Mental Distress and Labor Productivity

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12/07/2020

1 Introduction

According to the National Alliance on Mental Illness, approximately 1 in 5 adults in the U.S. faces a mental illness in a given year. Furthermore, only 43% of adults with a mental disorder utilize treatment services. With such high prevalence and such low treatment rates, it is important to examine what economic burdens may be attributable to mental illness and what can be done to address the issue.

The productivity loss generated by mental illness is one of the most commonly studied phenomena within the economic literature on mental health. There are two forms of productivity loss that are often examined: presenteeism and absenteeism. These terms refer to being less productive on the job and being absent from work, respectively. Workers with mental illness likely face greater levels of presenteeism and absenteeism when compared to their mentally healthy coworkers. This paper aims to empirically test for the presence and magnitude of this greater level of absenteeism in hopes of determining the magnitude of this indirect cost of mental illness.

Failure to consider indirect costs like the productivity loss associated with mental illness in workers may explain the movement toward mental healthcare cost containment methods undertaken by some firms. One such method comes in the form of implementing managed care programs for mental health. These plans require that a care manager decides on treatment duration and type, and usually have an annual cap on inpatient and outpatient services. The more stringent design of these plans may deter some employees from ever seeking treatment for their mental disorder. Additionally, if an employee under a managed care plan does choose to seek treatment, the cost-saving design of the plan might mean they are not receiving the most beneficial type of treatment. This in turn results in substantial productivity loss associated with symptom severity (Goetzel et al. 2002, 327), meaning the total cost savings associated with movement to these plans might be overestimated. In favor of this argument, a study from Rosenheck et al. (1999) find that the introduction of mental healthcare cost containment methods in a firm decreases the utilization of mental health services by employees. Simultaneously, utilization of medical services is found to increase, indicating that untreated mental illness can result in higher medical costs and that cutting costs in the area of mental health does not necessarily mean cutting healthcare costs as a whole. On top of this, these researchers find evidence of greater productivity loss in workers with mental disorders after the introduction of these policies. Nevertheless, the increasing focus in recent years on containing healthcare costs indicates that employers may not take indirect responses to changes in health coverage like these into account when making investment decisions on employee healthcare.

Not only should productivity loss be taken into account when making investment decisions, but also when enacting policies, whether they be workplace or public policies. A lack of adequate or affordable mental healthcare is not the only factor contributing to greater indirect costs associated with mental illness. A serious stigma is associated with mental illness that may cause individuals suffering to fear being judged negatively by peers. This stigma often contributes to an individual"s unwillingness to report diagnoses or seek treatment that will ease their symptoms. Policy initiative aimed at reducing the stigma associated with mental illness can improve treatment utilization rates, thus reducing the productivity loss and other costs associated with mental illness.

In this paper, I empirically measure the impact of mental illness on absenteeism. I also compare the impact of several other factors (physical health, healthcare utilization, job characteristics, and personal beliefs) on absenteeism among workers with and without a diagnosed mental illness by considering interactions between these factors and mental illness. I do this in hopes of determining which factors drive the discrepancy in absenteeism observed between workers with and without mental illness. In section II, I review economic literature examining the impact of mental illness on various areas of the labor force. In section III, I lay out the theoretical framework behind this study. Section IV discusses data and summary statistics, and section V explains the empirical hypotheses and econometric methods used to test them. Section VI gives results. Section VII provides discussion of the findings and summarizes main conclusions.

2 Review of Previous Literature

Research on the topic of mental health and productivity is not a new phenomena. However, few studies on the topic have been published since 2010 and many older studies on the topic are limited in their generalizability and robustness of results. It is the goal of this paper to utilize the modeling techniques of some of the relevant pieces of literature while improving on issues of generalizability.

Goetzel et al. (2005) derive important implications, though the study is empirically lacking. These researchers find a large negative relationship between mental illness and productivity. They loosely estimate monetary costs of productivity losses associated with types of illnesses based on a number of self-reported surveys that provide information on health conditions, work absences, and on-the-job productivity loss. Mental illness is estimated to be among the top four most costly illness categories in terms of productivity loss. However, these findings should be interpreted with caution, as estimates of these costs are derived using aggregated numbers of illness prevalence and national averages of hourly wages and hours worked per year, rather than individual-level micro-data.

Ashwood et al. (2017) also attempt to monetize the cost and benefits associated with mental health, or more specifically, improvements in mental health service utilization. The main focus of their study is a cost-benefit analysis of a program aimed at reducing stigma associated with mental illness in California. The most important take away, however, comes prior to the monetization of estimated effects, when researchers empirically test for impacts of program exposure on work absences and the ability to obtain employment. During this portion of the analysis, Ashwood et al. find evidence that adults with mental illness who have been exposed to the program exhibit fewer absences and a greater likelihood of employment compared to adults with mental illness who have not been exposed. This is most likely in response to the improved treatment utilization numbers observed among those who have been exposed to the program, implying that those in treatment for their mental health disorder exhibit better labor force outcomes than those who have a mental disorder but are not being treated.

In observation of low mental health service utilization numbers worldwide, Kohn et al. (2004) attempt to estimate the treatment gap (% of individuals who require care but do not receive treatment) for each type of mental health disorder. These researchers extensively review past empirical studies to find the best estimates of prevalence rates and treatment utilization for each of several mental disorders. These numbers are then used to calculate estimated treatment gaps for each mental disorder. The overall treatment effects are estimated to be 32.2% for schizophrenia, 56.3% for major depression, 56.3% for dysthymia, 56% for bipolar disorder, 55.9% for panic disorder, 57.5% for generalized anxiety disorder (GAD), and 59.5% for obsessive compulsive disorder (OCD). Due to differences in medical practices and cultural norms across countries, estimated treatment gaps for each disorder vary depending on the availability of treatment or the likelihood of being diagnosed within each of the countries studied. Many of the studies used to form these estimates do not account for adequacy of treatment or differences in socioeconomic status across regions. In terms of the United States, Kohn et al. are confident in their estimate of a 56.9% treatment gap for major depression and find evidence that this gap has decreased as it has become more common for health insurance to cover psychotropic medications, indicating that having health insurance is a dire factor when deciding to seek treatment in the United States.

Much of the literature on mental health and the labor force looks to identify a link between mental health and earnings or labor force participation. A study of particular importance among this group of literature comes from Cseh (2008) who analyzes the impact of depression on earnings across years. The data source permits Cseh to control for severity of depression by using a raw depression-scale score. Using this proxy for symptom severity indicates a significant and negative effect of depression severity on wages across years. This finding illustrates the importance of controlling for the severity of mental illness in analyses. However, Cseh failed to additionally recognize that the severity of any physical ailments should also be controlled for, as this is likely to impact labor force outcomes as well. In observance of this, I include a variable representing one's level of physical health, which is based on the presence of any physical health conditions and on health behaviors, in my analysis. I additionally proxy for the severity of either type of condition (physical or mental) using healthcare utilization variables that will be described later on.

French and Zarkin (1998) studied the impact of mental health on absenteeism and earnings. They define two models estimating absenteeism: one represents absence within the last 30 days as a dichotomous variable; the other contains a count variable representing total absences within the last 30 days. They employ logit regression to estimate the first absenteeism model and a negative binomial form estimates the second. They control for physical health in their model, however, they do not consider that the interaction between physical and mental health may play a role in predicting absenteeism. Both absenteeism models indicate that poor mental health has a significant positive impact on absenteeism. Additionally, they find evidence that poor mental health has a negative impact on earnings. Unfortunately, the degree to which results generated by French and Zarkin can be generalized to the working population poses major issue because they only have 408 observations and all workers in their sample share the same place of employment.

Bubonya et al. (2016) examine how interactions between poor mental health and job characteristics influence presenteeism and absenteeism among workers. This study solves many of the issues of the French and Zarkin study by utilizing a panel data source that is representative of the Australian working population and that yields a large sample size. These researchers find evidence that mental health has a significant impact on productivity, as well as significant differences in the impact of job characteristics on productivity between workers with and without mental illness. Particularly, they find that those who face mental distress see higher rates of both absenteeism and presenteeism. These higher rates of presenteeism among workers in poor mental health are less flexible to changes in job factors than the rates of presenteeism observed for mentally healthy workers, indicating that workers with mental illness may always face a greater level of productivity loss while at work, regardless of environmental factors. Conversely, absenteeism rates tend to vary more with changes in job factors for the mentally ill workers than mentally healthy workers, indicating that job factors only influence the lower levels of productivity in mentally ill workers through the channel of the decision making process on when to stay home from work. There are quite a few shortcomings with the Bubonya et al. study, including the form of the mental illness indicator variable, which is based on self-reported measures of emotional distress rather than information on actual diagnosed mental disorders. They also are unable to control for things like treatment or severity of the mental illness, which may be problematic because it is likely that individuals who are in intervention for their mental disorder see impacts more in line with mentally healthy workers than mentally ill workers who are not in some form of intervention. Bubonya et al. also do not consider access to health insurance as one of the job characteristics that may impact the effect of mental health on productivity, probably because health insurance is universal in Australia, whereas in the United States, employer-provided health insurance is most prevalent.

This study aims to contribute to the literature in the following ways: first, multiple categories of mental disorders are considered in creating my main mental disorder dummy variable, whereas much of the past literature has focused on one or two specific illnesses, mainly anxiety and depression. This can provide insight on the generalizability of such studies that only consider a specific array of symptoms. Second, I am able to divide the mental disorder dummy variable into multiple dummy variables that represent each category of mental illness included in the first portion of my analysis, allowing insight on how each specific disorder impacts labor market outcomes. Third, I analyze how the magnitude of the impact of various factors on absenteeism vary with mental health status. These factors include physical health, wage, hours worked, fringe benefits, healthcare utilization, and intrinsic beliefs. Understanding the interactions between these variables and mental illness can highlight the most relevant steps to be taken to reduce the impact that mental illness has on productivity in the future.

3 Theory

3.1 Framework

Principles of labor theory assume that the level of output produced by a firm depends not only on the inputs it holds, but the relative efficiency of each input. The below equation represents the production function for a two-input firm, firm A, which produces output level, Y^A, has capital input level, K^A, and labor input level, L^A. The efficiency of firm A's capital and labor inputs are represented by the marginal product of capital (MP_K^A) and marginal product of labor (MP_L^A).

$$Y^A = F^A(K^A, L^A)$$

$$\frac{\partial F^A}{\partial K^A} = MP_K^A,$$

$$\frac{\partial F^A}{\partial L^A} = MP_L^A,$$

MP_L^A can be determined by examining the productiveness of a firm's workers. This paper focuses on assessing what impacts a worker's level of productivity (MP_{Li}^A for worker i). Bubonya et al. (2016) discuss two ways in which a worker's relative productivity can be measured when we are interested in assessing productivity at the worker-level rather than firm-level: through observing the worker's absenteeism and presenteeism. Absenteeism refers to days in which a worker does not report to work due to a physical or mental ailment, while presenteeism refers to productivity loss faced at work due to a physical or mental ailment. Due to a lack of reliable data reporting the presenteeism of full-time workers, I focus on absenteeism in this analysis.

3.2 Health Production

Consider an individual's health as a good that gives utility. An individual can invest in the production of this good, and the more investment in health, the better off the consumer is (keeping in mind the law of diminishing returns). There are many factors impacting the level of health that an individual produces. Consider healthcare as an input good in the process of health production. For example, if an individual goes to the doctor when they are ill, the doctor may prescribe antibiotics or other medication to fight off the illness, thus aiding in the production of that individuals health. Preventative measures also aide in health production, such as annual physicals or seeing a doctor at the onset of pain or other symptoms to avoid further exasperating the issue. Access to healthcare will obviously impact healthcare utilization, and thus health production. For example, an individual with health insurance is probably more likely to obtain preventative care than someone with no insurance. Other factors such as having a regular doctor may also be tools in health production; a primary doctor relieves some of the burden of seeking care for minor ailments and the doctor knows about her health history, thus making health production easier.

Job characteristics also impact the production of health for workers. Perhaps most obvious is the influence wage has on health. Consider two individuals identical in every way except for the wage they are paid. The worker with the higher wage rate has more income to put toward health investment if they choose to do so. The higher paid worker may have greater means to buy fresh foods or join a gym than the low wage worker. Additionally, a high wage worker may have greater opportunity to separate themselves from polluted and overpopulated communities, which are another threat to health. The hours a person works probably also influences health, it is less clear how health may vary with hours. From one perspective, overworking oneself poses serious harm to one's health; from the other, working more hours may improve health if there is a substantial gain in income associated with the excess hours worked, for example, an individual offering to cover an overtime shift to make a higher-than-usual wage rate probably doesn't see many health effects since the additional work is temporary. Fringe benefits such as paid sick leave and vacation time may also support an individuals health *if these benefits are utilized when needed*. Paid sick leave may encourage an individual to stay home and get well when ill so as to avoid exacerbating symptoms. Vacation days clearly aide in health production being that downtime is a necessity for long term physical and mental health.

Finally, demographic factors such as age, race, and gender clearly impact the efficient level of health production of each individual. With the previous discussion in mind, consider the following health production function of some individual, i,

$$H_i = f_i^H(HC_i^H, J_i^H, X_i^H), \tag{1}$$

where HC_i^H, J_i^H, and X_i^H are the vectors of healthcare, job characteristics, and demographic variables influencing the level of health, H_i, produced by individual i, respectively. It should be noted that individual i's health can further be split into two categories: physical and mental. Noting this, it is valuable to consider that physical health is likely impacted by mental health, and vice versa. Thus, we can generate two new functions from equation (1):

$$PH_i = f_i^{PH}(MH_i, HC_i^{PH}, J_i^{PH}, C_i^{PH}, X_i^{PH}), \tag{2}$$

$$MH_i = f_i^{MH}(PH_i, HC_i^{MH}, J_i^{MH}, C_i^{MH}, X_i^{MH}), \tag{3}$$

where PH_i and MH_i are physical and mental health of individual i, respectively, and vectors HC_i^j, J_i^j, and X_i^j for $j = \{PH, MH\}$ are the factors impacting physical and mental health. Note that a distinction is made using separate superscripts to illustrate that there may be some factors that impact one type of health and not the other (though it is likely that if a factor impacts one type of health, it impacts the other).

As mental health is the main focus throughout this paper, our focus will be on elaborating upon the implications of equation (3). We can clearly see that the sign of the impact of each component suspected to be involved in the individual i's mental health production can be revealed simply by taking the partial derivatives of equation (3) with respect to each element. For simplicity of notation, assume each vector on the right hand side of equation (3) – except PH_i, which is assumed to be single valued – has two components so that $HC_{i,1}^{MH}$ is the first component of the vector representing factors of healthcare and $HC_{i,2}^{MH}$ is the second and $J_{i,1}^{MH}$ is the first component of the vector of job characteristics while $J_{i,2}^{MH}$ is the second. In what follows, I will discuss hypotheses I have pertaining to the link between physical health, healthcare, and job characteristics on mental health.

