Moderate to Severe Diagnosed Mental Disorders and Absenteeism

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Abstract

This study examines the relationship between mental health, job factors, and work absenteeism. I examine the impact of diagnosed mental illness (identified using clinical classification code structures from the MEPS), as well as qualitative self-report measures of point-in-time mental health, on annual health-related work absences for working adults. It investigates how job factors may alleviate or exacerbate this relationship. Findings indicate that individuals reporting high mental distress with an official diagnosis exhibit fewer absences than cohorts exhibiting equivalent distress levels and no diagnostic history. Mental illness contributes to increased absenteeism, amounting to about one extra day annually. Additionally, there is a clearly observable indirect influence of benefit packages promoting worker wellness: while these benefits generally increase absenteeism by encouraging labor substitution for time spent on health production, they mitigate the impact of mental illness on absenteeism.

1 Introduction

Comprehensive measures of individual productivity loss are, to some extent, unobtainable because unobservable personality characteristics and abilities affect a worker's true potential productive capacity. On the other hand, there are ways to analyze what factors drive specific definitions of productivity loss, such as productive time lost. In what follows, I consider two measures of productive time loss, though the main focus of this paper lies on absenteeism only. In the current context, presenteeism is defined as being unproductive while at work due to a physical or mental illness or injury, while absenteeism refers to work absences induced by physical injury or physical or mental illness. Based on the definitions of these two terms, it seems plausible to expect that workers suffering from mental illness exhibit greater levels of presenteeism and absenteeism than mentally healthy workers, all else equal. In this research, I empirically test this claim in regard to absenteeism by estimating the magnitude of differences in absenteeism induced by mental illness. I also estimate the effects of outside factors that may mitigate or amplify the impacts of mental illness on absenteeism. If absenteeism is significantly greater for workers with mental illness, the monetary value of a lost day of work may be considered an indirect cost posed by mental illness. A failure to consider such indirect costs associated with mental illness in workers can lead to an understated cost burden that may result in the under-provision of employee mental healthcare.

About 1 in 5 U.S. adults experience mental illness each year but only about 43% of these individuals receive treatment (National Alliance on Mental Illness [NAMI], n.d.). It is additionally reported that the average delay between the onset of psychological symptoms and treatment to reduce and manage these symptoms is 11 years. 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.

Research suggests that limited accessibility to mental healthcare through disintegration of medical health insurance and mental health insurance are one barrier that not only impacts one's ability to obtain treatment discretely and in a timely manner, but that such limitations also reduce productivity outcomes for the labor force. Goetzel et al. (2002) find that managed care plans for mental health discourage treatment utilization by requiring workers to reveal their mental health status to employers in order to be able to utilize the services; fear of stigma and discrimination moving forward may limit the appeal of utilizing such benefits. Additionally, these plans are highly micro-managed and may not lead to the best treatment outcomes (Cseh, 2008; Fletcher, 2013; Ashwood et al., 2016, Von Korff et al., 1992).

A study from Rosenheck et al. (1999) finds that the introduction of mental healthcare cost containment methods in a firm decreased the utilization of mental health services by its employees. Simultaneously, utilization of medical services was 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 found evidence of greater productivity loss in workers with mental illness after the introduction of these policies. Nevertheless, the increasing focus in recent years on containing healthcare costs suggests that employers may not take indirect responses to changes in health coverage like these into account when making investment decisions on employee healthcare.

Legislative changes impacting access to healthcare have been increasingly prevalent in recent United States history at both state and federal levels. Individuals classified as ”high-risk” by insurers, such as those facing chronic illness, are often thee most impacted by such changes in policy. U.S. employers have been largely reactive to such changes, often focusing on mitigating the rising costs of employee healthcare, a practice that may be at the expense of the well-being of workers. It is important to mitigate the potential misalignment between worker and employer incentives that may be exhibited by the contents of a worker's employment contract, and to acknowledge the potential for employers to ignore the risk of costs that may persist in the presence of health interruptions that inhibit a worker's ability to be productive at work or to be present at work at all. The employer that offers contractual benefits that promote worker health and well-being likely mitigates the risks of persistent health-related productive losses when such benefits incentivize workers to be in overall good health.

