The Effect of Macroeconomic Cycles on Chronic Health Conditions

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By

Jacob Harris Sherman

Lewiston, Maine
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Abstract

This study uses Behavioral Risk Factor Surveillance System data from 1995-2010 to examine how chronic health conditions are affected by changes in macroeconomic conditions. Demographics, time-varying fixed-effects, location time-invariant fixed-effects, and location time-varying fixed-effects are controlled for. Results indicate a weak countercyclical relationship between chronic health and the macroeconomy in the short-run and a procyclical relationship in the medium-run. Changes in unhealthy behaviors over time may provide an explanation for why chronic health changes in response to macroeconomic conditions, although further research is required to better understand the relationship between unhealthy behaviors and chronic health during macroeconomic fluctuations.

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Table of Contents

I. Introduction

Chronic health conditions have long been among the costliest, most common, and most preventable of health issues in the United States. According to the Centers for Disease Control and Prevention (CDC) seven out of ten individuals in the U.S. die each year from a myriad of chronic health conditions including heart disease, cancer, diabetes, and stroke. Many of these chronic health conditions, including the ones listed above as well as others, including arthritis and joint pain, lead one fourth of chronic health sufferers to report daily activity limitations. Excessive alcohol consumption, one of the major causes of chronic disease, is the third leading cause of preventable death in the U.S behind diet/physical activity and tobacco use.[1]

Given the public health implications of chronic health, understanding the factors that affect its incidence are important to the country at large. Recent health economics research shows that mortality and certain health conditions may behave differently in the short-run from the long-run in response to changes in macroeconomic conditions, i.e. during recessions or economic booms. Although research has covered how many health conditions respond to macroeconomic changes, little of this research brushes upon chronic health. As a result, this thesis will examine how chronic health changes in response to macroeconomic conditions. Section II reviews the literature relevant to macroeconomic changes affecting health. Section III describes the data used in this thesis. Section IV goes over the econometric methods employed to model chronic health. Section V presents results from these estimations. Section VI discusses the meaning behind the results, how they fit into the existing literature, and offers concluding remarks.

[1] See the CDC's “Chronic Diseases and Health Promotion” website for more informatory statistics on chronic health prevalence in the U.S. at http://www.cdc.gov/chronicdisease/overview/index.htm

II. Literature Review

The investigation into how macroeconomic fluctuations affect chronic health conditions is part of a broader literature that seeks to answer questions about how health changes in relation to the macroeconomy. As Ruhm (2006) notes, health is typically assumed to behave akin to a normal good, improving during economic growth and diminishing during economic contraction. This seems like a reasonable assumption given that income is both procyclical and an input into the production function of health theorized by Grossman (1972), leading to the conventional wisdom that health likely rises as income rises, and vice versa.[2] While research has clearly shown that health has improved as a result of long-run macroeconomic and technological improvements, less is certain about how health is affected by the macroeconomy in the short-run, for example, during recessions or temporary economic upturns.[3] The body of research starting with Brenner (1971) through Ruhm (2000) and beyond seeks to differentiate between the short-run and long-run impacts of the macroeconomy on health.

Early empirical research supporting the above assumption produced weak, mixed results that have been challenged methodologically. A new wave of research, starting with Ruhm (2000), fixed many of the shortcomings of earlier studies by using better data with improved econometric techniques, leading to the widely agreed-upon suggestion that health is countercyclical. In such a case, health diminishes during economic growth

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[2] Grossman's 1972 model of health production, based on human capital theory, is considered seminal in the field of health economics, as it looked as the individual as both a consumer and a producer of health. Income is an input into the production function of health (along with other inputs, including medical care, time, and diet) which outputs healthy days, increasing a person's utility. Higher income should therefore increase a person's number of healthy days, as income can be used to buy other inputs into the production of health.

[3] Findings by Pritchett and Summers (1996) of negative long-run income elasticity of infant and child mortality in developing countries are cited by Ruhm (2000) as research showing that long run economic growth leads to better health outcomes.

and improves during economic contraction. While some of the countercyclical nature of health can be explained by environmental factors and external sources of death that vary with the economy (such as pollution and traffic fatalities), much of the recent literature attempts to isolate the effect of the macroeconomy on specific health behaviors that contribute towards mortality and morbidity. These include unhealthy behaviors such as smoking and alcohol use, the use of preventive medical care, and the presence of chronic health conditions. This chapter summarizes the literature on this topic in order to give a proper context for the study of how macroeconomic fluctuations affect chronic health conditions.

The Beginning of Health Cyclicality Research

The first major studies into how temporary macroeconomic conditions affect health were conducted by Brenner (1971, 1973, 1975, 1979), who found that health is procyclical. Brenner (1971) finds that economic downturns are associated with increased rates of heart disease mortality using lagged macroeconomic variables with U.S. data from 1900-1967, as well as current economic conditions with New York data from 1915-1967, using the employment for nonagricultural industries as a proxy for overall employment. Replacing heart disease mortality with first admissions to mental hospitals as his dependent variable, Brenner (1973) finds negative correlations between both current and lagged manufacturing employment and health. Brenner (1975) relates cirrhosis mortality to lagged unemployment and long-run per capita income, finding that mortality is procyclical in the long run and countercyclical in the short run. Using his previous model on 1936-1976 data from England & Wales, Brenner (1979) finds that unemployment is correlated with total and age-specific mortality, with the largest effects occurring when unemployment is lagged between one to two years. Conversely, using Brenner's model and U.S. data from 1870-1975, Eyer (1977) finds that influenza death and ischemic heart disease mortality are procyclical. The author attributes this relationship largely to increased work hours and overtime resulting from periods of economic prosperity. This early research mostly finds that health improves during temporary macroeconomic fluctuations.

While this early research was significant in distinguishing between long-run upward changes in health due to economic growth and short-run changes in health due to variations in the business cycle, the previous findings have been challenged on technical grounds. A number of studies (Gravelle, et al. 1981; Stern, 1983; Wagstaff, 1985; Laporte, 2004; Ruhm, 2006) point out flaws in Brenner's lengthy time-series analysis, which include confounding factors not being controlled for, inconsistent sample time periods, multicollinearity, as well as likely omitted variable bias. Stern (1983) proposes that future studies employ longitudinal data, noting shortcomings in Brenner's use of aggregate time-series data where time-invariant area effects introduce bias that must be corrected. Similarly, Wagstaff (1985) concludes that Brenner's findings are not adequate to show that the social costs of unemployment include premature deaths.

Ensuing attempts to correct Brenner's mistakes lead to inconclusive or contradictory findings. Gravelle et al. (1981) employ a modified version of Brenner's 1979 model that includes a more robust unemployment series and controls for GDP rather than income on U.K. data from 1922-1976. The authors find no correlation between unemployment and mortality over long periods of time, leading to inconclusive overall findings that suggest that Brenner's model is not stable across different time periods. Using data from post-war Scotland, Forbes & McGregor (1984) also expand on Brenner's work by using models that include five- and ten-year unemployment lags while controlling for real per-capita health expenditures and long-run, deviations from long run, and short-run changes in real per-capita income. They report inconclusive results on the effect of unemployment on mortality, noting different results for different age groups, especially when controlling for long-term unemployment.[4] Similarly inconsistent results are found by McAvinchey (1988), who also improves upon Brenner's model by incorporating goodness-of-fit criteria that lead to shorter lag lengths for most unemployment variables than previous studies. Using his improved methods on data from West Germany, Italy, France, Ireland, and Switzerland, McAvinchey finds that mortality is procyclical, in contrast to Brenner’s work. A more recent study by Laporte (2004) fixes some of Brenner’s time-series issues by testing for unit root behavior and the stationarity of the variables while also using better U.S. data from 1948-96, finding that mortality is procyclical in the short run and countercyclical in the long run, with a greater overall effect in the long run.[5]

Advancements in Health Cyclicality Research

This first wave of research stemming from Brenner’s initial work produced mixed and inconclusive results. Based on these studies, the cyclicality of mortality varies based on countries, time frames, and age groups. In order to correct these issues, Ruhm (2000)

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[4] The authors find no effect of unemployment on mortality for the overall 15-74 year old age group, but do find results for the 40-69 year old age group. They also found that income has an insignificant effect on mortality.

