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The Effect of Job Loss on Overweight and Drinking

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Abstract

This paper examines the impact of job loss due to business closings on body mass index (BMI) and alcohol consumption. We suggest that the ambiguous findings in the extant literature may be due in part to unobserved heterogeneity in response and in part due to an overly broad measure of job loss that is partially endogenous (e.g. layoffs). We improve upon this literature by using: exogenously determined business closings, a sophisticated estimation approach (finite mixture models) to deal with complex heterogeneity, and national, longitudinal data from the Health and Retirement Study. For both alcohol consumption and BMI, we find evidence that individuals who are more likely to respond to job loss by increasing unhealthy behaviors are already in the problematic range for these behaviors before losing their jobs. These results suggest the health effects of job loss could be concentrated among "at risk" individuals and could lead to negative outcomes for the individuals, their families, and society at large.

Keywords

job loss; drinking; BMI; business closings; finite mixture models

Introduction

Losing a job can be stressful. Beginning with notification and culminating in reemployment, each phase of job loss—anticipation, termination, unemployment, and job search—can produce a forceful emotional response. The potential pathways of stress comprise an assortment of psychosocial and economic factors, including stigmatization, uncertainty, severance of social identity and role, unallocated time, and financial deprivation (Kasl and Jones 2000).

Individuals over 50 have been disproportionately represented among displaced workers in recent decades (Couch 1998). Job loss often induces forfeiture of critical health benefits (Beckett 1988), reduced wealth (Bernheim, Forni, Gokhale, and Kotlikoff 2000; Bernheim 1997), and obstacles to reemployment (Chan and Huff Stevens 2001; Hipple 1999). Further, when reemployed, workers over 50 experience significant wage penalties (Couch 1998; Huff Stevens 1997). A growing body of research has linked late-career job loss to a range of adverse health and chronic disease outcomes (Gallo, Bradley, Dubin, Jones, Falba, Teng, and Kasl 2006; Gallo, Teng, Falba, Kasl, Krumholz, and Bradley 2006) and mortality (Sullivan and von Wachter 2009). In this paper, we study the effect of business closures on body mass index and alcohol consumption using data on workers nearing retirement. We use finite mixture models to examine whether there are differential effects of job loss by latent class and, upon finding substantially heterogeneous effects, explore the determinants of the classes.

Alcohol misuse is a critical social concern for older individuals. Because older individuals have less lean body mass, they attain higher blood alcohol content for a given amount of alcohol consumed (Vestal et al. 1977), and for any given blood alcohol level, there is an intensified sensitivity to alcohol (Vogel-Sprott and Barrett 1984). Alcohol can contribute to difficulties with reaction, balance, and elements of cognitive function, increasing the probability of automobile collisions, falls, and both home and workplace accidents. In addition, alcohol use may exacerbate chronic health problems, such as high blood pressure, ulcers, and diabetes, which are more common among older individuals. There is, moreover, a potential for alcohol-drug interactions, as older people take more prescription and over-the-counter medications than younger individuals (Williams 1988). Risk of late-onset alcoholism (Hurt et al. 1988) is also of concern.

Obesity may be similarly problematic for the middle aged and near elderly. Obesity is a well-established risk factor for cardiovascular disease, high blood pressure, and diabetes, and some research has associated obesity with shorter life expectancy. Simulation data suggest that obese older persons can expect to live fewer years disability free than their normal weight counterparts and have higher incidence of diabetes, hypertension, and heart disease, with significantly burdensome healthcare costs paid by Medicare (Lakdawalla, Goldman, and Shang 2005).

Nevertheless, evidence on the effects of job loss on health behaviors has been decidedly mixed (McKee-Ryan, Song, Wanberg, and Kinicki 2005). This is especially true with regard to the health behaviors of interest in this research. Studies investigating the impact of job loss and unemployment on alcohol consumption have produced inconsistent results in terms of significance, magnitude and even direction of effect. Several assessments have found no relationship between unemployment and subsequent alcohol use (Broman, Hamilton, Hoffman, and Mavaddat 1995; Cook, Cummins, Bartley, and Shaper 1982; D'Arcy 1986; Gallo, Bradley, and Kasl 2001; Morris, Cook, and Shaper 1992; Morris, Cook, and Shaper 1994). Increases in alcohol consumption (Catalano, Dooley, Wilson, and Hough 1993; Janlert 1992) have been documented; however, it has been argued that these associations are related chiefly to selection (Kasl and Jones 2000). Reductions in alcohol consumption after job loss have also been reported in population-based studies (Iversen and Klausen 1986). Economic research linking macroeconomic conditions to health (Ruhm 2000, 2005) has found that recessions tend to reduce drinking, presumably in part due to reduced income.

Findings from research on changes in weight associated with unemployment are similarly ambiguous (Leino-Arjas, Liira, Mutanen, Malmivaara, and Matikainen 1999; Morris, Cook, and Shaper 1992; Morris, Cook, and Shaper 1994). Retrospective evidence (Leino-Arjas et al. 1999) has suggested a link between unemployment and BMI, but no panel study of which we are aware has found a significant change in BMI after job loss. One longitudinal study, which used data from the British Regional Heart Study (Morris, Cook, and Shaper 1992), did however find that middle-aged men who became unemployed had a higher risk of gaining more than 10% of their body weight (measured as a dichotomy) than similar continuously employed men.

There are several potential mechanisms that may help explain the wide variation in the individual behavioral responses to the stress of job loss. The first may be thought of as differences in stress-reactivity. Thus, although greater alcohol or food consumption might be employed to counterbalance neuro- or emotion-regulatory disturbances, reduced consumption or no change in consumption are equally plausible. So while there is evidence from animal, preclinical and clinical studies that stress leads to overeating and excessive drinking to self-medicate (Sinha, 2007), research on stress suggests substantial heterogeneity. To date, differences in response to stress have been explained by such factors as coping style, genetic proclivity, and other aspects of family history (Moore, Sikora, Grunberg, and Greenberg 2007). Secondly, income and substitution effects may also contribute to the ambiguity of earlier findings. Unemployment frequently diminishes income, creating financial constraints that may generally reduce the demand for food or alcohol, and alter the demand for specific items. Even so, the results of deprivation are again uncertain. For example, with less income, displaced workers may simply eat less or forgo alcohol use; however, they may simply substitute lower-priced, calorie-rich food or less costly alcohol for their normal consumption items. Finally, for some individuals, the increase in discretionary time due to unemployment may be used to pursue health-promoting behaviors, such as physical activity, that might precipitate weight loss or encourage alcohol temperance. Plausibly opposing effects render the net impact of job loss an open empirical issue.

