Unemployment and Health Behaviors:
An Individual-Level Longitudinal Analysis

Abstract: This study estimates the effect of unemployment on physical activity, obesity and smoking behavior by exploiting variation over time in the 2003-4 Medical Expenditure Panel Survey (MEPS). Within-individual fixed effect models demonstrate that a spell of unemployment *reduces* the probability of engaging in physical activity (Δ prob = -.12) relative to extended employment, but employment status has no appreciable effect on obesity or smoking. Robustness checks corroborate the main result and address endogeneity issues. The effect is primarily mediated in specific subgroups: workers under age 45, males and those in "blue collar" occupations. These findings differ from prior results which find a beneficial effect of *regional-level* unemployment on individual health behaviors. Nevertheless, calculations based on the estimates suggest that a subsidy to promote these behaviors in the unemployed population is probably not warranted.

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Introduction

Prevention has important implications for long-term health. Regular physical activity, frequently defined as rigorous activity sustained for at least 30 minutes three times per week or moderate activity sustained for at least 30 minutes five times per week, improves clinical outcomes in coronary heart disease, hypertension, diabetes, stroke, obesity, osteoporosis, mental health disorders and other chronic conditions.(CDC 1996) Avoiding obesity results in lower morbidity and mortality due to hypertension, diabetes, coronary heart disease (CHD), stroke, gallbladder disease, osteoarthritis, sleep apnea, respiratory problems, some cancers (endometrial, breast, prostate, and colon), pregnancy complications and psychological disorders (depression).(NIH 1998) Smoking is responsible for 90% of lung cancer deaths in the US and increases the risk of cardiovascular disease, respiratory disease, and other forms of cancers.(HHS 2004) While the epidemiological implications of prevention are relatively well-established, the economic determinants of these behaviors are not well understood. This dearth of information has led several recent publications to call for increased research focusing on the economics of prevention (Dunn, Andersen et al. 1998; Booth, Sallis et al. 2001; Philipson 2001; Cawley 2004; Sturm 2004; Sturm 2005; Yach 2006)

Understanding the determinants which influence decisions regarding prevention behavior is important for at least three reasons. First, health expenditures due to poor prevention are large. One analysis which relied on cost-of-illness estimates and attributable relative risk measures concludes that excess weight (both overweight and obesity) account for approximately nine percent of direct US health expenditures. (Finkelstein, Fiebelkorn et al. 2003) More recent preliminary evidence using instrumental variable techniques finds even larger estimates for obesity-related expenditures.(Meyerhoefer 2008) A separate cost-of-illness analysis estimates that 2.5 percent of direct health costs result from physical inactivity.(Colditz 1999)[1] A meta-analysis of smoking costs indicates that 6-14% of U.S. health expenditures result from smoking and evidence also points to significant costs due to early smoking-induced mortality.(Max 2001; Sloan 2004; Viscusi and Hersch 2008) Second, identifying the behavioral determinants of health-related behaviors allows for a more efficient policy response if warranted by an externality. Lastly, examining economic determinants helps corroborate theoretical linkages between

[1] While some of the obesity and physical activity expenditures may overlap since activity reduces obesity, recent epidemiological evidence suggests that some of the benefits resulting from physical activity such as improved cardiovascular functioning, affect health via pathways aside from weight reduction. [Blair, S. N. and T. S. Church (2004). "The fitness, obesity, and health equation - Is physical activity the common denominator?" Journal Of The American Medical Association **292**(10): 1232-1234.

economic conditions (income level, employment, etc.), health investment and health.(Grossman 1972; Grossman 2004)

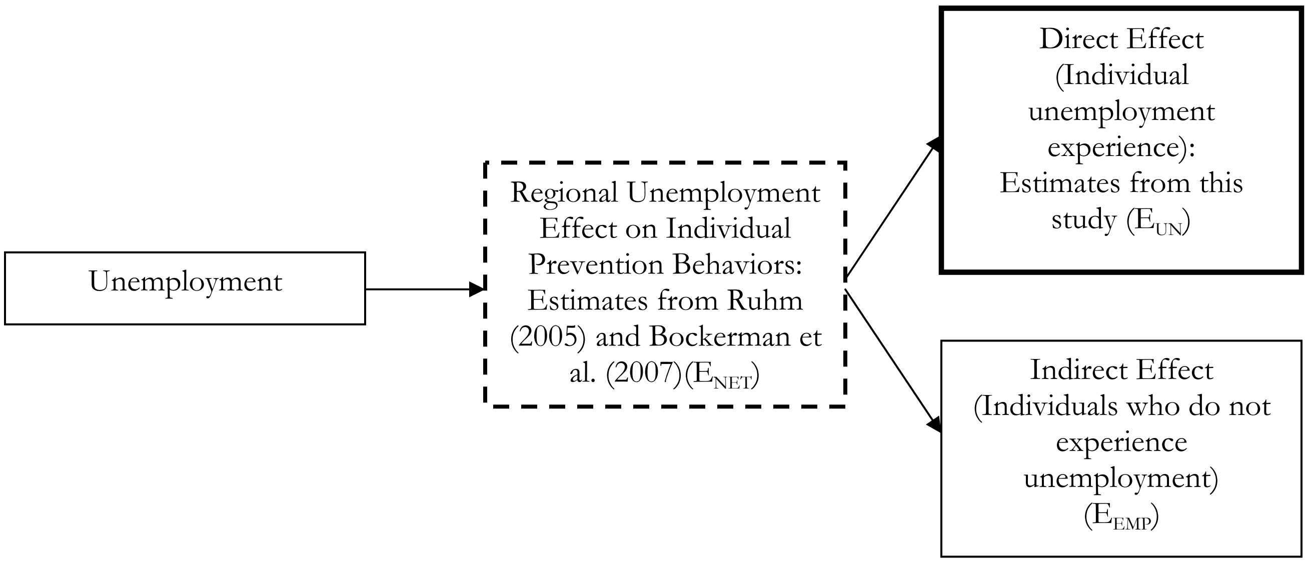
Two recent efforts investigate the effect of *regional* unemployment on individual health prevention behaviors, but the results conflict. A pooled cross-section analysis of the Behavioral Risk Factor Surveillance System (BRFSS) data from 1987 to 2000 in the US found that individual investments in prevention behaviors increase during temporary downturns in regional employment at the state level (Ruhm 2000; Ruhm 2005). However, recent findings from Finland which use a similar methodology and data set fail to detect this effect and, in some specifications, find the opposite result (Böckerman 2007). Both prior analyses used regional and temporal fixed effect (FE) specifications and relied on variation in the *regional* employment rate for identification. Ruhm's BRFSS analysis calculated employment elasticities and found that individuals adopted healthier behaviors when the regional employment rate declined. Elasticities relative to regional employment level were positive for smoking (+0.6), obesity (+0.4) and physical inactivity (+0.7) and the effects were most noticeable in those with the poorest prevention behaviors (2+ pack per day smokers, the severely obese or completely inactive individuals). Ruhm interprets these results as one of the potential explanations for the reduction in mortality and morbidity during regional economic downturns.(Ruhm 2000) However, the Finnish analysis, a potential confirmatory study which could have strengthened the generalizability of the US results, found no effect of employment level on BMI when both regional and year fixed effects were included in the model.[2]

The US and Finnish studies examine the effect of *regional-level* employment on prevention practices, but these studies do not follow the same individuals over time. The lack of individual-level longitudinal data precludes analysis of the individual's employment status on health behaviors. As indicated in Figure 1 and Equation 1, these studies estimate the aggregate effect of regional-level unemployment (E_{NET}). This estimate is composed of two separate effects 1) the effect on those that lose <u>jobs</u> (direct individual-level effect or E_{UN}) and 2) the effect on those who

[2] Since Ruhm includes year, month and time fixed effects in his analysis, the Bockerman et al. model with temporal and regional fixed effects is the most comparable result to the US analysis. Curiously, when Bockerman et al. relax either the year or region fixed effect, the elasticity between employment and obesity changes sign relative to Ruhm's analysis (it is significantly negative rather than positive). The inconsistency of results across countries may reflect differences in the underlying health status of the populations, relative homogeneity of populations or the different types of social programs instituted in both countries. For example, fewer Fins are severely obese, and as this is precisely the population where the effect on BMI was most extensive in the US context, one may reasonable expect that the effect of employment on BMI would be more muted in Finland. Social support and income redistribution policies may also change the affect that underlying macro-economic variables have on employment. The lower Gini coefficient, higher taxes and more significant redistribution in Scandinavia could also change the calculus of whether one adopts (or rejects) prevention activity during an unemployment spell.

do not experience a shift in their employment status, but may nevertheless suffer or gain from spillovers associated with an altered macroeconomic climate (indirect community-level effect on the employed population or E_{EMP}).

Figure 1
Aggregate, Direct and Indirect Effects of Unemployment on Health Behaviors



$$E_{NET} = \left(W_{UN} * E_{UN}\right) + \left(W_{EMP} * E_{EMP}\right) \qquad \text{Eq. 1}$$

Given that, even in recessions, unemployment usually occurs among less than 10 percent of the eligible workforce, the number of eligible workers without jobs is usually much smaller than the employed population ($W_{UN} << W_{EMP}$). Therefore, it is possible that a relatively minor effect on the employed population (E_{EMP}) could easily counterbalance the effects on the unemployed (E_{UN}) if there are differential effects between the two sub-populations. This study will estimate whether a spell of *individual* unemployment shifts prevention behaviors (E_{UN}). From a practical policy perspective, government benefits and programs focused on unemployment policy naturally are directed to those that lose their jobs so understanding the direct effects on this sub-population is appropriate[3].

[3] Even if there is an effect on individual behavior during unemployment other important criteria should be considered before implementing policy change in programs such as unemployment benefits. First, what are the short and long term health or cost implications of a temporary shift in prevention behaviors? This is a scientific question. Second, what is the nature of the externality? Lastly, will the costs or inefficiencies associated with programs to alleviate the externality be justified by the magnitude of expected social benefit?

Differences between the results presented here and the Ruhm findings may also reflect the alternative definitions of physical activity used in the separate analyses. The BRFSS focuses explicitly on "leisure time" physical activity—so activity mediated at work is not included. Naturally, this omission may be a potentially important factor in assessing the effects of unemployment on activity for those who are active at work. For example, an employed "blue collar" worker whose responsibilities include physical labor, but is not active outside of work, would be considered "inactive" in the BRFSS data. The MEPS questionnaire technically does not distinguish between activity at work, activity during leisure or activity at any other point—such as commuting by bicycle. This broader notion of activity may result in a different estimate of the effect of unemployment on physical activity relative to the BRFSS definition of physical activity. If active workers substitute leisure-time activity for work-based activity during a spell of unemployment, then the estimate relative to the more inclusive definition is biased upward.

