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Does Unemployment Decrease Cancer Mortality?

Benjamin Torres Galick
Macalester College, bgalick@gmail.com

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Macalester College Economics
1600 Grand Avenue
Saint Paul, MN 55105

bgalick@gmail.com

Abstract: Recent research indicates that healthier lifestyles during recessions decrease the most common U.S. mortalities, but not cancer. However, they combine specific cancer mortalities with different progressions into one, possibly obscuring cancer's link to unemployment. This paper estimates a fixed-effects regression model on unemployment and the nine most prevalent cancers between 1988 and 2002 using state-level panel data. Five cancers and total cancer are procyclical, and suggest that unemployment affects both incidence and gestation for some cancers. Consistent with the medical literature, this paper contradicts previous economic research and suggests that behavioral factors significantly impact cancer mortality.

I. Introduction

In November 2001, the NBER announced that the U.S. economy had entered recession in March 2001. Seven years after the NBER announcement, the nation's major cancer institutions announced that the death and incidence rates of the nation's leading cancers had been decreasing steadily for years (Jemal et al., 2008). Among the reasons, the authors cite improved diagnostic and screening modalities and other long-run technological developments. They also claim that declining risk factors, such as smoking, played a role. However, they failed to consider the cyclical nature of cancer mortality. This study examines how cancer mortality responds to short-run fluctuations in income and employment.

This paper takes a similar econometric approach to that of Ruhm (2000, 2005, 2007) and subsequent research (Neumayer, 2004; Svensson 2007; Johansson, 2004; Gerdtham & Johannesson 2005; Dehejia & Lleras-Muney, 2004), which found that many health indicators improve during and after recessions in the U.S. These results have been replicated across 23 OECD countries and within other modernized countries. This research indicates that unemployment contributes to healthier dietary and exercise behavior in addition to healthier smoking and drinking habits. These studies, however, do not find any significant relationship between recessions and cancer mortality. This study reexamines this link.

Previous studies only look at total cancer mortality and not individual cancers. Individual cancers may have similar developmental stages, but their different sites and pre-cancerous cells result in different invasive properties and survival rates. I argue that combining all cancer mortality into one index can hide mortality fluctuations because each cancer type is different from the others.

This study analyzes specific types of cancer in addition to total cancer mortality. I hypothesize that healthier lifestyle habits reduce some forms of cancer incidence and mortality during and after recessions. Unemployment's effects on behavioral factors and health are then considered through the labor-leisure choice model and again through a production function where individual's choices affect their health outcome. Similar to that of previous research, I estimate a state-based fixed-effect regression model using lagged unemployment rates and state-level panel data from 1988-2002 to investigate this relationship. I utilize state-level mortality, economic, and demographic data to control for other forces driving cancer mortality.

Consistent with previous research, I find that a sustained increase in unemployment does not significantly affect total cancer mortality after four years. However, my analysis finds that many specific cancer mortalities decrease when unemployment temporarily increases. Importantly, specific cancer mortalities with strong behavioral risk factors that follow cyclical trends (diet, exercise, and tobacco use) have the strongest statistical relationship with recessions. These findings across different cancers suggest a consistent mechanism. In the long run, however, unemployment's effect on cancer mortality disappears and long-term health trends dominate.

II. Literature Review

Brenner (1979, 1983) conducted the first research linking recessions and health, and found that health varies countercyclically with employment. That is, mortality increases with unemployment. Brenner used a time-series analysis of mortality rates in England and Wales and argued that lagged unemployment partially explained fluctuations in mortality. These findings seemed logical since greater accessibility and consumption of medical resources should naturally decrease mortality. This relationship would later be known as the absolute income hypothesis (Wagstaff & van Doorslaer, 2000), which predicts that greater income leads to greater individual and societal health.

Many authors (Stern, 1983; Wagstaff, 1985; Gravelle 1981) pointed to inaccurate survey data and criticized Brenner's empirical methods for not using cross sectional fixed-effects. Stern (1983) conducted a similar regression analysis and did not find any relationship between unemployment and mortality. Gravelle et al. (1981) criticize Brenner's choice of variables, arguing that the use of personal disposable income rather than GDP implies that government spending has ill effects on health by decreasing personal income. Wagstaff (1985) argues that there is no theoretical justification to determine the appropriate lag structure for unemployment's effect on health. Most importantly, however, these authors argue that using cross-sectional fixed effects in a regression model is necessary for meaningful results.

When Ruhm (2000) investigated the effect of recessions on mortality many years later, he found that U.S. mortality rates actually decreased during recessions between 1972-1991. His more robust analysis, using state-level panel data and state-based fixed effects, contradicted Brenner's earlier findings and illustrated mortality's procyclicality. He found a statistically significant decrease for total mortality, and for eight of ten specific mortality indices, including heart disease, flu/pneumonia, liver disease, vehicle accidents, other accidents, homicide, and infant and neonatal mortality. He found a countercyclical relationship for suicides and no general correlation for total cancer mortality. His subsequent analysis of the Behavioral Risk Factor Surveillance System (BRFSS)[1] microdata indicated that individuals reduce tobacco and alcohol use, increase physical activity, and improve their diet during recessions. He suggests that these behavioral changes lead to decreased mortality during recessions.

Ruhm obtains similar relationships in later studies (2003, 2005, 2007; Gerdtham & Ruhm, 2006; Ruhm & NBER, 2004), finding consistent results across 23 OECD countries for total mortality, cardiovascular disease, influenza/pneumonia, liver disease, motor vehicle fatalities and other accidents, but not cancer. He finds that smoking and height-adjusted weight decline during recessions and that income seems to play little role in affecting health care accessibility (Ruhm & NBER, 2004), suggesting that a decline in work hours, and subsequent increase in leisure time, leads to healthier lifestyles.

Many studies (Neumayer, 2004; Svensson 2007; Johansson, 2004; Gerdtham & Johannesson 2005; Dehejia & Lleras-Muney, 2004) corroborate Ruhm's findings for developed countries, suggesting that the mechanisms are similar across wealthy nations. These papers all suggest plausible mechanisms in individual behavior, consumption, and decreased risk factors such as air pollution (Chay & Greenstone, 2003).[2] Khan et al. (2004) also suggest that increasing wages during booms attract sick and disabled people into the labor force. This reduces their time and ability to care for their health. Ruhm (2000) suggests that the fall in leisure time makes it more costly for individuals to undertake health-promoting, time-intensive activities like exercise and visiting a doctor.

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[1] The BRFSS is a telephone survey collected monthly by the Centers for Disease Control. Data are collected for all 50 states, the District of Columbia, the U.S. Virgin Islands, and Guam on various individual health and behavior indicators including, for example, obesity and exercise, alcohol and tobacco use, and diet.

[2] These mechanisms are discussed in more detail in Section III.

Evidence also suggests that joblessness is associated with decreased alcohol and tobacco consumption (Ruhm 2000, Gerdtham & Ruhm, 2006), although U.S. binge drinking increases during recessions (Dee, 2001).

These studies support Ruhm's initial findings, but generally find no link between unemployment and total cancer mortality. The consensus is that total cancer mortality is not responsive to short run macroeconomic fluctuations (Ruhm, 2000, Ruhm & NBER 2004; Gerdtham & Johannesson, 2005; Neumayer, 2004; Gerdtham & Ruhm, 2002; Gerdtham & Johannesson, 2005), presumably because of limited behavioral risk factors.

These studies, however, aggregate all cancer mortality into one index as if they were the same illness. They do not take into account each cancer's different invasive properties. Different gestation periods and biological pathways for each cancer type can cloud results when the data are aggregated. Furthermore, previous research considers cancer incidence and mortality as a condition largely unaffected by lifestyle factors, while the medical literature indicates that cancer results from a combination of lifestyle, genetic, and some infectious agents (Campbell & McTiernan, 2007; Cummings & Bingham, 1998; Uauy & Solomons, 2005; Kay et al., 2002; Jemal et al., 2008). Previous research has not investigated the cyclical nature of early detection on cancer mortality. For this reason, this paper investigates the link between recessions and mortality rates for the nine most common cancers in the U.S. This paper uses lagged unemployment effects to account for different gestation periods, and applies known disease progression time frames to theorize whether behavioral changes reduce cancer incidence or mortality.

III. Theory

New medical technologies and greater health care accessibility have improved long run health. New therapeutic techniques improve disease treatment and recovery, and people live longer now than they ever have. The fact that we live longer now than we did 100 years ago is evidence that technological progress has improved long run health.[3] Improved medical technology is an example of a technological innovation that improves mortality directly, but there are also innovations that improve medical care indirectly. These indirect innovations impact mortality by increasing individual productivity, output and income, and thus allow individuals to afford more medical care. Regardless of the innovation, these technologies and their benefits to medical treatment will diffuse slowly. Medical technology will diffuse slowly because of the need for FDA approval, and because medical professionals will need to be trained in the new techniques. Indirect innovations will also slowly affect medical treatment and cancer mortality because of their indirect nature; the benefits to medical treatment will only be a fraction of the individual's increased income. The slow diffusion, coupled with regular innovations, should lead to a downward secular trend in cancer mortality over time. This justifies using a time-trend to control for the long-run technological forces driving cancer mortality in the empirical models I estimate below.