[5] Laporte rejects stationarity for total per capita health expenditures, unemployment, aggregate mortality and real GDP per capita, and integrates non-stationary variables by one degree. Inconclusive results after splitting the sample leads the author to apply the Hendry error correction mechanism (ECM) to variables in the model. Despite improvements to Brenner’s model, Ruhm (2006) notes that Laporte’s use of trend/cycle decomposition for GDP is not appropriate because variables are non-stationary and integrated by one degree.

ushers in the next wave of cyclical mortality research by resolving Brenner's technical issues in conjunction with the use of superior data. Ruhm uses data that covers all 50 states and the District of Columbia in the U.S. from 1972-1991 to identify the effect of unemployment on mortality rates for 10 different causes of death, controlling for demographics including age, race, education, state unemployment, and real per capita personal income. In contrast to earlier research, Ruhm includes fixed-effects for both state and year, a significant methodological first. The location-specific fixed-effect removes bias connected with time-invariant area effects, and the time fixed-effect removes bias connected with factors that differ evenly across locations over time.[6] Without the state fixed-effect, the possibility of omitted variable bias is introduced.[7] Ruhm finds that mortality is procyclical, as a one percentage point decline in state unemployment leads to a 0.5% lower death rate. He finds that state unemployment is significantly negatively associated with eight out of ten causes of death (deaths from cancer and liver diseases deliver inconclusive results), with motor vehicle death representing the most important cause of mortality affected by economic cycles.

The procyclical relationship of mortality found by Ruhm (2000) is backed up by other studies using data from both the U.S. and other countries. Johansson (2004) uses 1960-97 data from 23 Organization for Economic Cooperation (OECD) countries, discovering a 0.4% decline in mortality when unemployment increases by one percentage point, using Ruhm's model with the inclusion of country-specific linear time-trends

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[6] While not included in Ruhm (2000), other studies include additional fixed-effects. For example, Ruhm (2003) includes fixed-effects for to account for factors that vary within states over time, which lowers the chance of omitted variable bias, while Ruhm (2005) includes monthly fixed-effects in addition to yearly fixed-effects to account for seasonality in the dependent variable.

[7] Neumayer (2004) uses Ruhm's model both with and without the inclusion of state fixed-effects. He finds that the direction of cyclicality changes when including state fixed-effects, leading him to conclude that leaving these fixed-effects out leads to omitted variable bias.

fixed-effects and a work hours explanatory variable. Neumayer (2004) finds an even stronger procyclical relationship for mortality than Ruhm and Johansson. Using data on 16 German states from 1980-2000, the author finds that mortality declines by 1.1% when unemployment increases by one percentage point. Like Ruhm, the author finds insignificant effects of unemployment on cancer and liver deaths. Tapia Grandos (2005) uses data from 50 Spanish provinces from 1980-97, controlling for age structure and per capita GDP, finding that a one percentage point decline in unemployment leads to a 0.3% lower death rate. Lin (2005) finds that a one percentage point decline in unemployment leads to a 0.7% lower mortality rate, using data from eight Asia-Pacific countries from 1976-2001. In contrast to many of the studies using Ruhm's methods that find a procyclical relationship between mortality and the economy, Economou et al. (2004) find that mortality is countercyclical after attempting to improve Ruhm's model with additional covariates. They find a 0.3% increase in mortality when unemployment rises by one percentage point using data on 13 European Union (EU) countries from 1977-96. The methods of this study have been criticized by Ruhm (2006) and others, as it likely suffers from multicollinearity stemming from the use of additional covariates that vary with unemployment, the independent variable of interest in their study. These covariates include drinking, smoking, and pollution levels.

Why is Mortality Procyclical?

As a result of this largely overwhelming evidence in favor of Ruhm's findings across different countries and years of data, the second generation of cyclical mortality research has come to the consensus that mortality is indeed procyclical. Less is known, however, about what drives this relationship. Early studies like Brenner and Mooney

(1983) focused on how psychological determinants of mortality, including stress-induced unhealthy behaviors and changes in mental health due to stress, are affected by economic cycles. Ruhm (2000) proposes using Grossman's (1972) model of health production and demand as a better framework to use when investigating how health is affected by the macroeconomy. Grossman proposes that components of the gross investment production function for health include an individual's stock of human capital, time inputs (namely, nonmarket 'leisure' time), stochastic shocks, and medical care along with inputs that jointly produce other commodities in a person's utility function including baseline health (which depreciates over time), unhealthy behaviors, housing, recreation, and more. Individuals are assumed to maximize a total utility function where they choose between health and other consumption, where health is produced by these inputs.

In the long run, health is a normal good, but in the short run, according to Ruhm, increases in unemployment may lead to a decline in mortality because:

a) inputs are not fixed in the long run, therefore people are more flexible in adjusting time, consumption, and other production habits to maximize health, whereas that flexibility is lost in the short run, and
b) small, abrupt economic booms may cause those in weak health to die sooner than they otherwise would, while otherwise leaving overall mortality relatively unaffected.

Ruhm (2000) identifies four potential mechanisms by which mortality could therefore be procyclical, which I will later use to evaluate why chronic health varies with the economy. The mechanisms are as follows:

1. *The opportunity cost of time*. During economic upturns it becomes more costly to undertake health-producing activities, and the time price of medical care rises as time becomes more valuable and it's harder to schedule medical appointments. The result of these factors may be that health declines during economic upturns.
2. *Health as an input into production*. During economic expansions, pollution and joint products of economic production increase.[8] Additionally, job hours are presumably extended during upturns coupled with increased job-related stress, and health is an input into goods and services, therefore health may go down as job-related stress or employment's physical exertion increases. Increasing incomes in an economic upturn may lead people to work more, (possibly) resulting in the above process, depending on each person's labor supply curve.[9]
3. *External sources of death* (including non-work accidents). Various unhealthy behaviors may be normal goods (procyclical) due to mechanisms 1 or 2, or for other unrelated reasons. These include drinking and driving, motor vehicle fatalities, smoking, overeating, and other unhealthy behaviors. Income, of course, affects the prices of not only time (covered above) but also the prices of different goods e.g., alcohol and cigarettes, and thus changes in income perhaps partially explain variations in external sources of death during macroeconomic fluctuations.
4. *Migration flows*. It is easy in certain countries, for example the United States or in member nations of the European Union, to migrate between states based

[8] At least in the short run this is likely true. Theoretically, society can use the resulting economic growth to mitigate pollution and other joint factors of economic production in the long run through regulations or other policies designed to align the social and private cost curves of economic production. Joint factors of economic production that have an individual-level effect are likely harder to mitigate in the short run.
[9] Increasing incomes could also lead some people to work less, again depending on the shape of their labor supply curves.

on local economic conditions. Mortality rates during economic cycles may be affected by whether poor local economic conditions induce healthy or unhealthy people to migrate to places with better local economic conditions.

In order to better understand why mortality is procyclical, many studies have used the above mechanisms as a framework for analysis along with examining specific factors of mortality more closely. Ruhm (2000) identified motor vehicle fatalities as one of the most significant factors behind changes in mortality. Subsequent studies confirm the large effect of motor vehicle fatalities on mortality fluctuations, with a one percentage point increase in unemployment reducing traffic deaths by 1.3%, 2.0%, and 2.1% in various countries across time (Neumayer, 2004; Tapia Granados, 2005; Gerdtham & Ruhm, working paper).

In terms of evaluating how external sources of death affect mortality, many studies have used microdata to look into specific unhealthy behaviors. Ruhm (1995) and Ruhm and Black (2002) find that alcohol drinking is procyclical, and therefore a probable factor behind why mortality as a whole is procyclical. On the other hand, Ruhm (2000), using U.S. state-level data from the Center for Disease Control's (CDC) Behavioral Risk Factor Surveillance System (BRFSS), finds that alcohol use is countercyclical, with a one percentage point increase in state unemployment leading to a statistically insignificant 0.35% decrease in alcohol use. The author explains that this result is counter to his earlier research, possibly because the unemployment coefficient for alcohol abuse is statistically insignificant because there were both changes in drinking patterns over time due to public health campaigns on the health benefits of moderate drinking and the study did not control for alcohol taxes in the states he examined. Davalos et al. (2012) find similar results to Ruhm (2000), except using recent panel data from the National Epidemiological Survey on Alcohol and Related Conditions (NESARC), also finding that alcohol use is countercyclical.