This study contributes to the literature on behavioral effects of job loss along three dimensions. First, we use business closings as our measure of job loss. Business closings provide an exogenous source of stress, so that our findings are less susceptible to problems associated with selection. Job loss has frequently been represented by layoff or some combination of involuntary termination (e.g., layoff, plant closing, and firing) in other studies. However, layoffs and firing are likely to be endogenous (e.g., due to worker incompetence), and the use of these measures may have biased earlier findings (Charles and Stephens 2004; Dooley, Fielding, and Lennart 1996; Gibbons and Katz 1991; Hu and Tabor 2005; Weiss 1995). In contrast, business closings are more typically occasioned by external influences, such as an organizational decision to restructure or relocate business units (Brand, et al. 2008; Mandal, et al. in press). Note that one cannot conclusively state that business closures are exogenous events. For example, it may be the case that workers with unhealthy behaviors are steered by their preferences or market forces to jobs in weak business. Nevertheless, we expect such business closings to be much more exogenous than a measure that included all types of job loss.

Second, we use a finite mixture model (FMM) methodology to better address the complicated potential relationships among job loss, alcohol use, and BMI. We propose that the complexities of the relationship are not appropriately handled by traditional methodology, which may have led investigators to draw erroneous conclusions about the effect of job loss on health behaviors. Traditional statistical analyses have been unable to account for essential unobserved heterogeneity—in this case, individual differences in response to the stress of job loss. FMM permits estimation of the effect of business closings on health behaviors among groups of individuals whose response to stress is distinct from the average. Our findings illustrate that traditional modeling techniques, even when stratified by the customary attributes that presumably pick up much of the crucial heterogeneity in

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response to stress (e.g., gender, race, and education), are incapable of detecting behavioral changes within subgroups after job loss. Finite mixture models have received increasing attention in the statistics literature mainly because of the number of areas in which such distributions are encountered (see McLachlan and Peel, 2000, and Lindsay, 1995, for numerous applications). Econometric applications of finite mixture models include the seminal work of Heckman and Singer (1984) to labor economics, Wedel, et al. (1993) to marketing data, El-Gamal and Grether (1995) to data from experiments in decision making under uncertainty, and Deb and Trivedi (1997) to the economics of healthcare.

Finally, our research topic is both timely and germane to the ongoing debate on the impacts of job loss. Adverse impacts of business closings are presently of interest to policy makers, given the extraordinary number of recent job losses associated with the current economic recession. Global economic interdependence and the failure of financial markets linked especially to housing have precipitated a nearly unprecedented loss of employment, with major business closures in both goods-producing and service sectors of the U.S. economy. Nearly 2.6 million jobs were eliminated in 2008, with over 1.9 million of the job losses occurring in the 4-month period from September through December, following the collapse of major lenders, investment banks, and financial institutions, and the near ruin of the U.S. automobile industry. White collar jobs, often protected in prior recessionary periods, have witnessed almost unparalleled elimination. Despite nascent federal efforts to stabilize the economy, employment losses continue to mount. In February 2009, alone, the number of unemployed individuals increased by 851,000, as the unemployment rate rose to 8.1%, its highest level in 25 years (Bureau of Labor Statistics).

Data

Our data were drawn from the Health and Retirement Survey (HRS), a nationally representative study of men and women age 50 or older, begun in 1992 and designed to investigate health and economic consequences of older individuals as they advance from work to retirement. The original HRS cohort, first surveyed in 1992, consisted of individuals born between 1931 and 1941 and their spouses. A sample of individuals born before 1923 was added soon thereafter. An additional sample of individuals born between 1923 and 1930 was added in 1998. Baseline surveys were conducted face-to-face. Follow-up interviews, completed every two years, were completed by telephone or mail. More detail on the HRS is available elsewhere (Juster and Suzman 1995). Our study takes data from both the original HRS and Version H of the data prepared by RAND.[1]

We used data from the first nine HRS waves (1992-2008) to investigate the behavioral effects of business closings. To isolate individuals who were at risk for job loss, our analysis sample was restricted to HRS participants who met the following criteria at any data collection year: (1) were working for pay, but not self employed; (2) reported a minimum of two years of continuous employment; and (3) provided at least one follow-up response. The baseline application of the tenure criterion circumscribes undesirable sample heterogeneity deriving from the inclusion of seasonal workers and those with weak labor force attachment (Couch 1998; Jacobson, LaLonde, and Sullivan 1993); its reapplication limits the effects of multiple job loss. After dropping observations with missing values for the main variables in our analysis, our final analysis sample numbered 20,557.

The explanatory variable of interest, business closure, is represented by a binary variable that records employment change between survey waves. As such, retrospective data are

[1]The RAND HRS Data file is a longitudinal data that includes the most frequently used HRS variables. It was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

necessary for the creation of this variable. Thus, at each follow-up wave we first identified employment discontinuities. Among sample members who reported that they were no longer working for the previous wave's employer, we then considered responses to the following survey question: Why did you leave that employer? Did the business close, were you laid off or let go, did you leave to take care of family members, or what? Individuals who indicated that business closure was the reason for their departure were assigned a 1 for the indicator variable; otherwise, a 0 was assigned. Note that we do not include self-employed individuals in our analysis. Note also that the sample consists of two types of individuals, those who have been continuously employed for at least 2 years prior to the survey and those who are unemployed due to a business closing. Other unemployed individuals, those who chose to retire or otherwise left the labor force as well as those who were employed but not continuously so, are eliminated from the sample.[2]

We investigated the effect of business closings on two dependent variables in this study: daily drinking behavior and Body Mass Index (BMI). Drinking behavior (DRINKS) was measured by the number of alcoholic drinks (i.e., beer, wine, liquor) consumed per day, which was first asked at HRS Wave 3. In previous HRS waves, drinking was measured categorically. Thus the relevant sample size for the analysis of daily drinking behavior is 19,699. It was based on responses to the following survey question, In the last three months, on the days you drink, about how many drinks do you have? Non-drinkers were assigned a 0 value for this variable. The average number of drinks in a single day is a marker for heavy, hazardous, abusive, or dependent drinking. It is preferable to weekly quantity-frequency measures, which may mask abusive alcohol use on single days. BMI is a continuous variable, taken from the RAND HRS, and was calculated as weight, in kilograms, divided by the square of height, in meters.