First I hypothesize that increases in physical health positively impact mental health. That is,

$$\frac{\partial MH_i}{\partial PH_i} > 0.$$

The sign of the impact of job characteristics on mental health may vary based on the type of specific factor. First, consider the case when the first job characteristic in vector J_i^{MH} has a positive impact on mental health such that we observe

$$\frac{\partial MH_i}{\partial J_{i,1}^{MH}} > 0.$$

Examples of such job features for which I hypothesize the above condition will hold are those relating to income, such as wage, bonuses, raises, etc. As previously discussed, it is likely that wage has a positive impact on health because of the greater resources to invest in health. Another line of thinking may be that if an individual receives a boost in their wage, or similarly, receives a bonus, they may feel appreciated for their work or may exhibit higher self-confidence which can be illustrations of better mental wellness. I hypothesize that fringe benefits may also be in this category of job characteristics, such as paid sick leave or vacation days, as these are tools that can be used to address burn-out, which poses harm to mental health, without the risk of losing income.

On the other end, assume that factor $J_{i,2}^{MH}$ is such that

$$\frac{\partial MH_i}{\partial J_{i,2}^{MH}} < 0.$$

This will likely hold for factors that contribute to job stress, such as hours worked. The more hours an individual works, the less time they have for recuperation and self-care.

Unlike job characteristics, I believe factors of healthcare will have positive impacts on mental health so that

$$\frac{\partial MH_i}{\partial HC_i^{MH}} > 0.$$

An in access to healthcare likely increases mental health through improving access to mental health services themselves, or through the channel of positively impacting physical health. For factors of healthcare utilization, it is plausible to observe a positive impact because greater utilization may imply some form of treatment.

Now that mental health production has been analyzed, consider determinants of a worker's productivity.

3.3 Absenteeism

Each worker's rate of absenteeism depends on what impacts their decision to either stay home or go to work when ill (Bubonya et al. 2016, 16). A multitude of factors may be able to explain differing levels of absenteeism (represented by A_i for worker i) observed between workers. This idea is demonstrated in equation (4), where H_i represents measures of individual i's health, vector HC_i contains characteristics of an individual's healthcare access and utilization, J_i is a vector containing individual i's job characteristics, and X_i is a vector representing individual i's demographic factors. Variables in each vector represented in equation (4) are expected to influence the typical worker's decision making process in the event that they can either stay home from work, or go to work and be less productive on the job. As noted in the previous section on health production, the overall health of a worker (H_i) can be further split into categories of physical (PH_i) and mental health (MH_i), which are each likely to have differing magnitudes of impact on a worker's productivity, resulting in equation (5).

$$A_i = f_i^A(H_i, HC_i, J_i, C_i, X_i) \tag{4}$$

$$A_i = f_i^A(PH_i, MH_i, HC_i, J_i, C_i, X_i) \tag{5}$$

Represented in vector J_i of equations (1) and (2) is the particularly important consideration that fringe benefits provided by a job may impact a worker"s decision about when to stay home. If, for example, a worker is granted paid sick leave, he or she is probably more likely to stay at home when faced with an illness or ailment. Conversely, an employee without paid sick leave may exhibit greater presenteeism because of their perceived need to "tough it out" and go to work on days that symptoms of illness are pervasive. Vector J_i also may include factors like individual i's wage rate and typical hours worked per week, as these factors may influence decisions on when to stay home. For example, a higher wage increases the opportunity cost associated with absenteeism, and a greater number of hours worked per week may imply a position of higher responsibility, causing the employee to feel there would be more backlash if she were absent than if she were at work while exhibiting presenteeism. Job characteristics as a cohesive unit can also impact productivity based on how they influence an individual's job satisfaction. If a worker exhibits little job attachment, they may be more prone to shirking.

When considering job characteristics such as hours and wage and how these factors impact absenteeism, it is important to discuss the issue of potential simultaneity. Using information on a worker's hours worked per week and their hourly wage rate, we can observe his or her marginal revenue product of an additional day of work (equivalently, of one less absence). It is reasonable to assume that the magnitude of this marginal revenue product will impact absenteeism – the higher the worker's marginal revenue product, the greater the opportunity cost of an additional absence. Conversely, it may also be reasonably argued that absenteeism impacts the worker's marginal revenue product, as it reduces the hours that the individual is actually working. As we will see later, the data is not detailed enough to establish the exact number of hours an individual has worked, rather I only have information on their *typical* work week, so an empirical analysis of marginal revenue product and its simultaneity with absences is not useful. However, the discussion of this theoretical simultanaeity does point to the importance of treating hours and wage as potentially endogenous variables, as unobservable characteristics impacting these factors may be correlated with unobservable factors impacting absenteeism. This issue will be further discussed in the empirical methodology section.

Components of vector HC_i include whether a worker has health insurance, whether they have a primary care doctor, and the frequency of health service utilization. In isolation, healthcare utilization likely has a positive impact on absenteeism, as the higher the rate at which an individual utilizes healthcare, the greater the likelihood that this utilization has, at some point, cut into work time. The isolated impacts of health insurance and having a regular doctor on absences is less clear. It should also be noted that the encompassing impact of healthcare on absences likely depends on how characteristics of healthcare impact an individual's health. For example, if greater utilization is an indicator of more preventative care measures to improve one's health, utilization may have a positive impact on productivity. On the other hand, if utilization rates are to be thought of as a proxy for severity of health issues or ailments, we might anticipate a negative overall impact on productivity. This idea will be discussed further later.

Given that some of the factors impacting absenteeism may also impact mental health, the *total effect* that mental health has on absenteeism will vary based on the values of the factors that equations (3) and (5) have in common. That is, changes in any of the right hand side factors of equation (3) will impact mental health, thus impacting absenteeism. Therefore, the total effect of mental health on absenteeism is given by the following:

$$\frac{\partial A_i}{\partial MH_i} = \left.\frac{\partial A_i}{\partial MH_i}\right|_{\Delta k_i=0,\forall k} + \frac{\partial A_i}{\partial MH_i} * \frac{\partial MH_i}{\partial PH_i} + \frac{\partial A_i}{\partial MH_i} * \frac{\partial MH_i}{\partial J_i^{MH}} + \frac{\partial A_i}{\partial MH_i} * \frac{\partial MH_i}{\partial HC_i^{MH}} + \frac{\partial A_i}{\partial MH_i} * \frac{\partial MH_i}{\partial X_i^{MH}}, \quad (6)$$

where $k_i = \{PH_i, HC_i, J_i, X_i\}$. We can see that the sign and magnitude of the total impact of mental health on absenteeism depends on the sign and magnitude of each term in equation (6). I hypothesize that the *isolated* effect of mental health on absenteeism, $\left.\frac{\partial A_i}{\partial MH_i}\right|_{\Delta k_i=0,\forall k}$, is negative; better mental health implies less absenteeism. The sign of each of the rest of the terms is straight forward from here. Simply plug in the hypothesized sign of each partial derivative from the mental health production function, which have been laid out in section 3.1.1.

In addition to the total effect of mental health on absenteeism, other valuable information can be drawn from equation (5). We can consider how the impact on absenteeism induced by each of the factors related to mental health will vary given a change in mental health. With this information we can determine the sources of variation in absenteeism by comparing workers in poor mental health to workers in good mental health. First, consider physical health. The total effect of physical health on absenteeism is given by the following equation.

$$\frac{\partial A_i}{\partial PH_i} = \left.\frac{\partial A_i}{\partial PH_i}\right|_{\Delta MH_i=0} + \frac{\partial A_i}{\partial PH_i} * \frac{\partial PH_i}{\partial MH_i}.$$

That is, the total effect of physical health on absenteeism is equal to the isolated impact prior to considering an interaction with mental health plus the interaction effect between physical and mental health. Similar equations can be developed for each of the factors anticipated to vary with mental health, however, for the sake of this paper I only form hypotheses of the sign of the interaction effects for each variable of interest because this tells us differences across absence rates posed by differences in mental health. I hypothesize the following:

$$\frac{\partial A_i}{\partial PH_i} * \frac{\partial PH_i}{\partial MH_i} < 0.$$

That is, improvements in mental health have a negative effect on the magnitude of the total impact physical health has on absenteeism. This is because I theorize that increases in physical health decrease absenteeism and improvements in mental health likely positively impact physical health.

Now consider the total impacts of the job characteristics interacting with mental health, $J_{i,j}^{MH}$ for $j = 1, ..., m$ and m is the total number of variables in vector J^{MH} and the following hypothesis:

$$\frac{\partial A_i}{\partial J_{i,j}^{MH}} * \frac{\partial J_{i,j}^{MH}}{\partial MH_i} < 0. \tag{7}$$

I hypothesize that the above condition holds for every factor in J_i^{MH} that increases the cost of staying home from work (thus decreasing absences, $\left(\text{(i.e., } \frac{\partial A_i}{\partial J_{i,j}^{MH}} < 0\right)$, such as wage, and $\frac{\partial J'_{m,i}}{\partial MH_i} > 0$ assuming that workers in better mental health will see higher wages than those in poor mental health. This condition also holds for factors that decrease the cost of staying home from work if it is reasonable to assume that the impact of these factors becomes smaller as mental health improves. One such example might be whether the job offers paid sick days. If this is the case, the cost of staying home when ill decreases thus increasing absences. Additionally, I argue that the magnitude of this influence of paid sick leave on absences is somewhat mitigated when a worker displays improvements in mental health. That is, a worker in good mental health will probably utilize the benefit of paid sick leave less often than a worker in poor mental health. A similar example would be hours, as a high number of hours worked poor week may cause an individual to be more susceptible to illness which would increase their absences; however this increase is probably smaller in magnitude for a worker in good mental health than a worker in poor mental health.

Next, consider healthcare utilization variables that interact with mental health. For $HC_{i,j}^{MH}$ when

$j = 1, ..., m$ and m is the total number of variables in vector HC^{MH}, I hypothesize the following:

$$\frac{\partial A_i}{\partial HC_{i,j}^{MH}} * \frac{\partial HC_{i,j}^{MH}}{\partial MH_i} < 0. \tag{8}$$

First off, I theorize that $\frac{\partial A_i}{\partial HC_{i,j}^{MH}} > 0$ when $HC_{i,j}^{MH}$ is a value representing the amount of health services utilized. The greater the utilization of such services, the more likely that these services will cut into work time. Additionally I predict that $\frac{\partial HC_{i,j}^{MH}}{\partial MH_i}$ is likely negative as improvements in mental health may imply less treatment services are necessary. This condition may hold for healthcare access variables as well

$$\frac{\partial A_i}{\partial MH_i'} * \frac{\partial C_i'}{\partial MH_i} < 0, \tag{9}$$

if variable C_{1i}' of vector C_i' is some belief that makes it more likely that individual i will be properly treated for illnesses (such as an openness to medical intervention, or the belief that one receives a higher quality of care when they do utilize medical services), thus resulting in fewer illness-related absences. It is likely that individuals with mental illness will be more sensitive to such a trait due to the greater need of these individuals to seek treatment in order to reduce negative psychological symptoms. Therefore, I theorize the impact of such a trait will be more negative for these individuals.

Finally, for the opposite type of belief, i.e., one that decreases the likelihood of seeking medical intervention to cure illness (such as an aversion to seeking medical help), I hypothesize that the interaction will have a positive impact, i.e.,

$$\frac{\partial A_i}{\partial C_i'} * \frac{\partial C_i'}{\partial MH_i} > 0. \tag{10}$$

Individuals with mental illness will be more sensitive to such an aversion and so I predict that the impact of such a trait will be more positive for workers with mental illness.

These general hypotheses are broken down into variable-specific hypotheses in the empirics section of this paper.

4 Data and Sample Characteristics

4.1 Data

The data used in this study comes from the Medical Expenditure Panel Survey (MEPS) which provides nationally representative information on demographic and employment characteristics, healthcare utilization, and the general health status of each individual within a surveyed household. Each household is interviewed three times per year for two years (so, six interviews total per household), with interviews typically scheduled to occur every four months. I compile the MEPS Full Year Consolidated Data File (FYCD) and Medical Conditions File (MCF) for years 2010 to 2015 to create my dataset. Most variables controlled for in my analysis are from the FYCD. The MCF gives information on each individual"s diagnosed medical conditions, including specific mental health disorders. Using the MCF, I am able to obtain information on diagnosis and utilization of mental health services and merge this with the FYCD data to identify which individuals in the sample are diagnosed with a mental disorder. It is important to note that because I am using information on *diagnosed* mental disorders to construct my mental health variable, mental disorder prevalence rates reported by my sample may not be representative of actual prevalence rates across the U.S. population. This is because a significant portion of the population meeting the criteria for a diagnosable mental illness never seek medical help, and thus, are never officially diagnosed. According to the 1999 Surgeon General's report on Mental Health, there is a large gap between mental health treatment practices in the real world and mental health treatments suggested by research, which may cause individuals to be skeptical about reporting negative psychological symptoms to mental health professionals. The same report also discusses the negative societal stigma associated with mental illness, which is another potential reason for the discrepancy between diagnosis and prevalence rates of mental illness.

Each of the FYCD files contain an average of three variables representing each interview question asked to individuals (if we wanted all variables representing responses to one particular interview question, we would have three variables for each year). This is because most survey questions are asked in each of the three interviews conducted in each year, so there are variables representing an individual's answer in each round. I use several procedures to consolidate such variables into new variables that are representative of the full year in which the individual is observed (for example, the wages reported for an individual in each round of a particular year are averaged out to represent that person's average wage for that year). After combining the MCF and FYCD datasets for the years of interest, I keep only those individuals that are present for at least one interview during each of the two years. This utilizes the panel structure of the MEPS by generating a sample with two observations per individual (one for each year they participate). Individuals who do not answer any of the questions used to derive the variables used in my analysis are removed from the sample. Finally, the dataset is cut down further to exclude military personnel or veterans, those reporting a job change occurring between any of the three interviews in a given year, and self-employed individuals. After these changes, the sample represents full-time working adults, aged 18-64, and contains 30,454 observations and 15,227 individuals.

4.2 Variables

Dependent variables: The dependent variable of interest in this study represents individual absenteeism in the form of a count variable. This variable equals the total number of absences from work due to an injury or illness in a given year.

Health Explanatory Variables: A binary variable representing the presence of any of the diagnosed mental disorders included in analysis was created using information from the MCF. This is done using condition codes provided by the MCF that group specific diagnoses into broader categories of illness. I use my own discretion when choosing which mental health disorder categories to include in analysis. I only select those exhibiting symptoms that are likely to be pervasive while at work in order to avoid any downward bias of the effect of mental illness. Therefore, I do not include sexual disorders in this analysis, though the MCF does provide information for individuals with such disorders. Using the MCF, binary variables representing each specific type of mental disorder were also created. The FYCD files of the MEPS provide a continuous variable representing a raw scale-score of physical health that is derived based on information about health habits and doctor advisories reported by respondents. This physical health scale-score is the main explanatory variable representing physical health. Body mass index and a binary variable indicating presence of an individual work limit due to an ailment are also used as measures of general health.

Healthcare Utilization Explanatory Variables: A dummy variable indicating whether the individual has health insurance is created to use as a control variable. To represent medical service utilization, I derive several variables, including variables representing the total number of prescription medication fills in the past year, as well as the total number of inpatient, outpatient, or ER visits in the past year. Separate model specifications were testing to determine whether to include all, some, or just one of the variables representing the total number of inpatient, outpatient, or ER visits. A specification including a total medical utilization variable (equal to the sum of the total inpatient, outpatient, and ER visit variables) was determined to produce the best fit.

