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ABSTRACT

As economic expansions raise employment and wages, associated shifts in income and time constraints would be expected to also impact individuals' health. This study utilizes information from the Behavioral Risk Factor Surveillance System (1990-2007) to explore the relationship between the risk of unemployment and the consumption of various healthy and unhealthy foods. Estimates, based on fixed effects methodologies, indicate that a higher risk of unemployment is associated with reduced consumption of fruits and vegetables and increased consumption of "unhealthy" foods such as snacks and fast food. In addition to estimation of the average population effect, heterogeneous responses are also identified through detailed sample stratifications and by isolating the effect for those predicted to be at highest risk of unemployment based on their socio-economic characteristics. Among individuals predicted to be at highest risk of being unemployed, a one percentage point increase in the resident state's unemployment rate is associated with a 2-8% reduction in the consumption of fruits and vegetables. The impact is somewhat higher among married individuals and older adults. Supplementary analyses also explore specific mediating pathways, and point to reduced family income and adverse mental health as significant channels underlying the procyclical nature of healthy food consumption.

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"People may indulge themselves a little bit more when times are tough."
-Jack P. Russo, investment firm analyst, quoted in Haughney (2009)

I. INTRODUCTION

As economic expansions raise employment and yield financial benefits, associated shifts in income and time constraints would be expected to also impact individuals' health. While it may be intuitive to suppose that improved macroeconomic conditions would improve population health due to rising incomes, the evidence is surprisingly mixed. A number of studies point to health and health behaviors being countercyclical, or increasing during recessions. These studies indicate that strengthened economies or income receipt are associated with increases in acute myocardial infarction, mortality, alcohol consumption, smoking, physical activity, diet, and other outcomes related to health.[1] The effects are mainly temporary, and there is some evidence that the adverse effects dissipate in the longer run. Xu and Kaestner (2010), for instance, estimate the structural effect of wages and hours worked on health behaviors among low-educated individuals, and find that an increase in working hours is associated with higher cigarette smoking, a reduction in physical activity, and fewer visits to the physician. They also find that increases in wages, due to expanded economic activity, are associated with higher levels of cigarette consumption.

Other studies find the opposite or no effect (Charles and DeCicca 2008; Dee 2001; Novo et al. 2000). Sullivan and von Wachter (2009), for instance, use administrative data on the quarterly employment and earnings of Pennsylvanian workers in the 1970s and 1980s matched to Social Security Administration death records covering 1980–2006 to estimate the effects of job displacement on mortality. They find that for high-seniority male workers, mortality rates in the

[1] See Evans and Moore 2009; Ruhm 2007; Gerdtham and Ruhm 2006; Ruhm 2005; Ruhm and Black 2005; Dustmann and Windweijer 2000; Ruhm 2000; and Ettner 1997.

year after displacement are 50%–100% higher than would otherwise have been expected. They also find that workers with larger losses in earnings tend to suffer greater increases in mortality.

The National Income and Product Accounts, maintained by the Bureau of Economic Analysis, reveal a steady increase over time in real expenditures on food services (which includes consumption at limited-service restaurants, such as fast-food outlets, and full-service restaurants), with slight increases during downturns. (See Figure 1, Top Panel.) The correlation between these expenditures and the national unemployment rate is 0.21 (1947-2007), suggesting that unhealthier food consumption may be somewhat countercyclical. Similarly, expenditures on food consumed for off-premise consumption (which includes purchases at grocery stores) tends to be slightly procyclical.

Prior studies that estimate the structural effect of individual work status or wages on health outcomes fail to account for potential pathways that operate ecologically. For instance, macroeconomic conditions may impact individual health outcomes or behaviors even if the individual does not become unemployed or experience a reduction in earnings. Prior studies that rely on a reduced-form approach, relating health outcomes to measures of macroeconomic conditions, do capture all potential pathways but they have generally estimated a population average effect, which can mask considerable heterogeneity. Reduced-form effects also often do not shed light on the specific pathways that drive observed associations between macroeconomic factors and health. While prior studies have considered health behaviors such as smoking, drinking, physical activity, and preventive healthcare utilization, they have generally not considered how individuals' eating habits respond over the business cycle.[2]

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[2] In addition to other outcomes, Ruhm (2000) does look at daily servings of fruits and vegetables, in addition to grams of fat consumed daily, using 1987-1995 data from the BRFSS.

This study contributes to the literature by addressing these limitations. Specifically, we utilize micro-level data representative of the U.S. population from the Behavioral Risk Factor Surveillance System, spanning 1990 through 2007, to explore the relationship between the economic cycle and food choices. The focus on healthy and unhealthy food consumption is policy-relevant given that caloric intake and nutrition are proximate inputs into obesity and overall population health. If the economic cycle impacts individuals' health-related outcomes, then the effect would also be more easily identifiable in a statistical sense on health behaviors; health outcomes and obesity, on the other hand, tend to be cumulative and may not respond readily or over the short-term. We proxy the business cycle with area (state- and county-specific) unemployment rates to capture the link between the risk of being unemployed and food consumption choices using a fixed-effects methodology. In addition to estimating the average population effect, this study also identifies heterogeneous responses across various demographic groups and further estimates the impact for those who are predicted to be at highest-risk of unemployment. Results indicate that the consumption of healthier foods such as fruits and vegetables increases when the unemployment rate decreases, or that a healthy diet is procyclical. While the reduced-form captures the net effect of unemployment risk on health behaviors operating through all (and potentially competing) pathways, we also implement supplementary analyses to identify the importance of specific hypothesized pathways. These models point to reduced family income and adverse mental health as significant channels underlying the procyclical nature of healthy food consumption.

II. ANALYTICAL FRAMEWORK

The objective of this study is to assess the extent to which the risk of unemployment impacts healthy and unhealthy food consumption. This question can be framed within a modified static version of the human capital model for the demand for health (Grossman, 1972, 2000). Grossman combines the household production model of consumer behavior with the theory of human capital investment to analyze an individual's demand for health capital. In this paradigm, individuals demand health for its consumptive and investment aspects. That is, health capital directly increases utility and also reduces work loss due to illness, consequently increasing healthy time and raising earnings.[3] The individual may also derive direct utility from consuming high-calorie foods, though this may raise body mass index and adversely impact health. Thus, the individual maximizes a utility function that contains health (H) and other household goods (Z), in addition to caloric intake (F), as arguments.[4]

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

Utility is increased at a diminishing rate with respect to all arguments. Maximization occurs subject to the following production constraints for health, caloric intake, and other household commodities, each of which is produced using time inputs (TH, TF, TZ) and relevant market inputs (M, J, X); E represents an efficiency parameter and is typically proxied by the individual's educational attainment.[5]

(2) $H = H[F, M, TH; E]$

(3) $F = F[J, TF; E]$

(4) $Z = Z[X, TZ; E]$

Equation (2) denotes that health is produced with caloric intake, other market inputs M (for instance, medical care) and time inputs TH (for instance, exercise). Caloric intake (or food

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[3] Investment in health capital may also raise earnings by raising the marginal product of labor and consequently the wage rate.
[4] Expanding the above model to an intertemporal context does not alter the main conclusions or the directions of the comparative statics. See Grossman (2000) for a full exposition of the general intertemporal model. Also, see Ruhm (2010) for an extension of the model to incorporate a dual decision-making framework based on neuro-biology and behavioral economics.
[5] See Grossman and Kaestner (1997).

consumption) is produced with market inputs (J) and time (TF), as indicated in equation (3). For simplicity of exposition, we assume that healthy food consumption on average is low in calories and its production is more intensive in both market and time inputs, relative to unhealthy "junk" food consumption. Equation (4) denotes the analogous production function for other household commodities. All inputs have positive and diminishing marginal products with one exception; it is assumed that ($\partial H/\partial F \equiv H_F$) < 0 denoting that high caloric "junk" food consumption has an adverse effect on health.[6]

In addition to production constraints, the individual also faces income and time constraints.

(5) $P^M M + P^J J + P^X X = W*TW$

(6) $T = TW + TH + TF + TZ + TL$

Equation 5 notes that total income (product of wage W and work time TW) is exhausted on all market expenditures where P^i (i=M, J, X) represents the price of the market input. Equation (6) notes that total time (T) consists of time at work (TW), time inputs in the production of health (TH), caloric intake (TF), and other commodities (TZ), and time lost due to illness (TZ). Note that investments in health reduce time lost to illness and therefore raise total available time for other pursuits including work ($\partial TL/\partial H \equiv TL_H < 0$); this is the investment return to health.

Maximizing utility subject to the full income constraint results in the following first-order condition with respect to caloric intake (F), equating marginal benefits to marginal costs:

(7) $U_F / \lambda = [P_J J_F + W*TF_F] - [H_F (U_H / \lambda)] + [H_F (TL_H)(W)]$[7]

[6] More realistically, H_F is expected to be non-monotonic, such that both very low or very high caloric intake has adverse effects on health. The monotonicity assumption on H_F is made for convenience and does not materially affect the general conclusions from this framework.
[7] Subscripts denote derivatives with respect to the subscripted variable.

The marginal benefit of high caloric intake ("junk" food consumption) includes the direct marginal effect of such consumption on utility (U_F), monetized by the marginal utility of wealth (λ). The costs of high caloric intake comprise three components. The first term represents the direct marginal cost of caloric intake, which depends on market and time inputs. The second term represents the monetized value of the loss in utility due to the adverse health effect. The third term represents the value of the foregone time, as high caloric intake adversely impacts health and increases the time lost to illness.

Whether unemployment risk increases or decreases healthy food consumption (and vice versa for unhealthy food consumption) depends on how unemployment risk affects the marginal benefits and marginal costs of such food consumption. A higher probability of being unemployed or reduction in hours worked (TW ↓) raises total available time but reduces income. This tends to reduce the direct marginal cost of food consumption that is relatively more intensive in time inputs and less intensive in market inputs. Noting that healthy food consumption is generally more intensive in both market and time inputs relative to unhealthy snacks and fast-food consumption, the effect is ambiguous depending on the relative intensity of market versus time inputs. Greater availability of time tends to raise the demand for home-cooked meals and healthy food consumption, but lower income tends to raise the demand for cheaper fast-food and unhealthy food consumption.