Smoking and obesity/physical inactivity are other unhealthy behaviors that have been widely studied. Initial efforts by Ruhm (2000) find that smoking is procyclical, such that a one percentage point increase in state unemployment leads to a 0.3% decrease in the number of current smokers. Ruhm (2005) gets stronger results by using U.S. data from 1987-2000, finding that a one percentage point increase in state unemployment leads to a 0.6% decrease in the number of current smokers. This decline is strongest among moderate to heavy smokers, with a 1.0% decline among those who smoke 20 or more cigarettes daily, and a 1.1% decline among those who smoke 40 or more cigarettes a day. In contrast, a working paper by Muttarak et al. (2012) that uses BRFSS state-level data from 2006-2010 looks at how smoking was affected by the recent U.S. economic crisis, finding no relationship between the state unemployment rate and smoking for the whole population.

When it comes to obesity and physical activity, Ruhm (2000) finds that Body Mass Index (BMI) is procyclical using BRFSS state-level microdata, with a one percentage point increase in state unemployment leading to a 0.016% reduction in average BMI. This one-point increase in state unemployment lowers the expected probability of being in an undesired weight range by 0.21% for the severely obese, 0.17% for being overweight, or 0.06% for being underweight. In order to decompose the declines in BMI into various factors, Ruhm examines exercise and healthy meal preparation, which may go up as unemployment rises due to the opportunity cost of time going down. He finds that both exercise and physical activity rise as unemployment rises, and finds a statistically insignificant rise in fruit/vegetable consumption as unemployment rises. In a National Bureau of Economic Research (NBER) working paper by Dave and Kelly (2010), BRFSS microdata is used from 1990-2007 to examine the relationship between unemployment and the consumption of fruits/vegetables in greater detail than Ruhm. They find that fruit/vegetable consumption is procyclical, in contrast to Ruhm, such that a one percentage point increase in state unemployment is associated with a 2-8% reduction in fruit/vegetable consumption, with a greater impact among older adults and married couples. The authors pose reduced family income and negative changes in mental health as possible reasons for this procyclical relationship. One possible reason that this study's results differ from Ruhm's is that David and Kelly use more years' worth of data than Ruhm.[10] Ruhm (2005) finds a one percentage point increase in state unemployment related to a decline of 1.4% for obesity, 1.5% for physical inactivity, and 1.8% for multiple health risks. The greatest changes are among the least physically active and the most severely obese, supporting Ruhm's earlier research showing that changes generally tend to be greatest at the extreme ends of the behavioral spectrum. In short, the procyclical nature of a variety of unhealthy behaviors likely contributes to the procyclical nature of mortality.

While there is a substantial body of research on how specific unhealthy behaviors are affected by the macroeconomy, little exists on how macroeconomic fluctuations affect chronic health conditions. Some work by Ruhm (2003) finds that acute problems are more susceptible to macroeconomic conditions than chronic conditions, finding a

[10] Ruhm (2000) acknowledges his limited years' worth of data as a potential shortcoming in his analysis of fruit/vegetable consumption.

statistically insignificant 1.1% increase in the prevalence of chronic conditions for a 1% decline in unemployment, using 1972-1981 data on U.S. states from the National Health Interview Surveys (NHIS). Chronic conditions studied include diseases of the heart, arthritis, chronic obstructive pulmonary disease, diabetes, and six others. The effect of unemployment on chronic health is greater for the 30-55 age groups (with coefficients increasing between 1.1%-1.3%) while diseases of the heart exhibit the strongest procyclical pattern. In concert, these findings suggest that chronic health may exhibit a procyclical relationship with respect to the macroeconomy.

The section on chronic health from Ruhm's (2003) study represents the most comprehensive findings thus far on how macroeconomic conditions affect chronic health. Other than Ruhm (2003), almost no health cyclicality research exclusively or even partially examines chronic health. Because of this dearth of existing research on chronic health conditions, this thesis will examine how chronic health conditions are affected by macroeconomic conditions, drawing upon the theories and models proposed by Ruhm and others while using a different data source than Ruhm (2003), the BRFSS, to examine specific chronic health conditions including angina, arthritis, asthma, diabetes, heart attack, prostate cancer, and stroke. The goals of this thesis are as follows:

1. To provide a methodological framework for evaluating how chronic health changes in relation to the macroeconomy, building upon the wealth of prior research in the health cyclicality space, in order to guide and influence the direction of future chronic health cyclicality research.
2. To reach preliminary conclusions on the cyclicality of chronic health with respect to economic cycles.

III. Data

In order to examine how chronic health is affected by macroeconomic conditions, this thesis merges data on both chronic health and the macroeconomy. Data on chronic health conditions came from the CDC's BRFSS, a large cross-sectional telephone survey. With interviews conducted every month from 1984 to the present, the BRFSS is able to provide a wealth of data on U.S. adults age 18 and up by state, year, and month. It has grown from over 12,000 observations in 1984 to over 500,000 in 2011; the BRFSS is now the largest telephone survey in the world. State health departments, coordinating with the CDC, conduct phone interview to members of households in all fifty states, as well as Guam, Puerto Rico, and the U.S. Virgin Islands. In order to provide a compensating mechanism to rectify the fact that telephone coverage varies by state and by subgroups within states, the BRFSS provides post-stratification sampling weights to account for bias related to the probability of nonresponse and selection for the creation of population-specific estimates.

Data from 2011 was excluded from this study, as 2011 is considered a baseline year for analysis by the CDC due to the advent of cell phone-only respondents with an improved weighting methodology. Chronic health data from 1995-2010 was used in order to ensure adequate sample sizes for respondents to chronic health-related questions. Specifically, data on high blood pressure, high blood cholesterol, heart attack, angina, stroke, asthma, arthritis, and prostate cancer from the BRFSS was used to construct several dependent variables measuring chronic health. The most common chronic ailment in the BRFSS data was chronic joint pain in the last twelve months by percent of individuals, followed by ever having high blood cholesterol, ever having arthritis, and ever having hypertension. Advantages of the BRFSS over other health cross-sectional surveys are its large sample size and the availability of data at the individual level. Each individual is asked basic demographic information in concurrence with health-related questions. The state in which the interviewee is located and the year and month of the interview are recorded; collectively, the state/year/month data is used to match individuals with corresponding macroeconomic information at the state/year or state/year/month level, and the demographic data allows for the use of relevant subgroup-level controls.

Most of the chronic health questions contained in the BRFSS ask whether or not a person has ever had a specific chronic condition, followed by additional questions relating to that condition. Few questions ask whether or not specific symptoms of chronic conditions are present or absent during a time period, for example during the last twelve months. This makes the construction of dependent variables comparable to the ones by Ruhm (2000, 2005) and other studies difficult, as most of the literature uses indicators of health within a time period as dependent variables that match up with time-varying macroeconomic data. [11] The only major chronic condition that is reliably measured within a specific time period in the BRFSS is joint pain: it asks whether the individual experienced chronic joint pain within the last twelve months. See Table 1, *Descriptive Statistics of BRFSS Variables*, for data on the variables. As chronic health is mostly absent from the health cyclicality literature, consensus is lacking on how to construct a chronic health dependent variable from the BRFSS data the same way that concensus has been reached for research on aggregate mortality or unhealthy behaviors.

[11] For example, Ruhm (2000) uses the annual mortality rate (the number of deaths within the last 12 months) as his dependent variable, which matches up 1:1 with the annual state-level unemployment rate (the state unemployment rate average for that 12 month period).