In this paper, I empirically measure the impact of mental illness on worker absenteeism. I use the Medical Expenditure Panel Survey (MEPS) to compile a large dataset that is rich with information to mitigate the risk of omitted variable bias. My main analysis involves the interaction between mental health and various fringe benefits to determine how aspects of employment contracts impact the magnitude of the effect of mental illness on absenteeism. Additionally, I estimate a model that includes two measures of mental health: a dichotomous variable indicating a diagnosed mental health disorder, and an index of general psychological distress; this is in acknowledgement of within-group heterogeneity of symptoms among those diagnosed with mental illness. To conclude my analysis, I briefly illustrate the relationship between mental illness and a the variable representing psychological distress and the impact on predicted absences.

2 Theory of Absence Behavior

In what follows, the phenomenon of illness-related absenteeism is defined as a process of simultaneous labor supply and labor demand optimization.

2.1 Supply of Labor

Time allocation models of labor supply consider the decision making process associated with market goods as well as time, with time modeled as a scarce resource. For intuitive purposes, individuals in a household are modeled as producers that take intermediate inputs such as time and market goods to produce useful commodities for the household to enjoy (Becker, 1965). For example, consider the consumption of a final good, a meal. One utilizes inputs such as ingredients purchased from the store and the time spent to cook a meal. If not cooking the meal oneself, the process still involves either the cost of gas or delivery fees, tips, and time. Something as simple as watching television can also be defined by a production process, without loss of generality, as it requires a positive time allotment and market services such as streaming platforms and cable packages as well as a working television. For final products c_k for $k = 1, .., K$, an individual faces the following utility function:

$$U = u(c_1, c_2, ..., c_K), \text{ with } \frac{\partial U}{\partial c_k} > 0 \; \forall k. \tag{1}$$

Each final good c_k can be defined by its respective production process that turns market goods and time into final units of consumption. For final good c_k, this process is characterized by

$$c_k = f_k(T_k, x_k; e_k), \tag{2}$$

where T_k is a vector of time inputs allocated to the production of final good c_k, x_k is a vector of market goods used in production, and e_k represents the efficiency of the process, characterized by exogenous factors such as one's age or education level (referring back to the example above, e_k may also be characterized by one's cooking skills). In each case, the efficiency factor, e_k, impacts how much time and how many market goods are required to achieve a certain level of a final good, and may or may not be equivalent across production processes. Given each production process, f_k, utility function (1) can be rewritten as

$$U = u(f_1, ..., f_K) = u(x_1, ..., x_K; T_1, ..., T_K). \tag{3}$$

The separability between time and market inputs exhibited by (3) demonstrates that household production is bounded from above due to the scarcity of income and time resources.

Of particular interest in this paper is the process of producing health which acts as the final good to be "consumed". I define the production of health status, H, in the following manner:

$$H = f_h(T_h, x_h; MH, PH, e_h), \tag{4}$$

where T_h is a choice of time allotted to the development of health, such as time spent exercising and utilizing health-care services, x_h is a vector of market goods utilized in health production, such as vitamins and supplements or health insurance coverage, MH and PH are "innate" endowments of mental and physical health, respectively, which characterize an individual's health productive capacity, e_h is a vector of non-health-related factors driving the efficiency of the production process, such as education, age, or quality of care, and (4) is a concave function exhibiting diminishing returns to factor inputs. Function (4) innovates the health production function proposed by Grossman (1972).

In my current framework, the baseline endowment of health (MH and PH prior to the commencement of an arbitrary time period) characterizes the feasible set of attainable levels of health given available time and market inputs, and preferences over how these inputs are allocated[1].

Define C as a conglomerate final good that nests each of the production functions of final goods besides health, $c_k, ..., c_{K-1}$, within it so that one can write

$$C = f_c(T_c, x_c, e_c), \tag{5}$$

where $T_c = \sum_{k=1}^{K-1} T_k$ and $x_c = \sum_{k=1}^{K-1} x_k$. (1) can be rewritten in the following manner:

$$U = u(C, H) \equiv u(f_c, f_h) \equiv u(x_c, x_h; T_c, T_h), \tag{6}$$

so that the level of utility realized depends on choices of market inputs and time allocations. It is assumed that an individual maximizes their utility subject to the time constraint,

$$T = T_c + T_h + N, \tag{7}$$

where T is total time available and N is time allocated to occupational work, as well as a budget constraint,

$$I = wN + V = p_c x_c + p_h x_h, \tag{8}$$

where I is total income, V is non-earned income such as monetary gifts or inheritances, w is the market wage rate and p_i for $i = \{c, h\}$ are vectors of input prices corresponding to the market goods utilized in the production processes (5) and (4). The time constraint can be substituted into (8) to yield a single "full income" constraint,

$$\begin{aligned} w(T - T_c - T_h) + V &= p_c x_c + p_h x_h \\ \implies wT + V &= p_c x_c + p_h x_h + wT_c + wT_h. \end{aligned} \tag{9}$$