The health-income model suggests the relationship between income and health seen in figure 3.1. Societal health increases as technology and income increase, but at a

[3] Medical technology and cancer therapies such as the constant improvement of cancer chemotherapy, surgical techniques and screening methods have become more effective and accessible to the general public (Peto & Faston, 1989).

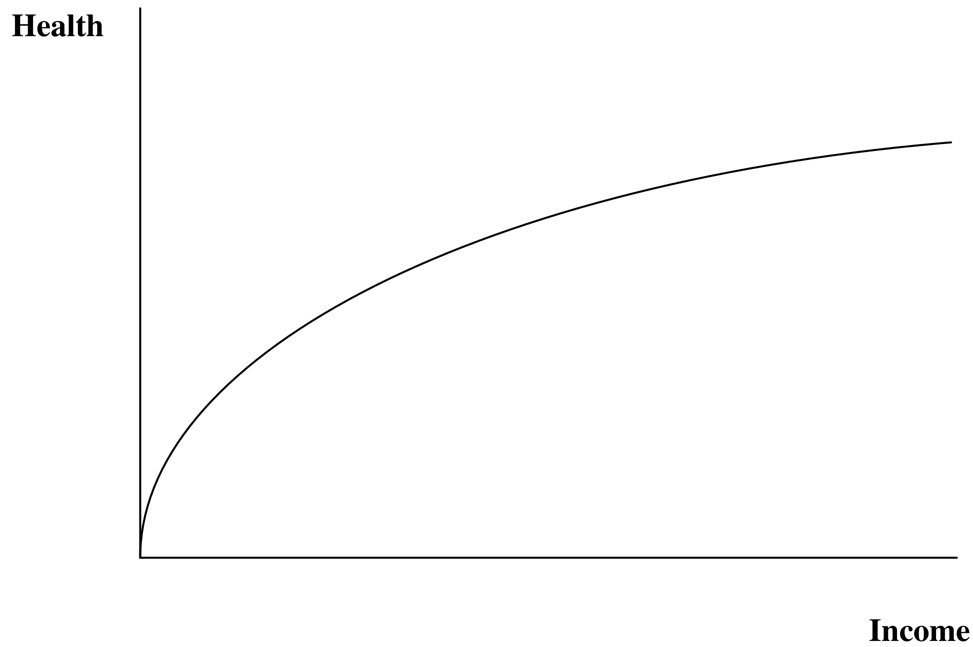

Figure 3.1: Health-Income relationship. As income and medical technology increase, societal health increases (Wagstaff & van Doorslaer, 2000).

diminishing rate.[4] These long run trends are separate from short run unemployment and income fluctuations. By stripping away the impact of technological change, I focus on the cyclical determinants of health in the U.S.

Unemployment can affect cancer mortality four ways: through changes in income, altered behavior, environmental effects, and through altered diagnostic utilization. Lower incomes decrease one's ability to afford health care. This leads to lower health care accessibility, decreased consumption of health-producing activities, and presumably worse health outcomes. However, lower income also means individuals purchase less alcohol and tobacco. The income effect therefore suggests an ambiguous relationship between unemployment and mortality rates.

[4] Clean drinking water, sewage treatment, proper shelter, and adequate diet do the most to ensure health. Every medical prevention or treatment thereafter improves health, but by diminishing amounts relative to the basic necessities.

Behavioral effects, however, generally suggest a negative relationship. Consider the labor-leisure choice model. When an individual experiences unemployment, he or she must forgo consumption and increase leisure. When total consumption decreases, consumption of expensive goods (like tobacco and alcohol) also tends to decrease. Ruhm (2000 & 2003) find that individuals eat healthier[5] and are more likely to engage in health-producing time-intensive exercise. Previous papers indicate that lower household income and food stamp participation tend to increase intake of inexpensive, calorie dense foods (Meyerhoeffer & Pylypchuk, 2008; Philipson et al., 2004; Jyoti et al. 2005). However, households do not always utilize the food stamp program when they qualify, and uptake is likely to be slow. Consequently, the cyclical unemployment effect on food stamp program participation is uncertain due to unemployment's relatively high frequency. Furthermore, the number of people qualifying for the food stamp program relative to the whole population is fairly small, and those who do not utilize the program will outweigh the dietary changes of food stamp program participants.

In the diagnostic effect, an individual's future health coverage often becomes uncertain during his or her transition into unemployment. Individuals have the option of maintaining their health care coverage through COBRA,[6] but utilization is often low due to its high cost. Uncertain future health care coverage leads individuals to use their health benefits while they still have them. They get diagnostics and treatment that they have previously delayed. This can result in early detection of cancerous cells, which can significantly improve an individual's prognosis. The diagnostic mechanism should be

[5] Individuals decrease their daily amounts of fat consumed. Neumark-Sztainer et al. (2000) also find that families tend to eat fast food when faced with busy schedules, suggesting that time constraints strongly affect diet.
[6] COBRA is a government law mandating that insurance companies give employees the ability to continue their health insurance after leaving their employment.

strongest with moderately invasive cancers, because mortality will remain largely unaffected for both the most and least deadly cancers.

These theories are consistent with the intertemporal substitution of labor model from the real business cycles literature (Mankiw, 2007; 528-537). When people are faced with unemployment or decreased wages, they increase investment in activities that will give them a greater future return. People might exercise more during recessions because increased health may allow them to take advantage of the eventual rise in labor demand, or simply because the opportunity cost of exercise is lower.

Individuals can spend their new leisure time exercising, but they may also pursue sedentary activities. As long as they perform some exercise, however, individuals increase their activity level (assuming work requires physical inactivity). If individuals pursue a completely sedentary lifestyle during bouts of unemployment, then the long-run trend will remain unaltered. Individuals who normally exercise during employment will likely continue exercising during unemployment because their time constraints have been relaxed.

Environmental changes during recessions can also alter health outcomes. Health can be an input in the production of some goods and services. Many occupations have workplace hazards, psychological stress,[7] physically demanding labor, or extended working hours. Furthermore, other procyclical factors like industrial pollution have been shown to affect infant and neonatal mortality (Chay and Greenstone, 2003).

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[7] Workplace stress may increase during economic booms, but unemployment stress may also increase during recessions. Stress as a mechanism for cancer mortality is therefore ambiguous. However, stress has not been found to influence an individual's cancer incidence or mortality (Johansen & Olsen, 1997).

Recessions → (Income Effects
Behavioral Effects
Environmental Effects
Diagnostic Effects) → Mortality Rates

Figure 3.2: Income effects can adversely affect health during unemployment, while behavioral effects can have an ambiguous effect, and environmental effects are

The four channels discussed above are summarized in Figure 3.2. Employment is not itself a risk factor. Rather, it affects mortality rates though other well-established risk factors.

We would expect incomes and workplace hazards (environment) to decrease, and exercise (behavior) and health care utilization (diagnostic) to increase during recessions. Unemployment can affect health differently through these four channels. Whether the beneficial behavioral, diagnostic and environmental effects outweigh the adverse income and behavioral effects of unemployment with respect to cancer is the empirical question of this paper.

Another way to look at this issue is to view health as the output of a modified Cobb-Douglas production function. These mechanisms suggest the following relationship:

$$H = \eta I^{\gamma_1} B^{\gamma_2} N^{\gamma_3} D^{\gamma_4} \tag{1}$$

where H is health, η is a constant linking the intermediate variables and health through common factors like proper sanitation and other public health goods, I is income, B is a composite variable of behavioral factors that affect health (such as exercise and smoking), N is a composite variable of health-affecting environmental factors, and D represents the diagnostic effect. Each γ_i is a number between 0 and 1, because each factor's impact on health diminishes as the factor grows larger. This model illustrates that both positive and negative income, behavior, and environment effects impact overall health, but at a diminishing rate.

As discussed above, I, B, N, and D vary with unemployment. These relationships can be restated in the following equations:

$$I = \omega_1 E^{\lambda_1} \tag{2}$$

$$B = \frac{\omega_2}{E^{\lambda_2}} \tag{3}$$

$$N = \frac{\omega_3}{E^{\lambda_3}} \tag{4}$$

$$D = \frac{\omega_4}{E^{\lambda_4}} \tag{5}$$

where E is the employment rate, each ω_i are parameters linking employment and the intermediate variables, and each λ_i represents employment's effect on the intermediate variable. Substituting equations 2-5 into equation 1 gives the following relationship:

$$H = \eta \omega_1^{\gamma_1} \omega_2^{\gamma_2} \omega_3^{\gamma_3} \omega_4^{\gamma_4} E^{\lambda_1\gamma_1 - \lambda_2\gamma_2 - \lambda_3\gamma_3 - \lambda_4\gamma_4} \tag{6}$$

The equation can then be simplified, placing H as a function of E:

$$H = \alpha E^{\beta} \tag{7}$$

where $\beta=\lambda_1\gamma_1-\lambda_2\gamma_2-\lambda_3\gamma_3-\lambda_4\gamma_4$ and $\alpha=\eta\omega_1^{\gamma_1}\omega_2^{\gamma_2}\omega_3^{\gamma_3}\omega_4^{\gamma_4}$. Note that β and α capture the net effect of all these factors. The log transformation of Equation 7 then gives a linear relationship between H and E:

$$\ln H = \ln \alpha + \beta \ln E \tag{8}$$

This relationship states that the logged health measurement is a function of the logged employment rate.