Table 1
Descriptive Statistics of BRFSS Variables

Variable	Mean	SD	N, size of sample
Demographics:			
Age			
Continuous	51.3	17.74	4,218,892
18-44	36.7%	0.48	4,218,892
45-64	37.7%	0.48	4,218,892
65 and older	25.6%	0.44	4,218,892
Race			
White	80.7%	0.39	4,211,865
Black	7.9%	0.27	4,211,865
Hispanic	6.2%	0.24	4,211,865
Mixed race or other	5.3%	0.22	4,211,865
Marital status			
Married	55.1%	0.50	4,251,218
Divorced	13.8%	0.35	4,251,218
Widowed	12.4%	0.33	4,251,218
Separated	2.3%	0.37	4,251,218
Education			
Less than high school	10.6%	0.31	4,239,882
High school graduate	31.0%	0.46	4,239,882
Some college	26.8%	0.44	4,239,882
College graduate	31.6%	0.46	4,239,882
Gender			
Male	38.9%	0.49	4,251,943
Female	61.1%	0.49	4,251,943
Dependent Variables:			
"Have you ever had a chronic condition?"			
High blood cholesterol	37.6%	0.48	1,781,607
High blood pressure	31.6%	0.46	2,225,054
Diabetes	9.2%	0.29	4,247,283
Heart attack	5.8%	0.23	2,776,704
Angina	5.9%	0.24	2,765,213
Stroke	3.8%	0.19	2,782,592
History of asthma	12.7%	0.33	3,618,317
Arthritis	33.4%	0.47	2,010,670
Prostate cancer	5.0%	0.22	560,540
Any chronic condition	44.4%	0.50	4,251,562
"Have you had a chronic condition in the last 12 months?"			
Chronic joint pain	42.2%	0.49	376,582
Asthma attack (if you have asthma)	52.6%	0.50	46,453
Either chronic joint pain or asthma	43.4%	0.50	420,813
"How many chronic conditions have you ever had?"	0.8	1.13	4,252,671

BRFSS data has not been weighted using post-stratification probability weights. By not weighting, the above summary statistics reflect the composition of the population due to the survey bias related to the probability of nonresponse and selection with states and subgroups.

Therefore, I constructed three different dependent variables measuring chronic health to mitigate the shortcomings of individual models with subsequent models.

The first is a binary dependent variable ("Have you ever?") that takes on a value of one if an individual has had any of the above chronic health conditions at least once in his or her lifetime. Out of a sample size of 4,251,562 individuals, 44.4% of people have had, in their lifetimes, one of the chronic health conditions studied. I expect this variable to be a weaker measure of chronic health in relation to the macroeconomy than a similar variable that measures whether or not a respondent has had one of these chronic health conditions within, say, the last twelve months.

The second binary dependent variable ("Last 12 months?") measures whether or not an individual has experienced chronic joint pain or an asthma attack within the last twelve months if the individual currently has asthma. Although this variable is more akin to the variables used in most of the health cyclicality literature, its weakness is that it only measures two chronic health conditions. The sample size for this variable is noticeably smaller than the first, such that while 43.3% of respondents reported experiencing chronic joint pain or an asthma attack in the last twelve months, there are only 420,813 individuals in the sample.[12]

A third dependent variable ("Number of chronic conditions?") uses the same chronic health indicators that the first variable uses, but sums up the number of chronic health ailments that individuals have had across their lifetimes, as reported in their interviews in a specific year and month. This variable shares many of the pitfalls of the first, but has the advantage of measuring the accumulation of multiple chronic health

[12] The sample size here is roughly 1/10th the size of the first dependent variable's sample size.

conditions by individuals over time. This dependent variable may be relevant for study if macroeconomic conditions affect the development of additional chronic conditions among prior chronic condition sufferers.[13]

Independent variables proxying the condition of the macroeconomy include data on state unemployment rates from 1995-2010 at the year and month level from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS). State-level income data from 1995-2010 comes from the U.S. Department of Commerce's (DOC) Bureau of Economic Analysis (BEA). Quarterly state aggregate personal income data was divided by yearly state-level population estimates by the U.S. Census Bureau in order to create a measure of per-capita state income. Quarterly state per-capita incomes were then adjusted to 2000 U.S. dollars with the (U.S. city average, seasonally adjusted, all items) Consumer Price Index (CPI) provided by the BLS. Additional data on state and month level average weekly earnings and average hours worked per week from 2007-2010 came from the BLS. Average weekly earnings were also adjusted to 2000 U.S. dollars using the CPI.

IV. Econometric Methods

The basic econometric specification estimated below is:

$$H_{isym} = \alpha_y + X_{isym}\beta + E_{sym}\gamma + S_s + M_m + \varepsilon_{isym} \tag{1}$$

[13] Evidence supporting this comes from the fact that while 44.4% of individuals have suffered from at least one chronic condition in their lifetimes, as measured by the first dependent variable, 24.2% have suffered from two, 11.3% have suffered from three, and 8.9% of individuals have suffered from four or more chronic conditions in their lifetimes. One individual in the sample suffered from nine different chronic conditions in his or her lifetime!

Where:

- H_{isym} is one of the three dependent variables described above that measures the chronic health of individual *i* in state *s* at time *t* in month *m*,
- X_{isym} is a vector of demographic characteristics containing information on age, gender, race/ethnicity, education, and marital status,
- E_{sym} measures macroeconomic conditions, and includes, depending on the model, the state unemployment rate by year and month, the per-capita state income by quarter, weekly earnings by state by month and year, and average work hours by state by month and year,
- α_y is a yearly fixed-effect that controls for chronic health determinants that vary by year uniformly across states,
- M_m ,similarly, is a monthly fixed-effect that controls for seasonality-related chronic health determinants that vary uniformly across states, and
- S_s captures time-invariant determinants of chronic health that do not vary over time.

The result of these fixed-effects is that only within-state variations in the macroeconomy are studied relative to changes in other states.

The introduction of fixed-effects into health cyclicality models was pioneered by Ruhm (2000), as previously noted, who incorporated state and year fixed-effects when examining how mortality changed during economic cycles. Ruhm (2005) and other studies also included the monthly fixed-effects that account for seasonality. Because BRFSS data contains information on the month of the survey interview, health cyclicality models built with BRFSS data are able to include monthly fixed-effects. While earlier studies only included the above fixed-effects, Ruhm (2003) notes the major shortcoming that Eq. (1) has, namely, that it does not account for factors that vary both across states and time. As a result, Ruhm presents a second "preferred" equation that incorporates a vector of state-specific yearly time trends ($S_s Y$):

$$H_{isym} = \alpha_y + X_{isym}\beta + E_{sym}\gamma + S_s + M_m + S_s Y + \varepsilon_{isym} \tag{2}$$

As such, with the exception of some results in the basic specification below, all of the following regressions include the state-specific yearly time trends fixed-effects.

This thesis corrects for heteroskedasticity by clustering at the state level in order to create unbiased standard errors, and therefore efficient estimates. While Ruhm (2000) corrects for heteroskedasticity by weighing observations by the square root of the state population, more recent studies (Johansson, 2004; Dave and Kelly, 2010; Davalos et al., 2011) all cluster at the state level.[14] Most health cyclicality research uses cluster-robust standard errors since Bertrand et al. (2004) pointed out that many studies fail to produce consistent standard errors, recommending that state-year data be clustered on states rather than state-year pairs. Failing to cluster standard errors typically results in underestimated standard errors and overstated t-statistics.[15] While clustering generally makes findings less significant, it has become standard practice in much social science research using panel or cross-sectional data, including most studies using BRFSS data.

V. Results

[14] Normally it is recommended to cluster on the same level upon which fixed-effects would be used. In this case, fixed-effects are used at both the state and state*year level, which is why Bertrand et al.'s (2004) recommendation to cluster at just the state-level is important to note.

[15] This was confirmed using equations (1) and (2). Smaller standard errors, higher t-stats, and lower p-values resulted when clustering was not included in the models, indicating that clustering at the state level is necessary to produce accurate standard errors, both when clustering is simply excluded, and also when using Stata's default Huber-White sandwich heteroskedasticity corrector without clustering.

Table 2, *Basic Specification for all Four Macroeconomic Independent Variables*, presents the basic specification for equations (1) and (2). All models include demographic controls, and except for the first two columns of the full sample estimations, which exclude location and time-varying fixed-effects, all models control for state, year, month, and time-varying state fixed-effects. Again, except for the first two columns of the full sample estimates, which only estimate the “have you ever?” and “last 12 months” dependent variables, all three dependent variables are measured in the hope of capturing the advantages and disadvantages of each. For each dependent variable, models are estimated once using just the unemployment rate, and again using both the unemployment rate in conjunction with state per-capita personal income as independent variables representing macroeconomic conditions. The basic specification is also re-estimated on the bottom half of Table 2 in order to incorporate an additional independent variable measuring average weekly work hours (by state/year/month), which is included in each model, and average weekly personal income (also by state/year/month), which is swapped for state per-capita personal income in every other model. The subsample only includes years 2007-2010, as those were the only years for which the BLS had data on the additional independent variables.