Socioeconomic covariates were drawn from a number of domains. Demographic variables include age, gender, race, marital status, and education. Work-related variables comprise occupation, physical demands, and job stress. We control for occupational category to control for characteristics such as physical demand of the job and reemployment probabilities. Depressive symptomatology was a health-related control. Geographic regional variables were also included in most specifications.

Three additional variables were used in our later analysis of the determinants of whether an individual responds to job loss (i.e. latent class membership). They are a measure of risk aversion, financial planning horizon, and cognition. To infer risk preferences, the HRS asked respondents to choose among four different gambles, trading off certain and uncertain job opportunities and income. From this information, a risk aversion variable was developed, which ranged from 1 (least risk averse) to 4 (most risk averse).[3] Risk preferences

[2]Note that our sample selection criteria along employment lines as well as on missing values introduces the issue of survey non-response. In principle, it would be desirable to reweight the sample to account for such issues. However, there is little guidance in the literature to its implementation in the panel context. As is well known, the use of incorrect sampling weights in least squares or maximum likelihood estimation can introduce bias in settings where unweighted estimates are unbiased (but inefficient). Taking these points into consideration, we have chosen not to attempt to calculate resampling weights for our analysis. Our analysis does use the original sampling weights, however.

[3]The first gamble was presented as follows: Suppose you are the only income earner in the family, and you have a good job You are given the opportunity to take a new and equally good job, with a 50-50 chance that it will double your income and a 50-50 chance that it will reduce your income by a third. Would you take the new job? If the answer was no, the respondent was presented with the second gamble: Suppose the chances were a 50-50 chance that it would double your income and a 50-50 chance that it would cut your income by 20 percent. Would you still take the new job? If the answer to the first question was yes, the interviewer asked: Suppose the chances were a 50-50 chance that it would double your income and a 50-50 chance that it would cut your income by half. Would you still take the new job? Based on their choices, we created a variable that took the value 1 if the individual chose the riskiest option (50-50 chances of doubling their income or reducing it by half); 2 if they chose the job with even chances of doubling their income or reducing it by a third; 3 if they chose the job with even chances of doubling their income or reducing it by a fifth and 4 if they chose to stay with their current job.

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questions were asked of all respondents, excluding proxies, in 1992; they were not repeated in the 1994 and 1996 waves. From 1998 onward, selected respondents answered the risk preferences questions based on their cohort, age, and/or random selection. Assuming that risk attitude is a time invariant trait, we replaced missing data from the post-1992 HRS waves with responses from the previous wave. For participants who answered these questions in more than one wave prior, we took the mean of the previous responses.

To measure planning behavior the HRS asked respondents: In deciding how much of their (family) income to spend or save, people are likely to think about different financial planning periods. In planning your (family's) savings and spending, which of the time periods listed in the booklet is most important to you [and your (husband/wife/partner)]? We created a variable that took the value 1 if respondents answered next few months; 2 if they answered next year; 3 if they answered next few years; 4 if they answered the next 5-10 years; and 5 if they answered longer than 10 years. As with the risk preferences battery, this question was asked of all respondents, excluding proxies, in 1992, and was not repeated in the 1994 and 1996 waves. In 1998 and 2000, respondents were selected to answer this question based on a combination of their cohort and random selection. In 2002, individuals who were 65 years and older were not asked this question. We also treated planning horizon as a time invariant trait and applied the same data replacement approach, described above, as we used for the risk attitudes variable.

The HRS included a set of questions measuring the cognitive status of respondents. Based on responses to these questions, we constructed a cognitive score that was the sum of three separate measures: immediate word recall, delayed word recall, and series seven. The total score varied from 0 to 25, with a higher score representing a greater cognitive function. The immediate word recall measure counted the number of words that individuals could recall immediately after a list of 10 words was read to them by the interviewer. The delayed word recall measure counted the number of words from the same list that the individual could recall after five minutes. For the series seven measure individuals were asked to serially subtract seven starting from 100. This measure was the number of correct answers. The series seven question was not asked in 1992 and 1994 and none of these questions were asked of proxy respondents.

Table 1 provides a detailed description of the dependent and independent variables while Table 2 provides summary statistics for those who lost their job through business closings (511 observations) and separately for those who did not (20046 observations). For most of the variables, there are no significant nor substantial differences across the two groups. Education and income are the exceptions for which there are significant differences at the 5% level. Individuals who suffered job losses through business closings had lower pre-job loss income and have lower levels of education.

Econometric Methods

The basic econometric model for BMI, a continuous variable, is given by

$$E\left(BMI_t \mid BC_{t-1}, BMI_{t-1}, X_{t-1}\right) = \alpha BC_{t-1} + \gamma BMI_{t-1} + X_{t-1}\beta$$

where BC is an indicator for job loss due to business closing between times t-1 and t. For notational convenience, we subscript BC with t-1. Time-invariant socioeconomic characteristics are denoted by X which is measured at time t-1. In addition, we include BMI_{t-1} to control for baseline BMI. Equation (1) is first estimated by OLS. However, if BMI is drawn from distinct subpopulations, as we have argued above, the OLS estimate of α is the average of the effects across subpopulations, thus may hide substantive differences in α

across the subpopulations. Thus, we also estimate equation (1) using a finite mixture model, where the subpopulations are assumed to be drawn from normal distributions. The model is described in more detail below.