Equation 8 specifies cancer mortality as a function of contemporaneous unemployment rates. The health effects of unemployment should also last past the year of unemployment. Since cancer can take many years to develop, increased unemployment should affect cancer mortality rates in the years following its increase. This justifies analyzing unemployment's lagged effects on cancer mortality. This paper estimates contemporaneous changes and various lag structures.

State-level policy attitudes towards health care funding and state geographical features that impact cancer mortality are all important factors omitted from equation 8. They are also nearly impossible to control for individually. Instead, I use state-based fixed-effects, and control for contemporaneous correlation among states to account for these effects. Demographic controls are included separately. This model tests the hypothesis that recessions decrease specific cancer mortality.

IV. Cancer Biology

Cancer is a disease in which an individual's normal cells mutate, causing them to grow uncontrollably, invade and destroy surrounding tissues, and sometimes spread to other areas of the body. Most cancers follow a similar progression. Once a normal cell transforms into a cancerous cell, it can become malignant and proliferate uncontrollably. Each cancer type has different properties, however. They develop from different tissues, grow in vastly different environments, and have different causes, leading to different invasive properties. This is why pancreatic and lung cancers are often fatal within a few years, while some men can live with prostate cancer for years and not know.

The medical community typically measures a cancer's invasive properties by their one and five year survival rate. Less invasive cancers have higher survival rates, and more invasive cancers have lower survival rates. The survival rates for each cancer type in this study are included in Table 4.1. These differing survival rates are why total cancer mortality regression analyses do not adequately represent these diseases: they are inherently different diseases with varying invasive properties linked together by common progression stages.

Cancers all stem from mutations in a normal cell's genetic material. These mutations can occur from carcinogens (harmful particles or chemicals), radiation, infection, and a combination of many other factors. A cancer's risk factors depend on the tissue type the cancer cells transform from, and what combination of factors that tissue is exposed to. As an individual grows older, the collective damage to genetic material can build up. This combined with a cell's increasing inability to repair and protect itself

Table 4.1: Cancer survival rates for all ages and from year of diagnosis

	Survival Rates				
Cancer	1 year	2 year	3 year	5 year	10 year
All	80.5	74.0	71.6	67.2	58.5
Bladder	91.2	86.3	84.7	81.6	75.7
Prostate	100.0	99.9	99.9	99.2	94.6
Ovarian	75.8	67.0	55.0	44.5	36.7
Skin	97.7	96.4	94.3	92.3	89.7
Breast	97.9	95.8	93.9	90.5	80.6
Lung	43.3	26.9	21.3	16.2	10.9
Colon & Rectum	84.2	76.7	73.1	66.0	55.6
Pancreas	24.2	11.4	8.5	5.4	3.1

Source: Ries LAG et al., SEER Cancer Statistics Review 1975-2005, National Cancer Institute.

Table 4.2: Specific Cancer Risk Factors

Cancer	Major Risk Factors	Minor Risk Factors	Other Factors
Bladder	Age, smoking, chemical	Limited fluid intake	Caucasians, men

	exposure, chronic bladder inflammation		
Prostate	Age, smoking	Diet, obesity, lack of exercise, prostate inflammation and infection	Men, African-Americans, less in Asians & Hispanics
Ovarian	Age, obesity, no/few children, no breastfeeding, breast cancer, diet	Male hormone use, tobacco use	Oral contraceptives reduce risk
Skin	Sun exposure, light or fair skin, albinism, age	Chemical exposure, smoking, HPV infection	Fair skin, Men
Breast	Age, genetic factors, early menarche, late menopause, obesity, alcohol, lack of exercise	No/late childbirth, oral contraceptive and hormone therapy use, no breastfeeding	Women, Caucasian and African-American, less in Asians, Hispanics and Native-Americans
Lung	Smoking, radon, asbestos, pollution	Diet	
Colon & Rectum	Age, inflammatory bowel disease, diet, obesity, lack of exercise	Smoking, heavy alcohol use, type 2 diabetes	African-American
Pancreas	Age, smoking, obesity, lack of exercise, chronic pancreatitis	Diabetes, cirrhosis, chemical & pesticide exposure, alcohol, diet, *H. pylori* infection	Men, African-American

Source: American Cancer Society

result in higher cancer incidence and mortality as age increases. The major and minor risk factors for each cancer type in this study are included in Table 4.2.

In addition to genetic factors, the American Cancer Society (ACS) indicates that many behavioral and environmental factors (as opposed to heredity) contribute to an individual's cancer risk. They claim that these effects count for as much as 75%-80% of all U.S. cancer incidence and mortality. 30% of all cancer deaths can be attributed to tobacco use, and another 35% can be attributed to nutrition, physical activity and obesity (ACS, 2008). The cancers with the strongest behavioral risk factors include that of the breast, colon, rectum, and lung, while evidence suggests less of a link with pancreatic, ovarian and prostate cancer.

V. Summary Statistics and Data

This analysis uses state-level cancer mortality data from all 50 states and the District of Columbia for the nine most common cancer types and total cancer mortality. Annual state-level unemployment data come from the Bureau of Labor Statistics. State-level demographic data compiled from the U.S. Census Population Estimates Program,[8] U.S. Current Population Survey (CPS),[9] and U.S. CPS March Supplement are used as control variables. These variables include the elderly (aged 65 and over) and racial demographics as a percentage of the total population. Racial demographic data are included because genetic differences predispose certain races to different types of cancer. This measures the size of the population most likely affected by cancer, and is therefore better than median age. Percent urban population is included to control for possible income, behavioral, environmental, and diagnostic differences between urban and rural areas.[10] I calculated the racial composition and elderly population variables from CPS data. The number of doctors includes other, non-physician, primary health care professionals (for example, nurse practitioners) because they can also contribute to cancer detection and treatment. Furthermore, the small sampling of doctors in some states can cause significant random error.

The blue-collar variable includes operators, fabricators, laborers, tradesmen, and other workers in physically demanding or repetitive occupations. Agriculture workers

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[8] U.S. Census Bureau, Population Division, Population Estimates Program. Accessed at http://www.census.gov/popest/estimates.php on November 24, 2008.
[9] U.S. Census Bureau Current Population Survey.
[10] Some percent urban population data points surpass 100% because I calculated them from U.S. Census population estimates on the state and county level. I did not correct for the measurement error because I could not know the bias for all data points.

include farmers and people in constant contact with livestock. Both are percentages of the total population.

Household health insurance coverage data have been gathered by the CPS March supplement since 1988. Households are considered uninsured if no one in the household has insurance. The values are higher than state uninsured rates, but they are comparable to these rates. Although it does not perfectly reflect access to health care, it is the best measure available. This study uses household health insurance coverage to measure health care accessibility instead of real per capita GDP because GDP is highly collinear to unemployment rates, and health insurance coverage dictates an individual's health care utilization more than income.

Cancer mortality data and population estimates come from the Centers for Disease Control (CDC).[11] In addition to total cancer mortality, the data include the nine most fatal cancers in the U.S. by number of deaths: lung, colon, breast, prostate, pancreatic, ovarian, bladder, rectal, and skin cancer. These data are annual mortality rates per 100,000 people by state. For states with small populations (most notably Alaska and Wyoming), the number of observations is sometimes very low. With the exception of a missing skin cancer datum (corresponding to North Dakota in 2001), the data set is continuous and balanced for all 50 states and D.C. for all years from 1988 to 2002.

Annual unemployment data from the U.S. Bureau of Labor Statistics[12] go as far back as 1984 to consider lagged effects without dropping data. The data are summarized in table 5.1.

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[11] Centers for Disease Control and Prevention, National Center for Health Statistics. CDC WONDER On-line Database, compiled from Compressed Mortality File 1999-2005 Series 20 No. 2K, 2008. Accessed at http://wonder.cdc.gov/cmf-icd10.html.

[12] U.S. Bureau of Labor Statistics. Accessed at http://www.bls.gov/lau/.