Economic Conditions and Chronic Health

Overall, the basic specification provides mixed evidence on the effect of macroeconomic conditions on the prevalence of chronic health conditions. When fixed-effects for state time-varying factors are excluded from the model, a one percentage point

Table 2

Basic Specification for all Four Macroeconomic Independent Variables

Dependent variable:	Have you ever?		Last 12 months?		Have you ever?		Last 12 months?		# Chronic conditions?	
Full sample estimates	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)
State unemployment rate	-0.00047**	-0.00020	-0.00182	0.00215	0.00040	-0.00083	0.00023	-0.00077	0.00210	-0.00130
	(0.00021)	0.00021	0.00457	0.00686	(0.00102)	(0.00107)	(0.00390)	(0.00449)	(0.00213)	(0.00249)
State personal income		0.00000**		0.00001		0.00000**		0.00000		-0.00001**
		0.00000		0.00001		(0.00000)		(0.00001)		(0.00000)
State, time fixed-effects	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
State*year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Dependent variable:	Have you ever?		Last 12 months?		# Chronic conditions?	
Subsample 2007-2010	(a)	(b)	(c)	(d)	(e)	(f)
State unemployment rate	-0.00073	0.00133	0.06288**	0.04637**	-0.00075	0.00450
	(0.00138)	(0.00155)	(0.02211)	(0.01884)	(0.00325)	(0.00345)
Average work hours	0.00036	0.00179	0.01983	0.01557	0.00164	0.00539
	(0.00096)	(0.00159)	(0.02286)	(0.03344)	(0.00228)	(0.00345)
State yearly income	0.00000**		0.00008		0.00001**	
	(0.00000)		(0.00006)		(0.00000)	
State weekly income		-0.00009		0.00038		-0.00023
		(0.00008)		(0.00083)		(0.00018)
State, time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
State*year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes

All full sample estimates include demographic controls, fixed-effects for state and time (including year and month), and use the state unemployment rate, or state unemployment as well as state per-capita personal income (in 2000 U.S. dollars) as independent variables. The "have you ever?" and "last 12 months?" dependent variables are measured without state*year fixed-effects for the full sample, but all other estimates include state*year fixed-effects in order to capture chronic health determinants that vary across both location and time. The ‘average work hours’ dependent variable is added to subsample estimates, which are only estimated for the years 2007-2010, as those are the only years that the BLS provides average work hours data for by state, year, and month. Subsample estimates also included either state per-capita personal income or state weekly income (in 2000 U.S. dollars) as independent variables in addition to the state unemployment rate and average work hours. Robust standard errors are produced by clustering at the state level and are reported in parentheses. *p-value < 0.10 **p-value < 0.05 *** p-value < 0.01

decrease in unemployment is estimated to increase the full sample probability of having ever had a chronic health condition by 0.05 percentage points, or by 0.11%.[16] When time-varying state fixed-effects are included, standard errors become higher, resulting in insignificant coefficients on unemployment for all three dependent variables in the full sample. While the size of these unemployment rate coefficients vary between the three dependent variables, each of their directions becomes reversed from positive to negative when the personal income independent variable is added in addition to the unemployment rate. State per-capita personal income coefficients are close to zero, and are statistically significant for both the "Have you ever?" and "Number of chronic conditions?" dependent variables. That the "Have you ever?" dependent variable no longer reaches statistical significance when state time-varying fixed-effects are added to the model suggests that chronic health may be unrelated to the macroeconomy for the full sample.

Similar results are present when the "average work hours" independent variable is added to the subsample, as both the "Have you ever?" and "Number of chronic conditions?" dependent variables still exhibit negative and insignificant unemployment coefficients with significant state per-capita personal income coefficients of zero. Interestingly, the coefficients on the "Last 12 months?" dependent variable become larger and statistically significant when the "average work hours" independent variable is added, both with the inclusion of the state per-capita personal income ("state yearly income") independent variable and the state weekly income independent variable. A one percentage point increase in unemployment is estimated to increase the subsample

[16] 0.11% is 0.00047 (the coefficient) /0.444 (the variable mean) = 0.00105 x 100%, rounded to one decimal point. Percentage changes henceforth are calculated by dividing the coefficient by the dependent variable sample mean reported in Table 1.

probability of having exhibited chronic health symptoms in the last twelve months by 6.29 percentage points, or by 14.5% when state yearly income is included, and by 4.64 percentage points, or by 10.7% when state weekly income is included in the model. This significant result contradicts the largely insignificant results from estimating the full sample, though the opposite directions of the negatively significant “Have you ever?” coefficient from the full sample without state time-varying fixed-effects and the positively significant “Last 12 months?” coefficients from the subsample may be attributed to differences in how these two dependent variables are constructed. For both the full sample and the subsample, the state per-capita personal income coefficients are insignificant for the “Last 12 months?” dependent variable, as well as the weekly income coefficients in the subsample.

Results from the basic specification above for the full sample with the inclusion of probability weights are reported in Appendix 1. Like the coefficients reported in Table 2, the analogous coefficients using probability weights largely fail to reach statistical significance and are of similar magnitude to the ones reported here. Due to the similarity between the results with and without the sampling weights, I decided not to use them in the remaining estimations.[17]

Demographic Stratifications and Migration Estimates

Table 3, *Demographic-Specific Estimates,* offers estimates for subsamples stratified by race, gender, age, and employment status. Akin to prior estimations, both

[17] Health cyclicality research typically uses sampling weights. For example, Ruhm (2000) uses sampling weights for BRFSS data, and Ruhm (2003) incorporates sampling weights in his estimations when using data from the National Health Interview Survey Cumulative Core File. With more time, it would be interesting to re-estimate all of the results using the BRFSS sampling weights.

Table 3
Demographic-Specific Estimates

Dependent variable:	Have you ever?		Last 12 months?		# Chronic conditions?	
Subsamples:	(a)	(b)	(c)	(d)	(e)	(f)
White (unemployment)	0.00023	-0.00085	-0.00141	-0.00254	0.00145	-0.00217
	(0.00103)	(0.00102)	(0.00401)	(0.00470)	(0.00216)	(0.00244)
White (personal income)		0.00000*		0.00000		-0.00001**
		(0.00000)		(0.00001)		(0.00000)
Black (unemployment)	0.00022	-0.00016	0.00720	0.00850	0.00232	0.00000
	(0.00249)	(0.00294)	(0.01025)	(0.01080)	(0.00554)	(0.00629)
Black (personal income)		0.00000		0.00000		-0.00001
		(0.00000)		(0.00001)		(0.00001)
Hispanic (unemployment)	0.00456**	0.00192	-0.00009	-0.00212	0.01058**	0.00860
	(0.00188)	(0.00284)	(0.00922)	(0.00942)	(0.00516)	(0.00590)
Hispanic (personal income)		-0.00001		-0.00001		0.00000
		(0.00000)		(0.00001)		(0.00001)
Male (unemployment)	0.00037	-0.00039	0.00094	0.00158	0.00330	0.00132
	(0.00131)	(0.00123)	(0.00624)	(0.00662)	(0.00322)	(0.00358)
Male (personal income)		0.00000		0.00000		0.00000
		(0.00000)		(0.00001)		(0.00000)
Female (unemployment)	0.00047	-0.00108	-0.00022	-0.00223	0.00140	-0.00289
	(0.00133)	(0.00143)	(0.00434)	(0.00489)	(0.00263)	(0.00302)
Female (personal income)		0.00000*		-0.00001		-0.00001**
		(0.00000)		(0.00001)		(0.00000)
Age: 18-44 (unemployment)	0.00079	0.00076	-0.00211	-0.00069	0.00068	0.00096
	(0.00092)	(0.00114)	(0.00505)	(0.00545)	(0.00140)	(0.00164)
Age: 18-44 (personal income)		0.00000		0.00000		0.00000
		(0.00000)		(0.00001)		(0.00000)
Age: 65+ (unemployment)	0.00081	-0.00032	0.00854	0.00722	-0.00117	-0.00419
	(0.00132)	(0.00145)	(0.00883)	(0.00958)	(0.00347)	(0.00387)
Age: 65+ (personal income)		0.00000		0.00000		-0.00001
		(0.00000)		(0.00001)		(0.00001)
Employed (unemployment)	0.00058	-0.00025	-0.00190	-0.00120	0.00136	-0.00070
	(0.00114)	(0.00126)	(0.00410)	(0.00504)	(0.00208)	(0.00214)
Employed (personal income)		0.00000		0.00000		0.00000**
		(0.00000)		(0.00001)		0.00000
Unemployed (unemployment)	-0.00179	-0.00334	0.00805	0.00606	-0.00319	-0.00168
	(0.00285)	(0.00310)	(0.01292)	(0.01505)	(0.00608)	(0.00652)
Unemployed (personal income)		0.00000		-0.00001		0.00000
		(0.00000)		(0.00002)		(0.00001)