The left-hand side of the second line in (9) represents full income – the income received when an individual chooses to allot all available time to occupational labor. The above general definition of a single maximization constraint can

[1] While levels MH and PH are assumed to be exogenously determined, they are likely to be characterized by a number highly correlated factors so that individuals exhibiting a relatively low level of MH, may be more likely to exhibit relatively low endowments of PH, and vice versa.

be altered easily with necessary changes to notation.

The results of the current utility maximization problem are more intuitive if the production functions (5) and (4) are redefined, noting that $T_c \equiv t_c C$, $x_c \equiv b_c C$, $T_h \equiv t_h H$, $x_h \equiv b_h H$, where t_i and b_i for $i = \{c, h\}$ are vectors of the input time per unit and market goods per unit required to produce levels of final goods C and H, respectively[2]. With this, a single resource constraint can be expressed as

$$(p_c b_c + w t_c)C + (p_h b_h + w t_h)H = wT + V, \tag{10}$$

where the full price of each unit of the final good, C and H, is the sum of both the direct costs (prices of market goods) and indirect costs (time away from work) associated with each unit produced (Becker, 1965, 6). Now the individual maximizes utility by choosing optimal levels of b_i and t_i for $i = \{c, h\}$. The individual will allot additional units of expenditure and time up to the point at which the marginal utility resulting from an additional unit of the respective input equals zero; this is equivalent to saying that available resources will continue to be allotted to production processes until the marginal product of the input is zero. It should be noted that choices of market good inputs and time inputs are not independent. A condition of utility maximization is that the marginal rate of substitution (MRS) between these types of inputs be equal to the ratio of per-unit input costs.

At this point of the analysis, it is assumed that an individual has enough information to maximize their utility by choosing optimal bundle $\{C^*, H^*\}$. Given this decision, more information on an individual's preferences over home production (and thus, preferences over labor) can be revealed. Decisions on labor supply in the current set up can be intuitively illustrated by examining the demand for "forgone income". Define the right-hand side of (10) S, which is thus full income that would arise if allotting all available time to work. The demand for forgone income $L(C^*, H^*)$, is then

$$L(C^*, H^*) = S - I(C^*, H^*), \tag{11}$$

where I is an individual's observed income. $L(C^*, H^*)$ can be thought of as the indirect cost of utility-seeking; it is the potential earnings lost when an individual allots positive units of time to the production of health and the conglomerate consumption good

Note that utility maximizing non-workers, without loss of generality, exhibit

$$L(C^*, H^*) = wT = V = (p_c b_c + w t_c)C + (p_h b_h + w t_h)H. \tag{12}$$

In such an instance, any general individual could place a price on their own labor (reflected by a reservation wage) after optimizing their potential utility. Determinants of whether an individual enters the labor force or stays out may be based on unobservable features that impact the efficiency of certain inputs in health production. Henceforth, focusing on individuals who exhibit some positive level of labor supply, (11) can be further defined as

$$L^* = w(T_c^* + T_h^*), \tag{13}$$

for short run fixed wage, w, which is greater than or equal to the individual's reservation wage that optimizes their utility in any given period.

Equation (11) can further be dissected such that $I(C^*, H^*)$ is defined as

$$I = b_c p_c C + b_h p_h H. \tag{14}$$

Plugging $T_c + T_h = T - N$ into (13) and then plugging it and (14) into (11) yields

$$w(T - N) = S - b_c p_c C - b_h p_h H, \tag{15}$$

which can be rearranged and simplified as follows:

$$\begin{aligned} -wN &= V - b_c p_c C - b_h p_h H \\ \implies N &= \frac{b_c p_c C + b_h p_h H - V}{w}. \end{aligned} \tag{16}$$

[2]Note that t_h and/or b_h are decreasing in measures of the efficiency of the health production process, MH, PH, and e_h. t_c and/or b_c are decreasing in efficiency factor e_c.

Now, hours of work is expressed a function of health status.