Table 5.1: Summary Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
Annual Unemployment Rate	969	5.6	1.8	2.3	14.7
Total Cancer Mortality	765	203.41	33.35	81.3	274.0
Colon	765	17.27	3.87	3.9	27.9
Rectum	765	2.43	0.67	0.4	5.1
Pancreas	765	9.90	1.78	2.2	15.8
Lung	765	55.05	12.75	14.5	87.2
Skin	764	2.40	0.65	0.2	4.2
Breast	765	15.85	3.00	5.5	23.9
Ovary	765	4.97	0.96	1.1	7.6
Prostate	765	12.64	2.70	2.6	25.9
Bladder	765	4.21	1.05	0.7	7.2
Percent Age 65+	765	12.48	1.98	3.69	18.32
Doctors per 1,000 People	765	3.53	1.25	0.36	8.98
Percent Blue Collar Workers	765	18.57	3.38	6.06	28.09
Percent Urban Population	765	74.61	19.51	28.88	100.37
Percent Black	765	9.54	11.21	0.07	66.42
Percent Hispanic	765	5.76	7.15	0.24	38.76
Percent Agriculture Workers	765	2.51	1.93	0.26	10.90
Percent Female	765	52.70	1.21	48.56	57.32
Percent Household Health Insurance Coverage	765	20.62	5.99	9.11	40.22

Source: U.S. Centers for Disease Control, U.S. Bureau of Labor Statistics, U.S. Current Population Survey, U.S. Current Population Survey March Supplement, U.S. Census Population Estimates Program. Note: Cancer mortality rates are per 100,000 people. All data are state-level from 1988 to 2002 except unemployment, which begins in 1984.

VI. Analysis

The basic econometric specification is:

$$\ln H_{jt} = \alpha + \mu X_{jt} + \beta \ln(U_{jt}) + S_j + t + \varepsilon_{jt} \qquad (8)$$

where U_{jt} is the state unemployment rate of state j in year t, S_j controls for state-based fixed-effects, t is a time trend,[13] X_{jt} is a vector of supplementary regressors summarized in

[13] This paper includes a time trend instead of year fixed effects like the previous literature for three reasons. First, I assume new medical technology does not “shock” medical treatment. Instead, new medical advances have relatively slow uptake. The invention may be rather discrete and the technological diffusion and adaptation can take time. Second, many different medical innovations invented and introduced at

Table 5.1, and ε_{jt} is the error term. Along with a larger elderly population, mortality rates are expected to increase when the rural population increases. While the elderly population is at higher cancer risk, people living in rural areas will likely experience greater cancer mortality due to decreased accessibility to health care resources. Like all recent research, state based fixed-effects are included to control for state-specific factors that can influence cancer mortality, such as local health care policies, physical geography, etc. For example, states with higher UV exposure are hypothesized to have higher skin cancer mortality rates.

Heteroskedasticity hypothesis testing resulted in rejecting the null hypothesis of homoskedasticity. I use adjusted standard errors to resolve these complications. I found serial correlation only in estimates concerning ovarian cancer. This study uses a GLS estimator as a separate robustness check for all regressions. The results are consistent across estimations, so I present the Prais-Winsten estimation due to its ease of use and more robust standard errors. Uncentered variance inflation factor tests and simple correlation coefficients found significant collinearity between many of the variables, the greatest of which is between agricultural workers and urban population. I include these variables because they are theoretically important and the magnitudes of their simple correlation coefficients are all below 0.60, except between agricultural workers and urban population (Appendix A attached). The Dickey-Fuller test indicates non-stationarity in many independent and dependent variables. However, the Dickey-Fuller test also rejects the null hypothesis of a unit root in the error terms, suggesting cointegration. Table 6.1 summarizes the main results of the Prais-Winsten model with panel-corrected standard

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different times will smoothen out cancer mortality. Lastly, yearly fixed effects will be highly collinear with business cycles, thus hiding the effects of state unemployment rates.

errors assuming heteroskedasticity and contemporaneous correlation across panels. Regressions with a random effects model eliminate most unemployment significance, however previous authors have indicated the empirical superiority of the fixed effects model.

The results in Table 6.1 suggest that contemporaneous state unemployment rates affect specific cancer mortalities. Only colon cancer was significantly procyclical (a negative correlation with contemporaneous unemployment), while ovarian and prostate cancer were countercyclical. However, including lagged unemployment rates is more reasonable since cancer is a function of an individual's previous health. When two lagged unemployment terms are included in the regressions, four specific mortalities are procyclical. These are colon, rectal, pancreatic and lung cancers.

One limitation to this approach stems from the fact that all cancers are inherently different from each other. Using the same lag structure does not allow for differences between each cancer to be observed. That is, unemployment will impact different cancer mortalities in different ways and at different times. To be less restrictive, I let the data indicate the best lag structure. Table 6.2 indicates the lag structure with the highest adjusted-R^2 values for each cancer (see Appendix B for full regression results). This analysis indicates that many cancers are significantly procyclical while others follow an unclear cyclical trend.

Table 6.1: Fixed-Effects Estimates of Contemporaneous Cancer Mortality and for a Two Year Lag Period

State Unemployment	Colon	Rectum	Pancreas	Lung	Skin	Breast	Ovary	Prostate	Bladder	Total Cancer
t	-0.058**	-0.053	-0.032	0.012	-0.001	0.010	0.066***	0.062**	0.017	-0.005
	(0.03)	(0.04)	(0.03)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)
t	-0.052*	0.027	-0.034	0.012	-0.002	0.009	0.053	0.032	-0.017	-0.005
	(0.03)	(0.06)	(0.04)	(0.02)	(0.07)	(0.02)	(0.04)	(0.06)	(0.04)	(0.01)
t-1	0.045	-0.13	0.038	0.043	0.027	0.018	0.041	0.065	0.062	0.007
	(0.04)	(0.09)	(0.06)	(0.03)	(0.10)	(0.04)	(0.06)	(0.08)	(0.06)	(0.02)
t-2	-0.179***	0.037	-0.119**	-0.138***	-0.085	-0.057**	-0.068	-0.067	-0.039	-0.023*
	(0.04)	(0.07)	(0.05)	(0.03)	(0.07)	(0.03)	(0.04)	(0.05)	(0.04)	(0.01)

Cancer site: Colon through Total Cancer.

Notes: The first row includes results from regressions using contemporaneous unemployment only. The second row includes results from regressions using the contemporaneous unemployment rate and two annual lags. All regressions include a time trend and control for state fixed effects, demographic characteristics (listed in Table 5.1) and health care accessibility at time t (n=765). Dependent variables are the natural logs of specific mortality rates per 100,000, and unemployment variables are the natural logs of the state unemployment rates. Lagged health care accessibility is not included on the premise that insurance companies will deny coverage for pre-existing conditions. Full regression results are included in Appendix B.
Key: * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6.2: Cancer Mortalities with Optimal State Unemployment Lag Structure

Unemployment Year	Colon	Rectum	Pancreas	Lung	Skin	Breast	Ovary	Prostate	Bladder	Total Cancer
t	-0.063**	-0.03	-0.034	0.008	-0.002	-0.008	0.053	-0.001	0.017	-0.013
	(0.03)	(0.06)	(0.04)	(0.02)	(0.07)	(0.02)	(0.04)	(0.05)	(0.02)	(0.01)
t-1	-0.025	-0.091	0.038	-0.006	0.027	0.007	0.041	0.07		-0.001
	(0.04)	(0.09)	(0.06)	(0.03)	(0.10)	(0.03)	(0.06)	(0.07)		(0.02)
t-2	-0.064	0.007	-0.119**	-0.025	-0.085	0	-0.068	-0.024		-0.013
	(0.06)	(0.09)	(0.05)	(0.04)	(0.07)	(0.04)	(0.04)	(0.07)		(0.02)
t-3	-0.033	-0.054		-0.100***		-0.099**		-0.126*		0
	(0.06)	(0.10)		(0.03)		(0.04)		(0.07)		(0.02)
t-4	-0.093**	0.082				0.099***		0.185***		-0.001
	(0.04)	(0.10)				(0.04)		(0.07)		(0.02)
t-5		0.047				-0.079***		-0.157***		-0.027**
		(0.09)				(0.02)		(0.05)		(0.01)
t-6		-0.161***								
		(0.06)								

Note: (See note in Table 6.1) The listed regressions illustrate the state unemployment lag structure that has the best statistical fit as measured by the adjusted R^2. All cancers seem to follow some degree of cyclicality except skin, ovarian and bladder cancers.
Key: * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6.3 illustrates the effects of a sustained one-percentage point increase in state unemployment rates on cancer mortality rates, and figure 6.1 graphically illustrates this change in mortality for selected cancers. This analysis, based off of the results in Table 6.2, indicates procyclicality for colon, rectal, pancreatic, lung, breast, and total cancer mortality; countercyclical trends for ovarian and prostate cancer; and no trend for skin and bladder cancer. The significant and negative findings for total cancer mortality are inconsistent with previous research. However, these results do not break the 5% confidence level.