If married women increase their labor supply to compensate for the reduction in household income due to their spouse's unemployment or reduction in hours of work, then there may be a decrease in effective available time if females are relatively more efficient in household production; household income may increase or decrease depending on whether the wife's increased labor supply compensates for the husband's loss in earnings. This shift in time and income constraints within the household would also affect the direct marginal cost of food consumption.

A reduction in wages during economic downturns also reduces the opportunity cost of time lost to illness due to higher caloric intake and unhealthy food consumption (third component of marginal costs in equation 7). This in turn would reduce the demand for healthy food consumption and raise the demand for fast-food or other high-caloric unhealthy food consumption.

The marginal cost of food consumption is further impacted by any changes in relative food prices over the economic cycle. In general, data from ACCRA do not show substantial cyclicality in the relative price of fruits/vegetables in conjunction with the economic cycle. The correlations between food prices and the unemployment rate are consistently negative, as expected, since food prices tend to decrease during economic downturns and increase during expansions. (See Figure 1, Bottom Panel.) Yet the correlations are very low, ranging from -0.0117 to -0.2534 in magnitude.[8] Hence, this is not likely to be a significant mechanism through which unemployment may impact caloric intake. Nevertheless, we estimate models controlling for food prices to assess the importance of this channel of effect in our analyses of potential mechanisms.[9]

The marginal benefits of unhealthy food consumption may also increase during economic downturns. It is well-documented in the literature that unemployment leads to higher levels of stress, depression, and psychological distress (Dooley et al., 1994). This may raise the marginal utility of high-caloric unhealthy food consumption (U_F). Studies have shown that individuals

[8] The ACCRA food prices we analyzed pertain to potatoes, milk, eggs, beef, steak, sausage, fried chicken, hamburgers, lettuce, bananas, and margarine, for which we had the most observations.
[9] BLS price indices for various types of food generally fall with rising unemployment, as expected. See Christian and Rashad (2009) for more detail on trends in food prices from 1950 to 2007.

who are depressed tend to consume more calories and consume greater amounts of junk food (Wurtman 1993). While causality is difficult to establish in these studies, part of the underlying mechanism may be consistent with the "self-medication" hypothesis. For instance, research has shown that individuals with mental disorders are more likely to smoke and drink in order to alleviate symptoms of mental distress, and there is evidence of a causal link from depression to substance abuse (Saffer and Dave, 2005).

Other specific mechanisms may further explain how individuals' food consumption responds to the risk of unemployment. For instance, loss of health insurance and reduced access to care, as a result of job loss, may impact eating habits. Numerous studies have shown that physician advice and interventions are successful in influencing patient behaviors such as smoking, drinking, exercise, and diet (U.S. Preventive Services Task Force 2003, 2004). Reduced contact with physicians due to loss in coverage may lead to an increase in unhealthy behaviors. On the other hand, the pure ex ante moral hazard effect operates in the opposite direction; loss of health insurance may promote more healthy behaviors since the individual now bears the full cost of illness and medical care. Dave and Kaestner (2009) show that these two opposing effects are generally of similar magnitudes, at least among older adults, such that the net effect of health insurance on health behaviors is close to zero.

Some studies have also pointed to higher rates of watching television among unemployed individuals (Raynor et al., 2006). This may raise individuals' exposure to fast-food advertising, and subsequently increase the demand for such unhealthy food consumption. Chou, Rashad, and Grossman (2008) show that individuals' fast-food consumption is indeed responsive to the frequency of television-viewing and to advertising by fast-food outlets.

The above discussion is conditional on a given demand for physical health. Note that caloric intake is both a consumption good providing direct utility as well as an input into the individual's health production. Thus, the demand for various foods comprises direct demand as well as input demand derived from the individual's underlying demand for health. If the individual's demand for health decreases with a higher risk of unemployment, then this scale effect translates into a higher demand for caloric intake and unhealthy food consumption, *ceteris paribus*. The literature has generally found mixed evidence with respect to the behavior of mortality over the economic cycle, though more recent studies, as cited above, tend to find that mortality rates, with the exception of suicide, tend to move in a procyclical manner. Rising suicide rates during economic downturns may point to a reduced demand for health, at least among the most vulnerable and affected populations. However, it is difficult to disentangle from the procyclicality of other mortality indicators whether this reflects shifts in the underlying demand for health or direct shifts in health behaviors with subsequent effects on health.

Overall, the theoretical framework suggests that there may be good reason to believe that individuals respond to the risk of unemployment by varying their food consumption due to shifts in the marginal costs and benefits. However, the direction of the impact is ambiguous depending on the relative intensity of time and market inputs in the production process and the importance of other potential channels of effect. There may also be considerable heterogeneity across different segments of the affected population.

III. METHODOLOGY

The first-order condition (equation 7) implies the following reduced-form demand function pertaining to measures of food consumption (HC):

$$(8) \qquad HC_{ist} = B_0 + B_1 \, UNEMP_{st} + X_{ist}\,\Pi + \mu_s + \nu_t + \varepsilon_{ist}$$

The above specification denotes that food consumption for the i^{th} individual, residing in geographic area *s* in year *t*, is a function of the risk of unemployment (UNEMP) and other observable exogenous characteristics such as age, gender, race, education, and marital status (X), with ε representing an individual-level classical disturbance term.

The risk of unemployment is proxied by the unemployment rate in the respondent's area of residence (state or county, in alternate specifications). Rather than the individual's actual unemployment status, it is this *risk* of unemployment that is the relevant and appropriate determinant in the demand for food consumption. First, the individual's actual unemployment status is endogenous to their food consumption choices and other health behaviors. The use of area unemployment rates bypasses potential non-random selection into actually unemployment and shifts in the individual's food consumption. Second, actual unemployment only partially captures potential pathways through which the economic cycle may affect food choices. Even if an individual is not actually unemployed, the economic downturn would be expected to impact the marginal costs and benefits of caloric intake. For instance, as noted above, psychological distress due to the risk of unemployment or due to the unemployment of a spouse or family member may lead to a lower (higher) demand for healthy (unhealthy) food consumption. The decline in household wages or labor supply, even if the individual remains employed, would also be expected to shift the marginal cost of food consumption. Third, the use of area unemployment rates more proximally captures the effect of the economic cycle since within-area changes in the unemployment rate are strongly countercyclical. Individual shifts in unemployment on the other hand are a function of the economic cycle as well as other observed and unobserved individual-specific factors. Thus, the parameter of interest is B_1, which is the reduced-form net impact of the unemployment risk on the individual's food choices operating through all (and potentially competing) channels of effect.

While the area-specific unemployment rate is plausibly exogenous to the individual's food consumption, the possibility of other cofounding area-specific factors remains. To account for this "statistical endogeneity," specifications control for area fixed effects (μ_s), which capture all unobservable time-invariant area-specific factors, and time fixed effects (ν_t) to capture all unobserved national trends. In addition, alternate specifications also control for state-specific linear trends to account for systematically-varying unobserved factors within a given state over time. Equation (8) is estimated via ordinary least squares, and standard errors are adjusted for arbitrary correlation across individuals within a given area (state or county, in alternate models).

The estimation strategy proceeds in four parts. First, we estimate equation (8) with area and time fixed effects, alternately utilizing the respondent's resident state- and county-level unemployment rates to capture the risk of unemployment. Models are estimated alternately for the full sample and for healthy individuals for two reasons. First, health status may be endogenous to food choices; thus, restricting the sample to individuals in good health leads to a more homogeneous sample and bypasses this endogeneity. Second, restricting the analysis to healthy individuals isolates the direct demand for food consumption, whereas analysis on the full sample allows the models to capture the input demand for food consumption derived from the underlying demand for health.

The parameter B_1, in equation (8), captures the average population effect of the risk of unemployment on consumption choices. Since this average overall effect may mask considerable heterogeneity, next we also estimate differential effects based on models stratified across socio-demographic factors. Furthermore, the affected population – that is, individuals who are most at risk of unemployment during an economic downturn and therefore most responsive in their consumption choices – is likely to be small. In this case the overall population effect, which represents an intent-to-treat effect, substantially underestimates the response amongst the affected population. Thus, we also modify the analysis to isolate the effect of unemployment risk among those who are most impacted by it.

We do so by exploiting the fact that certain socio-demographic groups (such as low-educated individuals) are much more likely to become unemployed as the unemployment rate rises in their state. Specifically, the following logit model is estimated to predict the unemployment status of an individual residing in area *s* at time *t,* based on the area unemployment rate (UNEMP), predetermined or exogenous individual-specific characteristics such as age, gender, race/ethnicity, education, marital status, and health status (X), and interactions between these factors and the area unemployment rate. Indicators for state and year are also included.

$$(9) \qquad UNEMPLOYED_{ist} = \alpha_0 + \alpha_1 \, UNEMP_{st} + X_{ist}\,\theta + \sum_{k=1}^{K} \varphi UNEMP_{st} X_{kist} + \gamma_s + \tau_t + \omega$$

The parameter α_1 and the vector $\Sigma\varphi$ capture the impact of area-specific unemployment rates on the individual's actual unemployment status, allowing the effects to differ across socio-demographic cells.

The predicted probability (or propensity) of being unemployed captures variation across individuals with respect to their risk of unemployment. Note that this propensity score is clearly exogenous since it is a linear combination of the area unemployment rate and individual-specific predetermined factors. Thus, whether or not the individual is actually unemployed, the propensity score measures their proximal risk of being unemployed based on their socio-demographic characteristics and their surrounding unemployment rate. We then estimate a modified version of equation (8) by interacting the area unemployment rate with this individual-specific propensity of being unemployed (denoted RISK).