I restrict the analysis to physical activity, weight status and smoking, since these indicators of prevention are more likely to respond in the short-run to employment shocks more so than other prevention decisions such as infrequent vaccinations. Finally, the analyses address the potential for endogeneity in three ways. First, the primary analyses focus on within-individual changes over time. This approach eliminates any concern that the estimated effect of unemployment on health behaviors simply represents unmeasured differences *across* individuals. Nevertheless, time-variant endogeneity within an individual (such as in the case when a health shock proceeds, or even leads to, a change in employment and activity by an individual) may bias the causal estimation of the effect of unemployment on behavior. This concern is addressed both directly by accounting for lagged health status and health conditions as covariates in some specifications and by examining sub-groups which are less likely to suffer from this bias. Lastly, the high frequency of employment data in this particular data source allows for examination of employment patterns *prior* to periods in which prevention behavior is recorded – hence the effects that are found are more likely causal (as opposed to the case in which data is only collected simultaneously for both employment and prevention).

I conclude that those individuals who actually stop working *reduce* their physical activity ($E_{UN\text{-}PA} < 0$, Δ prob [physical activity] = -.12), but do not appear to change weight status or smoking behavior appreciably ($E_{UN\text{-}BMI}=0$, $E_{UN\text{-}SM}=0$). Subgroup analyses suggest that much of the effect on physical activity is mediated in the males, those under 45 and "blue collar" workers. This paper finds there is no behavioral "dividend" associated with unemployment for those that actually lose their jobs—perhaps since the broader definition of physical activity in the MEPS includes activity during work or leisure time. Nevertheless, a calculation which relies on the parameters from this study and other estimates in the literature suggests that, even under the most extreme assumptions, the size of the health externality induced by the behavioral change during unemployment is relatively modest.

Theory

Prior research highlights reduced time cost as the fundamental reason explaining shifts in health behaviors during a spell of unemployment. The main prediction, at least in regards to time-intensive physical activity, contends that activity investments increase during unemployment. These frameworks and conclusions are limited in three ways. First, there is little discussion in regards to how the direct effect of lower income impacts activities during an unemployment spell. Reduced income is particularly important for health-related consumption behaviors such as eating and smoking. Second, other time uses compete for the hours which previously were directed to work. Activities such as job search and home production may limit the effects of reduced income during a spell of unemployment and potentially offer a more attractive time investment than time-intensive prevention behaviors—thereby obviating the conclusion that physical activity unequivocally increases during unemployment. Lastly, health behaviors occur jointly (Cawley 2004).

My model, a static variant of Grossman's health capital model (Grossman 1972), addresses each of these lacunae. First, it directly accounts for both income and substitution effects (lower income, more time). Second the model jointly investigates multiple health behaviors (physical activity, obesity and smoking). Finally it proposes different forms of time investment. The model generates comparative statics for the response of physical activity, caloric intake and smoking to an exogenous shift in wages (unemployment may be thought of as an extreme case in which work time and wages fall to zero). Future extensions may adopt a dynamic approach, but the relatively short run nature of unemployment lends itself to static framework.

As detailed in the appendix, the basic construction of model is as follows: First, consider utility as a function of consumption (Z) and health (H).

$$U = U(H, Z)$$

The production of health (H) stems from both the underlying level of health capital and the rate at which one's health stock gets converted into healthy days.[4] The model applies a constant conversation between health capital and healthy days. The determinants of health capital include the consumption of medical care (MC), time spent receiving medical care (T_{MC}), time directed toward physical activity (T_{PA}), the quality of food (Q_F , also indicative of price), goods consumption (X, including smoking) and time directed toward income replacement activities such as home production or job search (T_{IR}). Some types of consumption, X, may improve health while others detract or have no effect on health.

$$H = H(T_{PA}, T_{MC}, MC, Q_F, T_{IR}, X)$$

I define income replacement effort as activities which substitute for income during non-work hours. Examples include cooking, yard work or, if one extends the definition of income to include future income, job search. Home production may improve utility either through consumption or health.

Consumption (Z), the second major utility component, depends on a leisure time component (T_L) and the non-food physical goods or services consumed by the individual (X) and food consumption (F). Inputs into utility function rely on "bundles" of both temporal and monetary investment.

$$Z = Z(X, T_L, F)$$

Technically, the model differentiates between non-food and food consumption (X vs. F). In regard to food consumption, two choices are made in the model—food quality (reflected in price) and income replacement time investments such as home production (which is partially directed toward food preparation). In this case, I submit that health increases with higher quality (higher priced) food and greater home production. Food options exist along a continuum in which quality and price are correlated. Quality is characterized by the nutrient density of foods. Lower quality foods contain "excess calories" which do not satiate the consumer, but do contribute to weight gain (for example, products with few vitamins but are high in corn starch and fat, such as an Oreo). Consumers "select" their quality level along with time allotted to food preparation (a portion of T_{IR}) jointly.

$$F = F(T_{IR}, Q_F)$$

[4] Note that increases in healthy days may be valued for both A) production value (if directed toward labor time) or B) the psychic value of health. If individuals gave full weight to the production value of health, unemployment (wage=0) would result in cessation of all physical activity in a static model (a dynamic approach may recognize future benefit of current activity and result in a less drastic response)

In regards to medical care, the model adopts a fixed coefficients approach (exogenous constant (B) which defines the relationship between time directed to medical care and medical care utilization. Relaxing this constraint does not appreciably change the qualitative results found in the model.

$$MC = BT_{MC}$$

The primary constraints in the model are time and income. Time allocation categories include work (T_W), leisure, physical activity, medical care, sick time and income replacement. Note that sick time (T_S) reflects the health investment contributions of the individual.

$$T^* = T_W + T_L + T_{PA} + T_{MC} + T_{IR} + T_S$$

$$T_S = T_S(T_{PA}, T_{MC}, MC, P_F, T_{IR})$$

Income depends on non-wage income (I), wage level (W) and time devoted to work. Income is exhausted on medical care, consumption and food consumption (F). Prices for medical care (P_{MC}), food (P_F) and leisure goods or services (P_X) are exogenous. The constraints on time and income can be combined into one "total income" constraint. Individuals exhaust all resources in the model.

Constraint: $P_{MC}MC + P_X X + P_F F(T_{IR}) = I + WT_W$ where $T_W = T^* - T_L - T_{PA} - T_{MC} - T_{IR} - T_S$

Given the utility function and constraint, the resulting Legrangian results in seven first order conditions for each of the endogenous choice variables and the multiplier (T_{PA}, T_{MC}, T_L, T_{IR}, Q_F, X and λ):

$$Ł = U + \lambda[(WT_L + WT_{PA} + (W + BP_{MC})T_{MC} + WT_{IR} + WT_S + P_x X + P_F(Q_F)F(T_{IR})) - (I + WT^*)]$$

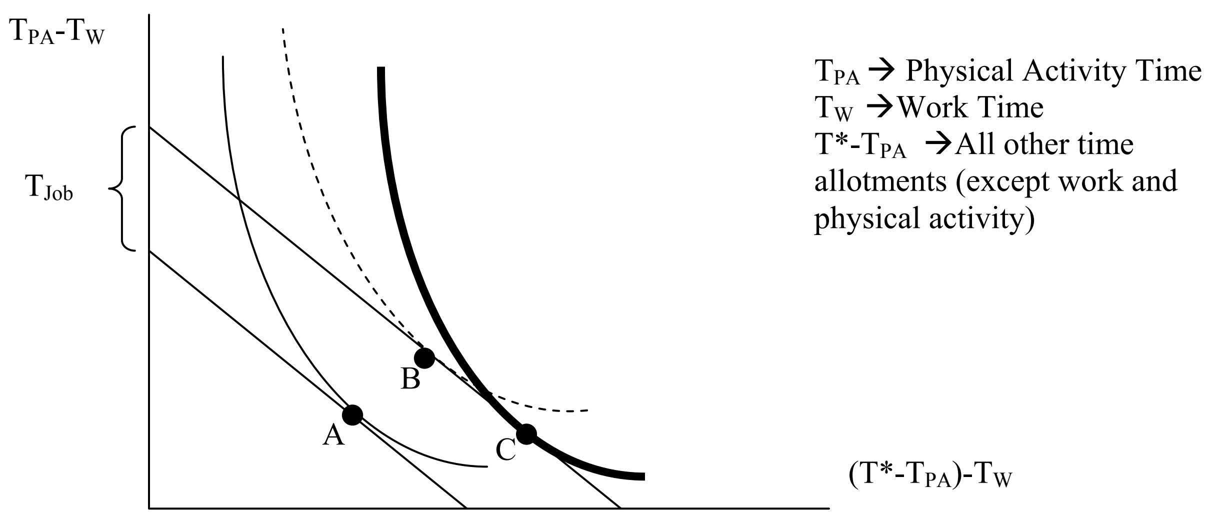
By assuming wage is exogenous and the utility function is additively separable (such that utility of cross partial derivatives equals zero), it is possible to sign the expected shift in physical activity, weight change and smoking (a form of consumption) relative to a reduction in wage. A negative (positive) sign suggests that these factors increase (decrease) as a result of unemployment (when wage and work time falls to 0). Details on the derivation of the comparative statics are provided in the appendix.

Physical Activity

Prior literature (Ruhm 2005) stresses that lower time costs after job loss increase time-intensive activities such as physical activity. [5] A model with limited time investment options (for example, no home production or food consumption variables) yields an unequivocal increase in physical activity during unemployment. (Keuffel 2008) However, in this model, even when wage drops to zero, the comparative static result is ambiguous. A key feature of the model which leads to ambiguity is the potential for substitution toward income replacement or home production which A) reduces available time for other activities (such as physical activity investments) and B) does not necessarily contribute to health. Hence, individuals can substitute non-active income replacement, home production or leisure time for physical activity during an unemployment spell. Figure 1 reflects the classic consumer theory graphic to represent how an expansion in non-work time associated with job loss potentially results in either an increase (A →B) or reduction (A→C) in physical activity depending on the nature of the indifference curve and underlying utility function.

<u>Figure 2</u>

Time Budget and Indifference Curves



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[5] Interestingly Ruhm (2005) examines leisure time physical activity as it is the only measure available in BRFSS dataset. The MEPS data examined here theoretically elicits physical activity independent of whether it occurs during work or leisure.

The comparative static analysis (Table A1 in the appendix, Figure 3) indicates that the effect of unemployment on physical activity investment is ambiguous. The ambiguous prediction reflects a tradeoff between simultaneous "total income" increase (via more time) and "total income" decline (via reduced wage income). If income effects dominate time effects, unemployment *reduces* physical activity investment as individuals shift time toward income replacement or home production activities to adjust for lost income.[6]

In the model, physical activity is purely a temporal investment. If physical activity also requires income-dependent monetary investments that are sensitive to shifts in income (e.g. gym membership, running shoes), the reduction in income due to job loss should result in even lower physical activity investment, ceteris paribus. In addition, an individual's environment does not shift as a result of a change in employment in the model. Evidence suggests that shifts in environment may influence prevention behaviors such as physical activity and weight. (Sallis, Bauman et al. 1998; Booth, Sallis et al. 2001; Chou, Grossman et al. 2004; Lee and Moudon 2004; TRB 2005; Wilkin, Mallam et al. 2006). However, given the short time frame of this analysis, migration is likely limited. Overall, the model indicates that valuing the cost of time during a spell of unemployment via wage alone is overly simplistic and the theoretical result is less clear than prior frameworks suggest.