The results in Table 6.2 and 6.3 suggest behavioral mechanisms for each cancer. Colon and rectal cancers seem to have fairly lengthy and significant procyclical effects, while pancreatic and lung cancers seem only to affect mortality after a few years. Since prostate cancer has such a long gestation period, it is difficult to interpret the significant results from time t-3 to t-5.[14] However, it appears that prostate cancer tends to follow a countercyclical trend. This might suggest a connection between gestation length and positive correlation with unemployment. Mortality also increases in the case of ovarian cancer, suggesting that recessions decrease survival rates through the income effect. Decreased health care accessibility appears to play a more important role in prostate and ovarian cancer survival rates than lifestyle or behavioral factors.

These results are consistent with the known link between behavioral factors and cancer risk. The cancers with the greatest lifestyle links (breast, colon and lung) follow a procyclical trend consistent with the behavioral effects theory, while of those with less lifestyle risk factors, only pancreatic cancer follows a procyclical trend while ovarian and

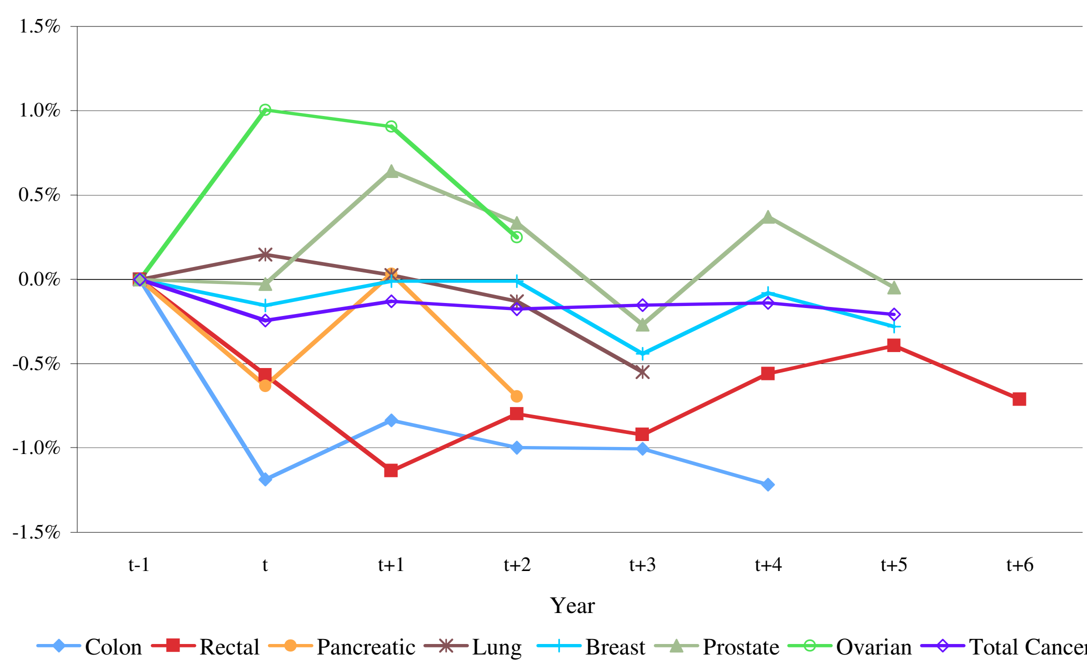
[14] Both breast and prostate cancers have positive coefficients sandwiched between negative coefficients. This unusual and unexpected coefficient structure could be due to multicollinear problems, but decreased mortality in one year means that there are more people to die from that cancer in the following year.

Table 6.3: Predicted Effect of a Sustained One Percentage Point Increase in State Unemployment Rate Beginning in Year t.

Cancer	t	t+1	t+2	t+3	t+4	t+5	t+6
Colon	-1.19%	-0.84%*	-1.00%***	-1.01%***	-1.22%***		
Rectal	-0.57%	-1.14%**	-0.80%**	-0.92%***	-0.56%**	-0.39%**	-0.71%***
Pancreatic	-0.63%	0.03%	-0.70%***				
Lung	0.15%	0.02%	-0.13%	-0.55%**			
Skin	-0.04%	0.24%	-0.35%				
Breast	-0.16%	-0.01%	-0.01%	-0.44%**	-0.08%	-0.28%**	
Ovarian	1.00%	0.90%**	0.25%				
Prostate	-0.03%	0.64%	0.33%	-0.27%	0.37%`	-0.05%	
Bladder	0.32%						
Total Cancer	-0.24%	-0.13%	-0.18%	-0.15%	-0.14%	-0.21%*	

Notes: (See note in Table 6.1) Numbers indicate the effect of a one percentage point increase in state unemployment rates beginning in year t and lasting until the end of the period on the indicated cancer mortality. Figures are the percent mortality changes over the entire period. Lagged unemployment rates are included until the indicated time, and are the same as in Table 6.2. For complete regression results, see appendix B. Significance is determined by an unpaired two-tailed t-test.
Key: * significant at 10%; ** significant at 5%; *** significant at 1%

Figure 6.1: Effect of a sustained one percentage point rise in state unemployment rates on cancer mortality



prostate cancers follow a countercyclical trend. The potential for successful cancer treatment might affect cancer cyclicality. Cancers must be sufficiently treatable for behavioral and lifestyle factors to affect mortality, but sufficiently invasive so that changes in mortality rates can be observed.

Given the relatively long gestation periods, lifestyle and behavioral factors might affect cancer mortality for several years. The finding that lagged unemployment affects cancer is consistent with this biological reality. These estimations suggest the time frame at which unemployment most affects specific cancer mortality.

Comparing the lagged effects of unemployment with survival rates for each cancer type can help illustrate how unemployment can affect cancer mortality. If unemployment affects cancer mortality beyond the time frame when most people pass away, then unemployment likely prevents disease incidence rather than affecting progression. This is likely the case for pancreatic and lung cancer. As illustrated in Table 4.1, pancreatic and lung cancers are both extremely deadly diseases, with most people (around 76% and 57%, respectively) dying within the first year of diagnosis. Since cancer mortality decreases two and three years after an increase in unemployment, it is improbable that unemployment affects cancer survival. Instead, better lifestyle habits likely reduce pancreatic and lung cancer incidence, which then translates into decreased mortality years later.

Healthier lifestyles can also affect cancer mortality through increased cancer survival. They can give people better chances to fight the disease. Such is likely the case with colon and rectal cancer mortality, which decrease the year of and the year after a sustained rise in unemployment. About 24% of individuals with colorectal cancer die within the first two years of diagnosis. The fact that colon and rectal cancer mortality decrease during this time frame indicates that more people are surviving these forms of cancer. The significant and negative coefficients indicate decreased mortality for those currently with the disease. However, these cancers also benefit from decreased cancer incidence. After ten years with these cancers, about 44% of individuals die. Most of these fatalities occur within the first three years of diagnosis. Similar to pancreatic and lung cancers, cancer mortalities decrease significantly after this period. The highly significant and negative coefficients at time t-4 and t-6 for colon and rectal cancers, respectively, suggest that new cancer cases decrease in the years immediately following increases in unemployment. The highly statistically and economically significant values illustrate how important lifestyle factors are to cancer incidence and survival.

The most revealing findings are those of colon and lung cancer. A sustained one-percentage point increase in unemployment decreases total deaths from these cancers by around 2,600 and 3,500 people over their respective lag period. The predicted changes in nationwide specific cancer mortality over the indicated lag period are listed in Table 6.4.

Not all cancer mortalities seem to respond to business cycles. It is unknown whether skin cancer's major risk factor (UV exposure) has cyclical trends like the other risk factors.[15] The same is true with bladder cancer and chemical exposure. U.S. regulations for the most part limit an individual's exposure to toxic chemicals.

The previous results are robust across different specifications. Additional regression analyses replace the time trend with year fixed-effects. As expected, yearly

[15] Individuals may spend more time tanning at the beach because they have more disposable time, but they may also spend less time at the beach because of less disposable income. Work-related UV exposure may decrease, however total exposure may remain unchanged due to substitution with leisure-related UV exposure.

fixed-effects regressions were less significant than those with time trends. The unemployment rate's collinearity with time fixed-effects masks much of the unemployment rate's variation. However, the slow uptake of medical technologies and constant innovation justifies using a time trend rather than yearly fixed-effects.

Table 6.4: Predicted Nationwide Change in Cancer Mortality

	Colon	Rectum	Pancreas	Lung	Skin
Over entire lag period	-2,598	-373	-678	-3,484	-80
Until peak	-2,598	-373	-678	-3,484	-80

	Breast	Ovary	Prostate	Bladder	Total Cancer
Over entire lag period	-697	110	-87	42	-7,220
Until peak	-734	267	536	42	-7,220

Note: Calculations are based off of the regressions in Table 6.2. Predicted cancer mortality changes over the entire lag period are calculated at the end of the lag period, while changes until the peak are determined until the most significant year.