Internal Characteristics: The MEPS design allows me to control for certain internal beliefs and characteristics of each individual. I am able to create dummy variables indicating each individual"s level of aversion to seeking medical services in the case of illness. I also construct dummy variables based on categories of each individual"s beliefs about the quality of their healthcare and their perceived level of access to medical resources granted by their healthcare. Finally, I include dummy variables for individual risk-aversion (low, neutral, moderate, high).

Occupational Explanatory Variables: The main occupational variables of interest are hourly wage, typical hours worked per week, and dummy variables indicating whether an individual"s employer offers paid sick leave and paid vacation leave. Dummy variables for union workers and for occupation type are also used as controls.

Other Control Variables: Controls for gender, race, age, family size, and education are included in the model. Year dummy variables are also included to account for time fixed effects.

4.3 Descriptive Statistics

The sample consists of 14,356 (47%) male observations and 16,096 (53%) female observations. Of the male observations, 10.14% (1,456) represent an individual with a diagnosed mental disorder. For females in my sample, mental disorder prevalence rates are much higher. About 19% (3,062) of females observations indicate a diagnosed mental disorder. Due to the magnitude of the difference in prevalence rates among males and females, tables including sample means are separated out by gender. The sample means reported in Tables 1-4 are constructed using representative weights provided in each year of the MEPS FYCD dataset. Each of Tables 1-4 contains a column describing each variable. Column (3) of each table lists the weighted sample means for persons with a diagnosed mental disorder, while column (4) lists these means for persons without a diagnosed mental disorder. Results of t-tests to determine whether the differences in means between persons with and without a mental disorder are significant are reported in column (5).

4.3.1 Individuals with and without Mental Illness

Table 1 gives the weighted sample means of the dependent variable, demographic and personal characteristic variables, and job characteristic variables for male respondents. The table reports that the mean number of absence days taken by males with a diagnosed mental disorder is about twice as high as the mean number of absence days taken by males without a diagnosed mental disorder. This discrepancy in weighted means is highly statistically significant. Males report obtaining a bachelor's degree at a similar frequency regardless of if they have a mental disorder or not and men with a mental disorder report continuing education beyond a bachelor's degree at a higher frequency than mentally healthy men. This greater frequency of higher educational attainment among males with mental health disorders could imply that those with more education have more stressful jobs due to higher expectations from employers, leading to the onset of negative psychological symptoms, or that individuals with mental illness stay in school longer due to problems finding jobs. The mean wage of males with a mental disorder is found to be slightly higher than those without, which at first glance contradicts empirical evidence that wages of mentally ill workers are typically lower than wages of mentally healthy workers (Cseh 2008), however, accounting for the fact that these mentally ill men report higher levels of education might explain this deviation.

Table 2 reports descriptive statistics for variables representing physical health, healthcare utilization, and personal belief variables for male respondents. As anticipated, males with a mental disorder report a lower mean rating of overall physical health and higher average bmi than those without a mental disorder. Table 2 additionally reports that males with a mental disorder in my sample report a work limit at over three times the frequency of males without. A greater portion of men with a mental disorder within the sample have health insurance and a primary doctor compared to mentally healthy men. This may be due to the greater necessity of medical care among individuals with a mental disorder. Other observations of particular interest are the discrepancies between the mean number of medical events and mean number of prescribed medications between mentally ill males and mentally well males. The table reports that males with a mental disorder have a mean medical service utilization of 7.67 events, more than twice the mean of their mentally well counterparts. Mean total prescribed medication fills within the past year for mentally ill men is reported to be 14.83 which is almost triple the mean of 5.13 observed for mentally healthy men in the sample. Table 2 also indicates that mentally ill men are more likely to be unsure how to rate their level of care received, as only about 53% of them are represented in the $badmodhc$ and $modgoodhc$ variables. Means also indicate that males with a mental disorder are less often likely to partake in high risk activity than males without, on average, though this may depend on the specific type of disorder. For example, an individual with severe depression may be less likely to take risks because of the symptoms associated with depression such as a negative affect, whereas someone in a manic phase of bipolar disorder or someone with a psychotic disorder may have euphoric symptoms that drive them to take more risk.

Table 3 gives the representative sample means of the dependent variable, demographic and personal characteristic variables, and job characteristic variables for female respondents. The table reports that women with a diagnosed mental disorder in the sample report absences with a mean of 6.29 days per year, compared to the mean of 3.93 days per year for women without a diagnosed mental disorder. This discrepancy in means is statistically significant at the 1% level, but is much lower than the discrepancy in mean absence days observed between men with and without mental illness. However, comparing the mean values of absences days for both groups of women to the mean values of absence days for both groups of men reveals that women report higher levels of average absences, meaning they are more prone to absence than men in general. Unlike the phenomena observed for males, females are equally likely to have obtained at least a bachelor's degree regardless of their mental health status.

Table 4 reports weighted sample means for physical health, healthcare utilization, and personal beliefs for women. Similar to observations made when comparing males, females with a mental disorder report an average level of physical health below females without mental illness. Table 4 also indicates that females with a mental disorder exhibit work limits at three times the frequency of women without. About 94% of mentally ill females and 91% of mentally well females among the sample have health insurance, which are higher frequencies than those reported for males overall. Something else to note is that the discrepancy in the frequency of having a primary doctor between females with and without a mental disorder is smaller than this discrepancy between males with and without a mental disorder in my sample, and women more frequently have a primary doctor than men do, regardless of mental health. The average number of medical related events for women with a mental disorder is about twice as high (11.39) as the mean for women without a mental disorder (5.54). There is also a large discrepancy in the mean number of prescription fills, with mentally ill females reporting a mean of 18.83 prescription medication fills per year and mentally well females reporting a mean of 7.23. This discrepancy makes intuitive sense if we assume that individuals facing mental illness are likely to receive some sort of intervention via medications which typically have to be filled in each of the 12 months of the year. Finally, Table 4 also reports that a greater portion of females with a mental disorder believe that overcoming ailments may require medical help compared to females without mental illness in the sample.[1]

[1] *Note:* all three risk-taking dummy variables (*lowrisk*, *modrisk*, *highrisk*) will be included in each model because respondants were also able to report the valid response of "unsure" when asked about their likelihood of taking risks (i.e., "unsure" answers are the baseline). This is true for *nomedhelp* and *needmedhelp* dummy variables as well.

4.3.2 Individuals with Specific Mental Disorders

Table 5 provides weighted means for variables applying only to those with a diagnosed mental disorder. My unweighted sample reports a mental illness prevalence rate of about 14.8%, while the weighted sample reports a prevalence rate of 17.5%. This is compared to the national prevalence rate of mental illness, which is about 18.5% as reported by the National Alliance on Mental Illness. This discrepancy between the prevalence rates reported by my sample and the prevalence rates observed for the U.S. population may be due to the fact that the mental illness variable used in my analysis only indicates the presence of mental disorders that have already been diagnosed, as previously discussed. Therefore, I again emphasize that my sample reports prevalence rates for *diagnosed* mental illness rather than prevalence rates of mental illness in general. The table lists weighted means for each variable divided out by gender and a t-test statistic indicating whether the difference in these means is statistically significant. Diagnosed mental illness is more prevalent in females among my sample, which is a phenomena observed in the general U.S. population as well. Males are generally less likely to seek help for emotional distress than women, meaning men are less likely to be diagnosed with a mental disorder even if they meet diagnostic criteria (Recovery Across Mental Health, "Gender Differences in Mental Health"). Therefore, in the broader population, the discrepancy in the prevalence of *mental illness itself* (not just diagnosed mental illness, as it is defined in my sample) between males and females may be smaller than the discrepancy reported by my sample.

Among the specific mental disorders considered in my analysis, anxiety disorders (e.g., GAD, OCD, panic disorders, etc.) are reported most frequently among the sample. Mood disorders (e.g., major depressive disorder, bipolar disorder, etc.) are reported at the second highest frequency, followed by attention-defecit disorders, other miscellaneous mental disorders, and psychotic disorders (e.g., schizophrenia, paranoid disorders, etc.). Personality disorders (e.g., borderline personality disorder, narcissistic personality disorder, etc.) are reported at the lowest frequency across the sample. This may reflect the greater rarity of such disorders, as well as a lesser likelihood that individuals with these disorders will be diagnosed. These four disorder categories are not mutually exclusive, which is why summing the frequencies across the four categories can yield a number greater than one (i.e., a person may exhibit both a mood disorder and a personality disorder). A dummy variable representing the presence of comorbidity between two or more mental disorders indicates that this occurs with a frequency of 26% among the sample of women with a mental disorder and 19% among the sample of men with a mental disorder.

Table 5 also provides frequencies of each level of emotional severity reported among workers with mental illness. The emotional severity dummy variables are derived using a continuous variable thats value is determined by a scale score provided in the FYCD files of the MEPS. The scale score is computed based on answers to questions pertaining to negative psychological symptoms and emotional distress within the past 30 days. Levels of emotional severity on the lower end of the spectrum are reported for both men and women most frequently. More moderate levels of emotional severity are reported at similar rates for both mentally ill men and mentally ill women. High emotional severity is reported with the lowest frequency for both men and women. Among those with a diagnosed mental disorder, women more frequently report needing some form of treatment or intervention than men do (71% and 59%, respectively).

5 Empirical Methods

All models considered in this paper will estimate the count of days absent from work due to injury or illness per year. Because of the count nature of the dependent variable, I consider two distributions: poisson and negative binomial. I conclude that a negative binomial model best fits the data due to the presence of overdispersion. I also test a zero-inflated negative binomial but conclude that this specification does not fit the data any better than a basic negative binomial. I create year dummy variables for each year represented in the dataset and cluster observations at the individual level so that I am estimating a negative binomial accounting for heterogeneity across individuals and time fixed effects [2].

[2] I will additionally be looking into models specifying an individual random effects negative binomial to account for individual-specific unobserved heterogeneity in the future.

5.1 Model Estimating Count of Absence Days

Assuming y_{it} is our dependent variable (count of absence days), m_{it} is a matrix of explanatory variables, and m_t represents year dummy variables capturing time fixed effects, the baseline negative binomial model is given by equation (10).

$$p(y) = P(Y = y_{it}|m_{it}, m_t) = \frac{\Gamma(y_{it} + 1/\alpha_{it})}{\Gamma(y_{it} + 1)\Gamma(1/\alpha_{it})} \left(\frac{1}{1 + \alpha_{it}\mu_y}\right)^{\frac{1}{\alpha_{it}}} \left(\frac{\alpha\mu_y}{1 + \alpha_{it}\mu_y}\right)^{y_{it}}, \tag{11}$$

where α_{it} is a factor representing heterogeneity across the sample, and

$$\mu_y = e^{\beta m_{it} + \delta m_t} = E[y_{it}|m_{it}, m_t] \equiv E[A_{it}|MH_{it}, PH_{it}, HC_{it}, J_{it}, C_{it}, X_{it}, M_t] \tag{12}$$

where β and δ are parameters to be estimated. Notice from equation (11) that μ_y is equivalent to the conditional expectation of absence days (A_{it}). Thus, we can transform (11) using natural logarithms and arrive at the equation we truly want to estimate:

$$log(A_{it}) = \beta^0 + \beta^{MH} MH_{it} + \beta^{PH} PH_{it} + \beta^{HC} HC_{it} + \beta^J J_{it} + \beta^C C_{it} + \beta^X X_{it} + \delta M_t + u_{it} \tag{13}$$

where u_{it} is an error term following a gamma distribution. In equation (12), MH_{it} is an indicator variable equal to one when an individual has a mental illness, PH_{it} contains measures of physical health, HC_{it} includes variables pertaining to healthcare utilization, J_{it} contains variables representing employment and job characteristics, C_{it} is a vector of intrinsic personality and belief characteristics, X_{it} is a vector of demographic and personal characteristics, and M_t is a vector holding year dummy variables.

Since the dataset is of panel form, u_{it} is likely serially correlated for observations of the same individual in each of the two time periods they are observed ($t = 1,2$), i.e.,:

$u_{i1} = v_i + \varepsilon_{i1}$, for individual i in period t=1,

$u_{i2} = v_i + \varepsilon_{i2}$, for individual i in period t=2

$\implies cov(u_{i1}, u_{i2}) = \sigma^2_{v_i} \implies$ serial correlation observed in error terms for individual i

$\implies var(u_{it}) = \sigma^2_{v_i} + \sigma^2_{\varepsilon_{it}}$, for $t = 1,2$.

Ignoring this serial correlation reduces efficiency of our estimator. To resolve this issue, I cluster the sample at the individual level and compute standard errors that are cluster-robust and heteroskedasticity-robust.

The difficulty with nonlinear parametric models is that the dispersion and heterogeneity parameters are estimated directly from the data, meaning coefficient estimates will change in response to a change in the value of any explanatory variable. Therefore, we cannot simply interpret coefficient estimates as the marginal effect of a one unit rise in some explanatory variable, s, on dependent variable, y. I therefore calculate the average marginal effect (AME) of each explanatory variable on absence days. AME estimates will represent the average change in absences per year in response to a one unit change in the independent variable of interest, that is, in the results section I will report the following value for explanatory variable s:

$$AME(k) = \frac{1}{n}\sum_{i=1}^{n} f(\beta^{MH}MH_{it} + \beta^{PH}PH_{it} + \beta^{HC}HC_{it} + \beta^{J}J_{it} + \beta^{C}C_{it} + \beta^{X}X_{it} + \delta M_t)\beta^{s} \tag{14}$$

given that s is included in one of the vectors of explanatory variables in the baseline model, and n represents the number of observations in the sample.

As was previously stated in section 3 of this paper, examining the impact of mental illness on absenteeism requires forming hypotheses on the signs of each variable to be interacted with MH_{it}. I therefore hypothesize the following about the main explanatory variables of interest (that is, those that I later interact with mental health) in my model:

$\beta^{MH} > 0|_{\Delta k=0,\forall k}$, that is, the *isolated* effect of mental illness on absenteeism will be positive, given k is the matrix of variables to be interacted with MH_{it}.

$\beta^{PH_{physhlth}} < 0,$ as physical health is a scale score where higher values indicate better physical health and better physical health implies fewer absences.

$\beta^{PH_{worklim}} > 0,$ as having a work limit due to a physical or mental ailment will almost certainly increase absences.

$\beta^{HC_{insured}} < 0,$ if access to insurance implies a greater likelihood of receiving preventative care and early intervention, having insurance will result in fewer illness-related absences.

$\beta^{HC_{doc}} < 0,$ as having a primary doctor implies a greater likelihood of receiving routine checkups, which implies better health and fewer illness-related absences.

$\beta^{HC_{numevents}} > 0,$ a higher numbers of doctor or hospital visits implies poorer health or more severe ailments, which implies greater absences.

$\beta^{HC_{totalrx}} > 0,$ a higher numbers of prescription medication fills implies chronic health issues or more severe ailments, which imply greater absences.

$\beta^{J_{wage}} < 0,$ a higher wage means a higher opportunity cost of not working, implying less absenteeism.

$\beta^{J_{hours}} < 0,$ if working more hours implies a position of greater responsibility, I would expect an additional hour of work to induce less absenteeism.

$\beta^{J_{sickleave}} > 0,$ paid sick leave lowers the cost of being absent when ill, implying greater absences.

$\beta^{HC_{vaca}} > 0,$ assuming workers can use vacation days when ill, vacation time would increase illness-related absences.