(10) $HC_{ist} = \Gamma_0 + \Gamma_1\, UNEMP_{st} + \Gamma_2\, (UNEMP_{st}{*}RISK_{ist}) + \gamma\, HEALTH_{ist} + X_{ist}\, \Pi + \mu_s + \nu_t + \varepsilon_{ist}$

Equation (10) is analogous to a difference-in-difference-in-differences specification, where the coefficient of the interaction term represents the differential effect of the area unemployment rate among individuals most likely to be affected, relative to individuals who are least at risk of being unemployed. Specifically, the parameter Γ_2 captures the effect of the unemployment risk on food choices among those individuals predicted to be most at-risk of being unemployed, and Γ_1 captures the effect of unemployment risk on food choices among those individual who are at zero risk of being unemployed as predicted by the propensity score. As a falsification check, we expect Γ_1 to be insignificant and close to zero since individuals who are not at risk of being unemployed should not be affected by area unemployment rates. As a further specification check, we expect Γ_2 to be larger than B_1 (from equation 8) in absolute magnitude since the effects should be largest among the at-risk population (Γ_2) whereas B_1 captures the average effect among all affected and non-affected individuals.[10]

Finally, we implement an analysis of potential mediators to inform on the strength of the specific mechanisms underlying the impact of unemployment risk on food choices. The baseline specifications are parsimonious and only include exogenous socio-demographic factors so as not to “over-control” for factors that may be potential pathways. In alternate analyses, we re-estimate specification (10) by incorporating measures of actual work status, family income, food prices from ACCRA, mental and physical health, and health insurance coverage to gauge the

[10] Since the propensity score is a predicted value, we also estimate models with bootstrapped standard errors (using 50 repetitions), which Heckman et al. (1997) and Dehejia and Wahba (2002) use in a similar context. Results are almost identical, and doing this does not alter any conclusions regarding significance. Results are available from the authors upon request.

extent to which the estimated effect of the state unemployment rate on food choices can be explained by these mediators.

IV. DATA

Our analysis relies on the Behavioral Risk Factor Surveillance System (BRFSS), an individual-level data set representative of the population of the United States. As the largest telephone-based health survey available, the BRFSS has tracked health conditions and risk behaviors for adults 18 years of age and older in the US. The survey is conducted by state health departments in collaboration with the Centers for Disease Control. While only 15 states participated in 1984, the number grew to 33 in 1987, to 45 in 1990, and to all 51 states (including the District of Columbia) in 1996.[11] More than 350,000 adults are interviewed each year, with response rates hovering around 50%.[12] The average number of interviews per state ranged from approximately 800 in 1984 to around 3,500 in more recent years. These data are publicly available from the Centers for Disease Control at http://www.cdc.gov/brfss, and provide information on a variety of personal characteristics, including gender, age, education, marital status, family income, and state of residence.

Measures of food consumption are included, although not consistently. Moreover, these variables are occasionally 'module' variables, asked of only a limited number of respondents, rather than 'core' variables, asked of all respondents. Consumption of carrots, fruit, fruit juice,

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[11] The following 15 states were in the BRFSS in 1984: Arizona, California, Idaho, Illinois, Indiana, Minnesota, Montana, North Carolina, Ohio, Rhode Island, South Carolina, Tennessee, Utah, West Virginia, and Wisconsin. In 1985, Connecticut, the District of Columbia, Florida, Georgia, Kentucky Missouri, New York, and North Dakota entered the survey. In 1986, Alabama, Hawaii, Massachusetts, and New Mexico entered. In 1987, Maine, Maryland, Nebraska, New Hampshire, South Dakota, Texas, and Washington entered. In 1988, Iowa, Michigan, and Oklahoma entered. In 1989, Oregon, Pennsylvania, and Vermont entered. In 1989, Colorado, Delaware, Louisiana, Mississippi, and Virginia entered. In 1991, Alaska, Arkansas, and New Jersey entered. In 1992, Kansas and Nevada entered. Wyoming entered in 1994. Rhode Island, which entered the survey in 1984, was not in it in 1994. The District of Columbia, which entered in 1985, was not in the survey in 1995.

[12] Survey weights are included in the BRFSS to ensure that those included in the survey are reflective of the US population. In addition, the study shows that means for those responding and the general population are comparable. (See http://www.cdc.gov/brfss.)

green salad, and vegetables are asked consistently in years 1990-2007, with the exception of 2004 and 2006. The survey questions are generally phrased as follows: "How often do you eat (FOOD)?" Options are given for the respondent to record his/her answer in times per day, week, month, or year. Answers are converted to times per year for the purposes of this paper. While nutritionists caution using the terms 'healthy' and 'unhealthy' regarding foods in order to avoid classifying foods per se in preference for a focus on a balanced diet, we use the term healthy for the aforementioned foods as the food pyramid stresses their consumption. Moreover, most Continuing Surveys of Food Intakes by Individuals show consumption of fats, oils, and sweets, meant to be consumed sparingly, to be higher than recommended.[13] Consumption of snacks, hamburgers, hot dogs, French fries, and fried chicken is not as frequently observed in the BRFSS, yet we also analyze these outcomes in order to compare these results with those of our healthy food outcomes.

State unemployment rates are obtained from the Bureau of Labor Statistics, Local Area Unemployment Statistics (LAUS). An individual is classified as unemployed if he/she does not have a job, has actively looked for work in the prior four weeks, and is currently available for work. Individuals working part-time and discouraged workers are not included among the unemployed. While more family members are likely to seek work during downturns and thus increase the unemployment rate, there has been limited empirical evidence for this added-worker hypothesis.

In alternative specifications accounting for potential mediators, we also include measures of actual work status (whether the individual is currently working, either employed for wages or self-employed), real total family income, mental health (number of days in the past month that mental health was not good), physical health (number of days in the past month that physical

[13] See http://www.ars.usda.gov/Services/docs.htm?docid=14392.

health was not good), self-reported general health status (indicators for whether the respondent reported general health as Excellent, Very Good, Good, Fair, or Poor), and current health insurance coverage from any source, all derived from the BRFSS.

Data on food prices are obtained from the American Chamber of Commerce Researchers Association (ACCRA), a research organization based in Arlington, VA, available at the city level.[14] While there is some concern with aggregating these prices, as all cities are not included in every quarter, state- and MSA-level aggregations have been used elsewhere (Chou et al. 2004; Rashad 2007; Rashad 2009). In 1968, the first year ACCRA collected data, 147 cities were in the sample, but reached 200 by 1978, 250 by 1986, and has exceeded 300 since 1990. As of 1999, ACCRA cities represented more than 70% of the urban U.S. population, including more than 80% of the population in the 50 largest metropolitan areas (Council for Community… 2008). We first divided ACCRA prices by the ACCRA Cost of Living Index to account for differences across cities, aggregated by state and quarter, then aggregated by state and year to form annual state-level estimates for each price.

We restrict the sample to individuals between the ages of 21 and 64 and further exclude retired individuals from the analyses, in order to focus on working-age adults who have completed their schooling.[15] This yields a final sample size of about 1.25 million for the analysis of healthy food consumption, and about 61,500 for the analysis of unhealthy food consumption. Table 1 presents the means of the relevant variables over the sample period, for the full sample and by employment status. The average percentage unemployed of 9.2% is higher than the national average for the time period as it includes those not actively seeking work and those

[14] In collecting their data, ACCRA does its pricing in chain supermarkets and chooses the lowest price available (not necessarily a consistent brand), which alleviates potential concerns with consumer substitution within a category. ACCRA typically prices items during the Thursday, Friday, and Saturday of the pricing period (Council for Community… 2008).
[15] Further restricting the age range to 25-59 does not materially alter the results.

unable to work. Individuals who are not unemployed in our sample report significantly higher consumption of fruits, carrots, green salad, vegetables, and snacks. The raw statistics suggest, therefore, that healthy food consumption is generally procyclical. However, the unemployed also tend to somewhat older, have fewer years of education, and are more likely to be female, unmarried, and non-White, which may explain part of the differential in eating habits. Unemployed individuals further report significantly lower family income, are more likely to be uninsured, and have lower levels of mental and physical health, all of which may be potential pathways that mediate the impact of economic stress on eating habits. The multivariate models presented next address these possibilities.

V. RESULTS

Table 2 presents estimates of the conditional impact of the state unemployment rate on measures of healthy food consumption, based on equation (8). A higher unemployment rate in the respondent's state of residence is associated with lower levels of consumption of fruits, juice, carrots, green salad, and vegetables. The effect is statistically significant at conventional levels for three out of the five outcomes, and is jointly significant across all models at the five percent level. Nevertheless, the magnitude of the impact is expectedly small since it represents the average impact over all individuals; a one percentage point increase in the state unemployment rate will reduce the annual frequency of fruits and vegetables consumption by between 1.3 and 2.5 times, approximately one percent of the sample mean.

The effects of other factors are consistent with prior studies. The frequency of fruits and vegetables consumption is generally lower among males, with the exception of fruit juice. Healthy food consumption also increases with education, consistent with the hypothesis that educated individuals are more allocatively efficient and tend to choose healthier inputs (Cutler and Lleras-Muney, 2006; Kenkel, 1991). Healthy consumption is also generally rising over the life cycle, across the observed sample age range. There is some evidence that married individuals may have a higher frequency of healthy consumption, relative to never-married individuals, whereas those who are divorced tend to consume fruits and vegetables on fewer occasions. Some significant racial and ethnic differences also emerge. Blacks tend to consume fruit juice more frequently and vegetables less frequently, relative to whites, whereas individuals of other race are generally found to have a higher frequency of all forms of healthy food consumption. Individuals of Hispanic origin also generally consume more servings of fruits and vegetables.[16]

Table 3 presents models for measures of unhealthy food consumption. These estimates should be interpreted with caution due to the limited sample sizes; as noted in the previous section, measures of fast food and other forms of unhealthy consumption are available only for a small number of states across a few intermittent years in the BRFSS. The estimated effects are individually and jointly insignificant due to inflated standard errors and the lack of statistical power. Nevertheless, the direction of the effects is consistent across all measures and suggests that a higher risk of unemployment may raise the frequency of unhealthy food consumption by between one-half to three percent. This suggests that individuals may be substituting unhealthy for healthy food consumption during periods of high unemployment. The effects of other factors are generally opposite in sign to those estimated for healthy food consumption, again suggesting a substitution effect rather than just an overall decrease in the frequency of food consumption.