H1.A: The theoretical effect of unemployment on physical activity is ambiguous. However, if unemployment motivates heavy investment into inactive income-replacement activities and home production as a way to address income decline, unemployment will result in a *reduction* in physical activity.

The degree to which individuals realign their time allotments during a spell of unemployment depends on the relative productivity of each time investment. While the theoretical model

[6] The countervailing effects that exogenous factors, such as the price of medical care (P_{MC}), have on $\partial T_{PA} / \partial Unemp$ underscores the basic intuition underlying the comparative static result (Appendix, Table A5). Higher prices for medical care (P_{MC}) accentuate the uptake of physical activity in the event of job loss since the decline in income motivates greater substitution toward time-focused activities that directly contribute to utility when alternative investments, such as medical care, cost more. In the case of P_{MC}, components two and four in Table A1 indicate this effect. However, given that effective price of medical care incorporates both a monetary component and a time component, the expansion of available time results in one component (component six, Table A1) which reduces $\partial T_{PA} / \partial Unemp$.

focuses on individual-level choices and behaviors, it is likely that characteristics of the home, such as family size or marital status, influence the relative productivity of investments into home production for an individual (and away from physical activity).(Ahn, Jimeno et al.)

H1.B: Married individuals will reduce physical activity more dramatically during unemployment spells than single individuals due to economies of scale in home production. Larger families have an ambiguous effect on activity incentives since home production activities may benefit a larger number of individuals, but these tasks also may get distributed across other family members.

Obesity

In this model, weight choice hinges on time-dependent and income-dependent inputs. The individual makes two choices related to caloric intake (F)—A) food quality (as indicated by higher food price for higher quality, nutrient-dense food types) and B) time allotted to home production (which includes activities such as cooking and allows for healthier home food preparation). Increases in food price/quality and home production result in improved (lower) caloric intake (F). I assume that reductions in caloric intake improves health as the vast majority of the US population is not underweight and would not medically suffer from marginally reduced culinary consumption. The results from the comparative statics analysis (Time for Home Production:Table A2; Food Quality: Table A3) suggests that the income shock reduces the capacity to purchase high quality food (particularly if one's competing medical expenditures are high) and may lead to an increase in BMI and obesity, but the lower cost of time likely also results in a greater allocation of time toward home production (reducing weight). On net, caloric intake likely decreases during an unemployment spell. If the assumed positive correlation between food quality and price is relaxed unemployment decreases BMI to a greater degree than proposed in the model.

H2: If the temporal shift toward home production improves diet more than the effects of a reduction in wage income detracts from nutrient quality of food, unemployment *reduces* caloric intake (F), BMI and the probability of obesity.

Smoking

In this model, smoking is a form of consumption. Some literature asserts unique product characteristics associated with smoking products (such as tolerance in the "rational addition" literature). Hence, purchasing behavior for smoking goods may differ relative to most products.(Becker and Murphy 1988) Nevertheless, smoking products do exhibit characteristics of normal goods--the extensive and intensive elasticity response of smoking to price, generally in the range of approximately -0.4, suggest that reductions in income decrease smoking.(Kenkel 2000). Smoking, as with other forms of consumption, accrues both time (T_L) and monetary cost ($X{*}P_X$). In the case of smoking, the expansion of one's time budget during a spell of unemployment likely has a limited effect on smoking behavior relative to the effect mediated by a reduction in income. Under this condition, unemployment *reduces* the propensity to smoke ($\partial \text{Smoke}/\partial \text{Unemp} < 0$).

H3: Assuming that income effects dominate time effects, unemployment *reduces* smoking behavior. However, as is the case with shifts in BMI, the process of adjustment may occur over a long duration.

Figure 3 summarizes the primary mechanisms and theoretical expectations suggested by the model.

Figure 3
Theory Expectations

Behavior	Time or Income Intensive	Effects of Unemployment on Behavior	Theory Mechanism	Theory Expectation
Physical Activity	Time	↑ Time: Increase PA (Effect A)	Low Cost of Time (Wage=0) leads to a greater investment in time intensive activity	Effect B > Effect A $\frac{\partial PA}{\partial Unemp} < 0$
		↓ Income: Decrease PA (Effect B)	Incentive to allocate time toward non-active income replacement (T_{IR}) to replace current income or generate future income	
Obesity	Time / Income	↑ Time: Decrease BMI (Effect C)	Increased investment in T_{IR} (including cooking) reduces net caloric intake	Effect C > Effect D $\frac{\partial BMI}{\partial Unemp} < 0$
		↓Income: Increase BMI (Effect D)	Decreased income shifts consumption toward lower cost, lower quality foods with poorer nutrient density (Oreos)	
Smoking	Income	↑ Time: No Effect	None	Effect E $\frac{\partial Smoke}{\partial Unemp} < 0$
		↓Income: Reduced WTP for smoking products (Effect E)	Smoking products are normal goods--reduce consumption	

Data

The Medical Expenditure Panel Survey (MEPS) is a nationally representative survey conducted by the Agency for Healthcare Research and Quality (AHRQ) which collects panel data on health services spending, health insurance, demographics, employment, economic, health status, and other characteristics of survey respondents. MEPS includes a household component (HC) which tracks these data among individuals in households (or residential units) via computer assisted personal interviews (CAPI). Each panel of individuals is followed over a two-year period. Panel 8, conducted during the 2003 and 2004 MEPS surveys, serves as the primary sample for the analyses. Figure 4 shows the timing of questions for respondents in Panel 8 by round and indicates when prevention questions and employment questions were asked. Employment was tracked in each round while physical activity and obesity status (BMI) were determined in rounds three and five. Smoking is collected in rounds two and four.

<u>Figure 4</u>

MEPS Panel Data 2003/2004

<table>
<tr><td colspan="3">2003</td><td colspan="2">2004</td></tr>
<tr><td colspan="5">All rounds: Employment, Health Status, Wages/Income, Insurance, Marital Status</td></tr>
<tr><td><u>Round 1</u></td><td><u>Round 2</u>
Smoking</td><td><u>Round 3</u>
PA/BMI
Health Conditions</td><td><u>Round 4</u>
Smoking</td><td><u>Round 5</u>
PA/BMI
Health Conditions</td></tr>
<tr><td colspan="5">Retrospective interviews occur at the end of each round.
Employment status is recorded in each interview round.
PA and BMI are recorded in rounds three and five. Smoking is recorded in rounds two and four</td></tr>
</table>

Sample

9,045 residential units, a nationally representative sub-sample of the households responding to the 2002 National Health Interview Survey (NHIS), were selected for inclusion in MEPS Panel 8. At the residential unit level, the overall response rate for Panel 8 through Round 5 was 63 percent. MEPS queries all individuals within a household or residential unit. At the individual level, 12,207 Panel 8 respondents were in scope. After eliminating the elderly (>65) and youth (<18), 10,145 individuals remain. As the analyses will primarily focus on the effects on the employed population, the primary sample will include only those reporting employment in at least one of the five rounds in MEPS. This restriction reduces the sample to 8,252 individuals, although most of the specifications restrict the sample further to focus the comparison on particular types of shifts in employment patterns. Relative to the US population, the sample has a higher minority share due to intentional oversampling[7].

MEPS provides sample weights for each individual based on the multi-level stratification strategy and non-response rates. Specifically, person-level weights adjust for non-response over time and ensure that resulting estimates are consistent with Current Population Survey (CPS) population estimates based on six different variables (race/ethnicity, sex, age, poverty status, region [4 regions] and MSA status[Y/N]). Hence, descriptive analyses of a cross section of the data, such as estimated means, are sensitive to weighting and are appropriately weighted given strata, sampling unit and inverse probability weights (Deaton 1997; Machlin 2005). In the case of multivariate analyses examining causal relationships, unweighted regressions are consistent and more efficient so long as the factors upon which weighting occurs are exogenous within the model under consideration as is the case here (Wooldridge 2002; O'Donnell 2008). As most of the regressions are fixed or random effects estimations that examine *within* individual behavior keeping these factors constant, regressions will generally not require weighting.

Dependent Variables

The three outcomes measures are physical activity, obesity and smoking. MEPS records self-reported physical activity in binary fashion (Yes/No). Specifically the interview asks "do you currently spend half hour or more in moderate to vigorous physical activity at least three times a week". Note that the question does not specify whether this activity occurs at work, during home production, at leisure or as a consequence of transportation choice (walking, cycling). This reduces the concern that individuals answer only in reference to leisure-time physical activity—a common weakness of other surveys. The definition of physical activity in the questions maps fairly closely onto the definition used by the Centers for Disease Control and Prevention (CDC). According to the CDC moderate physical activity constitutes actions such as walking, gardening, bowling and doubles tennis at least 3 times per week for 20+ minutes per session. Similarly vigorous activity includes jogging, lifting weights and other activities which require extensive effort 3+ times per week for 20+ minutes.

As indicated in Table 1, 57 percent of the sample were active in Round 3 (Row 2 total share) and 58 percent were active in Round 5 (Column 2 total share). However, significant

[7] Some of the summary statistics which are disaggregated by year may have slightly larger sample sizes as some individuals participated in the just one year, but not both.

within-individual variation exists as just under a third of the sample changed their activity pattern between the two time periods.

There is no measure of caloric intake or net caloric intake in MEPS, but weight (adjusted for height) is reported. Obesity has an objective definition in accordance with the CDC guidelines -- any adult with a body mass index[8] over 30 is obese. The BMI calculation relies on self-reported weight and height. Table 2 indicates that in both periods, approximately 28% of the population reported obese status (Total for row 2 and column 2). Eleven percent of the individuals shifted into or out of obesity between the two reporting periods. Hence, I anticipate that finding significant results in the multivariate analyses is less likely when examining obesity given the limited variation in the outcome. Continuous BMI serves as an alternative outcome measure in sensitivity analyses. Current smoking behavior exhibits even stronger persistence, perhaps reflecting the addictive nature of cigarettes and nicotine.

In some studies of self-reported health behavior variables, concerns with biased reporting arise and motivate researchers to readjust estimations by comparing self-reported estimates to "gold standard" objective data to account for misclassification bias.(Burkhauser and Cawley 2008) Note, however, that the effects of misclassification bias are likely diminished in this study since most of the analyses examine within individual shifts over time. To the extent that individuals do not shift their reporting bias between periods, individual fixed and random effects results retain a higher level of validity than analyses relying on cross-sectional methods.