The basic econometric model for number of drinks per day (DRINKS), an integer valued variable, is given by

$$E\left(\mathrm{DRINKS}_t | BC_{t-1}, \mathrm{DRINKS}_{t-1}, X_{t-1}\right) = \exp\left(\alpha BC_{t-1} + \gamma \mathrm{DRINKS}_{t-1} + X_{t-1}\beta\right)$$

where, in addition to BC, measured between t-1 and t, and X, measured at time t-1, we include $\mathrm{DRINKS}_{t\text{-}1}$ as an additional regressor to control for baseline drinking behavior. Because the conditional mean is specified as an exponential function, DRINKS t-1 enters the argument of the exponent logarithmically. (A small number, 0.1, is added to $\mathrm{DRINKS}_{t\text{-}1}$ to bypass the log(0) issue. Note that the log(0) problem is not one that occurs for the outcome variable, i.e., on the left hand side. It is, however, related to the issue of how to specify the lagged value of the outcome variable on the right hand side of the regression specification given that the conditional mean is specified using a log link, i.e., an exponential mean.) Equation (2) is first estimated by Poisson regression. Again, if DRINKS is drawn from distinct subpopulations, the Poisson estimate of α is the average of the effects across subpopulations and may hide substantive differences in α across the subpopulations. Thus, we also estimate equation (2) using a finite mixture model with Poisson-distributed subpopulations.

In the finite mixture model, the random variable y is postulated as a draw from a population which is an additive mixture of C distinct classes or subpopulations in proportions π_j such that

$$g\left(y_1|\theta\right) = \sum_{j=1}^{C} \pi_j f_j\left(y_i|\theta_j\right), \quad 0 \le \pi_j \le 1, \quad \sum_{j=1}^{C} \pi_j = 1.$$

where the j^{th} density is $f_j\left(y_i \mid \Theta_j\right)$, $j = 1,\dots,C$ and Θ_j is the associated set of parameters.

In the case of the normal mixture for BMI, the component density for observation i is given by

$$f_j\left(y_i|\theta_j\right) = \frac{1}{\sigma_j\sqrt{2\pi}} \exp\left(-\frac{1}{2\sigma_j^2}\left(y_i - \alpha_j \mathrm{BC}_{t-1} - \gamma_j\, \mathrm{BMI}_{t-1} - \mathrm{X}_{t-1}\beta_j\right)^2\right).$$

The component density in the Poisson mixture for DRINKS is given by

$$f_j\left(y_i|\theta_j\right) = \frac{\lambda_{ji}^{y_i} \exp\left(-\lambda_{ji}\right)}{y_i!}$$

where $\lambda_{ji} = \exp(\alpha_j \mathrm{BC}_{t-1} + \gamma_j\ \mathrm{DRINKS}_{t-1} + \mathrm{X}_{t-1}\ \boldsymbol{\beta}_j)$. Other applications of normal mixtures include Morduch and Stern (1997) and Conway and Deb (2002), while an early application of finite mixture of Poisson densities is Wang, Cockburn and Puterman (1998). The finite mixture models are estimated using maximum likelihood and takes sampling weights into account. All inference is conducted using standard errors which are adjusted for clustering at the individual level. These are implemented using the Stata package *fmm*.

The finite mixture model provides a natural and intuitively attractive representation of heterogeneity in a finite, usually small, number of finite mixtures latent classes, each of which may be regarded as a 'type' or a 'group'. Estimates of such finite mixture models may provide good numerical approximations even if the underlying mixing distribution is continuous (Heckman and Singer 1984; Laird 1978). In addition, the finite mixture approach is semiparametric—it does not require any distributional assumptions for the mixing variable—and under suitable regularity conditions is the semiparametric maximum likelihood estimator of the unknown density (Lindsay 1995).

A finite mixture characterization is especially attractive if the mixture components have a natural interpretation. However, this is not essential. A finite mixture may be simply a way of flexibly and parsimoniously modeling the data, with each mixture component providing a local approximation to some part of the true distribution. A caveat to the foregoing discussion is that the finite mixture model may fit the data better simply because outliers, influential observations or contaminated observations are present in the data. The finite mixture model will capture this phenomenon through additional mixture components. Hence it is desirable that such models be supported both by *a priori* reasoning and by meaningful *a posteriori* differences in the behavior of the latent classes.

We can use our finite mixture parameter estimates to calculate the posterior probability of being in each of the latent classes. Although the models assume that the prior (unconditional) probability of class membership is constant across observations (p), we can use Bayes Theorem to calculate the posterior probability of membership in each class, conditional on all (both time invariant and variant) observed covariates and outcome, as

$$\Pr(y_i \in k|\theta, y_i) = \frac{f_k(y_i|\theta_k)}{\sum_{j=1}^{C} \pi_j f_j\left(y_j|\theta_j\right)}, \forall k=1, 2, \ldots, C.$$

Thus the posterior probability varies across observations. Note that in the preferred specifications of the 2-component mixture regressions we include only time-varying independent variables because the lagged dependent variable absorbs the time-invariant variation, but in additional specifications we include time-varying regressors as well. However, in the posterior we use both time-varying and time-variant covariates. We use the estimated posterior probabilities to explore the determinants of class membership.

We note that quantile regressions have been used in similar contexts to study heterogeneous responses to treatments. In the context of our study, quantile regression methods have two limitations vis-à-vis finite mixture models. First, quantile regressions are not always well behaved in the context of count data. Second, although quantile regression methods may detect heterogeneous responses, they provide no way to characterize the source of the heterogeneity.

Results

For both of the outcomes, we present results from 2-component mixtures. For BMI, model selection criteria do not provide sufficient improvement in favor of the 3-component model as compared to the 2-component one. For DRINKS, the 3-component model failed to converge after a reasonable number of iterations, suggesting that the third component was likely attempting to fit a small number of outliers or otherwise influential observations. We first provide results from a preferred specification, which compares estimates generated by FMM models with estimates derived from traditional statistical analysis (i.e., OLS for BMI, Poisson regression for DRINKS). See Tables 3 and 6. We then provide results (Tables 4 and 7) of the FMM models for two extended specifications, the first of which adds additional demographic controls, and the second of which adds job-related variables. Finally, in Tables 5 and 8, we present estimates of latent class membership, or the posterior probability of belonging to one of the subgroups identified in the FMM analysis.