VII. Supplemental Results and Robustness Checks

The regression results in Appendix B have interesting results for many of the demographic and control variables. The most interesting results come from the age, doctor concentration, and year variables.

For all but the skin cancer regressions, age has a highly significant and positive coefficient. This is expected since an individual's cancer risk increases significantly with age. The most surprising finding is that age is not significant for skin cancer. This is a rather puzzling finding, especially since the medical community indicates that age is the second most significant skin cancer risk factor besides UV exposure. Perhaps states with a high elderly population and higher UV exposure are collinear to the state-based fixed-effects.

The result that the number of doctors per capita is also insignificant is also worth note. The number of doctors only significantly reduces colon and rectal cancer mortality. It is insignificant for all other cancers. There are four possible explanations for this. First, this finding could be due to a small sampling of doctors in the CPS. This can lead to highly volatile measurements of the number of doctors. Second, the doctor measurement could misrepresent accessibility to health care. One important factor in cancer prevention and treatment is access to health care. The number of doctors might not represent this factor as well as health insurance coverage does. Third, the number of doctors could be collinear to health insurance coverage, skewing the results. However, the correlation analysis indicates a fairly low (though significant) correlation coefficient of -0.1531. Fourth, it is possible that people crossing state lines for treatment (i.e. to the Mayo Clinic) could affect these results. If accurate, these results suggest that doctors do not play a significant role in cancer prevention or treatment. Although counter to common belief, these results support the behavioral effect hypothesis that lifestyle and behavioral factors play a significant role in cancer prevention and treatment. In fact, this suggests that behavior has a greater impact on cancer mortality than access to health care. This also implies that our current knowledge and treatment of cancer is severely limited. The fact that so many people die from cancer each year supports this, but the fact that cancer mortality has been decreasing does not.

These regression results also indicate that cancer mortality has been decreasing over this time period. In addition to total cancer decreasing over this period, deaths by colon, rectal, breast and prostate cancers have also fallen. However, deaths from pancreatic, skin and bladder cancers have been increasing over time. It is natural for specific cancer mortality growth rates to vary depending on the cancer. Greater public focus on breast and prostate cancer could explain why these mortalities have decreased and why other, less-known cancers have increased unnoticed. Furthermore, changing levels of carcinogens could explain increases and decreases in cancer mortality.

Concerning race, there are two possible ways race can affect cancer mortality. First, inherited genetic factors can predispose people of different races to specific cancers. Second, racial disparities in factors such as income and health care access can affect cancer incidence, gestation and mortality. While genetic factors can have either a positive or negative impact on cancer mortality, racial disparities should only increase cancer mortality. The ACS indicates that African-Americans have higher rates of colon, rectal, pancreatic, prostate, and breast cancer incidence and mortality. The results of this research suggest that a larger African-American community results in lower mortality for colon, rectal, breast, and ovarian cancers. This is largely inconsistent with the ACS. The results are only consistent with respect to pancreatic cancer. The ACS indicates that individuals of Hispanic descent are less prone to skin, prostate, and breast cancer. My results are consistent with Hispanic disposition to skin cancer, but not any other cancer.

The percent female population has been found to be insignificant for all cancers except for colon cancer. It is also insignificant for cancers that affect predominantly one sex (prostate, breast, and ovarian). These findings are both inconsistent with the medical community. However, there is not much variation in this variable across states, and results based off of these findings may be unfounded.

The percent urban population is only significant for rectal and total cancer mortality. Its positive sign suggests that urban populations are more susceptible to rectal cancer. The literature has largely indicated that an urban-rural cancer mortality gap does not exist (Shugarman, et al.; 2008). These results are mostly consistent with these findings, except the fact that total cancer mortality is highly significant while most of the specific mortalities are insignificant is puzzling.

The effect of a blue-collar labor force on cancer mortality is inconclusive; some mortalities increase, while others decrease. However, this can be due to different cancer risk factors rather than an incorrectly specified regression equation. The results suggest blue-collar workers are more prone to pancreatic and lung cancer while less prone to breast, ovarian, and prostate cancers. The positive coefficient for lung cancer is expected since blue-collar workers often smoke more than the general population. They are also exposed more to lower quality air at work.

Colon and skin cancer mortality increase while lung cancer decreases with more agricultural workers. Constantly working outside may expose agricultural workers to higher levels of UV radiation, thus increasing their risk of skin cancer. However, their constant exposure to fresh air and proper pesticide precautions may decrease their risk for lung cancer.

Household health insurance also has inconsistent results. Theory predicts that health insurance coverage reduces all types of cancer mortality. The results for breast and ovarian cancer are consistent with this theory, but lung and prostate cancers are inconsistent. Greater health insurance coverage for women (Bhandari, 2006) can explain this gender gap in mortality rates. It is also possible that people live longer in states with greater health coverage, thus raising the possibility that someone will die from lung or prostate cancer.

VIII. Conclusion

This study shows that some specific cancer mortalities are procyclical. That is, the percentage of people who die from certain cancers falls as unemployment rises. The effects of unemployment on total cancer mortality are largely insignificant, and thus consistent with previous research. Significant relationships between unemployment and the various mortality rates indicate that studying total cancer mortality instead of its individual components can be misleading. The various cancers' differing risk factors and gestation periods make them entirely different diseases.

These results suggest that a one-percentage point increase in unemployment will result in about 2,600 and 3,500 fewer deaths nationwide from colon and lung cancers, respectively in the following years. These results suggest that cancer mortality is significantly more dependent on lifestyle factors than previous economic research has suggested. While economists and the general public believe that cancer is largely controlled by factors beyond their control, the medical community has long known of cancer's significant lifestyle risk factors.

Although cancer mortality decreases during recessions, this does not justify tampering with unemployment rates to alter cancer mortality. Unemployment has many other negative consequences that justify its amelioration. Furthermore, the long run effects of sustained unemployment on cancer mortality are unknown. Theory suggests that a permanent decrease in output would increase cancer mortality through the income effect. The policy implications of this research suggest that decoupling healthy lifestyle habits and medical care from time and accessibility constraints would improve public health in the U.S.

Instead of considering cancer solely as an exogenous factor, further analyses should focus on cancer as a product of individual genetic and lifestyle factors. Previous research has established that unemployment's health effects depend on how individuals respond to their employment status. While individuals may live healthier in the U.S. during economic contractions, Svensson (2007) finds that Swedes lose more weight, have better diets and lower blood pressure during economic booms. Further research should investigate the factors that cause differing unemployment effects and whether these cancer mortality trends also exist for other countries. Future research should also investigate whether individual time constraints impact health care utilization in other modern nations and why unemployment affects lifestyles differently.

After the 2001 recession, the U.S. economy entered another expansionary phase lasting 73 months. In December 2007, the U.S. economy entered another prolonged recession. During the last 18 months, unemployment levels have risen rapidly. Considering this paper's findings, falling cancer mortality rates may soon follow.

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Appendix

Appendix A: Simple correlation coefficients between variables

	Logged Annual State Unemployment	% Age 65+	Doctors per 1,000	% Blue Collar Workers	% Urban Population	% Black	% Hispanic	% Female	% Agriculture Workers	% Household Health Insurance Coverage
Logged Annual State Unemployment	1.0000									
% Age 65+	-0.2232*	1.0000								
Doctors per 1,000	-0.1749*	0.0929*	1.0000							
% Blue Collar Workers	0.3058*	-0.1190*	-0.3473*	1.0000						
% Urban Population	0.0458	-0.0096	0.3872*	-0.3073*	1.0000					
% Black	0.1853*	-0.0465	0.1010*	0.0436	0.2194*	1.0000				
% Hispanic	0.1582*	-0.1712*	0.0625	-0.2200*	0.2596*	-0.0200	1.0000			
% Female	0.1574*	0.2741*	-0.0029	0.0047	0.2089*	0.4850*	-0.0327	1.0000		
% Agriculture Workers	-0.1050*	0.1850*	-0.2678*	0.0595	-0.6683*	-0.3375*	-0.1729*	-0.3435*	1.0000	
% Household Health Insurance Coverage	0.4981*	-0.1955*	-0.1531*	-0.0695	-0.0870	0.3006*	0.5233*	0.1320*	-0.1273*	1.0000

Note: The simple correlation matrix indicates statistically significant multicollinearity. However, many significant coefficients are relatively low.
Key: * significant at 1%