Table 1
Physical Activity Status during 2003/4
Sample: Panel 8, Adults Age 18-64, Employed at least one round
[Frequencies in brackets]

	Active (Rd 5)	Not Active (Rd 5)	Total
Active (Rd 3)	n=3,249 [.42]	n= 1,133 [.15]	n= 4,382 [.57]
Active (Rd 3)	n= 1,171 [.15]	n= 2,120 [.28]	n= 3,291 [.43]
Total	n=5,097 [.58]	n= 4,171 [.42]	n= 7,673 [1.00]

[8] BMI=kilograms/meter^2

Table 2
Obesity Status during 2003/4
Sample: Panel 8, Adults Age 18-64, Employed at least one round
[Frequencies in brackets]

	Not Obese (Rd 5)	Obese (Rd 5)	Total
Not Obese (Rd 3)	n=5,037 [.68]	n=415 [.06]	n=5,452 [.73]
Obese (Rd 3)	n=343 [.05]	n=1,635 [.22]	n= 1,978 [.27]
Total	n= 5,380 [.72]	n= 2,050 [.28]	n= 7,430 [1.00]

Table 3
Smoking Status[9] during 2003/4
Sample: Panel 8, Adults Age 18-64, Employed at least one round
[Frequencies in brackets]

	Non-Smoker (Rd 5)	Smoker (Rd 5)	Total
Non-Smoker (Rd 3)	n=4,686 [0.73]	n=186 [.03]	n=4,872 [.76]
Smoker (Rd 3)	n=225 [.04]	n=1,316 [.21]	n=1,541 [.24]
Total	n= 4,911 [.77]	n= 1,502 [.23]	n=6,413 [1.00]

Independent Variables

The primary explanatory variable of interest, employment, was collected at the end of each round of MEPS. Employment characterization transitions occur with regularity. Approximately 10% of the sample shifts employment status between round 3 and round 5 as indicated in Table 4. This is important since the within-individual changes in the employment characterization between years will provide the variation for identifying how unemployment effects prevention behavior. "Active workers" are the sample of interest. I define these as individuals reporting employment in at least one of the five rounds of MEPS.

[9] Note that smoking status was captured only as part of a survey sub-sample. As a result the total sample size is smaller than for the other two outcomes.

Table 4
Employment Status
Sample: Panel 8, Adults Age 18-64, Employed at least one round
[Frequencies in brackets]

	Unemployed (Rd 5)	Employed (Rd 5)	Total
Unemployed (Rd 3)	n=219 [.03]	n=378[.05]	n=597 [.08]
Employed (Rd 3)	n=412 [.05]	n=6,740 [.87]	n=7,152 [.92]
Total	n=631 [.08]	n=7,118 [.92]	n=7,749 [1.00]

Since employment is collected in each of the five rounds, it is possible to examine multiple periods to identify whether the individual's employment (or unemployment) spell lasts more than one period. Four primary characterizations of employment status are implemented in the study. "Long run employment" (LR employment) signifies employment for two or more MEPS rounds (including current reporting period) and "short run employment" (SR employment) indicates that the individual became employed at some point during the current round. Short run and long run unemployment are similarly defined. Table 5 disaggregates employment status for round 3 (2003) and round 5 (2004) for the primary sample.

Table 5
Duration of Employment Status
Sample: Panel 8, Adults Age 18-64, Employed at least one round
[Frequencies in brackets]

Employment Status	Duration of Employment Status	2003 (Rd 3)	2004 (Rd 5)
Employed	Short Run	n=282 [.03]	n=194 [.02]
	Long Run	n=7,232 [.89]	n=7,007 [.89]
Unemployed	Short Run	n=301 [.04]	n=251 [.03]
	Long Run	n=321 [.04]	n=378 [.05]
Total		n=8,136 [1.00]	n=7,830 [1.00]

Short Run = Current round only (1 round); Long Run = At least current and prior round (2 or more rounds)

In the econometric models, I use a variety of unemployment dummy variables to compare different types of shifts in employment status. In the base case, the outcome variable equals one if the individual has been unemployed for two or more periods in the current round and zero if the individual has been employed for two or more periods (Table 5). This specification allows for comparison after an equilibrium has been established. Several different alternative combinations are examined to see if the results change over different time horizons. In addition, some models use continuous or categorical measure of the extent of employment, specifically hours/week (continuous) and unemployed / part time employment / full time employment (categorical) as a potential way to check robustness of the results.[10]

Additional covariates posited to affect prevention decisions include health condition dummy variables measured in MEPS (activities of daily living deficits, angina, arthritis, asthma, hypertension, cognitive deficits, diabetes, emphysema, hearing difficulty, joint condition, prior myocardial infarction and "other heart" conditions, social impairment, prior stroke, vision deficits and walking impairment)[11] and health status variables (general health status, mental health status—both decreasing with greater status 1=excellent 5=poor).[12] Note that for the smoking analyses, specific conditions are not included since these are captured in the round after smoking status is ascertained. Demographic covariates include age category dummies (18-29, 30-49, 50-64), education category dummies (< High School, High School, Some College, College, > College), ethnicity/race dummies (Asian, Black, Hispanic, Native American, Pacific Islander, multiple races), marital status indicator variables (single, married, widow, divorced) and gender. Insurance status and income are included in some specifications. The insurance measure indicates whether the individual had any health insurance in the current round (1-yes, 0-no). Income includes an exhaustive list of income sources: wages, unemployment benefits, business income, worker compensation, dividends, sales, pensions, social security, rental/trust income, veterans' income, IRA income, alimony, refunds, child support, cash contributions, SSI, public assistance and other income. Income is reported in units of $1,000s and standardized to 2004 dollars using the Consumer Price Index.(Bureau of Labor Statistics 2008)

[10] In practice, most individuals cluster on or around 40 hours per week so there was limited ability to detect "dose-response" effects of either a continuous measure or a categorical measure of employment relative to the discrete characterization of employed vs. unemployed status.

[11] Given the potential for co-linearity, especially in the health condition variables, some specifications use summary variables which aggregate conditions with high correlation coefficients (>.80). For example, a dichotomous "cardiac condition" variable which is defined as '1' if the individual currently has any of the following conditions: Angina, Prior MI, "Other Heart Condition" or congestive heart failure (CHF). Similarly "sensory deprivation" is defined as 1 for those with either serious sight or aural deficiencies. Variable aggregation may sharpen the estimation and results in theory, but in practice little difference occurred as a result.

[12] The time-variant covariates synchronize with the outcome variable times. For example, in the smoking regressions, time-variant covariates from rounds 2 and 4 are used while the physical activity and obesity regressions rely on time-variant covariates from rounds 3 and 5.

Given the role of income in the theory model, I examine several potential measures in the for income econometric specifications. [13] At the individual level, annual income is self-reported in the data. As a shock in consumption due to a reduction in individual wages may be offset by family income, total family income and total family income per capita (not shown) are included. Table 6 summarizes potential measures. Nonlinear effects are accounted for using quadratic and logged values of income measures.

Table 6
Income Measures ($US, 2004)

Concept	Measure
Annual Income (Individual)	AI=Self-reported annual wage income
Family Annual Income (Family)	$FAI=\sum_{i=1}^{I} AI_i$; I=Number of working family members
Family Annual Income Per Person (Family)	FAIPP=FAI/N; N=Number of family members

[13] In some alternative specifications the model uses wage measures rather than income measures.

Table 7
Covariate Summary 2003/4 MEPS Sample
[Sample: MEPS Panel 8, Adults Age 18-64, Employed at least one round 2003/4]

Variable	Variable Measure	2003			2004		
		n	Mean	Stan.Dev.	n	mean	Stan.Dev.
Employment – Round 1	1-Yes 0-No	8,009	0.89	0.32	--	--	--
Employment – Round 2	1-Yes 0-No	8,140	0.93	0.26	--	--	--
Employment – Round 3	1-Yes 0-No	8,243	0.92	0.27	7,777	0.88	0.32
Employment – Round 4	1-Yes 0-No	--	--	--	7,776	0.93	0.26
Employment – Round 5	1-Yes 0-No	--	--	--	7,757	0.92	0.27
ADL limitation	1-Yes 0-No	8,249	0.002	0.05	7,742	0.00	0.06
Angina	1-Yes 0-No	8,201	0.01	0.07	7,733	0.01	0.09
Arthritis	1-Yes 0-No	8,178	0.12	0.32	7,709	0.13	0.33
Asthma	1-Yes 0-No	8,210	0.08	0.28	7,733	0.08	0.28
Hypertension	1-Yes 0-No	8,192	0.15	0.36	7,718	0.16	0.37
Cardiac Condition	1-Yes 0-No	8,205	0.04	0.21	7,735	0.04	0.21
Cognitive Impairment	1-Yes 0-No	8,218	0.02	0.13	7,754	0.02	0.13
Diabetes	1-Yes 0-No	8,211	0.04	0.19	7,734	0.04	0.20
Emphysema	1-Yes 0-No	8,208	0.00	0.07	7,734	0.01	0.07
Hearing Impaired	1-Yes 0-No	8,144	0.00	0.06	7,780	0.00	0.07
Joint Pain	1-Yes 0-No	8,183	0.28	0.45	7,710	0.27	0.45
Prior Heart Attach	1-Yes 0-No	8,203	0.01	0.10	7,734	0.01	0.10
Other Heart Condition	1-Yes 0-No	8,199	0.03	0.17	7,729	0.03	0.17
Sensory Deprivation	1-Yes 0-No	8,148	0.01	0.11	7,780	0.01	0.11
Social Impairment	1-Yes 0-No	8,247	0.02	0.14	7,760	0.02	0.14
Prior Stroke	1-Yes 0-No	8,209	0.01	0.08	7,735	0.01	0.09
Vision Impairment	1-Yes 0-No	8,139	0.01	0.09	7,779	0.01	0.09
Walking Impairment	1-Yes 0-No	8,233	0.05	0.23	7,748	0.05	0.22
Health Status	1-Excellent, 5-Poor	8,239	2.23	0.99	7,710	2.23	0.97
Mental Health Status	1-Excellent, 5-Poor	8,239	1.95	0.93	7,709	1.99	0.93
Age 18-29	1-Yes 0-No	8,252	0.29	0.46	--	--	--
Age 30-44	1-Yes 0-No	8,252	0.38	0.48	--	--	--
Age 45-64	1-Yes 0-No	8,252	0.33	0.47	--	--	--
Asian	1-Yes 0-No	8,252	0.05	0.21	--	--	--
Black	1-Yes 0-No	8,252	0.14	0.35	--	--	--
Hispanic	1-Yes 0-No	8,252	0.24	0.43	--	--	--
Multiple Races	1-Yes 0-No	8,252	0.01	0.12	--	--	--
Native American	1-Yes 0-No	8,252	0.00	0.07	--	--	--
Pacific Islander	1-Yes 0-No	8,252	0.01	0.09	--	--	--
< High School	1-Yes 0-No	7,794	0.21	0.41	--	--	--
High School	1-Yes 0-No	7,794	0.32	0.47	--	--	--
Some College	1-Yes 0-No	7,794	0.23	0.42	--	--	--
College	1-Yes 0-No	7,794	0.14	0.35	--	--	--
> College	1-Yes 0-No	7,794	0.10	0.29	--	--	--
Divorced	1-Yes 0-No	8,244	0.13	0.34	7,719	0.14	0.35
Married	1-Yes 0-No	8,244	0.56	0.50	7,719	0.57	0.50
Single (Never Married)	1-Yes 0-No	8,244	0.29	0.46	7,719	0.28	0.45
Widow	1-Yes 0-No	8,244	0.02	0.13	7,719	0.02	0.12
Male	1-Yes 0-No	8,252	0.50	0.50	--	--	--
Income	$1000's (2004 Dollars)	8,252	31.2	29.1	7,720	32.6	29.8
Wages [14]	$1000's (2004 Dollars)	8,252	28.8	27.4	7,720	30.1	28.4
Health Insurance	1-Yes 0-No	8,252	0.75	0.44	7,720	0.74	0.44

Time invariant variables are shaded

[14] Within the "working sample" for each year; 7,839 reported wages for 2003 and 7,525 reported wages for 2004.