I first estimate the negative binomial excluding vector C_{it} (so that β^C will be zero), and then add vector C_{it} to the model to determine if the average effects remain robust to adding variables that represent personal beliefs and intrinsic characteristics. The variables contained in vector C_{it}

represent an individual's propensity to partake in risky behaviors, perceptions about overcoming illness, and beliefs about quality of personal healthcare.

My hypotheses for coefficients on these variables are as follows:

$$\beta^{C_{lowrisk}} < 0$$

$$\beta^{C_{modrisk}} \neq 0$$

$$\beta^{C_{highrisk}} > 0,$$

i.e., being averse to risky behavior is anticipated to lead to fewer absences, being moderately prone to risky behavior has an ambiguous impact on absences, and being highly likely to take risks is anticipated to increase absences from work.

In terms of beliefs about the necessity of medical intervention, I hypothesize the following:

$$\beta^{C_{nomedhelp}} > 0$$

$$\beta^{C_{medhelp}} < 0,$$

as being averse to medical intervention may lead to worsening symptoms of illness, which may induce greater illness-related absence. Conversely, being open to medical intervention may prevent such worsening of symptoms, yielding fewer illness-related absences.

When considering how beliefs about the quality of healthcare one receives may impact absenteeism, I hypothesize:

$$\beta^{C_{badmodhc}} > 0$$

$$\beta^{C_{modgoodhc}} < 0,$$

as those who believe they are receiving a poorer quality of healthcare likely have not seen improvements in health after receiving care, thus requiring more absence days for injury or illness. Conversely, those who believe they receive a higher quality of care likely have seen improvements in their health after receiving medical care, and so this belief will be associated with less absences.

5.2 Interactions in the Negative Binomial Model

I add interactions to the baseline negative binomial regressions to consider how the true effect of mental illness on absence days may vary with changes in numerous factors.[3] My empirical hypotheses on each of these interactions are as follows:

$\beta^{MH*PH_{physhlth}} > 0,$

those with a mental disorder will see less improvement in productivity in response to an increase in physical health.

$\beta^{MH*PH_{worklim}} > 0,$

those with a work limit and a mental disorder will see greater absences than those with a work limit alone.

$\beta^{MH*HC_{insured}} < 0,$

those with mental illness are likely more sensitive to the negative impact of health insurance on absenteeism, given that these individuals are in greater need of affordable intervention than

[3]The full specifications for each regression described can be found in the appendix.

those without mental illness.

$\beta^{MH*HC_{doc}} < 0$

those with mental illness are likely more sensitive to the negative impact of having a primary doctor for a similar reason to that given above for $\beta^{MH*HC_{insured}}$.

$\beta^{MH*HC_{numevents}} < 0,$

whereas a high number of doctor- or hospital-related events may indicate a severe medical condition for those without mental illness, this number might imply continuous treatment of a mental disorder in workers facing mental illness, implying the positive effect of the number of events on absences will be smaller in magnitude for individuals with mental illness.

$\beta^{MH*HC_{totalrx}} < 0,$

the explanation behind this hypothesis is similar to that described above for $\beta^{MH*HC_{numevents}}$.

$\beta^{MH*J_{wage}} > 0,$

the cost of missing work is likely to remain lower for workers with mental illness even after a wage increase, implying that mental illness will mitigate some of the reduction in absences induced by a wage increase.

$\beta^{MH*J_{hours}} > 0,$

those with a mental disorder may negatively react to stressors like an additional hour worked per week, implying that this would lead to greater psychological symptoms, and thus, greater abseces.

$\beta^{MH*J_{sickleave}} > 0,$

workers with mental illness will be more likely to take advantage of paid sick leave than workers without mental illness.

$\beta^{MH*J_{vaca}} > 0,$

workers with mental illness will be more likely to find it necessary to use vacation days for illness than workers without mental illness.

$\beta^{MH*C_{lowrisk}} < 0,$

$\beta^{MH*C_{modrisk}} \neq 0,$

$\beta^{MH*C_{highrisk}} > 0,$

individuals with mental illness are probably more sensitive to levels of risk taking.

$\beta^{MH*C_{nomedhelp}} > 0,$

individuals with mental illness will be more sensitive to an aversion to seeking medical help than workers without a mental illness due to the greater need of these workers to seek continuous treatment to alleviate negative psychological symptoms.

$\beta^{MH*C_{medhelp}} < 0,$

individuals with mental illness will be more sensitive to an openness to seeking medical help than workers without a mental illness due to the greater need of these workers to seek continuous treatment to alleviate negative psychological symptoms.

$\beta^{MH*C_{badmodhc}} > 0,$

individuals with mental illness will be more sensitive to a lower quality of care than workers without mental illness.

$\beta^{MH*C_{modgoodhc}} < 0,$

individuals with mental illness will be more sensitive to a higher quality of care than workers without mental illness.

5.3 Analyzing Specific Mental Disorders in the Negative Binomial

I next consider how each specific category of mental disorder conglomerated in the MH_{it} dummy variable may impact absence days. MH_{it} indicates whether an individual has one or more of one of the following disorders: mood disorder, anxiety disorder, personality disorder, psychotic disorder, attention-deficit disorder, or other pervasive mental health disorder (beside sexual disorders). I therefore divide MH_{it} out into the following variables representing each disorder, respectively: MH_{it}^{Mood}, MH_{it}^{Anx}, MH_{it}^{Prsn}, MH_{it}^{Psyc}, MH_{it}^{Adhd}, MH_{it}^{Other}. I replace MH_{it} with these dummy variables in the model described in section 5.1, re-estimate the equation, and compute AME for each of the MH_{it}^{g} variables, assuming that g=(Mood, Anx, Prsn, Psyc, Adhd, Other). Because the subgroup of individuals with a personality disorder is so minute in both the male and female subsamples, I also re-estimate regressions excluding this subgroup of individuals, and find that this specification produces a better fit. Therefore, I report AME estimates from the regressions that eliminate this subgroup.

I next consider the model from section 5.2. I run separate regressions included interactions with explanatory variables of interest and each of the three mental disorder categories considered. In other words, I run a regression interacting each explanatory variable of interest with MH_{it}^{Mood}, then run a separate regression interacting each of these variables with MH_{it}^{Anx}, then interacting each of these variables with MH_{it}^{Psyc}, then with MH_{it}^{Adhd}, and finally, interacting these variables with MH_{it}^{Other}. AME of these interactions will be reported in the results section. My hypotheses for these specifications remain the same as the hypotheses laid out in section 5.1 and 5.2. Said differently, I believe that $\beta^{MH^{g}} > 0$.

6 Results

6.1 Baseline Negative Binomial Regressions

Average marginal effects (AME) of explanatory variables for the baseline model predicting the count of absence days per year are listed in column (1) of Table 6 for males. As hypothesized, having a mental disorder has a positive and significant impact on yearly absences. Focusing on column (1), on average, having a mental disorder is predicted to increase male absences by about 1.4 days per year. A man's physical health has a highly statistically significant, negative effect on absences per year, however, the value of this average effect may not be economically significant since a man's health scale score would have to drop by about 7.6 points before reporting an additional absence, on average. The number of doctor or hospital related events in a given year is found to be highly statistically significant in determining a male's yearly absences; on average, an increase in the number of events of this type increases male absences by a factor of about 0.59.

Since the magnitude of this impact is estimated to be smaller than half a day, this might suggest that the number of hospital or doctor visits does not necessarily proxy severity of an ailment, but rather treatment or preventative care measures, such as leaving work early for a routine health checkup. The number of prescription medication fills in a year is also estimated to have a highly statistically significant, positive effect on absences, though this effect is smaller in magnitude, with a one-fold increase in prescribed medications per year increasing absences by a factor of about 0.13. These estimates are consistent with my empirical hypotheses for these variables.

Whether an individual has a work limit is estimated to have the largest AME for males. Men with a work limit are estimated to report an average of over 5 additional absence days compared to men without a work limit. Hours worked is estimated to have a negative and highly statistically significant AME, however the economic significance of this variable is questionable because of its small magnitude of about -0.05. Wage is estimated to have a negative AME on absence days for men, however, this impact is only significant at the 10% level, as is the positive effect estimated for the paid sick leave dummy variable, though this impact is expected to hold more economic significance than hours or wage.

Several other control variables are additionally found to be significant in predicting absence days for males. Though AME of these variables are not presented in Table 6, a table presenting coefficient estimates for these and all other explanatory variables can be found in the appendix. These other significant variables include a dummy variable indicating whether an individual is in a union, as well as characteristics such as being black, age, and marital status.

Results of the model including dummy variables for beliefs about quality of healthcare, beliefs about whether medical help is necessary in overcoming illness, and measures of personal risk-taking are reported in column (2) of Table 6 for men. AME estimates remain robust to adding these variables to the baseline model. AME indicate that the dummy variable for males who believe that medical care may be needed to overcome an illness is significant at the 5% level and estimated to reduce absences by a factor of 0.72, on average, confirming my hypothesis on the sign of this effect. This might signify that those who are not averse to medical intervention will have better health outcomes than those who believe such intervention is unnecessary. Individuals believing they receive a quality of healthcare on the lower end of the spectrum are estimated to see greater absences by a factor of about 0.74, on average, but this effect is only significant at the 10% level.

AME estimates for the baseline regression for female respondents are listed in column (4) of Table 6. Similarly to males, mental illness is associated with a positive effect on absence days per year for females, though this effect is smaller in magnitude for females than for males, on average, and is only significant at the 10% level. Females in better physical health report less absence days; if a female were to improve her physical health, thus increasing her physical health scale-score by 5 points, she would report about one less absence on average. Similarly to males, the number of doctor or hospital related events and the total number of prescription medication fills are highly statistically significant in determining female absence days. A one-fold increase in the number of hospital or doctor related services utilized in a year is associated with an increase in absences by a factor of about 0.66, on average. This is larger than the AME of this variable reported for men, indicating that women are more sensitive to this variable. This could also indicate that the impact of the number of events is driven by more severe issues for women than for men (e.g., surgeries requiring bed rest may be more common in women). Similarly to AME estimates for men, the AME of a work limit is estimated to have the largest impact on absence days for women, increasing absences by about 5.81 days on average. Surprisingly, neither wage, hours worked, nor paid sick leave appear to be statistically significant in predicting female absences.

Though not included in Table 6, coefficient estimates generated by the baseline negative binomial also indicate that females experience a significant positive effect of being in a union on the log of absence days. The number of employees at a woman's place of work is also found to be highly statistically significant, though this effect has no economic significance. A key difference in the results for men and women is that the variable representing family size has a highly statistically significant, positive effect on the log of absence days for women, while no significant effect of this type is found for men. This probably illustrates a greater likelihood that mothers will stay home to care for ill children rather than fathers. Coefficient estimates for these variables can be found in the appendix.

The results for women remain robust to adding the belief and risk personality variables to the baseline model. These results are reported in column (5) of Table 6. The dummy variable indicating the belief that one is receiving a higher quality of healthcare is found to be significant in determining absence days. Women with this belief are estimated to report fewer absences by a factor of about 0.72, on average. This estimated average effect is consistent with my hypothesis.

6.2 Negative Binomial Regressions with Interaction Terms

To assess whether mental illness affects the impact of certain explanatory variables on absenteeism, I add interaction terms to the baseline models and reestimate the regressions, as described in section 5.2. Due to convergence issues for the coefficient of the interaction between the number of prescribed medications and mental illness, I am forced to leave this interaction out of the negative binomial regression for men. There is no such convergence issue in the regression for females, so this interaction is included in the regression for women. I first estimate the model including all interactions discussed in section 5.2 in order to observe whether any of the explanatory variables reported to have insignificant AME in columns (1), (2), (4), and (5) of Table 6 become statistically significant after adding interaction terms to the baseline regressions. The only variable that was estimated to be statistically insignificant in the baseline model that becomes statistically significant after adding interaction terms is the hours variable in the regression for women. I next re-estimate the equations, this time leaving out interactions that involve insignificant explanatory variables, so that I am only reporting AME estimates for interactions between mental illness and variables that are anticipated to vary with mental illness that also have significant isolated impacts on absences.[4]

Table 6 column (3) presents the AME estimates of each interaction included in the regression for male respondents. Estimates of isolated AME of most statistically significant explanatory variables remain relatively robust to adding these interactions. The estimate of the isolated AME of the mental illness variable becomes largely negative after adding the appropriate interactions, which is to be expected since the true impact now depends on the values of each variable interacted with it. The only other effect that seems to be significantly changed is that of the work limit dummy

[4]Full specifications of the regressions that I am reporting results for can be found in the appendix.

variable, which is reduced from an AME of about 5.4 to about 4.26. However, the effect of this variable is still highly statistically significant. The interaction between physical and mental health is estimated to be positive and significant for males, supporting the hypothesis that the reduction in absences induced by better physical health will be smaller for men with a mental illness. Specifically, the AME estimates reported in column (3) of Table 6 indicate that any improvement in absenteeism generated by better physical health is nearly completely negated for men with mental illness. Put differently, male workers facing mental illness will see a very small, economically insignificant decrease in absence days in response to an improvement in physical health.

Interaction estimates for men also indicate that male workers with mental illness see a smaller positive effect of an additional event of medical service utilization than their mentally healthy counterparts, confirming my hypothesis on the sign of this interaction. This may provide some support for my theory that service utilization may proxy treatment rather than severity of a condition for those with mental illness. For example, this negative interaction may be explained by the nature of common treatments for those with mental illness. If an individual with mental illness sees a psychologist every week, he will report a large number of events in which he has utilized medical services over the span of a year. However, while he is accruing a greater number of medical events, he is simultaneously receiving intervention to alleviate his negative psychological symptoms, so the negative impact that this additional service utilization has on productivity is somewhat negated. Results in column (3) also indicate that males with a mental illness are estimated to see virtually no impact of hours worked per week on absences. This finding points to important differences in how individuals with and without mental illness react to additional stressors. Whereas workers who are not mentally ill respond to additional hours by reducing absences (potentially indicating that a greater number of hours indicates undertaking greater responsibility at work), male workers with a mental illness will not change their behavior in response to additional hours worked per week.

Table 6 column (6) reports the estimated AME for each interaction included in the regression for women. Most isolated AME estimates for the significant explanatory variables are found to remain robust to adding these interactions. The mental illness variable is estimated to have a largely negative effect similar to that reported for men, however, the effect is not significant, indicating that mental illness *alone* may not influence absences for women, but rather it is the combination of mental illness and other factors that drives absence behavior observed among women. Put differently, the impact of mental illness on female absenteeism may be driven by differences in how women with and without mental illness respond to factors that impact absenteeism. Something of additional interest is that the explanatory variable for hours worked per week becomes significant at the 5% level after adding interactions. The magnitude of this negative AME is estimated to be similar to AME estimates of this variable reported for men. Observing the highly significant, positive AME estimate of the interaction between mental illness and hours provides additional evidence that there is a significant difference in how additional stressors impact mentally ill individuals versus individuals without mental illness. For women with a mental disorder, the impact of an additional hour of work per week, on average, actually *increases* absences, indicating that women with a mental disorder may view additional hours as an added negative stressor that might induce worsening psychological symptoms.