BMI Results

Considering the preferred specification, OLS estimates of the effect of business closure on subsequent BMI suggested no significant difference between participants who experienced business closure and those who did not. See Table 3. This contrasts with the results of the FMM model, in which two latent classes (components) were identified in proportions of 0.84 and 0.16, respectively. Members of the first latent class (Component 1) had small, but statistically insignificant decreases in BMI after business closure. In a markedly different manner, participants in the second latent class had large, statistically significant ($p<.05$) increases in BMI following business closure. On average, Component 2 members increased their BMI by over one unit. This one-unit change is similar to gaining 7 pounds for a 5 ft, 10 inch man who weighs 180 pounds before job loss.

These results are robust to the addition of other covariates in the extended specifications (Table 4). In addition to the specifications reported in Table 4, we considered quadratics in age and interactions of age with gender. Neither changed the estimates on business closing in any substantial way. We have also considered categorical specifications for BMI on the right hand side of the equation but their inclusions do not change the basic results in any way. Indeed, in each case the coefficient estimates on business closing are somewhat larger.

There are some other notable results that can be seen in Table 3. First, while older sample members had lower overall BMI, age had a substantially larger effect on individuals in Component 2. Second, lagged BMI was highly significant in both components and the coefficient is very close to one for individuals in Component 1. The coefficient was smaller in Component 2, suggesting less persistence in BMI among individuals in Component 2. Note that lagged BMI is a highly significant explanatory variable that presumably picks up much of the pre-existing differences in BMI, thus leaving relatively little to be absorbed by the time-varying independent measures.

As mentioned above, Component 2 is the smaller latent class with a mixing proportion of about 0.16, meaning that the probability that a sample individual is of this “type” is 16%. Individuals who were (*ex-post*) classified as being in Component 2 had an average BMI of 29.9 as compared to 27.1 among individuals in Component 1. In the top panel of Figure 1, we illustrate the component densities of the finite mixture model for BMI. At 29.9, the average BMI for Component 2 is on the verge of meeting the criteria for obese (BMI over 30), and clearly many members of this component are obese. At 27.1, the mean for Component 1 is just over the cutpoint for overweight (25 and above), but only a small percentage of these are likely to be obese. Indeed, we find that individuals in Component 2 were almost 22 percentage points more likely to be obese compared to those in Component 1. BMI in the overweight and especially obese range put individuals at increased risk of health problems.[4] Given that they are an older population, this effect compounds their already elevated risks. It is also noteworthy that the distribution associated with Component 2 has a substantially higher variance.

Several variables predict membership in the Component 2, as can be seen in Table 5. Those who are younger, have lower non-housing net worth, have higher depressive symptoms, are less educated and are female were significantly more likely to be in Component 2. Those in Component 2 also had higher job stress and were more likely to be in jobs requiring more physical effort prior to business closure. Being more risk averse significantly increased the probability of being in Component 2, but was significant in only one specification. While we expected that financial planning horizons and cognitive abilities might be significant in determining latent classes, they were not.

Daily Drinking Results

As with BMI, comparison of the single equation (Poisson in this case) results with FMM suggest considerable heterogeneity across two components, which occur in proportions 0.90 and 0.10. While business closure had a small effect on subsequent daily drinking in the Poisson regression, the FMM results indicated one group whose behavioral response to business closure is four times as large as the response of the other group. These results are displayed in Table 6. This group (Component 2) increased its daily consumption of alcohol by approximately 42 percent per day after business closure ($p<.01$). In contrast, members of the first latent class (Component 1) had small increases in daily drinking after business closure. Marginal effects calculated at the sample means of other covariates showed that individuals in Component 2 increased their alcohol consumption by 1.02 drinks beginning from a “baseline” of 1.55 drinks per day.

Over two drinks a day exceeds the maximum recommended amount for both men and women (for women the recommended maximum is 1 per day). Thus the additional alcohol consumption is likely to be harmful to the individual due to increased risk of accidents, interactions with medications, and harmful effects of alcohol for individuals with chronic diseases. Also, the additional alcohol consumption could have negative externalities due to increased drunk driving, negative impacts on family members, and impairments and accidents at home and at work (for the employed.).

Extended specifications controlling for the full set of demographic and employment variables are presented in Table 7 and show that the results are robust to the inclusion of these additional variables. In these specifications, a physically demanding job significantly reduces the number of drinks only for those in the second latent class while job related stress has no impact on either component.

Individuals who were (*ex-post*) classified as being in Component 2, the smaller latent class with a mixing proportion of 0.10, consumed an average of 1.2 drinks as compared to 0.7 drinks among individuals in Component 1. We found that, compared to individuals in Component 1, those in Component 2 were 32 percentage points more likely to be binge drinkers. A higher cognitive score was associated with a lower probability of belonging to Component 2 although this effect was statistically significant in only one specification (see Table 8). Risk aversion and financial planning horizon did not have any significant impact on the probability of belonging to Component 2.

In the bottom panel of Figure 1, we illustrate the component densities of the finite mixture model for DRINKS. The figure clearly shows that individuals in Component 2 are heavier drinkers, have greater variability in consumption, and are less likely to be non-drinkers.

[4]Other methods estimate not only body fat but also body fat distribution as excessive fat in the abdominal area in particular is associated with increased health risks. Such methods include measurements of skinfold thickness and waist circumference, waist-to-hip circumference ratios, and techniques such as ultrasound, computed tomography, and magnetic resonance imaging (MRI). While some of these indicators are more specifically correlated with health risks, however, the HRS does not have any of these other measures.

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Discussion

In this study, we used nationally representative data on U.S. workers nearing retirement to assess the effect of business closures on two important health behaviors: BMI and daily alcohol use. The recent severe economic downturn and resulting large increases in job loss coupled with the mixed results in the previous literature make our analysis especially timely and policy relevant. Indeed we show evidence that previous literature has likely failed to find important effects of job loss on health behaviors because of a focus on the average effect of job loss rather than the heterogeneous effects of job loss across the population.

In particular, we extended the literature in several ways. First, we use a measure of job loss that is plausibly exogenous; our focus on business closings helps to isolate a causal effect that is less likely driven by selection. Second, we extend previous empirical modeling strategies by using finite mixture models in order to capture heterogeneity in the effects of job loss on health. Third, our use of national panel data allows us coverage of the population of individuals over 50 years old as well as the ability to control for health measures before job loss.