[16] All measures from the BRFSS capture frequency of consumption (standardized to an annual basis). Data on the amount of consumption per occasion is not available. Unless the direction of effect for serving size per occasion is the *opposit*e of the effect for frequency *and* also larger in absolute magnitude, our general conclusions are not affected. Studies, in the context of other forms of consumption, have shown that frequency and total quantity are highly correlated (Thompson and Subar, 2001). We therefore interchangeably use frequency and quantity in our interpretation of the effects. We also estimated models controlling for the individual's body mass index (BMI), since BMI may be correlated with both the frequency and amount of food consumption, to account for any measurement errors. Estimates, with respect to both significance and magnitudes, remain robust.

For instance, males are found to consume more snacks, hamburgers, hot dogs, French fries, and fried chicken in substitution for lower consumption of fruits and vegetables. A similar effect is also found for low-educated individuals, who tend to consume more snacks and forms of fast-food and fewer fruits and vegetables.

The above estimates, being estimated across all individuals, may mask important heterogeneity across sub-populations. Tables 4 and 5 therefore estimate equation (8) for various samples stratified across additional dimensions. These stratifications may shed light on potential heterogeneous responses and possible mechanisms at play.

Table 4 presents estimates for the measures of healthy food consumption, based on models stratified across socio-demographics and health status. Table 5 presents similar estimates for measures of unhealthy consumption. Each cell represents a separate regression model and reports the marginal effect of the state unemployment rate on the relevant outcome. Since the demand for food consumption and caloric intake is partly a derived demand based on the individual's underlying demand for health, the first row restricts the sample to individuals who report themselves as being in good health in order to bypass this channel. In addition, individuals in poor health may be non-randomly selected into unemployment and unhealthy food consumption.[17] The impact of unemployment risk on healthy food consumption remains generally robust to excluding individuals in poor or fair health, suggesting that the effect of unemployment risk on the demand for fruits and vegetables is not confounded by shifts in the underlying demand for health. The positive effects of unemployment risk on unhealthy food

[17] First, individuals in poor health may be non-randomly selected into a higher risk of unemployment and greater frequency of healthy (unhealthy) consumption, which would attenuate (inflate) the effects if these individuals are included in the analyses. Second, consistent with Ruhm (2007), reductions in mortality over economic downturns may reflect an increase in the underlying demand for health, which in turn would increase the demand for healthy inputs and behaviors. Thus, limiting the sample to healthy individuals bypasses this derived input effect on the demand for healthy food consumption.

consumption (with the exception of snacks) become stronger, though this may indicate parameter instability due to limited sample size.

Rows 2 and 3 limit the sample to younger (ages 21-44) and older (ages 45-64) adults. Unemployment risk significantly reduces the frequency of healthy food consumption for both age groups in general, and there is some suggestive evidence that the impact may be slightly larger for older adults. With respect to unhealthy food consumption, unemployment risk tends to increase the frequency of snacks, hamburger, and hot dogs consumption more for older adults, though the effects are not statistically significant. This may be due to several factors, including the possible stress associated with recessions for older individuals, who likely have more responsibilities and personal obligations.

Rows 4 and 5 stratify the sample across gender. Males and females both respond to the risk of unemployment by reducing their healthy food consumption. Females, in particular, also respond by increasing their consumption of unhealthy foods, and the effect is jointly significant across all outcomes.

The final two rows present estimates based on models stratified across marital status. There is suggestive evidence the married individuals have a greater response to the risk of unemployment in terms of lower healthy consumption and higher unhealthy consumption; in both cases, the effects are jointly significant at the five percent level. Income and time constraints in addition to the psychological distress associated with the risk of being unemployed are likely to be compounded within a household context, thus eliciting a larger response among married individuals.

One challenge in our estimation of the expectedly small average population effect is the potential lack of statistical power. Despite the 1.25 million observations in the analyses of measures related to healthy food consumption, our main indicator varies at the state level. This yields on average 816 state-year cells and points of variation on the state unemployment rate, as the average model utilizes 16 years of data from the BRFSS. To address this issue, we exploit cross-equation correlation in the error terms since outcomes related to various forms of healthy (and unhealthy) food consumption are likely to be highly correlated for a given individual. Indeed, unadjusted data indicate positive correlation across all measures of fruits and vegetables consumption, and across all measures of fast-food and snacks consumption.[18] First, we transformed the dependent variables into standard normal deviates [(Y-mean)/standard deviation]. Transforming the dependent variables in this way allows us to obtain estimates of the effect of the state unemployment rate on healthy and unhealthy food consumption using a seemingly unrelated regression (SUR) framework, and in turn allows us to test joint hypotheses across equations. All effects are measured as changes in standard normal deviations of the dependent variables and we test whether the average effect across models of healthy and unhealthy food consumption, respectively, is statistically different from zero.

Table 6 presents these results. The p-value of the average effect is shown in brackets. Higher unemployment risk (as measured by the state unemployment rate) reduces healthy food consumption, and the effect is statistically significant across all samples. For instance, the estimate for the full sample indicates that a one percentage point increase in the state unemployment rate is associated with a 0.008 standard deviation decrease in healthy food consumption on average. The effect is expectedly small since it is averaged over the entire population. Similarly, higher unemployment risk is generally associated with higher unhealthy food consumption (with the exception of males and unmarried individuals), although the effect is significant only for females and for individuals in good health.

[18] Correlations range from 0.15 to 0.68.

The general pattern of results from the SUR analyses across socio-demographic groups is consistent with those reported in Tables 4 and 5. Older adults and married individuals are more responsive to unemployment risk with respect to the consumption of both healthy and unhealthy foods. For instance, associated with a one percentage point increase in the state unemployment rate, married individuals reduce healthy consumption by 0.009 standard deviations (SD) and increase unhealthy consumption by 0.022 standard deviations, on average. Females are also more responsive, relative to males, with respect to consuming unhealthy foods.

Table 7 presents models based on an alternate indicator of unemployment risk, as measured by the unemployment rate in the individual's county of residence. These models control for county and year fixed effects. While the resident county unemployment rate is more proximate to the individual, it may also be less salient since individuals may choose to work in other counties or relocate across counties within a given state.[19] The general patterns of the estimates remain robust across all outcomes and samples. Panel A indicates that a higher county-level unemployment rate reduces healthy food consumption across all outcomes and samples, though imprecise standard errors render some of these estimates statistically insignificant. Panel B indicates a generally higher frequency of unhealthy food consumption associated with a higher county-level unemployment risk, though there is heterogeneity across the groups as indicated in the results based on state-level unemployment rates. The magnitudes of these effects are considerably smaller than those reported based on state-level unemployment rates. This is not surprising due to greater measurement error in county-level unemployment rates and the ability of individuals to bypass high local unemployment by working or relocating across counties.

[19] Relocating across states is less common. Data from the Census indicates that 86.7 per 1,000 population migrated across states between 1995 and 2000 (Franklin, 2003).

The results thus far have represented the average population effect – that is, the intent-to-treat effect, the magnitude of which is expectedly small since only a small proportion of the population is likely affected by the risk of unemployment. Thus the average effect may be masking much stronger effects realized over the affected population most at risk of being unemployed. Table 8 presents estimates for healthy food consumption based on equation (10), isolating the differential effect based on this risk of being unemployed.[20] The coefficient of the interaction term (between the propensity of being unemployed and the state unemployment rate) represents the differential effect of unemployment risk on individuals who are most at risk of being unemployed (as predicted by the propensity score) relative to individuals who are not at risk of being unemployed.

Panel A presents the estimates for the full sample. Across all measures except fruit juice, unemployment risk significantly reduces healthy food consumption among the affected population. It is validating that these effects are generally significantly larger in magnitude relative to the average population effect. Among individuals at highest risk of being unemployed, a one percentage point increase in the state's unemployment rate is predicted to reduce the frequency of healthy food consumption by between 1.9 and 14.5 times more in a given year, relative to individuals who are least affected; this translates into a 2.1 to 7.9 percent reduction in fruits and vegetables consumption (evaluated at the baseline means). The coefficient of the state unemployment rate is generally insignificant and much smaller in magnitude. This is again validating in that the risk of unemployment is not having much of an effect on individuals who are not predicted to be at risk of being unemployed.

[20] We are unable to conduct analyses for outcomes related to unhealthy food consumption due to limited sample sizes which leads to highly inflated standard errors and parameter instability.

Panel B addresses the possibility that there may be unobserved state-varying factors that may be confounding the relationship between the unemployment risk and food consumption. These specifications control for state-specific linear trends, which account for systematically-varying unobserved state factors.[21] Magnitudes of the main effects and standard errors remain robust.

Table 9 presents supplementary analyses of the potential mediators and pathways that link the risk of unemployment to healthy food choices. To do this, we include measures of potential mediators in specification 10 and examine the change in the estimate of the impact of the state unemployment rate on healthy food consumption among those predicted to be at high-risk of being unemployed (coefficient of the interaction between state unemployment rate and the propensity of being unemployed). The first row presents the baseline estimates (also reported in Panel A of Table 8) from specifications that only control for exogenous and predetermined factors. In each subsequent row, we present estimates controlling alternately for actual work status, real family income, food prices, mental health, physical health, self-reported general health, and health insurance coverage. The final row presents estimates from the full extended specification that controls for all of these mediators and pathways. The final column in Table 10 also presents parallel estimates for an alternative indicator of healthy behavior, measuring whether the respondent currently takes vitamins or supplements, as a specification check. Similar to healthy food consumption, higher unemployment risk reduces the probability of taking vitamins by about 3.2 percentage points (5.8 % relative to the baseline mean).