The interaction between physical health and mental illness is not found to be significant for women, indicating that the impact of physical health on absenteeism does not significantly differ between women with and without mental illness. The interaction between the number of medical events and mental illness is estimated to be highly significant and negative; the increase in absences anticipated in response to the utilization of an additional medical service is smaller by a factor of 0.116 for mentally ill women. The interaction between prescribed medications and mental illness similarly indicates that the positive impact of an additional prescription on absences is smaller for mentally ill women, though the economic significance of this discrepancy is questionable. Results in column (6) of Table 6 additionally report that women with a mental illness who believe that they receive a higher quality of care see an increase in absence days, as is illustrated by the estimated positive AME of this interaction, which is larger in magnitude than the negative isolated AME estimated for the $modgoodhc$ variable. This finding provides evidence against my hypothesis on the sign of this interaction effect stated in section 5.2.

6.3 Negative Binomial Regressions by Specific Mental Illness

I next report results for the regression that divides the mental illness dummy variable out into indicator variables for anxiety, mood, and personality disorders. Variables found to be consistently insignificant are removed from the regression, including variables $insured$, doc, $vaca$, and bmi.[5] The AME estimates from this regression are reported in Table 7. The left-most column of Table 7 reports the name of each variable included in the regressions, as well as the interactions of certain explanatory variables with the specific mental health disorder indicator variable, MH^g ($g = Mood$ in columns (2) and (6), $g = Prsn$ in columns (3) and (7), and $g = Anx$ in columns (4) and (8)). The bottom three rows of this left-most column report interactions between disorders. Note that results are not available for the interaction between a diagnosed mood and diagnosed anxiety disorder. This is because no individuals in my sample report comorbidity between illnesses of these types.[6]

Column (1) of Table 7 reports the AME estimates of the negative binomial regression for men prior to adding any interactions. Column (2) reports AME estimates for men after adding interactions between significant explanatory variables and the mood disorder indicator variable to the regression. Column (3) reports AME estimates after adding interactions between significant variables and the personality disorder dummy variable and column (4) reports these estimates after adding interactions between these variables and the anxiety disorder indicator for men. Note that interactions with the $totalrx$ variable are not included in regressions for men due to convergence issues previously noted for the male regression in section 6.1. Column (1) of Table 7 reports that a diagnosed mood disorder has a highly significant effect on male absence days, with AME estimates indicating higher absences by about 2 days on average for men with a mood disorder. A diagnosed anxiety disorder is estimated to have a positive effect of about one day on average, and this is significant at the 5% level. Personality disorders are not found to be significant in predicting male absences.

[5]The full specification of each regression, as well as coefficient estimates for all variables included in the model for each specification, can be found in the appendix.

[6]The code used to compile data and create variables was checked multiple times after the discovery of this oddity to make sure it is not the result of a coding error. In future study, I plan to compile data from the MEPS for more years in order to obtain a larger sample that will hopefully report a significant number of individuals who have both a diagnosed mood and anxiety disorder.

Column (2) reports that the AME estimate of the mood disorder variable becomes largely negative after adding interaction terms to the model. This is to be expected after adding interactions between a binary variable and multiple continuous variables. The remainder of the explanatory variables seem to be relatively robust to adding these interactions. The magnitude of the AME estimate for the interaction between physical health and mood disorders outweighs the magnitude of the isolated negative AME estimate for physical health, meaning men with mood disorders are expected to have positive absences regardless of improvements in their physical health. Consistent with results reported in section 6.1, column (2) of Table 7 reports that men with a mood disorder see a smaller positive impact of the number of medical services utilized per year on absences. The interaction between personality disorder and mood disorder variables indicates a negative effect, on average, by a factor of about -2.78. This impact is only significant at the 10% level but may indicate that men with comorbid personality and mood disorders see fewer absence days than men with a mood disorder alone.

Column (3) reports that results remain robust to adding interactions between the personality disorder indicator and significant explanatory variables for males. The result for the interaction between the personality disorder variable and physical health indicates there is no significant difference in how the absences of men with or without a personality disorder react to a change in physical health. The interaction between the personality disorder variable and the variable representing the number of medical service events has an estimated AME of -0.12, indicating that men with a mental disorder of this type see a lower increase in absences in response to additional health service utilization compared to men without a personality disorder. An interesting finding is that the interaction between personality and mood disorder variables and between personality and anxiety disorder variables are both largely negative and highly significant, indicating that men with a mood disorder alone will see greater absences, but men with both a mood disorder and a personality disorder will see fewer absences. The same interpretation can additionally be applied to men with anxiety disorders.

Column (4) of Table 7 illustrates an expected shift in the AME of the anxiety variable to a largely negative AME estimate after adding interactions between anxiety disorders and other key significant variables. Results show a positive average interaction effect between physical health and anxiety disorders, though only significant at the 10% level. The negative interaction between the number of events and anxiety disorders is similar in magnitude to the interaction between this variable and personality disorders. A particularly interesting finding is that the interaction between hours and anxiety disorders is estimated to have a positive, highly statistically significant impact on absences about twice the size the absolute value of the isolated AME of hours on absence, indicating that men with an anxiety disorder respond to an additional hour of work per week by increasing absences by about half a day, while men without an anxiety disorder respond to an additional hour of work by decreasing absences by half a day, on average. This finding provides us key information, implying that anxiety disorders are the specific type of mental illness driving the difference in how male workers with mental illness and male workers without mental illness respond to changes in hours worked per week.

Column (5) of Table 7 reports AME estimates for women prior to adding interactions into the model. Column (5) indicates that anxiety disorders have a large positive impact on absences of about 1.32 days. Interestingly, mood disorders are not found to have any statistically significant impact on women's absences. Personality disorders are estimated to have a *negative* impact on absence days, though this estimate is only significant at the 10% level. This finding supports the odd result observed for males who have a mood or anxiety disorder that is comorbid with a personality disorder. The differing signs of the estimated AME of personality disorder versus mood and anxiety disorders may have to do with differences in the kind of psychological symptoms associated across these disorders, or differences in the ability to cope with symptoms across disorders.

Column (6) of Table 7 reports AME estimates for women after adding interactions between key explanatory variables and the mood disorder indicator variable to the regression. After adding these interactions, the AME estimate of the hours worked per week explanatory variable becomes negative and significant at the 5% level. The interaction between this variable and the mood disorder indicator illustrates that women with a mood disorder may be driving the difference in behavior observed between women with and without a mental illness in response to an increase in hours worked per week. Women with a mood disorder are reported to increase absences by a factor of about 0.20, on average, in response to an additional hour worked per week, while women without a mood disorder are anticipated to reduce absences by a factor of about 0.05. The number of medical events is reported to have a significant negative interaction with mood disorders, indicating that women with mood disorders see an impact in absence days of lesser magnitude than women without a mood disorder for an increase in medical services utilized.

Column (7) of Table 7 reports AME estimates for women after adding interactions between the key explanatory variables and the personality disorder indicator variable to the regression. Results of most explanatory variables remain robust to adding these interactions. Notably, the variable for hours worked per week remains insignificant after adding these interactions, providing further evidence that mood disorders are the specific type of mental illness driving the difference in behavior observed between women with and without a mental illness in response to changes in hours worked. Results additionally indicate that the number of medical services utilized within a year has a smaller average impact on women with a personality disorder than on women without a personality disorder.

Column (8) of Table 7 reports the AME estimates after adding interactions with the anxiety disorder indicator variable to the regression. Estimated AME for the interaction between the number of services utilized and the anxiety disorder variable are similar to those observed for the interactions of this variable and the personality disorder and mood disorder variables, though slightly larger in magnitude. Additionally, women with an anxiety disorder are anticipated to see a lesser increase in absence days in response to an additional prescribed medication, however this result is only significant at the 10% level and is not economically significant.

7 Discussion and Conclusion

This study has found evidence that the presence of a diagnosed mental disorder produces greater absenteeism among full-time workers. However, there are some potential issues with this study that I have discussed that keep me from claiming clear evidence of a causal effect[7]. My findings indicate that the impact of mental illness is more significant for men than for women, implying gender differences in the process of deciding when to go to work when ill. My analysis has also found evidence in support of the hypothesis that beliefs about when medical intervention is necessary and the quality of the personal healthcare one receives significantly impact absenteeism. More specifically, believing that medical intervention may be necessary to overcome an illness is estimated to reduce absences for men, which may imply that those who are proactive in seeking medical care see better productivity outcomes, probably through the channel of better health. A similar effect is found in women who believe they are receiving a higher quality of healthcare, similarly indicating that beliefs that increase the likelihood of utilizing medical services in the event of an illness or ailment may improve productivity.

My results indicate that a number of factors influencing absenteeism have impacts that vary with mental illness. For example, men without a mental illness report reduced absences in response to an increase in hours worked per week, whereas men facing mental illness report no change in behavior in response to an increase in hours. Additionally, women without mental illness respond to an increase in hours similarly to men without a mental illness (that is, they reduce absences in response), while women with a mental illness report an increase in absences in response to additional hours worked per weak. This illustrates differences in how individuals with and without mental illness respond to additional stressors. Individuals with mental illness may be overwhelmed by the additional stress of more responsibility at work, leading to worsening psychological symptoms that require them to stay home from work more often. Analyzing this result for specific categories of mental illness indicates that this difference in behavior in response to additional hours of work is driven by anxiety disorders in men and mood disorders in women. Future study should consider that the estimates for the hours worked per week and its interaction with mental illness may be biased due to potential endogeneity of the hours variable. The fact that the isolated effect of the hours variable is only found to be significant for women after adding the interaction between mental illness and hours may give evidence that an issue of this type is

[7] These issues, such as potential endogeneity of explanatory variables and a potentially non-representative sample, will be addressed upon expansion of this study.

present.

Another impact found to vary with mental illness that should be discussed is that of medical service utilization. An increase in the number of services utilized in a given year increases absences by a lesser amount for individuals with a mental illness than for individuals without, regardless of gender. This might indicate that this variable proxies for treatment among the subgroup of individuals with a mental disorder, rather than severity. This is plausible considering the continuous and frequent nature of treatment events for those with mental illness (e.g., therapy, medication monitoring and follow ups). If this is the case, this finding would support the argument that access to treatment is pivotal in reducing the additional productivity losses observed in those with mental illness. Future research should consider a two-stage model in which healthcare utilization is predicted using exogenous regressors and these predictions are then used in the absenteeism model as the healthcare utilization variable. This could give a more clear picture of whether the positive effect of healthcare utilization on absenteeism is driven by time cost effects or health effects (are the higher rates of absenteeism observed in response to higher utilization due to the greater likelihood of missing work to utilize a higher amount of services, or due to the chronic or severe health conditions that these higher rates of utilization might indicate, which would imply greater absences through the channel of poorer health?) Surprisingly, the impact of physical health on absenteeism is only found to vary with mental illness in men, pointing to further discrepancies across the sexes.

I plan to expand upon the analyses completed in this paper by conducting similar analyses of the subgroup of full-time workers with a diagnosed mental disorder, rather than full-time workers in general. By looking at only those with mental illness, I will be able to utilize variables that indicate whether an individual is receiving treatment for their specific mental illness(es) and how severe the symptoms of their particular illness(es) are. I will also be able to take a more in-depth look at comorbidity between disorders by considering a number of additional types of mental disorders, such as ADHD. Additional interactions may also be considered in future analyses of the subgroup of mentally ill full-time workers, such as the interaction between severity of each disorder and treatment, as it is likely that the extent to which treatment improves productivity in workers with mental illness varies with severity of the particular disorder.

Future study may want to consider conducting similar analysis using a variable for mental illness that is able to capture undiagnosed mental illness. For example, the MEPS FYCD files contain a variable measuring emotional distress in individuals. It may be likely that individuals reporting high levels of emotional distress are suffering from mental illness, even if they do not report a diagnosis. Using an emotional distress variable of this type to create the main mental illness variable, while additionally controlling for whether a mental illness has yet been diagnosed in each individual may provide important information on any similarities or differences in the behavior of individuals who have been diagnosed with a mental illness versus those who may indicate signs of mental illness but who have not yet been diagnosed. This would provide insight regarding the importance of prompt intervention and diagnosis.

To conclude, the indirect cost of productivity loss generated by mental illness is empirically evident among full-time workers. Evidence additionally indicates medical service utilization reduces the impact of mental illness on absences. Mental health carve outs and other barriers to mental health service utilization may have adverse impacts on the productivity of workers facing mental illness. Such impacts should be considered by employers and policy makers when making investment decisions on mental healthcare.

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Table 1: Means of Variables for Men Split out by Presence of Mental Illness

Variable Type	Variable Name	Descriptions	Mental Illness=1	Mental Illness=0	T-test
Dependent Variable (A_{it})					
	absencedys	Count of the total days an individual has been absent from work due to illness or injury in the past year.	4.95	2.52	5.92***
Demographic and Personal Characteristics (X_{it})					
	age	Age in years.	42.18	40.54	4.56***
	familysize	Number of individuals within the surveyed household.	2.41	2.78	-11.27***
	white	=1 if individual is white, =0 otherwise.	0.60	0.49	12.10***
	black	=1 if individual is black, =0 otherwise.	0.051	0.086	-6.33***
	hispanic	=1 if individual is of Hispanic ethnicity, =0 otherwise.	0.10	0.17	-11.53***
	otherrace	=1 if individuals is of another race, =0 otherwise.	0.25	0.25	0.79
	married	=1 if individual is married, =0 otherwise.	0.53	0.57	-3.85***
	belowhs	Individuals with less than high school education.	0.010	0.024	-6.52***
	highschool	Individuals with a high school degree or GED.	0.27	0.32	-3.95***
	somecoll	Individuals with some college or an associate's degree, but no 4-year degree.	0.31	0.29	2.50**
	bachdeg	Individuals with a bachelor's degree.	0.22	0.23	1.28
	bachplus	Individuals with schooling beyond a bachelor's degree.	0.17	0.11	5.18***
Job Characteristics (J_{it})					
	wage	Hourly basis.	23.19	22.87	2.46**
	hours	Typical number of hours worked per week.	41.14	41.90	-2.18**
	sickleave	=1 if individual's employer offers paid sick leave, =0 otherwise.	0.67	0.66	3.44***
	vaca	=1 if if individual's employer offers paid vacation leave, =0 otherwise.	0.77	0.76	1.54
	numemp	Number of workers employed at the individual's place of work.	150.6	145.90	1.87*
	union	=1 if individual is part of a labor union, =0 otherwise.	0.14	0.13	-0.43
	occ1	=1 if individual's occupation is in the class of sales, service, or administration, =0 otherwise.	0.29	0.31	-0.22
	occ2	=1 if individual's occupation is in the class of business, finance,or management, =0 otherwise.	0.27	0.25	1.83*
	occ3	=1 if individual's occupation lies within some other occupational category, =0 otherwise.	0.33	0.37	-3.87***

Note: column labeled mental illness=1 lists means for males with at least one diagnosed mental health disorder, whereas mental illness = 0 indicates means for men without a diagnosed mental disorder. Descriptive statistics are evaluated using individual-level weights provided by the MEPS, where weighted sample size for male respondents is $N_w = 167,760,926$. The *unweighted* sample size for men is $N = 14,358$. Individual's responding with "unsure" to questions represented by $nohelp$, $needhelp$,$lowrisk$, $modrisk$, and $highrisk$ are left out of descriptive statistics tables.