Accounting for sample heterogeneity via FMM estimation proved crucial to unmasking subpopulations whose health behaviors were affected by the stress of job loss. Our main results indicated substantial heterogeneity in the effect of business closure for both BMI and daily drinking behavior. While the majority of individuals experienced no behavioral effect of business closing, a smaller proportion reported adverse changes. Importantly, we show that this smaller proportion of individuals who respond to job loss by increasing unhealthy behaviors are individuals already pursuing unhealthy behaviors (pre-job loss), so that these further increases in unhealthy behaviors may be especially problematic. This qualitative result holds for both drinking and BMI. The broad consistency of the results across specifications, including the stability of the class probabilities across a wide variety of specifications, gives us confidence that the results are not spurious and specifically, not driven by the relatively small number of individuals who experience job loss due to business closing.

The results from this paper are of particular important given the current era of high job loss. Behavioral health responses to job loss may aggravate an already stressful situation for this vulnerable population of older workers. A better assessment of the empirical impact may pave the way for methods to better protect the health of those who respond particularly negatively to job loss.

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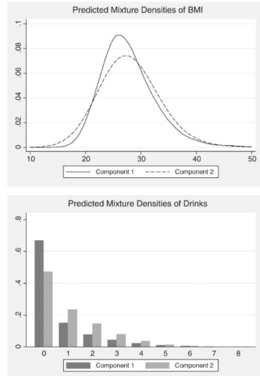

Fig. 1.
Predicted mixed densities BMI (top). Predicted mixed densities DRINKS (bottom).

Table 1

Variable Details

Variable name	Coding Algorithm/Variable details
Outcome Variables	
BMI	Body mass index
DRINKS	Number of drinks of alcohol per day on the days that they drink.
Independent Variables	All explanatory variables are lagged
Business Closure	1=Business closed between waves; 0=Otherwise
Age	Age in years
Male gender	1 = Male; 0 = Female
Married civil status	1 = Married; 0 = Not Married
Black race	1 = Black; 0 = Non-Black
Education	Years of education
Depressed	Abridged version of the Center for Epidemiologic Studies-Depression (CESD) Scale - sum of answers to eight questions that asked if during the past week, the respondent felt depressed, felt that everything he did was an effort, experienced restless sleep, could not get going, felt lonely, felt sad much of the time, enjoyed life and was happy. The last question was reverse coded so that a higher score represents more depressive symptoms. Note: Standardized to have mean zero and variance one.
Household Income	Total (respondent + spouse) household income. It is the sum of the following: earnings; household capital income; income from all pensions and annuities; income from social security disability and supplemental security income; income from social security retirement, spouse or widow benefits; income from unemployment and worker's compensation; income from veteran's benefits, welfare and food stamps; alimony, other income, and lump sums from insurance, pension and inheritance. Note: Divided by 10,000 for scalar consistency and deflated to 1992 USD. We used the logarithm value of income and added 0.01 to deal with the log(0) issue.
Job Stress	1 = Strongly agrees that current job involves lots of stress; 0 = Otherwise
Physical Effort	Extent to which job requires lots of physical effort: 1=all/almost all the time; 2=most of the time; 3=some of the time; 4=none/almost none of the time
Occupational Categories	Binary(1/0) indicators for the following categories: Managerial; Clerical & Administrative Support; Sales; Mechanical, Construction & Precision Production; Services (including private household, protective, food preparation, health and personal service); Operators, Fabricators & Laborers; Farming, Forestry & Fishery. The reference category was Professional and Technical Support and Armed Forces.
Risk Averse	1=Least risk averse; 2=3rd most risk averse; 3=2nd most risk averse; 4=Most risk averse
Financial Planning Horizon	1=Next few months; 2=Next year; 3=Next few years; 4=Next 5-10 years; 5=Longer than 10 years

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Variable name	Coding Algorithm/Variable details
Cognitive Score	Categorical variable takes values 0 to 25. Higher score represents greater cognitive function.
Region Dummies	Binary (1/0) variables for the following Census regions of residence: region 2 = Mid Atlantic; region 3 = EN Central and WN Central; region 4 = S Atlantic; region 5 = ES Central and WS Central; region 6 = Mountain and Pacific. The omitted category is region 1 = New England.

Table 2

Summary statistics by business closing status

	Did not experience business closing	Experienced business closing
Body Mass Index	27.773	27.970
Daily number of drinks	0.811	0.818
Age	59.721	61.123*
Married	0.721	0.728
Household income	6.330	4.773*
Manufacturing	0.142	0.129
Clerical & Administrative	0.168	0.164
Sales	0.082	0.125*
Mechanical	0.090	0.106
Service	0.137	0.129
Operator	0.123	0.202*
Farming, Forestry & Fishing	0.024	0.016
Depressive symptoms	1.062	1.171
Year 2	0.111	0.125
Year 3	0.178	0.170
Year 4	0.138	0.221*
Year 5	0.114	0.121
Year 6	0.169	0.137
Year 7	0.150	0.092*
Black	0.144	0.145
Male	0.498	0.495
Years of education	13.111	12.078*
Region 2	0.131	0.139
Region 3	0.264	0.266
Region 4	0.244	0.249
Region 5	0.150	0.168
Region 6	0.168	0.131*
Job stress	0.183	0.152
Physical effort	2.833	2.855
Risk aversion	3.274	3.345
Financial planning horizon	3.146	2.993*
Cognitive score	15.401	14.960*
N	20046	511

*Means are statistically different at the 5 percent level.