Methods

Econometric Models

An OLS model with individual fixed effects usurps the panel structure of the data to estimate the effect of an unemployment spell on the probability of physical activity, obesity or smoking. Specifically, the basic model is:

$$\left(Y_{it} - \overline{Y_i}\right) = \beta\left(x_{it} - \overline{x_i}\right) + \lambda\left(unemp_{it} - \overline{unemp_i}\right) + \varepsilon_{it}$$

where Y_{it} represents the outcome value, $unemp_{it}$ signals employment status, X_{it} is a vector of control variables and ε_{it} is the normally distributed error term. These variables have time (t) and individual (i) indexes. The coefficient of interest, λ, is interpreted as the change in the probability of the outcome associated with a shift in employment status. Robust standard errors are calculated to account for heteroscedasticity.[15] Models only rely on balanced panel data (individuals who contribute in both years of the panel survey). Given the dichotomous nature of the outcome variables, a fixed effect conditional logit model provides estimates which verify that the linearity assumption in the OLS context do not appreciably bias the estimates.(Wooldridge 2002) The logit models, however, only rely on those cases in which the outcome variable shifts over time and limits the likelihood of finding significant effects relative to the OLS approach. Marginal effects for the logit models are calculated at the covariate mean values with the fixed effects set to zero. The conditional logit fixed effect model is as follows:

$$\Pr[(0,1) \mid (0,1) \text{ or } (1,0)] = \frac{A}{A+1}$$

$$A = \exp[\beta(x_{i2} - x_{i1}) + \lambda(emp_{i2} - emp_{i1})]$$

Probit, logit and OLS random effect models (generally not shown) are also run, but given that assumptions regarding normality of the individual random effect term are likely violated, the fixed effects results are presented.[16] Analyses were conducted using Stata 10 software.

The regressions incorporate control variables such as income measures, insurance status, number of children, health status (in some cases), health condition variables and marital status. Fixed effect regressions do not estimate time-invariant controls that may affect health investment decisions such as demographics or educational attainment[17]. Given the theoretical focus on time and monetary components of "total income" the inclusion of income as a control has important

[15] The logit FE and RE models are not estimated with robust standard errors in Stata 10.
[16] Hausman tests also usually reject that the fixed effect and random effect models are similar.
[17] Educational attainment is only measured as of the beginning of round one in MEPS respondents.

implications for the interpretation of the λ coefficient as a measure of the effect mediated via the shock to time. Various measures of income are utilized to account for potential family-level dynamics or smoothing across individuals.

Lastly, a range of different types of unemployment and employment conditions are examined by shifting the definition of what constitutes a "spell" of unemployment and a "spell" of employment. The base case scenario compares within individuals changes in behavior if one has been unemployed for at least two periods relative to extended employment for at least two periods. These comparisons help distinguish the effects of short run vs. long run unemployment relative to short run and long run employment.

Identification Strategy

In each of the model specifications, the key identification assumption asserts that the error term is uncorrelated with either the control or employment covariates. Qualitatively, if omitted variable bias, simultaneity or reverse causation occur within the context of the model, then the results will suffer from bias. As indicated earlier, the first line of defense against endogeneity is the use of within-individual analysis over time to eliminate the effect of any unmeasured individual level time-invariant characteristics. Second, some of the remaining time-variant phenomenon are picked up using covariates. Lastly robustness checks which restrict the sample alleviate concerns that particular mechanisms affect the results. For example, consider an omitted variable bias scenario in which an unmeasured shock to an individual's health jointly affects both the ability to partake in prevention such as physical activity and employment status. Two primary robustness checks at least partially address this concern: A) Regressions on sub-samples which exclude individuals who are awarded workers compensation at any point and B) Regressions which exclude individuals who miss work due to conditions listed in the linked MEPS conditions file (an expansive array of diseases and conditions). Both of these checks aim to run analyses on "cleaner" sub-samples which are less likely to suffer from omitted variable bias. In cases of workers compensation (Check A), it is likely that the injury preceded the change in employment status so eliminating these cases is appropriate. In practice, relatively few individuals receive workers compensation, so this specification may retain some individuals whose health condition or injury impacted their ability to work productively and their health behaviors (especially physical activity). The second robustness check (Check B) offers a more comprehensive way to address this concern, but this approach is likely to also eliminate some individuals who do not become unemployed as a result of their health shock. In order to temper this effect I attempt to isolate those cases which report a condition or injury one round prior to an employment shift. For each round data exits for 1) whether an individual suffered a condition which resulted in a loss of work days 2) whether this particular condition also necessitated significant medical utilization (which I define as requiring one or more of the following: at least 1 condition-related hospital stay, at least 1 emergency room visit, 3 or more office visits or 3 or more outpatient visits). Elimination of individuals whose sickness spell precedes a shift in employment status aids in obviating omitted variable bias as an explanation for results (especially in the physical activity case).

Reverse causation considerations: Health Conditions, Health Status and Income

While primary emphasis to address endogeneity focuses on the relationship between unemployment (the variable of interest) and health-related behaviors, other potentially endogenous relationships related to control covariates in the model may provoke concern. One potential endogenous mechanism is reverse causation. Even after excluding the possibility of time-invariant characteristics via fixed and random effects, some argue that physical activity, obesity or smoking influence health or health status, rather than vice versa. This is not a major concern in this context for two reasons. First, health behaviors affect health over a long period of time (generally the effects accumulate over years or decades), but this study examines a relatively short time window (2 years). Some of the alternative specifications include lagged health status since theory contends that individuals invest in prevention behavior on the basis of their stock of health capital (proxied by health status). The use of a lag in the case of health status mitigates some endogeneity concerns. Over the long run health behaviors certainly impact health status, but in this relatively short-run context, it is more likely that decisions to participate in health prevention behaviors are guided by health status or health rather than the other way around. Smoking may suffer from reverse causation more so than the other two outcomes since some health risks, such as cardiac risk, respond relatively quickly to changes in smoking behavior.(Lightwood and Glantz 1997) Nevertheless, the majority of the diseases associated with smoking usually take decades to fully develop. For those who dismiss this temporal argument, finding similar estimates for the unemployment coefficient (λ) in models which exclude lagged health status or health condition covariates should quell endogeneity concerns.

Quality of life literature suggests that impact of health behaviors on perceived health status (or health related quality of life estimates) is moderated via an indirect link (lower morbidity). Based on cross-sectional analyses, evaluations of health status or health related quality of life (HRQL) respond to obesity status, but generally via health conditions such as those accounted for in the health conditions covariates.(Hassan, Joshi et al. 2003) Some evidence points to a direct effect, but these examples focus on dramatic weight reductions, such as those which result from bariatric surgery usually directed toward the morbidly obese-still a relatively small share of the population.(Fontaine and Barofsky 2001) Cross-sectional estimation using the BRFSS data link physical activity with improved health related quality of life scores, but these analyses are descriptive.(Brown, Balluz et al. 2003).

There is some evidence that health behaviors affect wages and income. Prior literature detects wage penalties for smoking and obesity, but, to my knowledge, no work has examined the effects of physical activity on wage. (Levine, Gustafson et al. 1995; van Ours 2004; Auld 2005; Bhattacharya 2005). As was the case with health status and health conditions, if the adjustment process for penalizing wages occurs over a long time frame for inactive or obese individuals and smokers, then the validity of models which include wage or income as covariates strengthens. Also, at least in regards to obesity, the wage effect appears confined to women. Hence, if the male sub-analysis in the obesity outcome regressions yields similar results to the women's case, the endogeneity concern dissipates, at least for the obesity models. The empirical model also assumes that health insurance and marital status do not shift as a result of physical activity, obesity and smoking over a relatively short time frame.

Results

Unadjusted analyses

Preliminary cross tabulations indicate that currently employed individuals are more likely to participate in physical activity (58% vs. 43%, $p<.01$). When the sample is restricted to only those that participate in the job market at least once during the two year period (the sample for multivariate analyses), the margin narrows, but remains significant (58% vs. 53%, $p=.03$)

Table 9
Cross-Tabulation of Employment Status and Physical Activity 2003
Sample: Panel 8, Adults Age 18-64
[Frequencies in brackets]

	Active (Rd 3)	Inactive (Rd 3)	Total	Active Share
Employed (Rd 3)	n= 4,357 [.44]	n= 3,187[.31]	n= 7,544 [.75]	.58
Unemployed (Rd 3)	n= 1,071 [.11]	n=1,394 [.14]	n= 2,465 [.25]	.43
Total	n= 5,428 [.55]	n=4,581 [.46]	n= 10,009 [1.00]	.54

Pearson Chi^2=153.2, p<.01

Table 10
Employment Status and Physical Activity 2003
Sample: Panel 8, Adults Age 18-64, Employed in at least one period
[Frequencies in brackets]

	Active	Inactive	Total	Active Share
Employed (Rd 3)	n= 4,357 [.53]	n= 3,187[.39]	n= 7,544 [.92]	.58
Unemployed (Rd 3)	n= 333 [.04]	n=292 [.04]	n= 625 [.08]	.53
Total	n= 4,690 [.57]	n=4,581 [.43]	n= 8,169 [1.00]	.57

Pearson Chi^2=4.72, p=.03

In reference to obesity, a similar cross-tab analysis using analogous samples finds a difference in obesity among workers vs. unemployed (26% vs. 32%, p<.01), but the difference is driven by those outside of the workforce. The comparison of employed vs. currently unemployed workers finds no significant difference in obesity (26% vs. 27%, p=.54). Unadjusted analyses for smoking behavior indicate that smoking occurs *more* commonly among the unemployed (27% vs. 23%, p<.01). The next section will explore whether these relationships hold up after adjustment.

Multivariate Analyses

Tables 11-13 present the results for a linear probability models for the three outcome variables using the worker sample. Most models use individual level fixed effects, but the random effects model using the base case covariates is also represented in the last column of each table.

In the case of physical activity, the coefficient for unemployment in the base case (Table 11, Model 1) indicates that long run unemployment *decreases* the probability of physical activity relative to long run employment (-.12; p<.05). Given a mean physical activity probability of .58 conditional upon employment, this effect represents a 21% percentage point reduction in activity. The direction, magnitude and significance of the unemployment coefficient result remains robust across several alternate fixed effect specifications (Models 2-6), albeit with slightly smaller effect sizes.[18] This key result is consistent with the overall theoretical expectation (H1.A). However, higher income appears to *decrease* the probability of physical activity. This result is indicated by a significantly negative coefficient on log income controls in Models 1-4. When income is removed from the regression (Model 5) the unemployment coefficient falls from -.12 to -.07, presumably since both the effects of time and income are absorbed by the unemployment coefficient in this instance. At first blush, this finding counters the expectations in regard to the specific mechanisms driving changes in physical activity (Figure 3) which posit an increase due to greater available time and a decrease due to lower income. Although the opposite appear to occur—recall that interactions between (increased) available time and (decreased) income may be the crucial factor which drives behavior and the income coefficients are estimated using both the unemployed and the employed sample. A model which includes an interaction term (not shown) between unemployment and income results in a positive coefficient. This result does suggest that, conditional on unemployment, higher income results in more physical activity and supports the specific theoretical mechanisms proffered in Figure 3.