Table 2: Means of Variables for Men Split out by Presence of Mental Illness

Variable Type	Variable Name	Descriptions	Mental Illness=1	Mental Illness=0	T-test
Physical Health Variables (PH_{it})					
	physhlth	A continuous scale score in which higher scores imply better physical health. Highest score reported is 72.07.	52.31	53.45	-4.22***
	bmi	Individual body mass index.	29.04	28.21	3.92***
	worklim	=1 if the individual has a work limit due a physical or mental ailment, =0 otherwise.	0.06	0.018	7.45***
Healthcare Utilization Variables (HC_{it})					
	insured	=1 if individual has health insurance, =0 otherwise.	0.92	0.87	9.24***
	doc	=1 if individual has a primary doctor to see in the case of a medical event or routine checkup. =0 otherwise.	0.79	0.67	12.52***
	numevents in the past year.	Number of doctor- or hospital-related events	7.67	3.35	13.09***
	totalrx	Total number of medications prescribed within the past year (including refills).	14.83	5.31	16.72***
Belief and Risk Variables (C_{it})					
	badmodhc	=1 if individual rates their healthcare below 7 on a scale from 1 - 11, that ranks worst to best. =0 otherwise.	0.062	0.029	4.73***
	modgoodhc	=1 if individual rates their healthcare 7 or above on a 1 - 11 scale ranking worst to best. =0 otherwise.	0.69	0.50	16.04***
	nomedhelp	=1 if individual believes they can overcome illness without medical help. =0 otherwise.	0.28	0.32	-2.22**
	medhelp	=1 if individual believes overcoming illness may require medical help. =0 otherwise.	0.58	0.54	2.42**
	lowrisk	=1 if individual “disagrees strongly” or “disagrees somewhat” that they are more likely to take risks. =0 otherwise.	0.60	0.55	2.34**
	modrisk	=1 if individual “agrees somewhat” that they are more likely to take risks. =0 otherwise.	0.22	0.22	-0.19
	highrisk	=1 if individual “agrees strongly” that they are more likely to take risks. =0 otherwise.	0.055	0.059	-1.39

Note: column labeled mental illness=1 lists means for males with at least one diagnosed mental health disorder, whereas mental illness = 0 indicates means for men without a diagnosed mental disorder. Descriptive statistics are evaluated using individual-level weights provided by the MEPS, where weighted sample size for male respondents is $N_w = 167,760,926$. The *unweighted* sample size for men is $N = 14,358$. Individual's responding with “unsure” to questions represented by $nohelp$, $needhelp$,$lowrisk$, $modrisk$, and $highrisk$ are left out of descriptive statistics tables.

Table 3: Means of Variables for Women Split out by Presence of Mental Illness

Variable Type	Variable Name	Descriptions	Mental Illness=1	Mental Illness=0	T-test
Dependent Variable (A_{it})					
	absencedys	Count of the total days an individual has been absent from work due to illness or injury in the past year.	6.29	3.93	8.83***
Demographic and Personal Characteristics (X_{it})					
	age	Age in years.	43.31	41.57	7.53***
	familysize	Number of individuals within the surveyed household.	2.46	2.75	-13.09***
	white	=1 if individual is white, =0 otherwise.	0.59	0.50	13.92***
	black	=1 if individual is black, =0 otherwise.	0.059	0.11	-11.92***
	hispanic	=1 if individual is of Hispanic ethnicity, =0 otherwise.	0.096	0.15	-9.66***
	otherrace	=1 if individual is of another race, =0 otherwise.	0.26	0.25	2.17**
	married	=1 if individual is married, =0 otherwise.	0.48	0.53	-3.93***
	belowhs	Individuals with less than high school education.	0.006	0.011	-5.27***
	highschool	Individuals with a high school degree or GED.	0.21	0.24	-4.94***
	somecoll	Individuals with some college or an associate's degree, but no 4-year degree.	0.37	0.33	4.43***
	bachdeg	Individuals with a bachelor's degree.	0.25	0.25	2.30**
	bachplus	Individuals with schooling beyond a bachelor's degree.	0.14	0.14	1.31
Job Characteristics (J_{it})					
	wage	Hourly basis.	20.43	20.03	4.34***
	hours	Typical number of hours worked per week.	36.62	37.10	-1.41
	sickleave	=1 if individual's employer offers paid sick leave, =0 otherwise.	0.70	0.69	3.52***
	vaca	=1 if if individual's employer offers paid vacation leave, =0 otherwise.	0.73	0.72	2.17**
	numemp	Number of workers employed at an individual's place of work.	150.60	147.60	1.41
	union	=1 if individual is part of a labor union, =0 otherwise.	0.13	0.11	2.15**
	occ1	=1 if individual's occupation is in the class of sales, service, or administration, =0 otherwise.	0.49	0.49	-2.20**
	occ2	=1 if individual's occupation is in the class of business, finance, or management, =0 otherwise.	0.32	0.32	2.43**
	occ3	=1 if individual's occupation lies within some other occupational category, =0 otherwise.	0.065	0.07	-3.68***

Note: column labeled mental disorder=1 lists means for women with at least one diagnosed mental health disorder, whereas mental disorder = 0 indicates means for women without a diagnosed mental disorder. Descriptive statistics are evaluated using individual-level weights provided by the MEPS, where weighted sample size for women is $N_w = 177,241,775$. The *unweighted* sample size for female respondents is $N = 16,096$. Individual's responding with "unsure" to questions represented by $nohelp$, $needhelp$, $lowrisk$, $modrisk$, and $highrisk$ are left our of descriptive statistics tables.

Table 4: Means of Variables for Women Split out by Presence of Mental Illness

Variable Type	Variable Name	Descriptions	Mental Illness=1	Mental Illness=0	T-test
Physical Health Variables (PH_{it})					
	physhlth	A continuous scale score in which higher scores imply better physical health. Highest score reported is 72.07.	51.01	52.72	-9.16***
	bmi	Individual body mass index.	29.25	27.70	7.68***
	worklim	=1 if the individual has a work limit due a physical or mental ailment, =0 otherwise.	0.055	0.019	8.16***
Healthcare Utilization Variables (HC_{it})					
	insured	=1 if individual has health insurance, =0 otherwise.	0.94	0.91	9.58***
	doc	=1 if individual has a primary doctor to see in the case of a medical event or routine checkup. =0 otherwise.	0.88	0.79	15.15***
	numevents	Number of doctor- or hospital-related events in the past year.	11.39	5.54	20.85***
	totalrx	Total number of medications prescribed within the past year (including refills).	18.83	7.23	28.17***
Belief and Risk Variables (C_{it})					
	badmodhc	=1 if individual rates their healthcare below 7 on a scale from 1 - 11, that ranks worst to best. =0 otherwise.	0.054	0.037	4.08***
	modgoodhc	=1 if individual rates their healthcare 7 or above on a 1 - 11 scale ranking worst to best. =0 otherwise.	0.82	0.69	18.24***
	nomedhelp	=1 if individual believes they can overcome illness without medical help. =0 otherwise	0.20	0.23	-4.02***
	medhelp	=1 if individual believes overcoming illness may require medical help. =0 otherwise.	0.71	0.65	6.30***
	lowrisk	=1 if individual d̈isagrees stronglyör d̈isagrees somewhatẗhat they are more likely to take risks. =0 otherwise.	0.74	0.71	5.02***
	modrisk	=1 if individual ägrees somewhatẗhat they are more likely to take risks. =0 otherwise.	0.12	0.13	-2.31**
	highrisk	=1 if individual “agrees strongly” that they are more likely to take risks. =0 otherwise.	0.027	0.028	-1.77*

Note: column labeled mental disorder=1 lists means for women with at least one diagnosed mental health disorder, whereas mental disorder = 0 indicates means for women without a diagnosed mental disorder. Descriptive statistics are evaluated using individual-level weights provided by the MEPS, where weighted sample size for women is $N_w = 177,241,775$. The *unweighted* sample size for female respondents is $N = 16,096$. Individual's responding with “unsure” to questions represented by $nohelp$, $needhelp$, $lowrisk$, $modrisk$, and $highrisk$ are left our of descriptive statistics tables.

Table 5: Means for subsample with at least one mental disorder, split out by gender

Variables	Descriptions	Females	Males	T-test
mood	=1 if individual has a mood disorder, =0 otherwise.	0.51	0.47	2.98**
anxiety	=1 if individual has an anxiety disorder, =0 otherwise.	0.64	0.57	4.36***
prsnlty	=1 if individual has a personality disorder, =0 otherwise.	0.002	0.001	0.37
psychotic	=1 if individual has a psychotic disorder, =0 otherwise.	0.007	0.009	-2.61***
adhd	=1 if individual has an attention-deficit disorder, =0 otherwise.	0.064	0.091	-3.68***
otherdis	=1 if individual has some other mental disorder besides a mood, anxiety, personality, psychotic, or attention-deficit disorder. =0 otherwise.	0.064	0.076	-1.50
comorbid	=1 if individual has other comorbid mental disorders, =0 otherwise.	0.26	0.19	5.05***
lowseverity	=1 if individual scores an 8 or below on the emotional severity scale provided by MEPS. =0 otherwise.	0.80	0.82	-2.58***
modseverity severity scale provided by MEPS. =0 otherwise.	=1 if individual scores between 9 and 15 on the emotional	0.16	0.15	1.60
highseverity	=1 if individual scores above 15 on the emotional severity scale provided by MEPS. =0 otherwise.	0.041	0.029	2.33**
numeps$_m h$	The number of medical service utilization events associated with the individual's mental disorder(s).	0.11	0.088	0.72
needtrtmnt	=1 if individual requires some form of medical treatment or intervention. =0 otherwise.	0.71	0.59	7.99***

Note: the emotional severity ranking is based on a scale score provided in the MEPS, based on answers to questions pertaining to mental distress in the last 30 days Descriptive statistics are evaluated using individual-level weights provided by the MEPS, where weighted sample size for females with a mental disorder is $N_{wf} = 40,429,225$, and weighted sample size for males with a mental disorder is $N_{wm} = 20,032,340$.
The *unweighted* sample size for females with a mental disorder is $N_f = 3,062$, and $N_m = 1,456$ for males with a mental disorder.

Table 6: Average Marginal Effects for Negative Binomial

	Dependent variable: absence_days					
	Males			Females		
	(1)	(2) belief and risk variables	(3) interactions	(4)	(5) belief and risk variables	(6) interactions
mental.ill	1.29***	1.28***	−2.62	0.72**	0.73**	−0.90
	(0.08)	(0.08)	(0.53)	(0.059)	(0.059)	(0.35)
physhlth	−0.18***	−0.18***	−0.17***	−0.18***	−0.18***	−0.18***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
insured	−0.005	0.01	0.017	−0.20	−0.28	−0.29
	(0.092)	(0.092)	(0.093)	(0.097)	(0.096)	(0.096)
doc	−0.35	−0.35	−0.34	−0.38	−0.45	−0.46
	(0.062)	(0.063)	(0.063)	(0.071)	(0.072)	(0.073)
numevents	0.60***	0.60***	0.63***	0.60***	0.59***	0.63***
	(0.031)	(0.033)	(0.034)	(0.034)	(0.034)	(0.037)
totalrx	0.11***	0.11***	0.13***	0.11***	0.104***	0.106***
	(0.025)	(0.026)	(0.027)	(0.024)	(0.025)	(0.026)
worklim	5.50***	5.59***	4.45***	4.64***	4.60***	5.17***
	(0.20)	(0.203)	(0.16)	(0.121)	(0.118)	(0.154)
wage	−0.025	−0.026	−0.018	0.003	0.001	0.0004
	(0.056)	(0.055)	(0.054)	(0.060)	(0.059)	(0.058)
hours	−0.011	−0.012	−0.011	0.039***	0.039***	0.021
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
sickleave	0.61**	0.63**	0.55**	0.071	0.11	0.16
	(0.068)	(0.068)	(0.069)	(0.075)	(0.074)	(0.072)
vaca	0.38	0.36	0.22	1.063***	1.04***	0.95**
	(0.08)	(0.08)	(0.08)	(0.069)	(0.069)	(0.079)
badmodhc		0.38	0.28		−0.12	−0.17
		(0.12)	(0.12)		(0.095)	(0.094)
modgoodhc		−0.018	−0.086		0.47	0.34
		(0.065)	(0.064)		(0.067)	(0.067)
nomedhlp		−0.27	−0.20		−0.058	−0.16
		(0.08)	(0.078)		(0.081)	(0.082)
medhlp		−0.42	−0.34		0.38	0.31
		(0.079)	(0.077)		(0.075)	(0.076)
lowrisk		0.36	0.32		−0.15	−0.15
		(0.064)	(0.063)		(0.066)	(0.067)
modrisk		0.45	0.39		0.28	0.25
		(0.082)	(0.082)		(0.081)	(0.081)
highrisk		−0.088	−0.044		0.46	0.50
		(0.114)	(0.111)		(0.145)	(0.147)
physhlth:mental.ill			0.12***			0.007
			(0.010)			(0.005)
numevents:mental.ill			−1.60***			−0.119***
			(0.068)			(0.003)
totalrx:mental.ill			−0.37**			−0.015
			(0.053)			(0.002)
worklim:mental.ill			0.77			−1.15
			(0.40)			(0.20)
hours:mental.ill						0.064**
						(0.006)
vaca:mental.ill						0.15
						(0.114)
sickleave:mental.ill			0.17			
			(0.15)			
Observations		14,358			16,096	
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 7: Average Marginal Effects for Negative Binomial with Interactions for Males

	Dependent variable: absence_days					
	(1) AME	(2) Mood Disorder Interactions	(3) Anxiety Disorder Interactions	(4) Attention-Deficit Disorder Interactions	(5) Psychotic Disorder Interactions	(6) Other Disorder Interactions
mood	1.74*** (0.12)	−1.85 (0.62)	1.60*** (0.136)	1.80*** (0.12)	1.77*** (0.117)	1.80*** (0.118)
anxiety	0.43 (0.088)	0.32 (0.091)	−3.55** (0.65)	0.46 (0.089)	0.44 (0.088)	0.45 (0.088)
adhd	−2.55*** (0.156)	−2.03*** (0.18)	−2.01*** (0.18)	0.69 (1.23)	−2.56*** (0.157)	−2.42*** (0.156)
psyc	4.47 (0.86)	5.54* (0.87)	4.98 (0.89)	4.54 (0.86)	20.99*** (1.59)	4.43 (0.86)
other	1.28 (0.22)	1.78** (0.24)	1.70* (0.27)	1.46 (0.22)	1.27 (0.219)	0.90 (1.17)
physhlth	−0.19*** (0.004)	−0.18*** (0.004)	−0.18*** (0.004)	−0.19*** (0.004)	−0.19*** (0.004)	−0.19*** (0.004)
numevents	0.60*** (0.031)	0.61*** (0.032)	0.604*** (0.032)	0.60*** (0.032)	0.60*** (0.031)	0.60*** (0.031)
totalrx	0.11*** (0.024)	0.13*** (0.024)	0.12*** (0.025)	0.11*** (0.024)	0.11*** (0.024)	0.11*** (0.024)
worklim	5.41*** (0.173)	4.42*** (0.146)	4.41*** (0.153)	5.58*** (0.174)	5.39*** (0.173)	5.38*** (0.175)
sickleave	0.67*** (0.057)	0.55*** (0.059)	0.55** (0.059)	0.69*** (0.058)	0.68*** (0.057)	0.66*** (0.057)
physhlth:MH^g		0.13*** (0.011)	0.11*** (0.011)	−0.011 (0.021)	*NA* *NA*	0.062 (0.019)
numevents:MH^g		−1.56*** (0.08)	−1.59*** (0.084)	0.12 (0.182)	3.34 (0.916)	−2.98*** (0.17)
totalrx:MH^g		0.13*** (0.065)	−0.099 (0.074)	−0.45 (0.172)	−8.45** (0.84)	−0.012 (0.126)
worklim:MH^g		0.89 (0.47)	4.41 (0.41)	−8.60*** (0.535)	−167.86*** (1.58)	2.39 (0.456)
sickleave:MH^g		0.01 (0.18)	0.70 (0.17)	−2.38** (0.285)	2.36 (0.742)	1.67 (0.338)
anxiety:mood		0.35 (0.18)	−0.56 (0.21)			
adhd:mood		0.31 (0.35)		−1.57 (0.32)		
psyc:mood		−11.85*** (0.95)			−16.89*** (1.46)	
other:mood		−2.27* (0.38)				−1.03 (0.383)
adhd:anxiety			0.24 (0.36)	1.52 (0.34)		
psyc:anxiety			−7.49** (0.91)		5.30 (0.834)	
other:anxiety			−2.03 (0.41)			−0.46 (0.365)
psyc:adhd				*NA* *NA*	*NA* *NA*	
other:adhd				−12.22*** (0.68)		−4.60 (0.741)
other:psyc					*NA* *NA*	*NA* *NA*
Observations	14,352					
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 8: Average Marginal Effects for Negative Binomial with Interactions for Females