Table 3

OLS and Finite Mixture Models for BMI

	OLS	Component1	Component2
Business Closure	0.168 (0.114)	−0.019 (0.085)	1.140** (0.502)
Age	−0.017*** (0.002)	−0.012*** (0.002)	−0.051*** (0.013)
Married	−0.001 (0.035)	0.007 (0.028)	−0.120 (0.189)
Hshold Income	−0.021 (0.017)	−0.006 (0.015)	−0.096 (0.099)
Manufacturing	0.012 (0.047)	0.036 (0.034)	−0.206 (0.288)
Clerical & Admin.	0.048 (0.048)	0.043 (0.037)	0.016 (0.279)
Sales	−0.006 (0.055)	0.051 (0.044)	−0.386 (0.313)
Mechanical	0.013 (0.054)	−0.030 (0.040)	0.075 (0.329)
Service	0.072 (0.056)	0.009 (0.041)	0.306 (0.334)
Operator	0.054 (0.054)	−0.048 (0.040)	0.466 (0.320)
Farm. & Forestry	−0.037 (0.083)	−0.003 (0.079)	−0.439 (0.479)
Depressed	0.005 (0.012)	−0.006 (0.008)	0.052 (0.057)
Lagged BMI	0.941*** (0.006)	0.987*** (0.004)	0.777*** (0.033)
π_1 [a]		0.842 (0.020)	0.158
Observations	20,557	20,557	20,557

[a] π_1 is the probability that an observation is in Component 1.

Robust standard errors in parentheses. Regressions also include year dummies.

*** p<0.01

** p<0.05

* p<0.1

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Table 4

Additional Specifications of the Finite Mixture Model for BMI

	Component1	Component2	Component1	Component2
Business Closure	−0.020 (0.086)	1.126** (0.494)	−0.076 (0.085)	1.169** (0.531)
Age	−0.012*** (0.002)	−0.050*** (0.014)	−0.011*** (0.002)	−0.047*** (0.015)
Married	0.009 (0.028)	−0.118 (0.189)	0.003 (0.028)	−0.071 (0.192)
Hshold Income	−0.006 (0.016)	−0.079 (0.101)	−0.007 (0.016)	−0.091 (0.106)
Manufacturing	0.040 (0.034)	−0.224 (0.293)	0.022 (0.035)	−0.309 (0.305)
Clerical & Admin.	0.029 (0.039)	−0.004 (0.294)	0.015 (0.041)	−0.134 (0.304)
Sales	0.054 (0.046)	−0.426 (0.324)	0.032 (0.046)	−0.518 (0.333)
Mechanical	−0.012 (0.044)	−0.049 (0.383)	−0.014 (0.046)	−0.121 (0.396)
Service	0.017 (0.045)	0.163 (0.349)	0.006 (0.047)	0.113 (0.367)
Operator	−0.029 (0.043)	0.257 (0.356)	−0.013 (0.046)	0.134 (0.367)
Farm. & Forestry	0.016 (0.080)	−0.655 (0.521)	0.029 (0.093)	−0.840 (0.560)
Depressed	−0.007 (0.009)	0.052 (0.058)	−0.011 (0.009)	0.047 (0.060)
Black	−0.134*** (0.037)	0.608** (0.244)	−0.132*** (0.039)	0.704*** (0.254)
Male	−0.049* (0.025)	0.075 (0.188)	−0.054** (0.026)	0.113 (0.195)
Yrs. of Education	−0.001 (0.005)	−0.017 (0.035)	−0.004 (0.006)	−0.024 (0.037)
Job Stress			0.038 (0.032)	0.214 (0.233)
Physical Effort			0.010 (0.012)	0.032 (0.097)
Lagged BMI	0.989*** (0.004)	0.773*** (0.033)	0.990*** (0.004)	0.771*** (0.034)
π_1 [a]	(0.004) 0.841	0.159	0.840 (0.020)	0.160
Observations	20,552	20,552	19,486	19,486

[a] π_1 is the probability that an observation is in Component 1.

Robust standard errors in parentheses. Regressions also include year and census region of residence dummies.

*** $p<0.01$

** $p<0.05$

* $p<0.1$

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Table 5

Determinants of the Posterior Probability of Being in Component 2 for BMI

	(1)	(2)	(3)	(4)	(5)
Age	-0.002^{***} (0.000)	-0.002^{***} (0.000)	-0.002^{***} (0.000)	-0.002^{***} (0.000)	-0.002^{***} (0.000)
Married	−0.004 (0.004)	−0.007 (0.005)	−0.007 (0.005)	−0.002 (0.005)	−0.001 (0.005)
Hshold Income	-0.015^{***} (0.002)	-0.011^{***} (0.003)	-0.010^{***} (0.003)	-0.005^{*} (0.003)	-0.006^{**} (0.003)
Manufacturing	0.012^{**} (0.006)	0.001 (0.007)	0.002 (0.007)	0.002 (0.007)	0.001 (0.007)
Clerical & Admin.	0.029^{***} (0.005)	0.024^{***} (0.007)	0.023^{***} (0.007)	0.006 (0.007)	0.004 (0.007)
Sales	0.019^{***} (0.007)	0.014^{*} (0.009)	0.015^{*} (0.009)	0.011 (0.009)	0.011 (0.009)
Mechanical	−0.011 (0.007)	-0.021^{**} (0.009)	-0.022^{**} (0.009)	−0.015 (0.010)	−0.012 (0.010)
Service	0.021^{***} (0.006)	0.016^{**} (0.008)	0.014^{*} (0.008)	−0.003 (0.009)	0.000 (0.009)
Operator	0.007 (0.006)	-0.013^{*} (0.008)	-0.015^{*} (0.008)	-0.020^{**} (0.009)	-0.016^{*} (0.009)
Farm. & Forestry	0.003 (0.011)	-0.029^{*} (0.016)	-0.031^{*} (0.016)	−0.027 (0.017)	−0.020 (0.017)
Depressed	0.006^{***} (0.001)	0.006^{***} (0.001)	0.006^{***} (0.001)	0.005^{***} (0.001)	0.005^{***} (0.001)
Black				0.022^{***} (0.007)	0.023^{***} (0.007)
Male				-0.036^{***} (0.005)	-0.036^{***} (0.005)
Yrs. of Education				-0.004^{***} (0.001)	-0.004^{***} (0.001)
Job Stress					0.016^{***} (0.005)
Physical Effort					0.005^{**} (0.002)

	(1)	(2)	(3)	(4)	(5)
Risk Aversion			0.005^{**} (0.002)	0.002 (0.002)	0.002 (0.002)
Financial Horizon			−0.004 (0.003)	−0.001 (0.003)	−0.001 (0.003)
Cognitive Score			−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.001)
Observations	20,557	12,208	12,208	12,204	12,111

Standard errors in parentheses. Regressions also include year and census region of residence dummies.