Employment status has no statistical effect on obesity in either the base case model (Table 13, Model 1) or a range of alternate specifications (Models 2-6). The negative sign of the unemployment coefficient follows the theoretical expectation (H2.A), but the limited magnitude is consistent with a model in which countervailing effects of greater time for food-related health investment (Figure 3, Effect C) and lower income resulting in the purchase of lower quality, nutrient-poor foods (Figure 3, Effect D) basically offset during a spell of unemployment. Regressions using overweight status (BMI>25) and continuous BMI do not yield significant results. As shifts in BMI are cumulative, it is also possible that the data window is too short to capture the longer-run effects of unemployment on weight.

Consistent with the theory expectation anticipating reduced smoking (H3), the unemployment coefficient for smoking is small in magnitude and insignificant across all models

[18] The inclusion of individual fixed effects has a substantive impact on the coefficient value. Without fixed effects the base case physical activity outcome regression (Model 1) equals -.06, about half the size of the fixed effect estimate.

(Table 13). None of the fixed effect models suggest that income (either individual or family level) affects smoking (after accounting for unemployment status).

Table 11: Physical Activity Determinants
OLS Fixed Effect Regression Results (Robust Standard Errors)
Sample: Panel 8, Adults Age 18-64, Employed in at least one period

Variable Set	Variable(s)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Unemployment	Unemployment (LR) vs. Employment (LR)	-.12*** [.04]	-.09*** [.03]	-.09*** [.03]	-.12*** [.04]	-.07** [.03]	-.08*** [.03]
Annual Income (2004)	Log Individual Inc.	-.01* [.005]	--	--	-.01** [.005]	--	-.003 [.004]
	Log Family Inc.	--	-.02** [.01]	--	--	--	--
	Log Family/Cap Inc.	--	--	-.02* [.01]	--	--	--
Insurance	Insurance (Current Round -Any	-.01 [.02]	-.01 [.02]	-.01 [.02]	-.01 [.02]	-.01 [.03]	.01 [.01]
Children	Child age dummy variables	χ^2=3.5 (p<.01)	χ^2=3.6 (p<.01)	χ^2=3.5 (p<.01)	χ^2=3.4 (p<.01)	χ^2=3.5 (p<.01)	χ^2=19.0 (p<.01)
Health Status Variables	Health Status (prior round)	--	--	--	χ^2 =1.1 (p=.36)	--	--
	Mental Health Status (prior round)	--	--	--	χ^2 =1.5 (p=.19)	--	--
Health Conditions	Health Condition dummy variables	χ^2=1.2 (p=.29)	χ^2 =1.1 (p=.32)	χ^2 =1.1 (p=.34)	χ^2=1.2 (p=.29)	χ^2=1.1 (p=.33)	χ^2=64.5 (p<.01)
Marital Status Variables	Single, Divorced Married, Widowed	χ^2 =.17 (p=.92)	χ^2 =.21 (p=.89)	χ^2 =.19 (p=.91)	χ^2 =.20 (p=.90)	χ^2=.18 (p=.91)	χ^2=18 (p<.01)
Sample Size		n=6,507	n=6,507	n=6,507	n=6,507	n=6,507	n=6,507
Regression Type		FE	FE	FE	FE	FE	RE
Rho		.53	.54	.54	.54	.54	.38

Health Status is a categorical variable (1-Excellent 2-Very Good 3-Good 4-Fair 5-Poor) and entered as four discrete variables when used. Rho is the variance in the outcome attributable to individual level variation. This balanced panel estimation captures two time points from each individual. The fixed effects model (Model 1) is structurally similar to the random effect model (Model 6) from a technical standpoint, but the p-value is relatively close to rejecting their congruence (p=.08)--I adopt the more conservative fixed effect model. In cases where income is entered using the absolute and squared term the income effect is not significant according to the joint f-test, but the unemployment coefficient retains significance and has a similar magnitude. The individual fixed effect has a substantive impact on the physical activity estimates—increasing the coefficient from -.06[.03, p=.05] to -.12 [.04,p<.01].

Table 12: Obesity Determinants
OLS Fixed Effect Regression Results (Robust Standard Errors)
Sample: Panel 8, Adults Age 18-64, Employed in at least one period

Variable Set	Variable(s)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Unemployment	Unemployment (LR) vs. Employment (LR)	-.01 [.02]	-.01 [.02]	-.01 [.02]	-.01 [.02]	-.02 [.02]	-.01 [.02]
Annual Income (2004)	Log Individual Inc.	.001 [.002]	--	--	.002 [.003]	--	.001 [.003]
	Log Family Inc.	--	.01** [.005]	--	--	--	--
	Log Family/Cap Inc.	--	--	.01** [.005]	--	--	--
Insurance	Insurance (Current Round -Any	.02 [.01]	.02 [.013]	.02 [.014]	.02 [.014]	.02 [.013]	.02* [.01]
Children (Any)	Child age dummy variables	χ^2=0.2 (p=.96)	χ^2=0.2 (p=.96)	χ^2=0.1 (p=.97)	χ^2=0.2 (p=.96)	χ^2=0.2 (p=.96)	χ^2=3.1 (p=.54)
Health Status Variables	Health Status (prior round)	--	--	--	χ^2 =1.1 (p=.36)	--	--
	Mental Health Status (prior round)	--	--	--	χ^2 =1.5 (p=.19)	--	--
Health Conditions	Health Condition dummy variables	χ^2=1.0 (p=.50)	χ^2 =0.9 (p=.53)	χ^2 =0.9 (p=.52)	χ^2=0.9 (p=.48)	χ^2=1.0 (p=.49)	χ^2=346.8 (p<.01)
Marital Status Variables	Single, Divorced Married, Widowed	χ^2 =1.7 (p=.16)	χ^2 =1.6 (p=.18)	χ^2 =1.8 (p=.15)	χ^2 =1.7 (p=.17)	χ^2 =1.7 (p=.16)	χ^2 =0.8 (p=.84)
Sample Size		n=6,290	n=6,290	n=6,290	n=6,286	n=6,290	n=6,290
Regression Type		FE	FE	FE	FE	FE	RE
Rho		.77	.78	.77	.77	.77	.72

Health status and mental health status are categorical variables (1-Excellent 2-Very Good 3-Good 4-Fair 5-Poor) and entered as four discrete variables in model 4. Similarly four dichotomous variables are entered for children of different ages (0-2, 3-5, 6-10, 11-17). The χ^2 statistic indicates the joint significance across all variables. Rho is the variance in the outcome attributable to individual level variation. This balanced panel estimation captures two time points from each individual. The fixed effects model (Model 1) is structurally different from the random effect model (Model 6). In cases where income is entered using the absolute and squared term the income effect is not significant according to the joint f-test on income terms—and the unemployment coefficient remains insignificant. The individual fixed effect has a limited effect on the model results, as analyses without and individual error term result in similar qualitative and quantitative results in regard to the employment effect.

Table 13: Smoking Determinants
OLS Fixed Effect Regression Results (Robust Standard Errors)
Sample: Panel 8, Adults Age 18-64, Employed in at least one period

Variable Set	Variable(s)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Unemployment	Unemployment (LR) vs. Employment (LR)	.001 [.02]	-.004 [.02]	-.001 [.02]	.002 [.02]	-.01 [.01]	-.01 [.02]
Annual Income (2004)	Log Individual Inc.	.001 [.002]	--	--	.001 [.002]	--	-.001 [.002]
	Log Family Inc.	--	.003 [.004]	--	--	--	--
	Log Family/Cap Inc.	--	--	.006 [.005]	--	--	--
Insurance	Insurance (Current Round -Any	-.004 [.01]	-.003 [.01]	-.004 [.01]	-.003 [.01]	.003 [.01]	-.03*** [.01]
Children (Any)	Child age dummy variables	χ^2=1.2 (p=.33)	χ^2=1.2 (p=.33)	χ^2=1.1 (p=.35)	χ^2=1.2 (p=.35)	χ^2=1.1 (p=.33)	χ^2=4.4 (p=.35)
Health Status Variables	Health Status (prior round)	--	--	--	χ^2=0.9 (p=.50)	--	--
	Mental Health Status (prior round)	--	--	--	χ^2=1.2 (p=.32)	--	--
Marital Status Variables	Single, Divorced Married, Widowed	χ^2 =8.3 (p<.01)	χ^2 =8.4 (p<.01)	χ^2 =8.4 (p<.01)	χ^2 =8.2 (p<.01)	χ^2=8.3 (p<.01)	χ^2 =67.8 (p<.01)
Sample Size		n=5,634	n=5,634	n=5,634	n=5,634	n=5,634	n=5,634
Regression Type		FE	FE	FE	FE	FE	RE
Rho		.84	.84	.84	.84	.84	.81

Health status and mental health status are categorical variables (1-Excellent 2-Very Good 3-Good 4-Fair 5-Poor) and entered as four discrete variables in model 4. Similarly four dichotomous variables are entered for children of different ages (0-2, 3-5, 6-10, 11-17). The χ^2 statistic indicates the joint significance across all variables. Rho is the variance in the outcome attributable to individual level variation. This balanced panel estimation captures two time points from each individual. The fixed effects model (Model 1) is structurally different from the random effect model (Model 6). The individual fixed effect has a limited effect on the model results, as analyses without and individual error term result in similar qualitative and quantitative results in regard to the employment effect.

Table 14: Non-linear Robustness Check – Baseline Model
Sample: Panel 8, Adults Age 18-64, Employed in at least one period

Covariate of Interest	Model	Outcome		
		Physical Activity	Obesity	Smoking
Unemployment dichotomous comparator variable (LR)	OLS Fixed Effects Model	-.12*** [.04]	-.01 [.02]	.001 [.02]
Unemployed (LR)=1 vs. Employed (LR)=0	Logit Fixed Effects Model	-.14*** [.04]	-.07 [.25]	+.08 [.48]

Coefficients represent marginal effects or changes in probability due to an extended unemployment spell relative to a period of extended employment. Standard errors are in brackets[SE]. Models contain the same covariates as those listed for Model 1 in Tables 11-13. Logit model estimators are initially reported as log odds ratios. The log odds are converted to marginal effects assuming the fixed effect equals 0 and the values of the other dependent variables are set at the mean (mfx command in STATA).

Non-linear Models

The qualitative results regarding employment status and prevention behaviors in the base case are robust--independent of whether linear or non-linear models are specified (Table 14). The closest analog to the OLS fixed effect specification is the logit fixed effect specification—a specification which results in similar quantitative and qualitative conclusions for each of the outcomes. After converting coefficients to marginal probabilities, the non-linear models produce slightly larger effects sizes than the OLS model—if anything the linear models appear to be conservative. Specifically the base case logit fixed effect model results in a marginal effect of unemployment relative to employment equal to -.14 (p<.01) as compared to -.12 (p<.01) in the OLS case. Probit, logit and OLS random effects model yields tighter standard errors and similar magnitudes across most coefficients, but these models are rejected by the Hausman tests.[19] Overall the results confirm that the linear probability models offer relatively sound coefficient values and significance levels. None of the alternative models yield a significant "unemployment effect" for either weight gain or smoking behavior.

