx Rates 55+ Population, 1999.
This map divides prescription rates into quintiles to make direct comparisons between mortality and prescriptions. Thus Maps 3 & 4 use the 55+ population. The rates are higher than the 18+ map (Map 2). Since 90.3% of all heart disease prescriptions are filled by those 55 and older in the U.S., but we are counting all prescriptions filled, Map 4 overstates crude prescription rates by 10%.

Figures 3 and 4: The distribution of crude heart disease mortality and crude heart disease prescription rates for populations age 55 and older are shown. Note that an arithmetic average has been calculated for prescription rates, from a therapeutic standpoint we do not know what an "average" prescription prevalence rate should be.

Map 5: High Heart Disease Mortality and High/Low Heart Disease Prescription Rates: This map **combines** the crude cause-specific **mortality rates** and crude disease-specific **prescription rates** as a method to identify a potential mismatch in rates. We focus on just those counties where the mortality rate is above average (more than one standard deviation from the U.S. mean), and prescription rates are either above or below average. Counties with either "average" mortality or "average" prescription rates are not highlighted. We highlight in **red** those counties with **high mortality and low crude heart disease prescription rates** (populations possibly at risk for under-prescription of heart disease medications) versus counties in **blue** that have **low heart disease mortality and high crude prescription rates** (suggesting possible appropriate levels of medication). Finally, **pink** counties have **high mortality and high crude prescription rates** (possibly a balance between risk and drug treatment). These are relative comparisons of rates, not necessarily statistically significant relationships.

General Conclusions: Our preliminary comparisons to other data sets confirm that **prescription rates are** highly correlated to self-reported prevalence of chronic disease and thus **an effective proxy for county-level disease prevalence rates**. These county-level rates are not available elsewhere. Thus it provides a complete (all counties) estimate chronic disease prevalence, including sparsely populated rural areas. Further, it relies on actual counts which can be plotted over time on a monthly basis. Despite the inherent limitations of crude rates, they can be valuable in identifying "absolute-levels" of hot and cold spots of prescription prevalence. The next step in the calibration of this model is to translate the “statistically significant” highs and lows into “medically significant” highs and lows. In other words, what would be an appropriate prescription rate, given the chronic disease prevalence and demographics of the resident population? Additionally, we plan on calculating spatial statistics to quantify the geographic patterns that are seen in these maps.

The design, layout and production of this poster are the work of Dallas Breen, Media Lab Coordinator, Social Science Research Center, Mississippi State University.

(Disclaimer) This research was made possible by a grant from the Office of Rural Health Policy, Department of Health and Human Services (Grant 1-R04RH03598-01-00) to the Social Science Research Center at Mississippi State University. Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the Office of Rural Health Policy.