Specifications that control for work status (Row 2) inform on the extent to which time constraints underlie the link between the economic cycle and healthy food consumption. If healthy food consumption is relatively more (less) intensive in time inputs, then it is predicted to

[21] Results are also robust to controls for state-specific quadratic trends.

increase (decrease) during unemployment due to greater availability of time and a lower opportunity cost, ceteris paribus. Shifts in household time constraints due to the substitution of the wife's labor supply for the husband's unemployment may also affect healthy food consumption. Controlling for work status causes the effects on fruits and vegetables consumption to become somewhat more negative, suggesting that healthy food consumption is relatively time intensive and that it may respond positively to the easing of time constraints. To the extent that taking vitamins is not a very time intensive pursuit, the coefficient magnitude is robust to controlling for work status.

Specifications reported in Row 3 control for real family income and its square. The effect magnitudes for fruits, vegetables, and salad consumption generally decline by between 30-53%. This is consistent with these forms of healthy food consumption being superior goods that respond to the drop in family income during periods of economic downturn.[22] A similar pattern is reassuringly also found with respect to taking vitamins.

The marginal cost of food consumption is further impacted by any changes in relative food prices over the economic cycle. Specifically, the price of fruits and vegetables tends to be procyclical. Since the price elasticity of such food consumption is negative, it is expected that controlling for food prices should raise the magnitudes of the adverse effects of the state unemployment rate on healthy food consumption. Estimates from Row 4 are generally very similar to the baseline estimates, suggesting that shifts in relative prices are not a major pathway underlying the link between unemployment risk and healthy food consumption. This is not surprising given that food prices are only weakly procyclical and are not strongly correlated with changes in local or national unemployment rates.

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[22] Separate specifications confirm that these measures of healthy food consumption increase with family income, albeit at a diminishing rate, and that family income is negatively associated with the state unemployment rate.

Estimates in Row 5 suggest that adverse effects on mental health and greater psychological distress resulting from the higher unemployment risk is a significant pathway underlying the effects. Controlling for measures of mental health, the coefficient magnitudes on fruits, vegetables and salad consumption decline (become less negative) by between 11-80%.

The next two rows alternately control for measures of physical health and self-reported general health status. If the demand for health is countercyclical (procyclical), then controlling for health status should make the effect magnitudes more (less) negative. We find this to be the case for vegetables consumption and for consuming vitamins. Shifts in magnitudes for the other measures are more inconsistent. The literature on how health status changes over the economic cycle is generally mixed, with Ruhm (2007) finding that mortality is countercyclical (with the exception of suicide) and Sullivan and von Wachter (2009) finding the opposite.

Unemployment may also be associated with loss of health insurance coverage, which may in turn increase healthy food consumption through a pure ex ante moral hazard effect or decrease healthy food consumption by reducing physician contact since physicians have been shown to be instrumental in encouraging healthy behaviors. Dave and Kaestner (2009) show that for some unhealthy behaviors, these two effects are roughly of equal and opposite magnitudes and cancel. Estimates reported in Row 8 are based on specifications that control for health insurance coverage. For fruits and salad consumption, the coefficients remain robust; for the consumption of fruit juice and carrots, the coefficients become less negative / more positive; and for the consumption of vegetables, the coefficient becomes more negative. In general, there is no consistent evidence that insurance coverage is a substantial mediating pathway.

The final set of specifications (row 9) controls for all of these mediating variables simultaneously. The coefficient magnitudes decline by between 17-52%, with most of this decline being driven by two pathways: declines in real income and adverse mental health. The parallel pattern of effects for an alternate but related healthy behavior, as reflected in the consumption of vitamins, also adds a note of confidence to the estimates. However, the fact that a significant negative effect on healthy food consumption still remains even after accounting for these mediator variables suggests that other mechanisms may also be at play which we are unable to examine (for instance, relating to increases in television watching, complementarity between leisure and food consumption, shifts in activities and resources within the household, changes in hours worked, and shifts in risk or time preference). Some of the mediator variables that we examine are also only crudely measured in the BRFSS; for instance, while we observe total family income and whether the individual is currently working, personal income and actual hours worked are not observed. Finally, these estimates should be interpreted with caution since some of these mediator variables are simultaneously determined with food choice. Overall, the pattern of estimates reported in Table 10 is nevertheless validating in that it suggests that at least part of the empirical link between the state unemployment rate and healthy food consumption reflects theoretically plausible pathways as hypothesized earlier.

VI. DISCUSSION

This study analyzes the effects of the business cycle, as proxied by area unemployment rates, on individuals' food consumption choices. A variety of methodological approaches is used to address the possible endogeneity of unemployment: state and county fixed effects to address area-specific unobserved time-invariant characteristics, state-specific trends to address systematically-varying unobservables over time within states, and seemingly unrelated regressions to account for the correlation across errors and data limitations. The specifications control for various confounding factors, and supplementary analyses also explore hypothesized mediating pathways. In addition to an estimation of the average population effect, heterogeneous responses are also identified through detailed sample stratifications and by isolating the effect for those predicted to be at highest risk of unemployment based on their socioeconomic characteristics.

Results, which remain robust across various specifications, indicate that a higher risk of unemployment is associated with reduced consumption of fruits and vegetables. Estimates also suggest substitution into increased consumption of unhealthy foods such as snacks and fast food, although this portion of the analysis is limited in statistical power. Specifically, among those who are predicted to be at the highest risk of unemployment, a one percentage point increase in the resident state's unemployment rate is associated with a 2-4% reduction in the frequency of fruits and vegetables consumption, and an 8% reduction in the consumption of salad. Since December of 2007 (the start of the latest recession), the national unemployment rate doubled from 5% to 10% over the following two years. The results from this study suggest that the frequency of fruits and vegetables consumption would decline by between 10-20 % among the most vulnerable populations such as low-educated individuals, ceteris paribus. Based on the stratified analyses, the impact may also be somewhat higher among married individuals and older adults.

Models further point to reduced family income and adverse mental health as significant pathways underlying the procyclical nature of healthy food consumption. This suggests that income-support programs, counseling, and access to mental health services, among those at highest risk of being unemployed, may be health promoting. The Patient Protection and Affordable Care Act, which goes into effect in 2014, views mental health coverage as an essential health benefit, and requires insurers to provide coverage at parity with coverage provided for other medical conditions.[23] Such coverage, by improving access to mental health services, may also moderate declines in healthy behaviors during recessions.

Although the results of this study should be interpreted with caution due to the aforementioned data limitations, they suggest that individuals do not necessarily choose healthier lifestyles during downturns for reasons other than investing in health in order to return to the labor force. Faced with constraints, individuals may in fact consume fewer healthy foods, which will likely have adverse effects on long-term health.[24]

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[23] Between 2010 and 2014, the 2008 Mental Health Parity and Addiction Equity Act applies, which requires mental health and substance abuse parity with respect to financial requirements and treatment benefits. However, the 2008 Act applies only to plans that already include mental health coverage in their benefits package and does not mandate coverage if not already offered. See Dave and Mukerjee (Forthcoming).

[24] The USDA recommends two and a half to three cups of vegetables on a daily basis for adults (http://www.mypyramid.gov). In our sample, the daily average for vegetables is 1.18 servings for the unemployed, but still only 1.25 servings for those not unemployed, suggesting that vegetable intake should be encouraged.

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Table 1
Summary Statistics

Variable	Description	Full Sample	Unemployed	Not Unemployed
State Unemp. Rate	State unemployment rate	5.568*** (1.417)	5.635 (1.382)	5.562 (1.422)
Unemployed	Dichotomous variable that equals 1 if respondent is out of work or unable to work	0.092 (0.289)	---	---
Fruits	Annual consumption of fruits	289.759*** (305.511)	270.285 (322.195)	291.917 (303.742)
Fruit Juice	Annual consumption of fruit juice	248.672*** (303.700)	255.301 (363.388)	247.929 (296.665)
Carrots	Annual consumption of carrots	96.096*** (154.792)	92.465 (167.589)	96.510 (153.397)
Green Salad	Annual consumption of green salad	181.709*** (187.952)	160.150 (189.509)	184.050 (187.188)
Vegetables	Annual servings of vegetables (not carrots, potatoes, or salad)	455.376*** (346.701)	430.526 (353.303)	457.657 (345.636)
Snacks	Annual consumption of snacks	119.856*** (167.966)	102.725 (150.884)	121.120 (169.109)
Hamburgers	Annual consumption of hamburgers, cheeseburgers, or meatloaf	76.944 (91.634)	79.527 (99.250)	76.804 (91.113)
Hot Dogs	Annual consumption of hot dogs	91.295 (201.530)	93.324 (148.974)	91.145 (204.835)
French Fries	Annual consumption of fries	64.594 (111.107)	65.688 (104.531)	64.543 (111.611)
Fried Chicken	Annual consumption of fried chicken	33.538*** (68.163)	45.265 (97.004)	32.706 (65.592)
Male	Dichotomous variable that equals 1 if respondent is male, and 0 if respondent is female	0.496*** (0.500)	0.478 (0.500)	0.498 (0.500)
Some High School	Dichotomous variable that equals 1 if respondent completed at least 9 but less than 12 years of school	0.072*** (0.258)	0.165 (0.371)	0.062 (0.242)
High School	Dichotomous variable that equals 1 if respondent completed exactly 12 years of schooling	0.304*** (0.460)	0.367 (0.482)	0.298 (0.457)
Some College	Dichotomous variable that equals 1 if respondent completed at least 13 but less than 16 years of school	0.269*** (0.443)	0.233 (0.423)	0.273 (0.445)
College	Dichotomous variable that equals 1 if respondent graduated from college	0.316*** (0.465)	0.151 (0.358)	0.333 (0.471)
Age	Age of respondent in years	39.468*** (11.489)	41.936 (12.365)	39.214 (11.364)
Married	Dichotomous variable that equals 1 if respondent is married	0.643*** (0.479)	0.452 (0.498)	0.662 (0.473)
Divorced	Dichotomous variable that equals 1 if respondent is divorced or separated	0.124*** (0.330)	0.224 (0.417)	0.114 (0.318)
Widowed	Dichotomous variable that equals 1 if respondent is widowed	0.018*** (0.134)	0.042 (0.200)	0.016 (0.126)
Black	Dichotomous variable that equals 1 if respondent is black and not Hispanic	0.098*** (0.297)	0.179 (0.383)	0.089 (0.285)