[19] No FE analog was run in the probit case.

Temporal Adjustment to Unemployment

Table 15 summarizes how the extent of unemployment affects health behaviors. By adjusting the dummy variables to focus on particular samples, such as comparing behavior under long-run unemployment (2 or more periods) and long-run employment (2 or more periods), an interesting pattern emerges. Many of the sub-samples simply have a limited number of within-individual comparisons (6 potential comparisons exist) and yield insignificant results, but the overall reduction in physical activity appear to occur after long-run unemployment—as confirmed in the base case. There are a few mildly significant results which suggest individuals cut back on smoking consumption during unemployment relative to employment (ΔProb [smoke] = -.02, p<.10) but much of the effect occurs among individuals with volatile employment pattern (those with a spell of long run unemployment and short run employment; ΔProb = -.07, p<.10). This pattern may be consistent with seasonal laborers who are particularly sensitive to income effects on consumption when not earning income. No significant temporal patterns were found between employment and obesity across any of the temporal comparisons.

Table 15

Employment Status Duration and Health Behaviors
OLS Fixed Effect Regression Results (Robust Standard Errors)
Sample: Panel 8, Adults Age 18-64, Employed in at least one period

Employment Status Comparison	Outcome		
	Physical Activity	Obesity	Smoking
Unemployed (LR only) vs. Employed (LR only)	-.12*** [.04]	-.01 [.02]	-.0005 [.02]
Unemployed (SR only) vs. Employed (LR only)	-.004 [.03]	.0002 [.02]	-.01 [.02]
Unemployed (LR only) vs. Employed (SR only)	.08 [.08]	.02 [.05]	-.07* [.04]
Unemployed (SR only) vs. Employed (SR only)	-.08 [.10]	-.03 [.06]	.002 [.05]
Unemployed (SR or LR) vs. Employed (SR or LR)	-.05 [.02]	-.003 [.01]	-.02* [.01]

[1]SR=short run (e.g. SR unemployment = unemployed in current round, employed in prior round); LR=long run (e.g. LR unemployment = unemployed in both current and prior round) Additional are those listed in column Model 1 for tables 11-13.. *p<.10,* *p<.05, ***p<.01

Robustness Checks for Omitted Variable Bias

Regressions using sub-samples which are unlikely to be contaminated with omitted variables produce similar or even slightly larger effects than the base case specification (Table 17). In order to limit concern that the results stem from spurious correlations with an omitted variables (specifically unmeasured health effects which impact both employment and health behaviors simultaneously for a particular individual), anyone who received workers compensation at any point during the survey was removed (n=84). This exclusion did not affect the magnitude or the significance of the estimate for unemployment in the physical activity regression (nor the obesity or smoking outcomes for that matter). The confirmatory result is not surprising given the relatively small number of excluded individuals.

A more comprehensive characterization of "potentially biased individuals" for exclusion—those who missed <u>any</u> work at all due to sickness at any point during the survey (n=3,703) —results in a larger estimated magnitude for physical activity in the remaining sample (Sample 3: ΔProb = -.21). If the excluded individuals included some who stopped work and cut back on physical activity simultaneously, the new estimate from the "decontaminated" sample should shift from -.12 toward zero, but this is not the case. If the exclusion criteria becomes less strict—removing only those who individuals who missed work with an illness *which resulted in significant medical utilization* (hospital stay, ER visit or 3 or more MD visits)—a similar result occurs (Sample 4: ΔProb = -.18). Interenstingly, these result suggests that, conditional on unemployment, relatively healthy workers *reduce* their physical activity more after unemployment (or increase it more upon re-employment) than less healthy members of the workforce.

Undoubtedly, this definition for "potentially biased individuals" results in false negatives being excluded from the sample. A more targeted approach which excludes only individuals who either A) experience at least one sick day in the period prior to unemployment (n=43 exclusions) or B) experience at least one work sick day in the period prior to the unemployment for a condition which resulted in significant medical utilization (n=25 exclusions) does not yield very many exclusions. As a result the coefficient estimates for the remaining samples produce similar results as the base case scenario. Overall, these tests suggest that the initial estimation does not suffer from omitted variable bias and, if anything, understates the magnitude of the result.

Table 16: Robustness Checks Examining the Effect of Unemployment on Outcomes across Different Samples

Sample	Physical Activity Coefficient [SE]	Physical Activity n	Obesity Coefficient [SE]	Obesity n	Smoking Coefficient [SE]	Smoking n
Sample 1: Base Case Criteria	-.12*** [.04]	6,507	-.01 [.02]	6,290	-.0005 [.02]	5,634
Sample 2: Base Case Criteria + No workers compensation	-.12*** [.04]	6,423	-.02 [.02]	6,210	.002 [.02]	5,558
Sample 3: Base Case Criteria + No days work loss due to medical condition	-.21*** [.05]	2,804	-.03 [.03]	2,683	-.03 [.03]	2,374
Sample 4: Base Case Criteria + No days work loss due to medical condition with significant utilization	-.18*** [.03]	4,831	-.02 [.03]	4,657	.01 [.02]	4,160
Sample 5: Base Case Criteria + No days work loss due to medical condition in period prior to unemployment (if any)	-.13*** [.04]	6,464	-.01 [.02]	6,247	.01 [.02]	5,593
Sample 6: Base Case Criteria + No days work loss due to medical condition with significant utilization in period prior to unemployment (if any)	-.13*** [.04]	6,482	-.01 [.02]	6,265	.02 [.02]	5,609

Base Case Sample: Panel 8, Adults Age 18-64, Employed in at least one period. Models are fixed effect OLS regressions. Variable of interest, unemployment (long run), equals 1 if the individual is unemployed for two or more periods and 0 if the individual is employed for two or more periods.

Table 17: Effect of Unemployment across Different Sub-groups

Sub-group	Outcome					
	Physical Activity		Obesity		Smoking	
	Coefficient [SE]	n	Coefficient [SE]	n	Coefficient [SE]	n
All (Base Case)	-.12*** [.04]	6,507	-.01 [.02]	6,290	.0005 [.02]	5,634
Age 18-29	-.19*** [.06]	1,696	-.02 [.03]	1,646	-.005 [.04]	1,395
Age 30-44	-.15** [.06]	2,549	.002 [.04]	2,453	.02 [.03]	2,242
Age 45-64	-.05 [.07]	2,262	-.02 [.04]	2,191	-.02 [.03]	1,997
Men	-.26*** [.06]	3,329	-.03 [.04]	3,236	.005 [.03]	2,849
Women	-.02 [.05]	3,178	-.01 [.03]	3,054	-.002 [.02]	2,785
"Blue Collar" Occupational Code	-.21*** [.07]	1,937	-.09** [.05]	1,863	.01 [.04]	1,654
"White Collar" Occupational Code	-.09* [.04]	4,527	.01 [.03]	4,385	-.01 [.02]	3,938
Married	-.14** [.06]	3,952	-.02 [.04]	3,796	-.08*** [.03]	3,409
Single / Divorced / Widowed	-.14** [05]	2,803	-.02 [.03]	2,736	.04 [.03]	2,434

Base Case Sample: Panel 8, Adults Age 18-64, Employed in at least one period. Models are fixed effect OLS regressions. Variable of interest, unemployment (long run), equals 1 if the individual is unemployed for two or more periods and 0 if the individual is employed for two or more periods.

Sub-group Analyses

The effects of unemployment on health behaviors, particularly physical activity, are concentrated in segments of the population. Adults under 45, men and "blue collar" workers reduce physical activity after unemployment relative to those of different ages, gender and occupation categories.[20]

While all three categorical age groups reduce activity in response to unemployment, the effect in the oldest cohort is smaller and not statistically significant. This is a particularly interesting finding since the reason for unemployment in this cohort is more likely to be early retirement—so perhaps the implications for early retirement, a more voluntary form of detachment from the labor force, differ from more traditional involuntary reasons for unemployment.[21] The 18-29 group demonstrated a more pronounced reduction in physical activity (-.19, $p<.01$) relative to the 30-44 group (-.15, $p<.01$). Perhaps this pattern is consistent with more youthful individuals limiting their health investment since their health stock depreciation is lower and the opportunity costs of investment, conditional on unemployment, are relatively large. It is perhaps more prudent to spend time seeking out more work rather than focus on maintaining health at a younger age.

These results do not provide any evidence that marital status or family size has a differential effect on the decision to participate in health behaviors relative to employment status. The coefficient for married and unmarried individuals is equivalent when separate analyses are conducted for both groups. These results counter hypothesis H1.B which contends that the increased productivity of home production due to spillover benefits for other family members should be larger for couples or those with families.

The dichotomy between "blue collar" occupation categories and "white-collar" service workers in regards to physical activity decline (-.21 vs. -.09) suggests that one of the

[20] Note that the subgroup analyses are not conducted using interaction terms, but rather by running the regression on the appropriate sub-samples. Interaction terms formed from two variables with discrete outcomes were dropped from the regression analysis.
[21] I also hoped to examine whether the reason for unemployment affected the nature of the behavioral response. However, within the sample, a very high percentage did not indicate that the unemployment was involuntary in the self-reported question. Many responded with reasons such as "wanted to spend more time with family" when asked why they no longer were working (even among men). Interestingly, a significant share of these subsequently returned to work. As such, it was not clear if the self-reported answers accurately reflected whether the decision to leave work was voluntary or involuntary.

reasons why the decline occurs may be the nature of work. MEPS does not discriminate between physical activity at work vs. at home. Hence when laborers become unemployed, they may show a dramatic decline in physical activity simply since their work required physical activity. The approach in the theory section assumes that physical activity and work are independent activities, but this result suggests that future theory approaches and empirical work could reasonably account for the possibility that work and activity are jointly conducted in some cases.

Policy Implications

The primary finding in these analyses indicates that physical activity, unlike obesity or smoking, is significantly reduced by unemployment. Whether or not this shift has policy implications depends on a three factors. First, presumably the behavioral change represents a utility enhancement for the individual given their new jobless circumstance. If there is an externality that is not factored into the physical activity decision, then a policy response may be warranted. This condition is necessary, but not sufficient. Second, the persistence of individual behavior change influences the size of potential externality. If the rate at which individuals reduce their activity upon unemployment exceeds the rate at which they reengage in physical activity after regaining a job (all other factors equal), then the size of the externality (if there is one) increases over time—and both short and long run effects matter. Third, the potential intervention (such as programs to encourage activity) has to affect behavior for a cost less than the amount of the externality.

One potential externality stems from moral hazard for insured medical costs. If an individual does not bear the full cost of additional medical care due to inactivity (either in the short term, perhaps via their COBRA employer-sponsored insurance or in the long term, via Medicare), the difference is the value of the externality (so long as premiums do not increase in response to inactivity). Table 19 offers a rough approximation of the expected magnitude of the marginal medical costs due to a 1% increase in the unemployment rate (and the share covered by Medicare). The estimates rely on several assumptions outside the scope of this specific research effort, so interpret these magnitudes with caution. The marginal additional short run medical costs due to inactivity resulting from unemployment are $15 million at the population level – not much. If one assumes that the change in activity becomes permanent, then the marginal discounted medical costs increase to approximately $346 million and roughly a quarter of that occurs after age 65 (presumably during Medicare coverage).