The basic specifications of Table 2 are re-estimated in Table 3 for various demographic categories, as well as the individual being either employed or unemployed at the time of the interview. All estimates include demographic controls, all fixed-effects. Coefficients either represent the state unemployment rate or the state unemployment rate as well as state per-capita personal income as independent variables. Robust standard errors are produced by clustering at the state level and are reported in parentheses. *p-value < 0.10 **p-value < 0.05 *** p-value < 0.01

unemployment as well as state per-capita personal income and unemployment are presented as independent variables. Most of the stratification coefficients fail to reach statistical significance; according to Ruhm (2003), who created similar stratified subsamples using National Health Interview Survey data, smaller sample sizes when creating demographic-specific estimates can lead to imprecise estimates and make comparison between demographic groups difficult.[18] A one percentage point increase in unemployment results in a statistically significant 0.46 percentage points (1.04%) increased probability in having ever had a chronic health condition among Hispanics, compared with statistically insignificant 0.022 and 0.023 percentage point (0.049% and 0.052%) increases among whites and blacks, respectively. The 1.04% increased probability in having ever had a chronic health condition among Hispanics given a one-point increase in unemployment is roughly ten times as large as the full sample's 0.11% increase (excluding state time-varying fixed-effects for the full sample), whereas the probabilities for the white and black subgroups are about half of the full sample probability.

These results provide firm evidence that changes in macroeconomic conditions affect racial and ethnic groups in different ways. Also among Hispanics, a one percentage point increase in unemployment is related to a significant 0.011 percentage point (1.32%) increase in the total number of chronic conditions that an individual has ever had in his or her lifetime, whereas the effects of unemployment on the total number of chronic conditions is both insignificant and smaller or negative for whites and blacks, respectively.

[18] While Ruhm (2003) uses a different set of data to produce his estimates, the size of his demographic samples relative to his full sample are similar to those in this study, raising the possibility that the issue of smaller sample sizes leading to imprecise estimates is generalizable to this study.

Unexpectedly, there are no statistically significant coefficients measuring the effects of macroeconomic conditions on any chronic health dependent variable on stratifications by gender or age group. Working-age Hispanic and black males are posited to be more affected by macroeconomic conditions than females, who are less likely to be primary wage earners than males, people 65 or more years old, who are more likely to be retired as well as Medicare beneficiaries, or whites, for whom unemployment does not increase by as much during economic downturns as other racial groups. While also never reaching statistical significance, the coefficients on population stratifications based on employment status suggest that macroeconomic conditions may affect employed and unemployed persons differently. Coefficients on the "Have you ever?" and "Number of chronic conditions?" dependent variables were positive for employed individuals and negative for unemployed individuals when personal income was excluded as an independent variable; conversely, coefficients on the "Last 12 months?" dependent variable were negative for employed individuals and positive for employed individuals.

Analogous to results from Table 2, adding the state per-capita personal income independent variable typically attenuates or reverses the direction of the unemployment coefficients. In the case of the statistically significant unemployment coefficients for Hispanics, adding personal income makes those coefficients insignificant. As before, personal income coefficient magnitudes are essentially zero.

Table 4, *Migration Estimates*, presents the basic specifications of Table 2, except now employing subsamples built on the ten slowest-growing and fastest-growing states

Table 4
Migration Estimates

Dependent variable	Have you ever?		Last 12 months?		# Chronic conditions?	
Slow-growing states	(a)	(b)	(a)	(b)	(a)	(b)
State unemployment rate	-0.00154	-0.00410***	-0.00503	-0.00781	-0.00294	-0.01012***
	(0.00118)	(0.00110)	(0.00874)	(0.01019)	(0.00270)	(0.00282)
State personal income		-0.00001***		-0.00001		-0.00002***
		(0.00000)		(0.00001)		(0.00000)
State, time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
State*year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Dependent variable:	Have you ever?		Last 12 months?		# Chronic conditions?	
Fast-growing states	(a)	(b)	(a)	(b)	(a)	(b)
State unemployment rate	0.00447	0.00332	-0.00555	-0.00927	0.01268	0.01040
	(0.00423)	(0.00381)	(0.01154)	(0.01150)	(0.00802)	(0.00736)
State personal income		0.00000		-0.00001		0.00000
		(0.00000)		(0.00001)		(0.00001)
State, time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
State*year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes

All estimates include demographic controls, all fixed-effects, and use either the state unemployment rate, or state unemployment as well as state per-capita personal income (in 2000 U.S. dollars) as independent variables. Dependent variables were estimated either for the ten slowest or fastest growing U.S. states based off of growth rates from the 2010 U.S. Census. Robust standard errors are produced by clustering at the state level and are reported in parentheses.
*p-value < 0.10 **p-value < 0.05 *** p-value < 0.01

from 2000 to 2010 according to the 2010 U.S. Census.[19] If there are significant differences between the results of these two subsamples, there is a strong possibility that migration flows affect the prevalence of chronic health conditions during economic cycles.[20] This study finds that a one-point decrease in the unemployment rate is significantly related to a 0.41 percentage point (0.92%) increase in the probability of ever

[19] The ten fastest-growing states are (in descending order) Nevada, Arizona, Utah, Idaho, Texas, North Carolina, Georgia, Florida, Colorado, and South Carolina. The ten slowest-growing states are (in ascending order) Michigan, Rhode Island, Louisiana, Ohio, New York, West Virginia, Vermont, Massachusetts, Illinois, and Pennsylvania.
[20] More complicated ways of measuring migration flows, such as the approach used by Miller et al. (2011, NBER) of estimating the semi-elasticity of state populations with respect to unemployment rates, were excluded due to time constraints.

having had a chronic health condition, and a 1.01 percentage point (1.27%) increase in the total number of chronic health conditions over an individual's lifetime for the ten slowest-growing states. While coefficients for the ten fastest-growing states never reach statistical significance, their coefficients are positive instead of negative, indicating a difference between the two subsamples.

As a result, some evidence that migration flows play a part in chronic health prevalence can be extrapolated due to the differences between these estimates. Interestingly, the coefficients on the ten slowest-growing states are only statistically significant when the personal income independent variable is added into the model, instead of its inclusion leading the unemployment coefficient to be negative. This suggests that income may play an important role in how migration affects the cyclicality of chronic health, especially relative to other models that include personal income as an independent variable.

Specific Chronic Condition Estimates

Estimates on models where specific chronic conditions are used as dependent variables are reported in Table 5, *Estimates with Specific Chronic Conditions as Dependent Variables*. The first eight chronic conditions reported make up the “Have you ever?” and “Number of chronic conditions?” dependent variables, while the last two comprise the “Last 12 months?” dependent variable. Significant results are found for ever having had high blood cholesterol, ever having had angina, and having had an asthma attack in last twelve months if one currently has asthma. Both high blood cholesterol and

Table 5

Estimates with Specific Chronic Conditions as Dependent Variables

Chronic condition:	High blood cholesterol		Hypertension		Diabetes		Heart attack		Angina	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
State unemployment rate	-0.00357***	-0.00322*	-0.00006	0.00034	-0.00035	-0.00071	-0.00027	-0.00059	-0.00084**	-0.00092**
	(0.00132)	(0.00175)	(0.00085)	(0.00104)	(0.00049)	(0.00058)	(0.00031)	(0.00038)	(0.00036)	(0.00044)
State personal income		0.00000		0.00000		0.00000		0.00000		0.00000
		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)
State, time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chronic condition:	Stroke		Prostate cancer		History of asthma		Had an asthma attack		Joint pain	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
State unemployment rate	-0.00016	-0.00031	-0.00007	0.00055	0.00017	0.00001	0.02072*	0.02466**	-0.00261	-0.00371
	(0.00031)	(0.00035)	(0.00070)	(0.00085)	(0.00039)	(0.00043)	(0.01033)	(0.00945)	(0.00444)	(0.00513)
State personal income		0.00000		0.00000		0.00000		0.00001		0.00000
		(0.00000)		(0.00000)		(0.00000)		(0.00001)		(0.00001)
State, time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