Hispanic	Dichotomous variable that equals 1 if respondent is of Hispanic origin	0.118*** (0.322)	0.150 (0.357)	0.114 (0.318)
Other Race	Dichotomous variable that equals 1 if respondent's race is other than white, black, or Hispanic	0.051*** (0.220)	0.062 (0.240)	0.050 (0.218)
Work	Dichotomous variable that equals 1 if respondent is employed	0.782*** (0.413)	0.000 (0.000)	0.861 (0.346)
Family Income	Real household income in thousands of 1982-84 dollars	33776.360*** (26876.690)	16511.030 (18551.980)	35452.550 (26969.770)
Mental Health	Number of days in past month mental health not good	3.448*** (7.465)	8.256 (11.314)	2.916 (6.698)
Physical Health	Number of days in past month physical health not good	2.915*** (7.049)	10.178 (12.405)	2.110 (5.626)
Health Plan	Dichotomous variable that equals 1 if respondent currently has health insurance	0.829*** (0.377)	0.673 (0.469)	0.846 (0.361)
Potato Price	Real ACCRA potato price in respondent's state of residence, in 1982-84 dollars	2.625*** (0.813)	2.759 (0.858)	2.611 (0.807)
Milk Price	Real ACCRA milk price in respondent's state of residence, in 1982-84 dollars	1.531*** (0.328)	1.587 (0.336)	1.526 (0.327)
Eggs Price	Real ACCRA eggs price in respondent's state of residence, in 1982-84 dollars	1.041*** (0.239)	1.080 (0.248)	1.037 (0.238)
Beef Price	Real ACCRA beef price in respondent's state of residence, in 1982-84 dollars	1.664*** (0.421)	1.736 (0.448)	1.657 (0.418)
Steak Price	Real ACCRA steak price in respondent's state of residence, in 1982-84 dollars	6.082*** (1.596)	6.382 (1.638)	6.051 (1.590)
Sausage Price	Real ACCRA sausage price in respondent's state of residence, in 1982-84 dollars	2.863*** (0.534)	2.935 (0.501)	2.856 (0.537)
Fried Chicken Price	Real ACCRA fried chicken price in respondent's state of residence, in 1982-84 dollars	0.910*** (0.136)	0.931 (0.135)	0.908 (0.135)
Hamburger Price	Real ACCRA hamburger price in respondent's state of residence, in 1982-84 dollars	1.990*** (0.375)	2.056 (0.377)	1.983 (0.374)
Lettuce Price	Real ACCRA lettuce price in respondent's state of residence, in 1982-84 dollars	1.002*** (0.232)	1.039 (0.235)	0.998 (0.231)
Banana Price	Real ACCRA banana price in respondent's state of residence, in 1982-84 dollars	0.464*** (0.063)	0.472 (0.060)	0.463 (0.063)
Margarine Price	Real ACCRA margarine price in respondent's state of residence, in 1982-84 dollars	0.722*** (0.141)	0.747 (0.144)	0.720 (0.141)

Notes: Standard deviation is reported in parentheses. Maximum number of observations is 2,858,973. BRFSS sample weights are used in calculating the mean and standard deviation. The sample excludes those who are retired. Unemployed individuals here are defined as out of work or unable to work, and retired individuals are omitted. Those not unemployed are employed, homemakers, or students. Asterisks indicate that the difference between the two groups is statistically significant at the following levels: *** p-value≤ 0.01; ** 0.01<p-value≤ 0.05; * 0.05<p-value≤ 0.1. Significance levels indicate that these two groups are systematically different.

Table 2
Impact of State Unemployment Rate on Healthy Food Consumption
BRFSS – Ages 21-64

Specification	1	2	3	4	5
Outcome	Fruits	Fruit Juice	Carrots	Green Salad	Vegetables
State Unemp. Rate	-2.5371* (1.3296)	-1.5611 (1.2987)	-1.8112*** (0.5841)	-1.9286** (0.8576)	-1.3309 (2.0566)
	Joint significance: p-value = 0.052				
Male	-77.9122*** (2.4027)	19.7784*** (1.9937)	-20.8496*** (0.6508)	-34.5025*** (0.7915)	-79.1652*** (2.6521)
Some High School	-31.9743*** (5.0534)	-16.2197*** (3.7555)	-12.6726*** (2.6873)	3.7379* (2.1883)	25.1520*** (3.4970)
High School	-15.3839** (5.8152)	-12.8413*** (4.7569)	-7.7122** (3.0147)	20.6287*** (2.2628)	51.6724*** (3.9877)
Some College	16.1221*** (5.9291)	3.2102 (5.2997)	4.5007 (3.2440)	42.6255*** (2.7077)	95.1522*** (4.0687)
College	73.7127*** (5.9636)	13.6147** (5.4894)	14.7149*** (3.3292)	64.7345*** (2.8776)	138.3072*** (4.5298)
Age	-0.9773*** (0.2872)	-11.2323*** (0.2505)	2.3958*** (0.1038)	2.3310*** (0.1622)	1.7102*** (0.2501)
Age Squared	0.0358*** (0.0033)	0.1227*** (0.0027)	-0.0190*** (0.0013)	-0.0095*** (0.0019)	-0.0113*** (0.0028)
Married	23.9464*** (1.7435)	-5.3077*** (1.1332)	3.8589*** (0.6099)	10.1032*** (0.7694)	30.5292*** (1.3509)
Divorced	-8.3301*** (1.4050)	-0.8597 (1.1246)	-1.9740*** (0.5423)	-3.3890*** (0.6953)	-9.5921*** (1.1729)
Widowed	-0.1125 (2.0713)	8.9839*** (1.8348)	0.4771 (0.9897)	-5.4421*** (1.0933)	-7.4795*** (2.1682)
Black	2.1223 (4.1021)	89.8564*** (3.3109)	-11.9787*** (1.1268)	-11.3401*** (1.8329)	-32.1538*** (4.9858)
Hispanic	39.1654*** (5.2944)	67.9373*** (5.5861)	19.0820*** (2.0101)	16.2605*** (3.3156)	-82.2068*** (9.2857)
Other Race	13.3346* (6.6995)	45.8611*** (5.0148)	9.0001*** (2.3988)	0.3194 (2.8921)	11.5655 (8.8347)
State Indicators	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes
Observations	1,251,638	1,252,098	1,242,795	1,254,689	1,248,964
R-Squared	0.055	0.032	0.020	0.046	0.054

Notes: Retired individuals are omitted from the analysis. Standard errors are adjusted for arbitrary correlation across individuals within each state, and are presented in parentheses. Asterisks denote statistical significance as follows: *** p-value≤ 0.01; ** 0.01<p-value≤ 0.05; * 0.05<p-value≤ 0.1.

Table 3
Impact of State Unemployment Rate on Unhealthy Food Consumption
BRFSS – Ages 21-64

Specification	1	2	3	4	5
Outcome	Snacks	Hamburgers	Hot Dogs	French Fries	Fried Chicken
State Unemp. Rate	2.5352 (2.6058)	0.7729 (1.6207)	0.6428 (1.7296)	2.0382 (2.3229)	0.3755 (1.0216)
	Joint significance: p-value = 0.774				
Male	10.0057*** (1.3360)	23.5854*** (0.9440)	42.5692*** (1.9975)	28.6107*** (1.2124)	11.1934*** (1.0569)
Some High School	24.2145*** (4.7393)	7.0521** (3.3806)	13.9810*** (5.0013)	-5.7524 (3.5101)	-0.8104 (3.9276)
High School	19.8734*** (4.0322)	2.9421 (3.3794)	0.4763 (4.2743)	-13.3224*** (3.5374)	-9.5725*** (2.5496)
Some College	11.1918** (4.6078)	-3.9841 (3.5593)	-11.3004** (4.1419)	-21.5768*** (3.7660)	-14.9473*** (2.8485)
College	4.7670 (4.8469)	-16.7763*** (3.6392)	-26.4997*** (3.6540)	-30.7264*** (3.7279)	-21.6490*** (2.8923)
Age	-0.4984 (0.4463)	-1.4184*** (0.3158)	-2.9884*** (0.5151)	-3.0134*** (0.2429)	-0.1228 (0.2427)
Age Squared	-0.0135** (0.0055)	0.0030 (0.0038)	0.0201*** (0.0059)	0.0168*** (0.0027)	-0.0003 (0.0028)
Married	5.6707*** (1.8920)	-3.0698* (1.6936)	3.4091 (2.5944)	-5.2454*** (1.3175)	-3.4274*** (0.6184)
Divorced	-3.8029** (1.5245)	0.4019 (1.5848)	-0.5401 (2.9891)	0.2978 (1.2271)	-3.4801*** (0.8334)
Widowed	-9.1987** (3.4300)	-3.9067 (2.9986)	-2.9755 (2.9939)	-4.9698** (2.2660)	-4.8075*** (1.4325)
Black	-6.1076* (3.3549)	-6.3902*** (2.2350)	-10.1304*** (2.9746)	-4.6292* (2.2828)	41.2505*** (1.5480)
Hispanic	-19.8768*** (3.7291)	-5.9438*** (1.2920)	-8.3116*** (2.7289)	-1.2946 (2.1777)	12.5828*** (2.1532)
Other Race	-14.7561*** (3.3837)	-2.8064 (4.2270)	-6.9405 (4.7189)	0.3761 (2.5276)	17.6833*** (2.8169)
State Indicators	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes
Observations	61,217	61,589	61,423	61,285	61,340
R-Squared	0.024	0.065	0.027	0.055	0.058

Notes: Retired individuals are omitted from the analysis. Standard errors are adjusted for arbitrary correlation across individuals within each state, and are presented in parentheses. Asterisks denote statistical significance as follows: *** p-value≤ 0.01; ** 0.01<p-value≤ 0.05; * 0.05<p-value≤ 0.1.