One of the major assumptions in the table posits that the annual marginal medical costs due to inactivity are $167. This is calculated based on an attributable risk study which determined 2.5% of medical costs, or about $167 per person per annum, stem from physical inactivity.(Pratt, Macera et al. 2000) It is possible that the expenditures would likely be higher as the duration of inactivity increases and individuals age (and conversely the marginal effect is lower for younger or more recently active individuals). Also, given that the duration analysis (Table 16) only detected a significant effect after two periods of unemployment and the Bureau of Labor Statistics reports that about one-quarter of unemployed experience a jobless duration greater than six months-the table assumes only 22 percent of newly unemployed shift their activity pattern.

It is possible to test the persistence assumption in the data to estimate whether the long run costs are likely to occur. Evidence from alternative regressions suggest that the probability of adopting physical activity after regaining work exceeds the probability of ceasing physical activity upon job loss. The λ coefficient reflects a weighted average of the effect of two changes: A) the change in outcome as one becomes employed and B) the change in outcome as one becomes unemployed. If one of these processes is primarily responsible for the magnitude of the estimate, the policy implications may differ substantively. For example, a net negative coefficient could result if individuals do not change their behavior upon employment, but do reduce their behavior after losing work. In this case there exists an unemployment "penalty" which exceeds the magnitude of the overall coefficient, λ, especially since it is the case that the individuals who return to the workforce do not then change their behaviors (at least in this stylized example). If the converse is the case, then unemployment does not have a significant effect on health behaviors, but individuals increase activity upon re-employment. The latter appears in the data. When an indicator variable for the direction of unemployment (valued at one when becoming unemployed and zero otherwise) is interacted with the unemployment dummy variable to ferret out whether the process of becoming unemployed has a differential effect relative to gaining employment, the shift from employment to unemployment reduces physical activity by -.06 in the base case model. However, for those that regain employment physical activity increases by an estimated +.29. If income is removed from the model, the effect of unemployment is almost negligible (-.02) and the effect of re-employment is +.24. There is a slight "penalty" associated with losing one's job, but a large benefit to regaining employment.

While more information on the duration of effects using a longer panel of data would help to specify which measure most accurately values the marginal medical costs attributable to inactivity after unemployment increases, the upper bound estimate ($173 Mill.) which assumes long run persistence in behavioral effects of unemployment is probably excessively large and the short run cost figure ($7.6 Mill.) is a better estimate of the financial implications of health behavior change due to a one percent shift in unemployment. Yet even this may be an over estimate as not all of these costs, even in the short run, are necessarily externalities—out-of-pocket payments, co-pays and individual risk-rated premiums are absorbed by the individual. Behavioral change can be an expensive and, in some cases, unsuccessful, endeavor so the costs of changing behavior may well exceed any reduction in the size of the externality. Also, if the externality is borne across multiple groups (Medicare, Medicaid, multiple private insurers) coordination of a policy response becomes more difficult. Under the dubious assumption that behavior resulting from unemployment becomes ingrained after reentering the workforce, Medicare would most likely absorb the largest share of the externality. If either Medicare or at-risk private insurers wish to counter the effects of these increased marginal costs, the costs are likely lower if programs appropriately target the sub-groups which demonstrated the largest behavioral responses (Table 18). The incentives for at-risk private insurers to offer behavioral modification programs are muted if the fixed costs associated with enrolling each individual are high and turnover between insurers occurs frequently. The key takeaway here is that the estimated size of the externality, to the degree it even exists, is small.

Table 18: Estimates of Marginal Medical Expenditures Attributable to Physical Inactivity due to a 1% Increase in Unemployment

	Age Cohort					
	16 to 24	**25 to 34**	**35 to 44**	**45 to 54**	**55+**	**Population**
US workforce size (Million adults, BLS)	18.7	31.3	33.2	34.6	27.2	145
Change in Unemployment Rate	.01	.01	.01	.01	.01	.01
Change in Number of Unemployed Individuals (Thousands of Adults)	187	313	332	346	272	1,450
Share of unemployment with duration > 26 weeks (BLS)	.22	.22	.22	.22	.22	.22
Change in Number of Unemployed Individuals >26 Weeks (Thousands of Adults)	41	69	73	76	60	319
Reduction in Prob. [Physically Active] due to unemployment (Table 18)	0.38	0.34	0.30	0.30	0.10	.24
Number of newly unemployed who reduce PA (Thousands of Adults)	15.6	23.4	21.9	22.8	6.0	76.6
Life expectancy (80) - mean age of age cohort	60	50	40	30	20	--
Marginal medical cost per person attributable to Inactivity (Pronk et al.)	$167	$167	$167	$167	$167	$167
Discounted Present Value of Lifetime Marginal Medical Costs per person (r=.03)	$4,622	$4,297	$3,860	$3,273	$2,485	$3,712
Discounted Present Value of 65+ Marginal Medical Costs per person (r=.03)	$527	$709	$952	$1,280	$1,720	$1,035
Short Run (Year 1) Total Marginal Medical Costs for Cohort ($M)[22]	$1.3	$2.0	$1.9	$1.9	$0.5	$7.6
Discounted Present Value of Lifetime Marginal Medical Costs for Cohort ($M, r=.03)	$36.1	$50.2	$42.4	$37.4	$7.5	$173
Discounted Present Value of 65+ Marginal Medical Costs for Cohort ($M, r=.03)	$4.1	$8.3	$10.5	$14.6	$5.2	$42.5

[22] This is the most likely scenario given the evidence that suggests activity increases after employment resumes and the behavior is not persistent.

Limitations

This study has important limitations which should be accounted for when interpreting the results and main findings. First, the time period spans only two years and evaluation of the effects of extended unemployment or employment spells on prevention are not possible. As there is some evidence that duration of unemployment impacts prevention effort, longer longitudinal studies are warranted.

Second, the limited sample size in some of the dichotomous employment characterizations and, more broadly, the concept of unemployment are worth considering when placing the results in context. The results suggest that only significant effects are found when comparing relatively long run (2 or more periods) unemployment vs. relatively long run employment (2 or more periods). Due to limited power and sample size the rarer employment characterizations (e.g. short run unemployment or short run employment), do not yield significant results, so we do not know if there is A) no effect or B) poor ability to detect effects due to limited sample. The definition of employment or unemployment also differ from the traditional BLS concept. In the MEPS data, I select a sample of employed workers based on whether they participate in the workforce during at least one of the five MEPS rounds. In some cases these individuals are officially leaving the workforce (say, to retire early). It is still the case that these individuals experience a reduction in income (in most cases) and an increase in available time—the two important economic phenomenons covered in the theory section. But it may well be that the behavioral changes after involuntary job loss differs from a change when individuals willingly cease working. If individuals smooth their consumption of physical activity more evenly across a planned departure from the workforce, then the estimate presented here is biased toward zero, especially if a significant share of the data sample exit the workforce voluntarily. Also one may contend that, on average, the sub-sample of individuals who experience long run unemployment and long run employment within a two year period may differ from the rest of the sample in a manner which observables cannot capture.

Third, conceptually the MEPS definition of physical activity includes an array of potential modalities for activity (leisure time, work, transportation), but it does not disaggregate the data according to modality nor type (vigorous vs. moderate) nor extent (minutes per week) nor frequency (times per week). Linked NHIS files indicate these margins for 2002 with respect to *leisure-time* physical activity for a share of the sample, but these data obviously are not tracked over time and not available for non–leisure activities. Specifically identifying which margins change over time across all modalities between periods of employment and unemployment would provide more targeted policy interventions—should intervention be warranted. However, as it appears that the externalities and role for intervention are contraindicated in this case, the limitation may be moot. Nevertheless, greater detail would help contribute to the emerging work which carefully examines the determinants of how and when time is invested in physical activity.(Jena 2006; Mullahy and Robert 2008)

Conclusions

This paper finds that unemployment decreases physical activity (H1.A, ΔProb[PA]=-.12), but has no net effect on obesity status or smoking behavior (H2,H3). What are we to make of these findings? First, unemployment has differential effects on those that lose their jobs and those who continue to work. Recalling Equation 1 and accepting the validity of both Ruhm's *positive* elasticity for physical activity and unemployment at the community level ($E_{NET} > 0$) and the *negative* effects among the unemployed presented here ($E_{UN} < 0$), the "indirect" impact associated with regional unemployment on those who continue to work must be positive ($E_{EMP} > 0$). Other studies are also proffering this conclusion with regard to health as opposed to health determining behaviors, although they generally are relying on panel rather than cross-sectional data to illustrate their point.(Miller 2009) Nevertheless, there is a growing appreciation that "own" vs. "other" unemployment exact differential effects on health and health behaviors and this study provides confirmatory evidence to this effect.

The concentration of the effects in particular subgroups (males, under 45 and blue collar workers) build on the findings from earlier work as well. The more inclusive definition of physical activity and the large reductions in activity among "blue collar" occupations suggest the work-mediated physical activity is an important modality to consider. In addition, some efforts to explain the increase in obesity rates at the macro-level contend that the shift toward service-oriented occupations with little physical activity are a crucial factor driving the "obesity epidemic".(Lakdawalla 2002; Lakdawalla, Philipson et al. 2005) While this study does not find an effect on obesity (perhaps due to the limited time frame of the data), the larger reduction in physical activity among "blue-collar" workers relative to service-oriented workers upon unemployment is consistent with a pattern in which job demands affect health behaviors.[23]

In regards to theory and the joint affects of time and income shocks, the shift *away* from physical activity, a time-intensive activity, during periods when wages drop to nil suggests that the productivity of alternate time uses (such income replacement/generation activities like job search or

[23] Note, however, that this study obviously compares job vs. no job rather than a comparison of active job vs. non-active job focused on in the obesity literature.

home production such as cooking) increase during these periods and "crowds out" the expected increase in physical activity due to lower opportunity time costs. Looking forward, examination of time diary data will lend itself toward substantiating the precise mechanisms and substitution patterns motivated during a reduction or cessation of work.(Mullahy and Robert 2008)

Lastly, while a precise magnitude of the externality associated with the reduction in physical activity is beyond the scope of this paper, the affect on Medicare expenditure for a 1% increase in the unemployment rate (1.5 million jobs) is unlikely to be more than $42 million according to a deteriministic model relying on external data sources and the findings from this research. If the costs associated with physical activity behavioral change programs exceed $29 per person (assuming all newly unemployed individuals are targeted), it is not advisable to initiate programs focused on changing physical activity during unemployment spells even under the assumption that individuals retain the poor health habits even after reengaging in the labor pool. Given the turnover within commercial health insurance plans, it is unlikely that the limited duration of the individual in the plan will justify the expenditure on behavioral modification from the perspective of the insurer. This study elucidates how health behaviors change as a result of unemployment, but the costs of "fixing" these behaviors are likely to exceed the benefits by a large margin.

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