All estimates include demographic controls, all fixed-effects, and use either the state unemployment rate, or state unemployment as well as state per-capita personal income (in 2000 U.S. dollars) as independent variables. The first eight dependent variables are based on answers to questions that asked whether or not an individual had experienced this chronic condition at some point in his or her life (the answers to these questions were used in concert to construct the "have you ever?" dependent variable). The last two are based on questions that asked whether or not symptoms of specific chronic health conditions were experienced within the last twelve months (the answers to these two questions were used to construct the "last 12 months?" dependent variable). Robust standard errors are produced by clustering at the state level and are reported in parentheses. *p-value < 0.10 **p-value < 0.05 *** p-value < 0.01

angina are procyclical, such that a one-point increase in the state unemployment rate leads to a 0.322 percentage point (0.86%) decline in ever having had high blood cholesterol, and a 0.092 percentage point (1.56%) decline in ever having had angina. The probability of having had an asthma attack within the last year, if one currently has asthma, increases by 2.47 percentage points (4.69%) when unemployment rises by one point.

The direction of these significant specific chronic health condition coefficients makes sense given that the “Have you ever?” and “Number of chronic conditions?” dependent variables have thus exhibited a procyclical relationship in relation to the macroeconomy, while the “Last 12 months?” dependent variable has exhibited a countercyclical relationship. Both the magnitudes and directions of the coefficients from Table 5 largely agree with the findings on specific chronic conditions by Ruhm (2003), who also finds that arthritis, stroke, and heart diseases are procyclical, while my results on diabetes and cancer differ. Ruhm used a different data set, different years’ worth of data, and used chronic health dependent variables that asked whether or not a respondent *currently* had that chronic health condition, in contrast to most BRFSS questions that asked whether or not a respondent had *ever* had a specific chronic health condition. In light of this, differences between our results are to be expected.

Lagged Macroeconomic Conditions

Although it appears thus far that macroeconomic conditions affect chronic health in the same time period that individuals’ answers to BRFSS questions are recorded, it may be possible that macroeconomic conditions affect chronic health over time.

Table 6

No, One, and Two Year Lags on Macroeconomic Conditions

Dependent variable	Effect after								
	0 years			1 year			2 years		
Have you ever?	0.00040	-0.00083	-0.00073	-.00061	-.00032	.00139	.00153	.00143	.00212
	(0.00102)	(0.00107)	(0.00138)	(.00079)	(.00082)	(.00107)	(.00108)	(.00115)	(.00156)
Personal income		0.00000**	0.00000**		0.00000	0.00000		0.00000	0.00000
		(0.00000)	(0.00000)		(0.00000)	(0.00000)		(0.00000)	(0.00000)
Work hours			0.00036			.00286*			.00133
			(0.00096)			(.00154)			(.00126)
Last 12 months?	0.00023	-0.00077	0.06288**	.00069	.00124	.00062	.01019*	.00924	-.00009
	(0.00390)	(0.00449)	(0.02211)	(.00391)	(.00387)	(.00887)	(.00550)	(.00603)	(.01592)
Personal income		0.00000	0.00008		0.00000	.00002		0.00000	0.00000
		(0.00001)	(0.00006)		(0.00000)	(.00004)		(0.00000)	(0.00000)
Work hours			0.01983			-.00472			-.00083
			(0.02286)			(.02043)			(.00227)
# Chronic conditions?	0.00210	-0.00130	-0.00075	-.00140	.00079	.00618*	.00674**	.00546*	.00601
	(0.00213)	(0.00249)	(0.00325)	(.00265)	(.00270)	(.00339)	(.00302)	(.00307)	(.00416)
Personal income		-.00001**	0.00001**		0.00000**	0.00000**		0.00000	0.00000
		(0.00000)	(0.00000)		(0.00000)	(0.00000)		(0.00000)	(0.00000)
Work hours			0.00164			.00728**			.00335
			(0.00228)			(.00347)			(.00292)

The basic specifications of Table 2 are re-estimated for one and two year lags on the macroeconomic independent variables, including the unemployment rate, state per-capita personal income, and average work hours. All estimates include demographic controls, all fixed-effects. Coefficients in the same row as the dependent variable names are measuring the unemployment rate coefficient; other independent variable coefficients, such as personal income and work hours, are italicized. Robust standard errors are produced by clustering at the state level and are reported in parentheses. *p-value < 0.10 **p-value < 0.05 *** p-value < 0.01

Ruhm (2003) presents two possible mechanisms explaining why the macroeconomy may not just have a contemporaneous impact on health, namely that a) job-related stress and the impacts from health investments, according to Grossman (1972), may accumulate over time, and b) in the medium run, agents have more flexibility in changing inputs that affect health than in the short run, such that permanent income growth will be associated with improved health. In order to address this possibility, Table 6, *No, One, and Two*

Year Lags on Macroeconomic Conditions, estimates adjustment paths for chronic health conditions for one and two year lags in independent variables measuring macroeconomic conditions.

Results suggest that chronic health may be affected by changes in the macroeconomy over time, as the directions on “Have you ever?” and “Number of chronic conditions?” coefficients become uniformly positive, indicating that chronic health as measured by these two dependent variables may be countercyclical in the medium run as opposed to procyclical in the short run. Interestingly, the “Number of chronic conditions?” coefficients become statistically significant for the first time for the full sample when one- and two-year lags are introduced, such that a one-point increase in unemployment is related to a 0.674 percentage point (0.84%) increase in the number of chronic health conditions that an individual has ever had. The “average work hours” coefficients also become significantly positive for the first time when a one-year lag is introduced, as a one-point increase in average work hours leads to a significant 0.286 and 0.728 percentage point (0.64% and 0.91%) increase in the probability of an individual ever having had a chronic health condition and the number of chronic health conditions that an individual has ever had, respectively. As before, personal income appears to have little effect on chronic health, even over time.

All in all, these adjustment paths provide important insight into specifically how chronic health changes over time with respect to macroeconomic conditions.

VI. Discussion and Conclusion

Evidence on Chronic Health

Mixed evidence on the cyclicality of chronic health ensues from this analysis, as different dependent variable proxies for chronic health exhibit different cyclical patterns in relation to macroeconomic changes. Overall, dependent variables measuring whether or not an individual has ever had a chronic health condition or how many chronic health conditions an individual has ever had tend to exhibit procyclical behavior. For example, a one-point decrease in unemployment is estimated to increase the full sample probability of having ever had a chronic health condition by 0.05 percentage points (0.11%) when state time-varying fixed-effects are excluded. On the other hand, the dependent variable measuring whether an individual has exhibited chronic health symptoms within the last year displays a significant countercyclical pattern for the full sample when the "average work hours" independent variable is added to the regression.

Two possibilities exist to explain the conflicting cyclicality findings between these measures of chronic health. First, assuming these measures proxy chronic health similarly, the resulting findings are inconclusive due to problems inherit in the construction of these dependent variables. If all dependent variables proxy chronic health similarly, then contradictory findings indicate that chronic health could be either procyclical or countercyclical. Second, these dependent variables do, in fact, proxy *different* aspects of chronic health status, such that together they inform an overall countercyclical relationship of chronic health. As the presence or development of chronic health conditions is related to heightened mortality, these findings are in contrast to some of the findings of health cyclicality research that mortality is procyclical in aggregate. In this case, chronic health may exhibit the opposite cyclicality pattern of other types of health status. This may be possible because dependent variables that proxy chronic health by asking whether or not a person has ever had a chronic health condition may go *down* due to increased mortality among individuals who are suffering or who have suffered from chronic conditions. In this case, negative coefficients for these dependent variables suggest that more individuals die from chronic health during economic downturns, which coincides with the significant negative coefficients suggesting that symptoms of chronic health worsen during rising unemployment. In this way, negative coefficients on the "Last 12 months?" dependent variable, in conjunction with positive coefficients on the other dependent variables, may suggest some sort of countercyclical pattern for chronic health. Lagging macroeconomic conditions appear to validate this, as the direction of the "Last 12 months?" unemployment coefficients and the unemployment coefficients of the other two dependent variables become reversed as time goes on, such that lagged two years, the cyclicality of chronic health is changed.[21]

Why is Chronic Health Countercyclical?