	Dependent variable: absence_days					
	(1) AME	(2) Mood Disorder Interactions	(3) Anxiety Disorder Interactions	(4) Attention-Deficit Disorder Interactions	(5) Psychotic Disorder Interactions	(6) Other Disorder Interactions
mood	0.88** (0.077)	−0.18 (0.438)	1.23** (0.097)	0.84** (0.079)	0.89** (0.077)	0.95** (0.078)
anxiety	0.20 (0.081)	0.44 (0.099)	4.75** (0.44)	0.19 (0.082)	0.204 (0.081)	0.23 (0.083)
adhd	−2.02*** (0.146)	−2.66*** (0.164)	−2.38*** (0.178)	11.98** (1.11)	−2.03*** (0.146)	−1.88** (0.146)
psyc	−0.11 (0.413)	1.11 (0.523)	1.21 (0.541)	−0.11 (0.412)	31.21** (2.65)	0.20 (0.412)
other	0.88 (0.141)	1.52* (0.156)	1.47 (0.193)	1.02 (0.142)	0.902 (0.141)	2.70 (0.933)
physhlth	−0.19*** (0.003)	−0.20*** (0.003)	−0.18*** (0.003)	−0.19*** (0.003)	−0.19*** (0.003)	−0.19*** (0.003)
numevents	0.59*** (0.037)	0.64*** (0.041)	0.59*** (0.035)	0.60*** (0.038)	0.59*** (0.037)	0.59*** (0.038)
totalrx	0.11*** (0.027)	0.11*** (0.029)	0.10*** (0.026)	0.11*** (0.027)	0.11*** (0.027)	0.104*** (0.027)
worklim	4.71*** (0.138)	5.08*** (0.162)	5.18*** (0.166)	4.66*** (0.141)	4.79*** (0.137)	4.66*** (0.141)
hours	0.04*** (0.003)	0.024* (0.003)	0.038*** (0.003)	0.039*** (0.003)	0.04*** (0.003)	0.36*** (0.003)
vaca	1.13*** (0.063)	1.09*** (0.070)	0.97*** (0.067)	1.13*** (0.063)	1.13*** (0.063)	1.13*** (0.064)
physhlth:MH^g		0.051* (0.006)	−0.036 (0.006)	−0.15** (0.015)	0.16 (0.069)	−0.04 (0.015)
numevents:MH^g		−1.88*** (0.065)	−2.15*** (0.094)	−3.90*** (0.133)	−12.14*** (0.504)	−3.35*** (0.117)
totalrx:MH^g		−0.20 (0.062)	−0.12 (0.061)	−0.15 (0.142)	−4.63*** (0.217)	0.46 (0.123)
worklim:MH^g		−1.53 (0.245)	−2.04* (0.227)	−2.01 (0.474)	6.07 (1.16)	−1.75 (0.608)
hours:MH^g		0.07 (0.007)	0.025 (0.006)	−0.013 (0.015)	−0.56*** (0.037)	0.20*** (0.012)
vaca:MH^g		0.19 (0.128)	0.92 (0.142)	2.57 (0.387)	36.86*** (0.893)	−0.73 (0.259)
anxiety:mood		−0.81 (0.14)	−0.61 (0.134)			
adhd:mood		2.47* (0.30)		2.13 (0.28)		
psyc:mood		−1.25 (0.683)			−5.33 (0.654)	
other:mood		−2.48 (0.324)				−1.21 (0.42)
adhd:anxiety			1.64 (0.283)	1.19 (0.28)		
psyc:anxiety			−1.71 (0.666)		−6.63* (0.673)	
other:anxiety			−1.16 (0.268)			−0.55 (0.303)
psyc:adhd				*NA* *NA*	*NA* *NA*	
other:adhd				−6.10** (0.586)		−2.60 (0.643)
other:psyc					−11.14*** (0.372)	4.10 (0.664)
Observations	16,086					

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: Average Marginal Effects for Negative Binomial with Interactions

	Dependent variable:							
	absence_days							
	Males				Females			
	(1) Psychotic Disorder Interactions	(2) Other Disorder Interactions	(3) Psychotic Disorder Interactions	(4) Other Disorder Interactions	(5)	(6)	(7)	(8)
mood	2.04^{***}	-5.48^{*}	1.94^{***}	1.86^{***}	0.87	-10.79^{***}	0.82	0.75
	(0.132)	(0.854)	(0.135)	(0.138)	(0.117)	(0.653)	(0.121)	(0.122)
anxiety	1.02^{**}	0.88^{*}	0.95^{**}	-7.50^{**}	1.32^{**}	1.33^{**}	1.37^{**}	2.10
	(0.131)	(0.143)	(0.134)	(0.937)	(0.110)	(0.118)	(0.117)	(0.583)
prsnlty	−0.135	0.06	1.00	0.04	-1.16^{*}	-1.24^{*}	6.85	−0.62
	(0.182)	(0.213)	(1.49)	(0.536)	(0.119)	(0.134)	(0.775)	(0.206)
physhlth	-0.14^{***}	-0.14^{***}	-0.13^{***}	-0.13^{***}	-0.21^{***}	-0.21^{***}	-0.20^{***}	-0.20^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
numevents	0.59^{***}	0.59^{***}	0.60^{***}	0.60^{***}	0.64^{***}	0.67^{***}	0.65^{***}	0.66^{***}
	(0.036)	(0.036)	(0.035)	(0.035)	(0.036)	(0.033)	(0.037)	(0.039)
totalrx	0.134^{***}	0.14^{***}	0.13^{***}	0.133^{***}	0.13^{***}	0.12^{***}	0.13^{***}	0.14^{***}
	(0.026)	(0.026)	(0.026)	(0.026)	(0.024)	(0.024)	(0.024)	(0.024)
worklim	5.57^{***}	5.50^{***}	4.47^{***}	4.50^{***}	5.88^{***}	6.15^{***}	5.63^{***}	5.45^{***}
	(0.261)	(0.273)	(0.184)	(0.189)	(0.123)	(0.133)	(0.126)	(0.131)
wage	-0.019^{*}	−0.016	-0.02^{*}	−0.017	0.001	−0.002	0.003	−0.0001
	(0.055)	(0.056)	(0.055)	(.055)	(0.067)	(0.067)	(0.069)	(0.069)
hours	-0.05^{***}	-0.047^{***}	-0.05^{***}	-0.05^{***}	−0.03	-0.05^{**}	−0.03	−0.03
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
sickleave	0.50^{*}	0.49^{**}	0.45^{**}	0.43^{**}	0.008	0.06	−0.04	−0.04
	(0.063)	(0.058)	(0.058)	(0.058)	(0.071)	(0.073)	(0.075)	(0.076)
badmodhc	0.58	0.65	0.55	0.35	0.03	−0.06	−0.08	−0.10
	(0.108)	(0.111)	(0.110)	(0.104)	(0.114)	(0.115)	(0.114)	(0.115)
modgoodhc	0.03	0.03	0.06	0.07	-0.69^{*}	-0.67^{*}	-0.71^{**}	-0.75^{**}
	(0.064)	(0.063)	(0.063)	(0.063)	(0.067)	(0.070)	(0.070)	(0.071)
nomedhlp	−0.103	−0.07	−0.11	−0.08	−0.66	−0.70	−0.70	−0.73
	(0.086)	(0.081)	(0.083)	(0.083)	(0.091)	(0.091)	(0.091)	(0.091)
medhlp	-0.63^{**}	-0.57^{*}	-0.59^{**}	-0.59^{**}	−0.06	−0.11	−0.08	−0.09
	(0.083)	(0.082)	(0.084)	(0.084)	(0.086)	(0.086)	(0.086)	(0.086)
physhlth:MH^g		0.19^{***}	0.06	0.07^{*}		0.02	−0.04	−0.01
		(0.018)	(0.019)	(0.012)		(0.008)	(0.003)	(0.007)
numevents:MH^g		-0.06^{**}	-0.12^{***}	-0.107^{***}		-0.11^{***}	-0.10^{***}	-0.121^{***}
		(0.007)	(0.006)	(0.006)		(0.004)	(0.004)	(0.005)
totalrx:MH^g			0.01			−0.02	−0.02	-0.03^{*}
			(0.013)			(0.003)	(0.003)	(0.003)
worklim:MH^g		−0.59	4.30^{*}	2.70		0.13	0.52	1.40
		(0.744)	(0.769)	(0.685)		(0.287)	(0.304)	(0.284)
hours:MH^g		0.007	0.07^{*}	0.10^{***}		0.25^{***}	−0.014	−0.005
		(0.011)	(0.012)	(0.010)		(0.017)	(0.013)	(0.011)
sickleave:MH^g		−0.47	0.38	0.75				
		(0.257)	(0.234)	(0.205)				
medhlp:MH^g		−1.01	−0.96	−0.08				
		(0.221)	(0.218)	(0.177)		(0.272)		
modgoodhc:MH^g						1.46^{*}	1.36	1.49^{*}
						(0.161)	(0.187)	(0.144)
psyc:other						1.46^{*}	1.36	1.49^{*}
						(0.161)	(0.187)	(0.144)
Observations	12,232				11,254			
Note:								*p<0.1; **p<0.05; ***p<0.01

9 Appendix

9.1 Equation Specifications

Table 10: Equation Specifications

Dependent variable: absencedys					
Males			Females		
Equation 1 Explanatory Variables (AME reported in column (1) of Table 6)	Equation 2 Explanatory Variables (AME reported in column (2) of Table 6)	Equation 3 Explanatory Variables (AME reported in column (3) of Table 6)	Equation 1 Explanatory Variables (AME reported in column (4) of Table 6)	Equation 2 Explanatory Variables (AME reported in column (5) of Table 6)	Equation 3 Explanatory Variables (AME reported in column (6) of Table 6)
mental.ill	mental.ill	mental.ill	mental.ill	mental.ill	mental.ill
physhlth	physhlth	physhlth	physhlth	physhlth	physhlth
bmi	bmi	bmi	bmi	bmi	bmi
insured	insured	insured	insured	insured	insured
numevents	numevents	numevents	numevents	numevents	numevents
totalrx	totalrx	totalrx	totalrx	totalrx	totalrx
doc	doc	doc	doc	doc	doc
worklim	worklim	worklim	worklim	worklim	worklim
wage	wage	wage	wage	wage	wage
hours	hours	hours	hours	hours	hours
sickleave	sickleave	sickleave	sickleave	sickleave	sickleave
vaca	vaca	vaca	vaca	vaca	vaca
numemp	numemp	numemp	numemp	numemp	numemp
union	union	union	union	union	union
occ1	occ1	occ1	occ1	occ1	occ1
occ2	occ2	occ2	occ2	occ2	occ2
age	age	age	age	age	age
familysize	familysize	familysize	familysize	familysize	familysize
white	white	white	white	white	white
black	black	black	black	black	black
hispanic	hispanic	hispanic	hispanic	hispanic	hispanic
married	married	married	married	married	married
highschool	highschool	highschool	highschool	highschool	highschool
somecoll	somecoll	somecoll	somecoll	somecoll	somecoll
bachdegree	bachdegree	bachdegree	bachdegree	bachdegree	bachdegree
beyondbach	beyondbach	beyondbach	beyondbach	beyondbach	beyondbach
	badmodhc	badmodhc		badmodhc	badmodhc
	modgoodhc	modgoodhc		modgoodhc	modgoodhc
	nomedhelp	nomedhelp		nomedhelp	nomedhelp
	medhelp	medhelp		medhelp	medhelp
	lowrisk	lowrisk		lowrisk	lowrisk
	modrisk	modrisk		modrisk	modrisk
	highrisk	highrisk		highrisk	highrisk
		physhlth:mental.ill			physhlth:mental.ill
		numevents:mental.ill			numevents:mental.ill
		totalrx:mental.ill			totalrx:mental.ill
		worklim:mental.ill			worklim:mental.ill
		sickleave:mental.ill			vaca:mental.ill
					hours:mental.ill
year 2010	year 2010	year 2010	year 2010	year 2010	year 2010
year 2011	year 2011	year 2011	year 2011	year 2011	year 2011
year 2012	year 2012	year 2012	year 2012	year 2012	year 2012
year 2013	year 2013	year 2013	year 2013	year 2013	year 2013
year 2014	year 2014	year 2014	year 2014	year 2014	year 2014