Table 4
Impact of State Unemployment Rate on Healthy Food Consumption
Differential Effects by Health Status and Demographics

Sample		Outcome				
		Fruits	Fruit Juice	Carrots	Green Salad	Vegetables
1	Good Health[1]	-1.9317 (1.4164)	-2.0297 (1.4577)	-1.9374*** (0.6300)	-1.9398** (0.8929)	-0.3723 (2.1539)
		Joint significance: p-value = 0.074				
2	Ages 21-44	-2.2046 (1.3438)	-1.3737 (1.5073)	-1.8722*** (0.5938)	-1.7693** (0.8204)	-0.8567 (2.2347)
		Joint significance: p-value = 0.053				
3	Ages 45-64	-3.4040** (1.5198)	-2.3704** (1.1355)	-1.7662** (0.6711)	-2.0267** (0.9767)	-2.0762 (1.9668)
		Joint significance: p-value = 0.072				
4	Males	-2.6278** (1.2331)	-2.7128* (1.4579)	-1.4197** (0.6151)	-1.9380** (0.7678)	-2.1856 (1.9949)
		Joint significance: p-value = 0.129				
5	Females	-2.5112 (1.5921)	-0.7884 (1.2960)	-2.0671*** (0.6425)	-1.8822* (0.9854)	-0.6553 (2.2188)
		Joint significance: p-value = 0.018				
6	Married	-2.5750* (1.4087)	-2.0239 (1.3666)	-1.9457*** (0.6272)	-1.5557* (0.8244)	-2.4009 (2.2648)
		Joint significance: p-value = 0.021				
7	Unmarried	-2.4609* (1.3964)	-0.6066 (1.4701)	-1.6016** (0.6009)	-2.4142** (1.0494)	0.2279 (1.9439)
		Joint significance: p-value = 0.079				

Notes: Each cell represents a separate regression model. Retired individuals are omitted from the analysis. Standard errors are adjusted for arbitrary correlation across individuals within each state, and are presented in parentheses. All models control for state and year fixed effects. Sample sizes range from 502,415 to 746,713. Asterisks denote statistical significance as follows: *** p-value≤ 0.01; ** 0.01<p-value≤ 0.05; * 0.05<p-value≤ 0.1.
[1] Sample is restricted to individuals who reported that their health is Excellent, Very Good, or Good. Sample sizes range from 1,041,488 to 1,051,231.

Table 5
Impact of State Unemployment Rate on Unhealthy Food Consumption
Differential Effects by Health Status and Demographics

Sample		Outcome				
		Snacks	Hamburgers	Hot Dogs	French Fries	Fried Chicken
1	Good Health[1]	-3.0113*** (0.7338)	14.0009*** (0.7098)	12.8333*** (0.9118)	7.2509*** (0.6084)	4.8392*** (0.5370)
		Joint significance: p-value = 0.000				
2	Ages 21-44	1.6897 (2.8537)	0.6347 (1.8463)	-0.3261 (2.2961)	2.5053 (2.7626)	1.1582 (1.2823)
		Joint significance: p-value = 0.739				
3	Ages 45-64	4.6601 (4.8224)	1.1179 (2.6926)	3.1482 (2.5376)	0.9173 (1.5319)	-1.4131 (1.1170)
		Joint significance: p-value = 0.566				
4	Males	2.2391 (2.6236)	-0.8504 (2.5265)	-1.6602 (2.8313)	1.8672 (3.9055)	-0.7765 (1.7464)
		Joint significance: p-value = 0.857				
5	Females	2.8759 (3.5699)	1.9331 (1.2824)	2.4948 (2.0912)	2.0442 (1.3303)	1.3183 (1.0347)
		Joint significance: p-value = 0.044				
6	Married	5.6289* (2.9086)	2.8548 (2.1063)	1.6961 (1.9614)	3.6320 (3.0972)	0.2075 (0.8825)
		Joint significance: p-value = 0.048				
7	Unmarried	-2.0127 (4.7920)	-2.7317 (2.1657)	-0.6536 (3.3521)	-0.1395 (2.4450)	0.5548 (1.6022)
		Joint significance: p-value = 0.851				

Notes: Each cell represents a separate regression model. Retired individuals are omitted from the analysis. Standard errors are adjusted for arbitrary correlation across individuals within each state, and are presented in parentheses. All models control for state and year fixed effects. Sample sizes range from 17,575 to 43,843. Asterisks denote statistical significance as follows: *** p-value≤ 0.01; ** 0.01<p-value≤ 0.05; * 0.05<p-value≤ 0.1.
[1] Sample is restricted to individuals who reported that their health is Excellent, Very Good, or Good. Sample sizes range from 9,986 to 10,047.

Table 6
Cross-Equation Estimates of the Average Effect of
State Unemployment Rate on Healthy & Unhealthy Consumption
Seemingly Unrelated Regression

Sample		Healthy Food Consumption	Unhealthy Food Consumption
1	All (Ages 21-64)	-0.0080*** (0.0031) [0.010]	0.0100 (0.0096) [0.297]
2	Good Health[1]	-0.0076** (0.0034) [0.024]	0.0699*** (0.0051) [0.000]
3	Ages 21-44	-0.0074** (0.0032) [0.021]	0.0098 (0.0108) [0.361]
4	Ages 45-64	-0.0094*** (0.0032) [0.003]	0.0120 (0.0159) [0.452]
5	Males	-0.0091*** (0.0032) [0.005]	-0.0001 (0.0130) [0.994]
6	Females	-0.0072** (0.0034) [0.032]	0.0189** (0.0078) [0.016]
7	Married	-0.0089*** (0.0031) [0.004]	0.0219* (0.0119) [0.084]
8	Unmarried	-0.0064* (0.0033) [0.054]	-0.0069 (0.0156) [0.658]

Notes: Models are jointly estimated using a seemingly unrelated regression framework, and control for all covariates, and state and year fixed effects, as noted in Tables 2 and 3. All outcomes are transformed into standard normal deviates (see text). Estimates of the average effect of the state unemployment rate on the five measures of healthy food consumption and the five measures of unhealthy food consumption are presented. Standard errors are reported in parentheses and adjusted for arbitrary correlation across individuals within each state, and associated p-values are reported in brackets. Retired individuals are omitted from the analysis. Asterisks denote statistical significance as follows: *** p-value≤ 0.01; ** 0.01<p-value≤ 0.05; * 0.05<p-value≤ 0.1.

[1] Sample is restricted to individuals who reported that their health is Excellent, Very Good, or Good.

Table 7
Impact of County Unemployment Rate on Healthy & Unhealthy Food Consumption

Panel A		Healthy Food Consumption				
		Fruits	Fruit Juice	Carrots	Green Salad	Vegetables
1	All (Ages 21-64)	-1.1158*** (0.3530)	-0.8221* (0.4422)	-0.4198* (0.2241)	-0.5234** (0.2381)	-1.3553 (1.3425)
2	Good Health[1]	-1.0383** (0.4129)	-0.8977* (0.4829)	-0.3570* (0.2154)	-0.5197** (0.2569)	-1.4849 (1.3940)
3	Ages 21-44	-1.1297*** (0.3795)	-0.5999 (0.5913)	-0.2684 (0.2167)	-0.3593 (0.2359)	-1.0441 (1.4566)
4	Ages 45-64	-1.4024*** (0.4718)	-1.3149*** (0.4515)	-0.6097** (0.2422)	-0.7682** (0.3369)	-2.0072 (1.3657)
5	Males	-1.1648*** (0.3955)	-0.9890** (0.4391)	-0.5751** (0.2744)	-0.5571** (0.2385)	-1.5036 (1.1446)
6	Females	-1.1064** (0.4309)	-0.6993 (0.5157)	-0.3000 (0.2268)	-0.4776* (0.2606)	-1.2419 (1.5059)
7	Married	-1.1215*** (0.4184)	-0.7100 (0.5034)	-0.4069* (0.2455)	-0.6459** (0.2674)	-1.1980 (1.2812)
8	Unmarried	-1.0802** (0.4466)	-0.9341* (0.4808)	-0.4360* (0.2429)	-0.3585 (0.3103)	-1.5582 (1.4598)

Panel B		Unhealthy Food Consumption				
		Snacks	Hamburgers	Hot Dogs	French Fries	Fried Chicken
1	All (Ages 21-64)	-0.1720 (0.5899)	0.4465 (0.3713)	-0.4795 (0.6434)	0.6651 (1.1042)	-0.2494 (0.2935)
2	Good Health[1]	1.4591 (0.7942)	1.3054* (0.5960)	0.4670 (0.3645)	2.6617 (2.3780)	-0.5276* (0.2478)
3	Ages 21-44	-0.6151 (0.6889)	0.7793 (0.4879)	-0.2248 (0.7084)	0.3740 (0.9349)	-0.2038 (0.4432)
4	Ages 45-64	0.9125 (1.1678)	-0.2785 (0.4984)	-0.9475 (0.8117)	1.3256 (1.6678)	-0.3808* (0.2291)
5	Males	0.5549 (0.8896)	0.1387 (0.6196)	-0.7609 (1.4342)	0.2183 (1.2170)	-0.3775 (0.4053)
6	Females	-0.6067 (0.8202)	0.8207** (0.3910)	-0.1347 (0.5635)	1.0263 (1.1174)	-0.1542 (0.3199)
7	Married	0.0680 (1.1471)	0.7751* (0.4030)	0.3766 (1.0889)	0.9962 (0.8731)	0.0559 (0.2062)
8	Unmarried	-0.5140 (1.0500)	0.0316 (0.9695)	-1.7839* (0.9014)	0.3880 (1.8925)	-0.6597 (0.6037)

Notes: Each cell represents a separate regression model. Retired individuals are omitted from the analysis. Standard errors are adjusted for arbitrary correlation across individuals within each state, and are presented in parentheses. All models control for county and year fixed effects. Sample sizes range from 502,413 to 1,254,682 for measures of healthy food consumption and from 17,574 to 61,588 for measures of unhealthy food consumption . Asterisks denote statistical significance as follows: *** p-value≤ 0.01; ** 0.01<p-value≤ 0.05; * 0.05<p-value≤ 0.1.
[1] Sample is restricted to individuals who reported that their health is Excellent, Very Good, or Good. Sample sizes range from 1,041,482 to 1,051,225 for measures of healthy food consumption and from 9,986 to 10,047 for measures of unhealthy food consumption.