In order to dissect exactly why chronic health is countercyclical, this thesis evaluates Ruhm's (2000) mechanisms with respect to the results presented above. If solid evidence is found in favor of his mechanisms, then chronic health may in fact be procyclical, if not, then chronic health is likely countercyclical.

[21] This is true for the last set of models for all three dependent variables (see Table 6, last column), although none of those coefficients are significant. On the other hand, the positive significant unemployment coefficient on the "Number of chronic conditions" dependent variable seems at contrast with the positive significant unemployment coefficient for the "Last 12 months?" dependent variable. It may be useful for future research to include additional years of lagged macroeconomic independent variables in order to see how the relationships between the dependent variables changes as time progresses.

First, his opportunity cost of time mechanism suggests that during economic upturns, it becomes more costly to undertake health-producing activities, and the time price of medical care rises as time is more valuable, making it harder to schedule medical appointments. Declining time prices can be measured via the “average work hours” independent variable, as working longer hours should increase the price of an individual’s time, especially in the short run when some inputs into health production are fixed. Work hours coefficients are insignificant for all three dependent variables when there is no lag in macroeconomic conditions, however, adding work hours as an independent variable turns the “Last 12 months?” coefficient from negative and insignificant to positive, which in conjunction with the positive work hours coefficient, suggests that increased work hours may lead to worsening chronic health.

Mixed evidence that time prices affect chronic health comes from the positively significant “average work hours” coefficients on the dependent variables measuring the probability of an individual ever having had a chronic health condition and the number of chronic health conditions that an individual has ever had. If increases in these two dependent variables do, in fact, represent fewer people dying from chronic conditions, these positive coefficients provide evidence against increased job-related stress or time prices causing changes in chronic conditions because the opposite is happening: as work hours increase, chronic health conditions are alleviated one year later. Surprisingly, increases in personal income resulting from longer work hours do not appear to be affecting chronic health, as personal income coefficients remain zero throughout the estimates. Thus, there may be some component of additional work hours other than increased income that leads, one year down the road, to more people having ever had chronic health conditions due to fewer people dying from them. One reason for this may be that working additional hours leads to more individuals being covered by employer healthcare plans that are able to pay for preventive medical care that alleviates chronic health conditions over time. If, on the other hand, increases in these two dependent variables proxy straight increases in the prevalence of chronic health conditions, these work hour coefficients suggest the opposite effect.

Second, Ruhm postulates that health may be an input into economic production. For example, economic booms may be accompanied by increased pollution that worsens health in the short-run. Initial evidence in favor of this mechanism comes from the work hours coefficients discussed above: specifically, the positive "work hours" coefficient on the "Last 12 months?" dependent variable, which is composed mostly of yes or no responses to whether or not an individual experienced joint pain within the last twelve months, suggesting that increased work hours are related to increased joint pain. Work may be a negative input to health if, perhaps, individuals working more hours in jobs requiring manual labor develop more joint pain in response to this additional work. Or, perhaps the sedentary nature of desk jobs aggravates joint pain for people who work longer hours. Another way to evaluate this second mechanism is to look at chronic health estimates stratified by employment status, as economic booms may require inputs of health from employed workers via the pathways identified above. Coefficients on both such stratifications fail to reach statistical significance, limiting the ability to use these results to draw conclusions about how health may be an input into production. Different directions on the "Last 12 months?" coefficients for employed and unemployed individuals suggests that there may be some difference in how macroeconomic changes affect chronic health for these two groups, but further investigation is required to better discern these differences.

Third, Ruhm identifies external sources of death, including the role of different unhealthy behaviors, in explaining why mortality may be procyclical. The effect of specific unhealthy behaviors on chronic health was not estimated, but the general findings of prior health cyclicality research suggest that unhealthy behaviors may be procyclical. Unhealthy behaviors are often inputs to chronic health conditions, for example, the Mayo Clinic (2011) lists smoking, drug abuse, and excessive alcohol consumption as inputs to heart disease. As such, procyclical unhealthy behaviors should lead to procyclical patterns of chronic health. Lung cancer caused by smoking, according to the CDC, is the leading cause of cancer deaths. Because chronic health was found to be countercyclical, this could represent a possible contradiction between prior research and the findings of this thesis.[22] On the other hand, the reversed direction on the dependent variable coefficients as successive macroeconomic conditions lags were introduced suggests that chronic health is possibly procyclical in the medium run, in agreement with unhealthy behavior research. It is possible that changes in unhealthy behaviors affects chronic health over time, such that procyclical patterns of unhealthy behavior slowly contribute to the development of chronic health conditions, explaining why chronic health may be procyclical when a two-year lag is introduced. Additional research more explicitly linking unhealthy behaviors to chronic health may shed light on how one affects the other.

[22] In some cases, unhealthy behaviors are found to be either countercyclical or not affected by macroeconomic conditions. See Ruhm's (2000) countercyclical findings on alcohol consumption and Muttarack et al.'s (2012) lack of a significant relationship between smoking and the macroeconomy.

Finally, Ruhm theorizes that the migration of individuals between states may explain some of the cyclical patterns of health. If the migration mechanism is present, it should be expected that the fastest-growing states, to which people are migrating because of better local economic conditions, should show significant differences in health status compared to the slowest growing states. In this case, the fastest-growing states could either be attracting healthier, younger people, leading to a weaker pattern of procyclical mortality, or could be attracting new migrants who bring disease, cause overcrowding, or are unfamiliar with medical infrastructure, leading to a stronger pattern of procyclical mortality. Differences in the directions of the "Have you ever?" and "Number of chronic conditions?" coefficients suggest that migration patterns may be affecting the prevalence of chronic health conditions, but the statistically insignificant coefficients on the fastest-growing states make comparing the two groups of states difficult.

Concluding Remarks and Directions for Future Research

In aggregate, results from this thesis weakly indicate that chronic health conditions are countercyclical in the short-run, and possibly procyclical in the medium-run. The direction of the posited relationship between chronic health and macroeconomic conditions is determined by interpretations of the three different dependent variables constructed to proxy chronic health. These results follow similar mixed results on the cyclicality of chronic health given by Ruhm (2003). The effects of unhealthy behaviors on chronic health over time may explain chronic health's medium-run procyclical relationship with the macroeconomy, however, future study is required to better inspect the relationship between unhealthy behaviors and chronic health. As Ruhm (2005) points out, using longitudinal data with person-specific fixed-effects may prove highly beneficial in teasing out the causal mechanism between health and macroeconomic conditions. Future research on the cyclicality of chronic health should carefully consider how dependent variables measuring chronic health are constructed. While the BRFSS contains solid data on unhealthy behaviors and medical services usage, its questions about chronic health conditions make it difficult to construct dependent variables that compare with those create in previous literature on the cyclicality of health. It would be interesting to see the methodology presented in this thesis applied to a different data source, perhaps one with data on chronic health mortality instead of prevalence. That being said, the CDC has recently added new chronic health-related questions to the BRFSS, so a reevaluation of chronic health in a few years using this data may also prove valuable. While this thesis has sought to uncover how chronic health changes with respect to the macroeconomy, further research should help to answer questions that still remain.

VII. References

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VIII. Appendices

Appendix 1
Basic specification, using probability weights

Dependent variable	Have you ever?		Last 12 months?		# Chronic conditions?	
Full sample	(a)	(b)	(a)	(b)	(a)	(b)
State unemployment rate	0.00227	0.00022	0.00079	-0.00033	0.00448	0.00113
	(0.00190)	(0.00199)	(0.00695)	(0.00710)	(0.00287)	(0.00367)
State personal income		0.00000*		0.00000		-0.00001
		(0.00000)		(0.00001)		(0.00000)
State, time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
State*year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes

All estimates include demographic controls, all fixed-effects, and use either the state unemployment rate, or state unemployment as well as state per-capita personal income (in 2000 U.S. dollars) as independent variables. Final sampling weights provided by the BRFSS were used as probability weights. Robust standard errors are produced by clustering at the state level and are reported in parentheses. *p-value < 0.10 **p-value < 0.05 *** p-value < 0.01