Appendix B

Colon Cancer	1a	1b	1c	1d
% Age 65+	0.043***	0.062***	0.068***	0.071***
	(0.01)	(0.01)	(0.01)	(0.01)
Doctors per 1,000	-0.007**	-0.006*	-0.006*	-0.006*
	(0.00)	(0.00)	(0.00)	(0.00)
% Blue Collar Workers	0.694*	-0.106	-0.321	-0.297
	(0.38)	(0.36)	(0.37)	(0.37)
% Urban Population	0.351	0.119	0.043	0.022
	(0.22)	(0.24)	(0.24)	(0.24)
% Black	-1.004***	-1.115***	-1.115***	-0.999***
	(0.30)	(0.30)	(0.29)	(0.30)
% Hispanic	-0.224	-0.089	0.03	0.084
	(0.18)	(0.18)	(0.18)	(0.18)
% Female	2.083***	2.400***	2.436***	2.556***
	(0.70)	(0.71)	(0.70)	(0.70)
% Agriculture Workers	1.259*	1.315**	1.446**	1.664***
	(0.71)	(0.63)	(0.62)	(0.61)
% Household Health Insurance Coverage	-0.303**	-0.108	-0.152	-0.179
	(0.13)	(0.14)	(0.14)	(0.14)
Year	-0.003*	-0.009***	-0.011***	-0.012***
	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment at time t	-0.058**	-0.052*	-0.058**	-0.063**
	(0.03)	(0.03)	(0.03)	(0.03)
Unemployment at time t-1		0.045	-0.024	-0.025
		(0.04)	(0.04)	(0.04)
Unemployment at time t-2		-0.179***	-0.016	-0.064
		(0.04)	(0.05)	(0.06)
Unemployment at time t-3			-0.145***	-0.033
			(0.04)	(0.06)
Unemployment at time t-4				-0.093**
				(0.04)
Unemployment at time t-5				
Unemployment at time t-6				
Constant	7.824**	20.166***	23.691***	25.022***
	(3.85)	(3.91)	(4.21)	(4.21)
Observations	765	765	765	765
Number of state	51	51	51	51
R^2	0.8808	0.8898	0.8924	0.8934
Adj-R^2	0.8705	0.8799	0.8826	0.8835

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Rectal Cancer	2a	2b	2c
% Age 65+	0.151***	0.156***	0.153***
	(0.02)	(0.03)	(0.03)
Doctors per 1,000	-0.014**	-0.013**	-0.013*
	(0.01)	(0.01)	(0.01)
% Blue Collar Workers	-0.659	-0.836	-0.582
	(0.73)	(0.74)	(0.77)
% Urban Population	1.174**	1.098**	1.083**
	(0.47)	(0.48)	(0.48)
% Black	-2.555***	-2.601***	-2.562***
	(0.86)	(0.86)	(0.83)
% Hispanic	-0.298	-0.294	-0.109
	(0.35)	(0.34)	(0.35)
% Female	-0.598	-0.544	-0.54
	(1.25)	(1.24)	(1.23)
% Agriculture Workers	-1.767	-1.835	-1.131
	(1.62)	(1.61)	(1.62)
% Household Health Insurance Coverage	-0.125	-0.031	-0.056
	(0.25)	(0.27)	(0.27)
Year	-0.006	-0.007*	-0.010**
	(0.00)	(0.00)	(0.00)
Unemployment at time t	-0.053	0.027	-0.03
	(0.04)	(0.06)	(0.06)
Unemployment at time t-1		-0.13	-0.091
		(0.09)	(0.09)
Unemployment at time t-2		0.037	0.007
		(0.07)	(0.09)
Unemployment at time t-3			-0.054
			(0.10)
Unemployment at time t-4			0.082
			(0.10)
Unemployment at time t-5			0.047
			(0.09)
Unemployment at time t-6			-0.161***
			(0.06)
Constant	10.633	12.875	19.380**
	(7.64)	(8.44)	(8.95)
Observations	765	765	765
Number of state	51	51	51
R^2	0.7170	0.7181	0.7229
Adj-R^2	0.6924	0.6928	0.6963

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Pancreatic Cancer	3a	3b	3c
% Age 65+	0.078***	0.085***	0.090***
	(0.01)	(0.01)	(0.01)
Doctors per 1,000	0.004	0.005	0.005
	(0.00)	(0.00)	(0.00)
% Blue Collar Workers	0.961**	0.679	0.453
	(0.48)	(0.49)	(0.50)
% Urban Population	0.335	0.233	0.19
	(0.27)	(0.27)	(0.28)
% Black	0.827**	0.770**	0.758*
	(0.38)	(0.39)	(0.40)
% Hispanic	-0.282	-0.256	-0.195
	(0.18)	(0.18)	(0.19)
% Female	-0.19	-0.092	0.013
	(0.83)	(0.83)	(0.83)
% Agriculture Workers	0.684	0.637	0.725
	(0.76)	(0.75)	(0.75)
% Household Health Insurance Coverage	-0.233	-0.123	-0.113
	(0.16)	(0.17)	(0.16)
Year	0.009***	0.007***	0.005*
	(0.00)	(0.00)	(0.00)
Unemployment at time t	-0.032	0.035	-0.034
	(0.03)	(0.04)	(0.04)
Unemployment at time t-1		-0.099**	0.038
		(0.05)	(0.06)
Unemployment at time t-2			-0.119**
			(0.05)
Unemployment at time t-3			
Unemployment at time t-4			
Unemployment at time t-5			
Unemployment at time t-6			
Constant	-17.335***	-13.376**	-9.472
	(5.19)	(5.47)	(5.77)
Observations	765	765	765
Number of state	51	51	51
R^2	0.7773	0.7799	0.7824
Adj-R^2	0.7580	0.7605	0.7628

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Lung Cancer	4a	4b	4c
% Age 65+	0.039***	0.054***	0.058***
	(0.01)	(0.01)	(0.01)
Doctors per 1,000	0.001	0.002	0.002
	(0.00)	(0.00)	(0.00)
% Blue Collar Workers	0.570**	-0.025	-0.173
	(0.29)	(0.28)	(0.29)
% Urban Population	0.126	-0.044	-0.096
	(0.17)	(0.20)	(0.20)
% Black	-0.257	-0.338*	-0.337*
	(0.17)	(0.20)	(0.20)
% Hispanic	-0.755***	-0.653***	-0.571***
	(0.12)	(0.12)	(0.12)
% Female	-0.011	0.226	0.251
	(0.51)	(0.52)	(0.53)
% Agriculture Workers	-1.880***	-1.833***	-1.742***
	(0.58)	(0.50)	(0.48)
% Household Health Insurance Coverage	0.133	0.275***	0.244***
	(0.09)	(0.10)	(0.09)
Year	0.003*	-0.002	-0.003*
	(0.00)	(0.00)	(0.00)
Unemployment at time t	0.012	0.012	0.008
	(0.02)	(0.02)	(0.02)
Unemployment at time t-1		0.043	-0.006
		(0.03)	(0.03)
Unemployment at time t-2		-0.138***	-0.025
		(0.03)	(0.04)
Unemployment at time t-3			-0.100***
			(0.03)
Unemployment at time t-4			
Unemployment at time t-5			
Unemployment at time t-6			
Constant	-2.083	7.116**	9.557***
	(3.00)	(3.05)	(3.15)
Observations	765	765	765
Number of state	51	51	51
R^2	0.9357	0.9399	0.9410
Adj-R^2	0.9301	0.9345	0.9356

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Skin Cancer	5a	5b	5c
% Age 65+	-0.03	-0.021	-0.021
	(0.03)	(0.03)	(0.03)
Doctors per 1,000	-0.011	-0.011	-0.012
	(0.01)	(0.01)	(0.01)
% Blue Collar Workers	-0.078	-0.444	-0.516
	(0.92)	(0.88)	(0.89)
% Urban Population	-0.253	-0.358	-0.372
	(0.48)	(0.49)	(0.49)
% Black	-0.818	-0.868	-0.813
	(0.77)	(0.77)	(0.77)
% Hispanic	-1.461***	-1.399***	-1.317***
	(0.41)	(0.41)	(0.41)
% Female	1.97	2.118	2.179
	(1.55)	(1.57)	(1.58)
% Agriculture Workers	7.642***	7.685***	7.971***
	(2.64)	(2.62)	(2.64)
% Household Health Insurance Coverage	-0.558	-0.471	-0.511
	(0.37)	(0.40)	(0.40)
Year	0.019***	0.016***	0.015***
	(0.00)	(0.01)	(0.01)
Unemployment at time t	-0.001	-0.002	-0.019
	(0.04)	(0.07)	(0.07)
Unemployment at time t-1		0.027	0.01
		(0.10)	(0.10)
Unemployment at time t-2		-0.085	-0.015
		(0.07)	(0.11)
Unemployment at time t-3			-0.107
			(0.13)
Unemployment at time t-4			0.093
			(0.11)
Unemployment at time t-5			-0.074
			(0.06)
Unemployment at time t-6			
Constant	-36.928***	-31.283***	-28.128***
	(9.51)	(9.50)	(9.76)
Observations	764	764	764
Number of state	51	51	51
R^2	0.6660	0.6670	0.6678
Adj-R^2	0.6370	0.6370	0.6363