Table 8
Differential Effects by Propensity of being Unemployed
BRFSS

Panel A	All Individuals Ages 21-64				
Specification	1	2	3	4	5
Outcome	Fruits	Fruit Juice	Carrots	Green Salad	Vegetables
State Unemp. Rate	-0.3358 (1.3972)	-2.3551 (1.4467)	-1.5497** (0.6330)	0.0403 (0.9052)	1.7462 (2.0888)
State Unemp. Rate * Propensity Score	-12.0258*** (1.2101)	1.8873** (0.7806)	-1.8562*** (0.2907)	-14.5227*** (0.5253)	-14.2143*** (0.7781)
State Indicators	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes
R-Squared	0.056	0.032	0.020	0.049	0.055
Observations	1,195,127	1,195,532	1,186,632	1,197,958	1,192,338

Panel B	All Individuals Ages 21-64				
Specification	1	2	3	4	5
Outcome	Fruits	Fruit Juice	Carrots	Green Salad	Vegetables
State Unemp. Rate	1.2531 (1.7169)	-1.1043 (1.6476)	-1.1502* (0.6765)	1.6415* (0.8684)	1.5358 (2.1945)
State Unemp. Rate * Propensity Score	-12.0738*** (1.2250)	1.7932** (0.7977)	-1.9354*** (0.2977)	-14.6776*** (0.5490)	-14.2617*** (0.7792)
State Indicators	Yes	Yes	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes	Yes	Yes
State-specific Trends	Yes	Yes	Yes	Yes	Yes
R-Squared	0.056	0.032	0.020	0.050	0.056
Observations	1,195,127	1,195,532	1,186,632	1,197,958	1,192,338

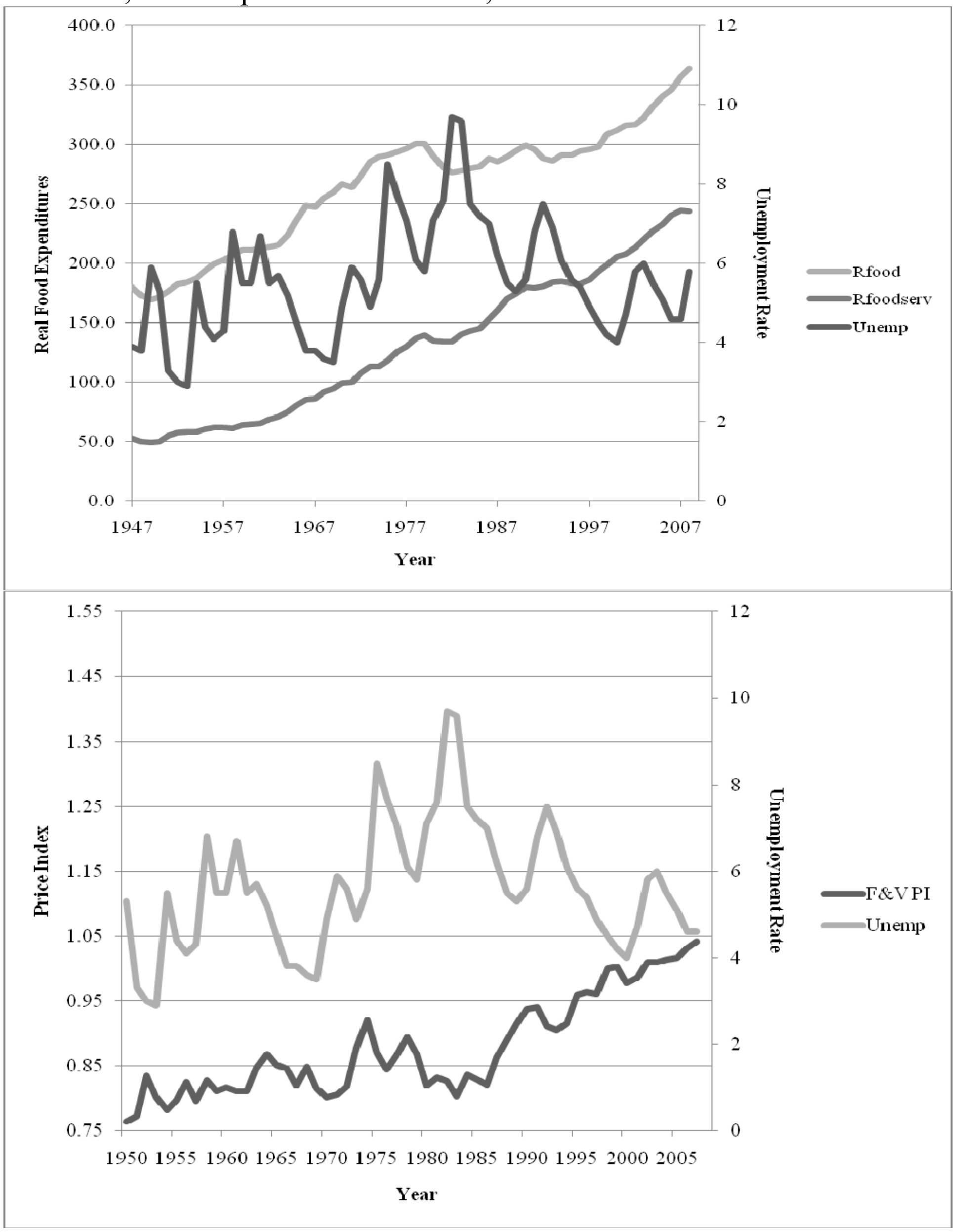
Notes: Each cell represents a separate regression model. Retired individuals are omitted from the analysis. The propensity score is estimated from a first-stage logit model predicting the probability of being unemployed as a function of the state unemployment rate, education, age, age squared, male, race indicators, marital status indicators, indicators for self-rated health, interactions between the state unemployment rate and each X, state indicators, and year indicators. Standard errors are adjusted for arbitrary correlation across individuals within each state, and are presented in parentheses. All models control for state and year fixed effects, in addition to the covariates noted in Table 2. Asterisks denote statistical significance as follows: *** p-value≤ 0.01; ** 0.01<p-value≤ 0.05; * 0.05<p-value≤ 0.1.

Table 9
Examining the Mechanisms of the Impact of the State Unemployment Rate
on Healthy Food Consumption

Specification	Outcome	Fruits	Fruit Juice	Carrots	Green Salad	Vegetables	Vitamins [1]
1	Baseline	-12.0258*** (1.2101)	1.8873** (0.7806)	-1.8562*** (0.2907)	-14.5227*** (0.5253)	-14.2143*** (0.7781)	-0.0318*** (0.0016)
2	Baseline with Work	-15.8037*** (1.2746)	-1.8510** (0.7741)	-3.5132*** (0.3128)	-14.5887*** (0.5526)	-17.3251*** (0.8067)	-0.0339*** (0.0018)
3	Baseline with Family Income	-6.9079*** (1.3097)	-3.3799*** (0.8150)	-3.4930*** (0.3608)	-10.1202*** (0.4913)	-6.6464*** (0.8122)	-0.0127*** (0.0016)
4	Baseline with Food Prices	-11.8645*** (1.2354)	1.8843** (0.8311)	-1.9721*** (0.3019)	-14.6343*** (0.5492)	-14.1437*** (0.8070)	-0.0318*** (0.0016)
5	Baseline with Mental Health	-7.9313*** (1.1708)	3.4006*** (0.8382)	-1.1273*** (0.3179)	-13.0942*** (0.5240)	-11.8569*** (0.8205)	-0.0343*** (0.0014)
6	Baseline with Physical Health	-11.6873*** (1.2778)	-0.0576 (0.8613)	-1.9864*** (0.3834)	-13.4951*** (0.5029)	-16.7739*** (0.9214)	-0.0440*** (0.0025)
7	Baseline with Self-Reported General Health	-12.0120*** (1.6512)	6.7471*** (1.3178)	0.1428 (0.5262)	-14.9907*** (0.6725)	-20.3740*** (1.1337)	-0.0496*** (0.0026)
8	Baseline with Health Insurance Coverage	-12.0120*** (1.6512)	6.7471*** (1.3178)	0.1428 (0.5262)	-14.9907*** (0.6725)	-20.3740*** (1.1337)	-0.0295*** (0.0015)
9	Baseline with All	-5.7759*** (1.3943)	-7.8231*** (0.9347)	-4.4945*** (0.4223)	-7.7284*** (0.5021)	-8.9794*** (0.9969)	-0.0263*** (0.0022)

Notes: Each cell represents a separate regression model. Retired individuals are omitted from the analysis. Coefficients from the interaction between the state unemployment rate and the propensity of being unemployed are presented. Standard errors are adjusted for arbitrary correlation across individuals within each state, and are presented in parentheses. All models control for state and year fixed effects, in addition to the covariates noted in Table 2. Asterisks denote statistical significance as follows: *** p-value≤ 0.01; ** 0.01<p-value≤ 0.05; * 0.05<p-value≤ 0.1.
1 Outcome represents a dichotomous indicator of whether the respondent currently takes vitamins or supplements. Sample sizes range from 232,407 to 268,596.

Figure 1
Unemployment Rate, Real Expenditures on Food, and Real Price Index for Fruits and Vegetables



Notes: Rfood pertains to personal consumption expenditures on food and beverages purchased for off-premises consumption. Rfoodserv pertains to personal consumption on food services. F&V PI pertains to the real price index for fruits and vegetables. Source for expenditures: National Income and Product Accounts, Bureau of Economic Analysis (BEA). Source for the national unemployment rate and price index: Bureau of Labor Statistics (BLS). Food expenditures were divided by the BLS Consumer Price Index for all urban consumers.