*** p<0.01

** p<0.05

* p<0.1

Table 6

Poisson and Finite Mixture Models for Daily Alcohol Consumption

	Poisson	Component1	Component2
Business Closure	0.182*** (0.061)	0.125** (0.057)	0.512** (0.240)
Age	−0.011*** (0.002)	−0.004** (0.002)	−0.041*** (0.009)
Married	0.006 (0.031)	0.003 (0.024)	0.062 (0.088)
Hshold Income	0.022 (0.016)	0.034*** (0.013)	−0.005 (0.032)
Manufacturing	0.090*** (0.033)	0.015 (0.026)	0.212* (0.120)
Clerical & Admin.	−0.020 (0.043)	−0.036 (0.030)	−0.040 (0.151)
Sales	−0.005 (0.044)	−0.048 (0.035)	0.064 (0.154)
Mechanical	0.161*** (0.042)	0.045 (0.035)	0.416*** (0.151)
Service	−0.023 (0.050)	−0.032 (0.040)	0.072 (0.175)
Operator	0.092** (0.043)	−0.028 (0.035)	0.391** (0.164)
Farm. & Forestry	0.161** (0.068)	−0.095 (0.071)	0.840*** (0.214)
Depressed	−0.003 (0.009)	−0.011 (0.008)	0.046** (0.021)
Lagged DRINKS	0.679*** (0.015)	1.024*** (0.015)	−0.871*** (0.117)
π_1 [a]		0.904 (0.006)	0.096
Observations	19,699	19,699	19,699

[a] π_1 is the probability that an observation is in Component 1.

Robust standard errors in parentheses. Regressions also include year dummies.

*** p<0.01

** p<0.05

* p<0.1

Table 7

Additional Specifications of the Finite Mixture Model for Daily Alcohol Consumption

	Component1	Component2	Component1	Component2
Business Closure	0.124** (0.055)	0.463** (0.235)	0.128** (0.055)	0.424* (0.219)
Age	−0.004*** (0.002)	−0.044*** (0.009)	−0.004*** (0.002)	−0.041*** (0.009)
Married	−0.010 (0.023)	0.015 (0.083)	−0.007 (0.023)	−0.021 (0.086)
Hshold Income	0.025* (0.013)	−0.028 (0.037)	0.033** (0.013)	−0.017 (0.039)
Manufacturing	0.002 (0.026)	0.079 (0.122)	0.010 (0.028)	0.070 (0.116)
Clerical & Admin.	0.004 (0.031)	0.011 (0.145)	0.020 (0.032)	−0.013 (0.141)
Sales	−0.056 (0.035)	−0.050 (0.160)	−0.041 (0.036)	−0.134 (0.156)
Mechanical	0.015 (0.037)	0.080 (0.156)	0.008 (0.038)	−0.059 (0.166)
Service	0.004 (0.041)	−0.023 (0.157)	0.038 (0.040)	−0.240 (0.163)
Operator	−0.039 (0.038)	0.104 (0.177)	−0.033 (0.040)	−0.094 (0.166)
Farm. & Forestry	−0.115 (0.071)	0.511** (0.236)	−0.094 (0.089)	0.314 (0.255)
Depressed	−0.008 (0.008)	0.056** (0.022)	−0.008 (0.008)	0.053** (0.023)
Black	−0.171*** (0.044)	0.073 (0.123)	−0.144*** (0.045)	0.013 (0.117)
Male	0.136*** (0.022)	0.580*** (0.093)	0.141*** (0.022)	0.581*** (0.093)
Yrs. of Education	0.001 (0.004)	−0.019 (0.015)	0.003 (0.005)	−0.025 (0.015)
Job Stress			−0.010 (0.023)	−0.126 (0.087)
Physical Effort			−0.006 (0.011)	−0.091** (0.042)
Lagged DRINKS	1.002*** (0.015)	−0.932*** (0.126)	1.006*** (0.015)	−0.864*** (0.121)
π_1 [a]	0.901 (0.006)	0.099	0.900 (0.006)	0.100
Observations	19,694	19,694	18,805	18,805

[a] π_1 is the probability that an observation is in Component 1.

Robust standard errors in parentheses. Regressions also include year and census region of residence dummies.

*** p<0.01

** p<0.05

* p<0.1

Table 8

Determinants of the Posterior Probability of Being in Component 2 for Daily Alcohol Consumption

	(1)	(2)	(3)	(4)	(5)
Age	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	−0.010***	−0.007*	−0.008*	−0.011***	−0.011***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Hshold Income	0.003	0.002	0.002	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Manufacturing	0.009*	0.007	0.007	0.003	0.003
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Clerical & Admin.	0.003	0.002	0.002	0.006	0.006
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Sales	0.004	−0.000	−0.002	−0.004	−0.004
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
Mechanical	0.024***	0.028***	0.026***	0.010	0.008
	(0.005)	(0.007)	(0.007)	(0.007)	(0.008)
Service	0.000	0.003	0.001	−0.000	−0.003
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Operator	0.009*	0.011*	0.008	−0.001	−0.003
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Farm. & Forestry	0.012	−0.003	−0.005	−0.019	−0.020
	(0.009)	(0.013)	(0.013)	(0.013)	(0.013)
Depressed	0.001	0.002	0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Black				−0.000	0.000
				(0.005)	(0.005)
Male				0.028***	0.029***
				(0.004)	(0.004)
Yrs. of Education				−0.001*	−0.001*
				(0.001)	(0.001)
Job Stress					0.002
					(0.004)
Physical Effort					−0.002
					(0.002)
Risk Aversion			−0.002	−0.001	−0.001
			(0.002)	(0.002)	(0.002)

	(1)	(2)	(3)	(4)	(5)
Financial Horizon			0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Cognitive Score			−0.001** (0.001)	−0.000 (0.001)	−0.000 (0.001)
Observations	19,699	13,282	13,282	13,278	13,169

Standard errors in parentheses. Regressions also include year and census region of residence dummies.

*** $p<0.01$

** $p<0.05$

* $p<0.1$