Table 11: Equation Specifications

Dependent variable: absencedys							
Males				Females			
Equation 4 Explanatory Variables (AME reported in column (1) of Table 7)	Equation 5 Explanatory Variables (AME reported in column (2) of Table 7)	Equation 6 Explanatory Variables (AME reported in column (3) of Table 7)	Equation 7 Explanatory Variables (AME reporting in column (4) of Table 7)	Equation 4 Explanatory Variables (AME reported in column (5) of Table 7)	Equation 5 Explanatory Variables (AME reported in column (6) of Table 7)	Equation 6 Explanatory Variables (AME reported in column (7) of Table 7)	Equation 7 Explanatory Variables (AME reported in column (8) of Table 7)
mood	mood	mood	mood	mood	mood	mood	mood
anxiety	anxiety	anxiety	anxiety	anxiety	anxiety	anxiety	anxiety
prsnlty	prsnlty	prsnlty	prsnlty	prsnlty	prsnlty	prsnlty	prsnlty
physhlth	physhlth	physhlth	physhlth	physhlth	physhlth	physhlth	physhlth
numevents	numevents	numevents	numevents	numevents	numevents	numevents	numevents
totalrx	totalrx	totalrx	totalrx	totalrx	totalrx	totalrx	totalrx
worklim	worklim	worklim	worklim	worklim	worklim	worklim	worklim
wage	wage	wage	wage	wage	wage	wage	wage
hours	hours	hours	hours	hours	hours	hours	hours
sickleave	sickleave	sickleave	sickleave	sickleave	sickleave	sickleave	sickleave
numemp	numemp	numemp	numemp	numemp	numemp	numemp	numemp
union	union	union	union	union	union	union	union
occ1	occ1	occ1	occ1	occ1	occ1	occ1	occ1
occ2	occ2	occ2	occ2	occ2	occ2	occ2	occ2
age	age	age	age	age	age	age	age
familysize	familysize	familysize	familysize	familysize	familysize	familysize	familysize
white	white	white	white	white	white	white	white
black	black	black	black	black	black	black	black
hispanic	hispanic	hispanic	hispanic	hispanic	hispanic	hispanic	hispanic
married	married	married	married	married	married	married	married
highschool	highschool	highschool	highschool	highschool	highschool	highschool	highschool
somecoll	somecoll	somecoll	somecoll	somecoll	somecoll	somecoll	somecoll
bachdegree	bachdegree	bachdegree	bachdegree	bachdegree	bachdegree	bachdegree	bachdegree
beyondbach	beyondbach	beyondbach	beyondbach	beyondbach	beyondbach	beyondbach	beyondbach
	badmodhc	badmodhc	badmodhc	badmodhc	badmodhc	badmodhc	badmodhc
	modgoodhc	modgoodhc	modgoodhc	modgoodhc	modgoodhc	modgoodhc	modgoodhc
	nomedhelp	nomedhelp	nomedhelp	nomedhelp	nomedhelp	nomedhelp	nomedhelp
	medhelp	medhelp	medhelp	medhelp	medhelp	medhelp	medhelp
	physhlth:mood	physhlth:prsnlty	physhlth:anxiety		physhlth:mood	physhlth:prsnlty	physhlth:anxiety
	numevents:mood	numevents:prsnlty	numevents:anxiety		numevents:mood	numevents:prsnlty	numevents:anxiety
	worklim:mood	worklim:prsnlty	worklim:anxiety		worklim:mood	worklim:prsnlty	worklim:anxiety
	sickleave:mood	sickleave:prsnlty	sickleave:anxiety		totalrx:mood	totalrx:prsnlty	totalrx:anxiety
	hours:mood	hours:prsnlty	hours:anxiety		hours:mood	hours:prsnlty	hours:anxiety
	badmodhc:mood	badmodhc:prsnlty	modgoodhc:anxiety		modgoodhc:mood	modgoodhc:prsnlty	modgoodhc:anxiety
	medhelp:mood	medhelp:prsnlty	medhelp:anxiety				
	mood:prsnlty	prsnlty:mood	prsnlty:anxiety		mood:prsnlty	prsnlty:mood	prsnlty:anxiety
		prsnlty:anxiety			prsnlty:anxiety		
year 2010	year 2010	year 2010	year 2010	year 2010	year 2010	year 2010	year 2010
year 2011	year 2011	year 2011	year 2011	year 2011	year 2011	year 2011	year 2011
year 2012	year 2012	year 2012	year 2012	year 2012	year 2012	year 2012	year 2012
year 2013	year 2013	year 2013	year 2013	year 2013	year 2013	year 2013	year 2013
year 2014	year 2014	year 2014	year 2014	year 2014	year 2014	year 2014	year 2014

9.2 Coefficient Estimates

Table 12: Coefficients for for equations (1) - (3)

	Dependent variable:					
	absence_days					
	Males			Females		
	(1)	(2)	(3)	(4)	(5)	(6)
		belief and risk variables	interactions		belief and risk variables	interactions
mental.ill	0.32***	0.32***	−0.75	0.14**	0.14**	−0.18
	(0.08)	(0.08)	(0.53)	(0.06)	(0.06)	(0.35)
physhlth	−0.04***	−0.04***	−0.05***	−0.03***	−0.03***	−0.04***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
bmi	0.001	0.001		0.01**	0.01**	0.01**
	(0.004)	(0.004)		(0.004)	(0.004)	(0.004)
insured	−0.001	0.002	0.005	−0.04	−0.05	−0.06
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)
numevents	0.90***	0.90***	0.97***	0.79***	0.78***	0.84***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
totalrx	0.12***	0.13***	0.15***	0.10***	0.10***	0.10***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
doc	−0.09	−0.09	−0.10	−0.07	−0.09	−0.09
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
wrklim	1.37***	1.38***	1.28***	0.90***	0.90***	1.05***
	(0.20)	(0.20)	(0.16)	(0.12)	(0.12)	(0.15)
wage	−0.08	−0.09	−0.07	0.01	0.002	0.001
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
hours	−0.003	−0.003	−0.003	0.01***	0.01***	0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
sickleave	0.15**	0.15**	0.16**	0.01	0.02	0.03
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
vaca	0.09	0.09	0.06	0.21***	0.20***	0.19**
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)
numemp	0.0002	0.0001	0.0001	0.0004***	0.0004***	0.0003**
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
union	0.24***	0.24***	0.23***	0.22***	0.22***	0.22***
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
occ1	0.06	0.06	0.05	−0.03	−0.03	−0.04
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
occ2	−0.09	−0.09	−0.10	−0.04	−0.04	−0.04
	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
age	−0.01***	−0.01***	−0.01***	−0.02***	−0.02***	−0.02***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
familysize	0.01	0.01	0.01	0.08***	0.08***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
white	−0.18**	−0.18**	−0.18**	−0.03	−0.03	−0.02
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
black	−0.38***	−0.38***	−0.39***	0.15*	0.15*	0.14*
	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)
hispanic	−0.16*	−0.15	−0.14	0.05	0.04	0.04
	(0.09)	(0.10)	(0.10)	(0.08)	(0.08)	(0.08)
married	−0.24***	−0.24***	−0.23***	−0.14***	−0.14***	−0.13**
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
highschool	0.09	0.09	0.10	−0.12	−0.11	−0.10
	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)
somecoll	−0.09	−0.09	−0.09	−0.08	−0.09	−0.08
	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)
bachdegree	−0.19	−0.19	−0.17	−0.32**	−0.33**	−0.32**
	(0.14)	(0.14)	(0.13)	(0.14)	(0.14)	(0.15)
beyondbach	−0.32**	−0.32**	−0.31**	−0.24	−0.24	−0.24
	(0.16)	(0.16)	(0.16)	(0.15)	(0.15)	(0.15)
badmodhc		0.09	0.08		−0.02	−0.03
		(0.12)	(0.12)		(0.09)	(0.09)
modgoodhc		−0.004	−0.02		0.09	0.07
		(0.07)	(0.06)		(0.07)	(0.07)
nomedhelp		−0.07	−0.06		−0.01	−0.03
		(0.08)	(0.08)		(0.08)	(0.08)
medhelp		−0.10	−0.10		0.07	0.06
		(0.08)	(0.08)		(0.08)	(0.08)
lowrisk		0.09	0.09		−0.03	−0.03
		(0.06)	(0.06)		(0.07)	(0.07)
modrisk		0.11	0.11		0.06	0.05
		(0.08)	(0.08)		(0.08)	(0.08)
highrisk		−0.02	−0.01		0.09	0.10
		(0.11)	(0.11)		(0.14)	(0.15)
physhlth:mental.ill			0.03***			0.001
			(0.01)			(0.01)
numevents:mental.ill			−0.46***			−0.02***
			(0.07)			(0.003)
totalrx:mental.ill			−0.11**			−0.003
			(0.05)			(0.002)
sickleave:mental.ill			0.05			
			(0.15)			
vaca:mental.ill						0.03
						(0.11)
wrklim:mental.ill			0.22			−0.23
			(0.40)			(0.20)
hours:mental.ill						0.01**
						(0.01)
yr10	−0.09	−0.09	−0.07	0.16	0.15	0.15
	(0.14)	(0.14)	(0.14)	(0.11)	(0.11)	(0.11)
yr11	−0.18	−0.19	−0.17	0.10	0.09	0.08
	(0.11)	(0.11)	(0.12)	(0.09)	(0.09)	(0.09)
yr12	0.01	0.01	0.04	0.17*	0.17*	0.18**
	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)
yr13	−0.04	−0.05	−0.02	0.13	0.13	0.13
	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.08)
yr14	0.003	−0.001	0.01	0.01	0.01	0.01
	(0.10)	(0.10)	(0.10)	(0.07)	(0.07)	(0.07)
Constant	2.64***	2.67***	2.87***	1.49***	1.44***	1.59***
	(0.40)	(0.40)	(0.36)	(0.32)	(0.32)	(0.34)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 13: Coefficients for isolated explanatory variables of equations (4) - (7)

	Dependent variable:							
	Males				Females			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
prsnlty	−0.04	0.02	0.30	0.003	−0.22*	−0.23*	1.29*	−0.12
	(0.19)	(0.21)	(1.49)	(0.54)	(0.12)	(0.13)	(0.77)	(0.21)
mood	0.56***	−1.32	0.58***	0.56***	0.16	−2.01***	0.15	0.14
	(0.13)	(0.81)	(0.13)	(0.14)	(0.12)	(0.65)	(0.12)	(0.12)
anxiety	0.28**	0.24*	0.29**	−2.15**	0.24**	0.25**	0.26**	0.40
	(0.13)	(0.14)	(0.13)	(1.04)	(0.11)	(0.12)	(0.12)	(0.58)
physhlth	−0.04***	−0.04***	−0.04***	−0.04***	−0.04***	−0.04***	−0.04***	−0.04***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
numevents	0.93***	0.94***	0.95***	0.95***	0.81***	0.84***	0.83***	0.84***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
totalrx	0.16***	0.17***	0.16***	0.16***	0.11***	0.11***	0.11***	0.12***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
worklim	1.53***	1.53***	1.34***	1.37***	1.09***	1.15***	1.06***	1.03***
	(0.26)	(0.27)	(0.18)	(0.19)	(0.12)	(0.13)	(0.13)	(0.13)
wage	−0.09*	−0.08	−0.09*	−0.10*	0.002	−0.01	0.01	−0.0004
	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)	(0.07)	(0.07)	(0.07)
hours	−0.01***	−0.01***	−0.01***	−0.02***	−0.01	−0.01**	−0.005	−0.01
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
sickleave	0.14**	0.14**	0.14**	0.13**	0.002	0.01	−0.01	−0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)
numemp	0.0002	0.0002	0.0002	0.0002	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
union	0.27***	0.26***	0.28***	0.27***	0.21***	0.22***	0.21***	0.22***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
occ1	0.07	0.09	0.07	0.07	−0.18**	−0.18**	−0.18**	−0.17**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.09)	(0.09)	(0.09)	(0.09)
occ2	−0.11	−0.10	−0.12*	−0.12*	−0.15*	−0.15*	−0.15*	−0.15*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)	(0.09)	(0.09)
age	−0.01***	−0.01***	−0.01***	−0.01***	−0.03***	−0.03***	−0.02***	−0.02***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
familysize	−0.004	−0.004	−0.004	−0.003	0.09***	0.09***	0.09***	0.09***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
white	−0.10	−0.10	−0.08	−0.08	0.06	0.07	0.06	0.05
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
black	−0.24***	−0.24***	−0.23***	−0.23***	0.18**	0.20**	0.18**	0.17*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
hispanic	−0.11	−0.11	−0.09	−0.10	0.13	0.14	0.13	0.13
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
married	−0.27***	−0.27***	−0.28***	−0.28***	−0.14**	−0.13**	−0.14**	−0.14**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
highschool	0.13	0.13	0.13	0.13	0.25	0.25	0.25	0.25
	(0.18)	(0.18)	(0.18)	(0.18)	(0.22)	(0.22)	(0.22)	(0.22)
somecoll	0.06	0.06	0.06	0.06	0.32	0.30	0.31	0.31
	(0.18)	(0.18)	(0.18)	(0.18)	(0.22)	(0.22)	(0.22)	(0.22)
bachdegree	−0.05	−0.05	−0.03	−0.04	0.04	0.04	0.03	0.04
	(0.18)	(0.18)	(0.18)	(0.18)	(0.23)	(0.23)	(0.23)	(0.23)
beyondbach	−0.18	−0.18	−0.15	−0.16	0.14	0.11	0.14	0.14
	(0.20)	(0.20)	(0.20)	(0.20)	(0.24)	(0.24)	(0.24)	(0.24)
badmodhc	0.16	0.17	0.16	0.16	0.01	−0.01	−0.01	−0.02
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)
modgoodhc	0.01	0.01	0.02	0.02	−0.13*	−0.12*	−0.13*	−0.14**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
nomedhelp	−0.03	−0.02	−0.03	−0.02	−0.12	−0.13	−0.13	−0.14
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
medhelp	−0.17**	−0.16**	−0.18**	−0.18**	−0.01	−0.02	−0.01	−0.02
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
yr10	0.03	0.05	0.03	0.02	0.25**	0.24**	0.25**	0.25**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)
yr11	0.05	0.06	0.03	0.03	0.17*	0.15	0.17*	0.17*
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
yr12	0.15*	0.17*	0.15	0.14	0.20**	0.18*	0.19*	0.20**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
yr13	0.09	0.10	0.08	0.08	0.13	0.13	0.13	0.13
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
yr14	0.18*	0.19**	0.18*	0.16*	0.10	0.11	0.09	0.10
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Constant	2.58***	2.62***	2.68***	2.79***	2.44***	2.73***	2.35***	2.41***
	(0.33)	(0.34)	(0.32)	(0.33)	(0.43)	(0.42)	(0.44)	(0.44)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: Coefficients for interaction terms of equations (7) - (14)

	Dependent variable:					
		Males			Females	
	(1)	(2)	(3)	(4)	(5)	(6)
physhlth:mood	0.05***			0.003		
	(0.01)			(0.01)		
worklim:mood	−0.23			0.02		
	(0.78)			(0.29)		
numevents:mood	−0.02***			−0.02***		
	(0.004)			(0.004)		
totalrx:mood				−0.004		
				(0.003)		
hours:mood	0.002			0.05***		
	(0.01)			(0.02)		
sickleave:mood	−0.17			0.03		
	(0.25)			(0.22)		
modgoodhc.mood				0.27*		
				(0.16)		
medhelp:mood	−0.21					
	(0.22)					
physhlth:prsnlty		0.02			−0.01	
		(0.02)			(0.01)	
numevents:prsnlty		−0.04***			−0.02***	
		(0.01)			(0.004)	
totalrx:prsnlty					−0.004	
					(0.003)	
worklim:prsnlty		1.29*			0.10	
		(0.77)			(0.33)	
sickleave:prsnlty		0.11				
		(0.23)				
hours:prsnlty		0.02*			−0.003	
		(0.01)			(0.01)	
medhelp:prsnlty		−0.29				
		(0.22)				
modgoodhc:prsnlty					0.27	
					(0.17)	
physhlth:anxiety			0.02			−0.002
			(0.01)			(0.01)
numevents:anxiety			−0.03***			−0.02***
			(0.01)			(0.005)
totalrx:anxiety						−0.01*
						(0.003)
worklim:anxiety			0.78			0.26
			(0.68)			(0.28)
sickleave:anxiety			0.27			0.15
			(0.21)			(0.17)
hours:anxiety			0.03***			−0.001
			(0.01)			(0.01)
medhelp:anxiety			−0.05			
			(0.19)			
modgoodhc:anxiety						0.28*
						(0.14)
prsnlty:mood	−0.88**	−2.85***		0.24	−0.67	
	(0.42)	(0.38)		(0.23)	(0.43)	
prsnlty:anxiety		−2.07***	−0.05		−0.85**	−0.01
		(0.27)	(0.56)		(0.39)	(0.24)

Note:
*p<0.1; **p<0.05; ***p<0.01