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Breast Cancer	6a	6b	6c
% Age 65+	0.070***	0.076***	0.076***
	(0.01)	(0.01)	(0.01)
Doctors per 1,000	-0.002	-0.002	-0.003
	(0.00)	(0.00)	(0.00)
% Blue Collar Workers	-0.650**	-0.895***	-0.948***
	(0.26)	(0.27)	(0.27)
% Urban Population	0.265	0.195	0.188
	(0.19)	(0.20)	(0.20)
% Black	-0.698***	-0.731***	-0.673***
	(0.24)	(0.23)	(0.23)
% Hispanic	-0.005	0.037	0.111
	(0.15)	(0.14)	(0.13)
% Female	0.233	0.331	0.39
	(0.47)	(0.46)	(0.46)
% Agriculture Workers	-1.073	-1.053	-0.766
	(0.68)	(0.70)	(0.70)
% Household Health Insurance Coverage	-0.259**	-0.202*	-0.238**
	(0.11)	(0.12)	(0.12)
Year	-0.015***	-0.017***	-0.018***
	(0.00)	(0.00)	(0.00)
Unemployment at time t	0.01	0.009	-0.008
	(0.02)	(0.02)	(0.02)
Unemployment at time t-1		0.018	0.007
		(0.04)	(0.03)
Unemployment at time t-2		-0.057**	0
		(0.03)	(0.04)
Unemployment at time t-3			-0.099**
			(0.04)
Unemployment at time t-4			0.099***
			(0.04)
Unemployment at time t-5			-0.079***
			(0.02)
Unemployment at time t-6			
Constant	32.061***	35.851***	38.801***
	(2.78)	(3.10)	(3.08)
Observations	765	765	765
Number of state	51	51	51
R^2	0.9147	0.9160	0.9179
Adj-R^2	0.9073	0.9085	0.9101

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Ovarian Cancer	7a	7b	7c
% Age 65+	0.049**	0.052**	0.054**
	(0.02)	(0.02)	(0.02)
Doctors per 1,000	-0.004	-0.004	-0.004
	(0.00)	(0.00)	(0.00)
% Blue Collar Workers	-0.813	-0.920*	-1.049**
	(0.50)	(0.52)	(0.51)
% Urban Population	0.022	-0.017	-0.041
	(0.37)	(0.38)	(0.38)
% Black	-1.129**	-1.150**	-1.157**
	(0.51)	(0.51)	(0.51)
% Hispanic	0.014	0.024	0.058
	(0.24)	(0.24)	(0.24)
% Female	-1.201	-1.164	-1.104
	(0.93)	(0.92)	(0.92)
% Agriculture Workers	-0.108	-0.126	-0.076
	(0.97)	(0.98)	(0.99)
% Household Health Insurance Coverage	-0.422**	-0.380*	-0.375*
	(0.20)	(0.21)	(0.21)
Year	0.002	0.001	0
	(0.00)	(0.00)	(0.00)
Unemployment at time t	0.066***	0.092***	0.053
	(0.02)	(0.04)	(0.04)
Unemployment at time t-1		-0.038	0.041
		(0.04)	(0.06)
Unemployment at time t-2			-0.068
			(0.04)
Unemployment at time t-3			
Unemployment at time t-4			
Unemployment at time t-5			
Unemployment at time t-6			
Constant	-1.939	-0.434	1.793
	(5.46)	(5.73)	(5.85)
Observations	765	765	765
Number of state	51	51	51
R^2	0.7474	0.7477	0.7485
Adj-R^2	0.7255	0.7254	0.7259

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Prostate Cancer	8a	8b	8c
% Age 65+	0.102***	0.106***	0.102***
	(0.02)	(0.02)	(0.02)
Doctors per 1,000	0.006	0.006	0.005
	(0.00)	(0.00)	(0.00)
% Blue Collar Workers	-0.929**	-1.090***	-1.107***
	(0.44)	(0.42)	(0.40)
% Urban Population	0.212	0.175	0.189
	(0.28)	(0.29)	(0.27)
% Black	-0.237	-0.251	-0.121
	(0.40)	(0.40)	(0.40)
% Hispanic	-0.384	-0.346	-0.239
	(0.27)	(0.27)	(0.26)
% Female	0.969	1.04	1.16
	(0.75)	(0.74)	(0.73)
% Agriculture Workers	-0.939	-0.895	-0.345
	(0.77)	(0.77)	(0.79)
% Household Health Insurance Coverage	0.444**	0.463**	0.404**
	(0.22)	(0.22)	(0.20)
Year	-0.015***	-0.016***	-0.018***
	(0.00)	(0.00)	(0.00)
Unemployment at time t	0.062**	0.032	-0.001
	(0.03)	(0.06)	(0.05)
Unemployment at time t-1		0.065	0.07
		(0.08)	(0.07)
Unemployment at time t-2		-0.067	-0.024
		(0.05)	(0.07)
Unemployment at time t-3			-0.126*
			(0.07)
Unemployment at time t-4			0.185***
			(0.07)
Unemployment at time t-5			-0.157***
			(0.05)
Unemployment at time t-6			
Constant	30.246***	32.915***	37.583***
	(6.16)	(6.01)	(5.34)
Observations	765	765	765
Number of state	51	51	51
R^2	0.8819	0.8825	0.8870
Adj-R^2	0.8717	0.8719	0.8763

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Bladder Cancer	9a	9b	9c
% Age 65+	0.053***	0.054***	0.055***
	(0.02)	(0.02)	(0.02)
Doctors per 1,000	-0.003	-0.003	-0.002
	(0.00)	(0.00)	(0.00)
% Blue Collar Workers	0.293	0.266	0.324
	(0.59)	(0.61)	(0.61)
% Urban Population	0.352	0.355	0.353
	(0.37)	(0.38)	(0.39)
% Black	-0.432	-0.427	-0.379
	(0.49)	(0.49)	(0.49)
% Hispanic	0.027	0.042	0.034
	(0.28)	(0.28)	(0.28)
% Female	0.32	0.338	0.384
	(1.07)	(1.08)	(1.09)
% Agriculture Workers	0.687	0.724	0.731
	(1.07)	(1.08)	(1.09)
% Household Health Insurance Coverage	0.049	0.033	0.036
	(0.20)	(0.21)	(0.20)
Year	0.009***	0.009***	0.009***
	(0.00)	(0.00)	(0.00)
Unemployment at time t	0.017	-0.017	-0.013
	(0.02)	(0.04)	(0.04)
Unemployment at time t-1		0.062	0.074
		(0.06)	(0.07)
Unemployment at time t-2		-0.039	-0.108
		(0.04)	(0.07)
Unemployment at time t-3			0.121
			(0.07)
Unemployment at time t-4			-0.094
			(0.07)
Unemployment at time t-5			0.03
			(0.04)
Unemployment at time t-6			
Constant	-17.671***	-17.046***	-17.759***
	(6.32)	(6.55)	(6.60)
Observations	765	765	765
Number of state	51	51	51
R^2	0.8322	0.8325	0.8330
Adj-R^2	0.8176	0.8174	0.8172

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Total Cancer	10a	10b	10c	10d
% Age 65+	0.059***	0.061***	0.063***	0.062***
	(0.00)	(0.00)	(0.00)	(0.00)
Doctors per 1,000	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
% Blue Collar Workers	-0.054	-0.153	-0.180*	-0.173
	(0.11)	(0.11)	(0.11)	(0.11)
% Urban Population	0.349***	0.320***	0.300***	0.306***
	(0.07)	(0.07)	(0.07)	(0.07)
% Black	-0.514***	-0.527***	-0.485***	-0.464***
	(0.10)	(0.09)	(0.09)	(0.09)
% Hispanic	-0.260***	-0.243***	-0.203***	-0.191***
	(0.06)	(0.05)	(0.05)	(0.05)
% Female	0.101	0.141	0.19	0.208
	(0.19)	(0.19)	(0.19)	(0.19)
% Agriculture Workers	-0.991***	-0.984***	-0.882***	-0.796***
	(0.18)	(0.18)	(0.18)	(0.18)
% Household Health Insurance Coverage	0.044	0.067	0.05	0.043
	(0.05)	(0.05)	(0.04)	(0.04)
Year	-0.001	-0.002**	-0.002***	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment at time t	-0.005	-0.005	-0.008	-0.013
	(0.01)	(0.01)	(0.01)	(0.01)
Unemployment at time t-1		0.007	-0.005	-0.001
		(0.02)	(0.02)	(0.02)
Unemployment at time t-2		-0.023*	-0.012	-0.013
		(0.01)	(0.02)	(0.02)
Unemployment at time t-3			0.016	0
			(0.02)	(0.02)
Unemployment at time t-4			-0.034***	-0.001
			(0.01)	(0.02)
Unemployment at time t-5				-0.027**
				(0.01)
Unemployment at time t-6				
Constant	6.592***	8.118***	9.199***	9.816***
	(1.47)	(1.55)	(1.49)	(1.48)
Observations	765	765	765	765
Number of state	51	51	51	51
R^2	0.9864	0.9867	0.9871	0.9873
Adj-R^2	0.9852	0.9855	0.9859	0.9861

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%