Taking the partial derivative with respect to health:

$$\frac{\partial N}{\partial H} = \frac{b_h p_h}{w} > 0. \tag{17}$$

Equation (17) expresses that better health induces more short-term labor supply. In (17), $b_h p_h$ represents the marginal cost of producing an additional unit of health using market goods and w is the per-unit time cost associated with the level of time allotted to producing health rather than working. The derivative $\frac{\partial N}{\partial H}$ can additionally be thought of as the marginal product of labor supply with respect to health. Rearranging (17) gives

$$\frac{\partial N}{\partial H} w = b_h p_h, \tag{18}$$

which states that an individual will continue to produce health up to the point where the marginal benefit of an additional unit of health (the additional labor income received for an additional unit of health) equals the marginal cost of an additional unit of health.

For the remainder of the analysis, define H^* as an individual's initial utility-maximizing level of health and N^* as the optimal level of labor supplied given this level of health at the start of an arbitrary period. In the short run, one's realized level of health, H, may differ from H^*. Further, define $\bar{H}$ as an individual's pivotal level of health – this is the minimum level of health for which an individual is willing to supply labor; if health status falls below this threshold, an individual is assumed to either leave the labor market or be let go by their employer. It follows that an individual will need to sometimes choose to substitute time away from labor to time producing health in order to ensure that their present level of health does not fall below $\bar{H}$.

Depending on rigidity of employment contracts and the degree to which one's contract prioritizes worker health by allowing unpenalized time away from work or the generosity of cost sharing through health insurance benefits, a worker will have various preferences over market and time resources used to produce health. At the beginning of each day, for example, a worker observes their state of health, then chooses a labor supply level that is optimal, contingent on contractual constraints[3]. As noted by the literature,

2.2 Absence Behavior and Fringe Benefits

In general, illness-related work absenteeism represents the substitutability between time spent earning wages and time spent nurturing illness[4] so that factors which make time inputs in health production more attractive relative to market inputs in health production are theorized to exacerbate absenteeism while factors that make market inputs relatively more attractive than time inputs in health production, such as benefits received on-the-job only, are anticipated to have a mitigating effect on the higher degree of absenteeism exhibited by a worker facing a low level of mental health endowment.

[3] Turning back to the initial decision on whether to supply any labor, and continuing to assume that an individual must simultaneously satisfy a time constraint and budget constraint while optimizing health and consumption, if two seemingly identical individuals with low mental health endowment each exhibit condition 18 but one supplies positive hours of work while the other does not, there must be a separate process that is not directly observable, for example, it may be that one individual has better access to treatment and therapy after work hours and substitutes leisure time for time on health production; an individual with more restrictive service accessibility may only have access to mental health specialists during working hours. This highlights quality and access constraints that may not be directly visible to an employer upon inception of benefit package offerings, but that have distinct and compounding effects on one's work performance in the long run.

[4] Bubonya et al. (2017) examine how interactions between poor mental health and job characteristics influence presenteeism and absenteeism among workers. 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.

Suppose that an individual receives payment s with $0 < s \leq w$ when they are absent from work due to illness. This reduces potential earnings lost from $w(T_c + T_h)$ to $wT_c + (w - s)T_h$. (16) thus becomes

$$\begin{aligned} N &= \frac{p_c b_c C + p_h b_h H - sT_h - V}{w} \\ &= \frac{p_c b_c C + (p_h b_h - st_h)H - V}{w}. \end{aligned} \tag{19}$$

The relationship between health and labor supply is now represented as

$$\frac{\partial N}{\partial H} = \frac{p_h b_h - st_h}{w}. \tag{20}$$

The sign of (20) illustrates that the direction of the relationship between labor supply and health depends on the choice of b_h relative to t_h. For positive s, there is some degree of reduction in the fall in consumption that would occur if an individual decreased their labor supply and increased t_h without receiving compensation s. Recalling the negative relationship between MH and T_h, I hypothesize that an individual in poor mental health will choose to increase the share of time-based inputs used in health production relative to market inputs when receiving paid sick leave because this type of fringe benefit supplements the cost of T_h (reduces the opportunity cost of missing work).

Next, consider the opportunity to receive bonus pay at a job. Suppose that the amount of the bonus is determined by a function, m, which is decreasing in the discrepancy between actual output that the worker produces and some output level, Y, that is determined by the firm. Income now additionally depends on on-the-job performance so that potential lost income becomes

$$w(T_h + T_c) + m(Y - F(N)), \tag{21}$$

where $F(N)$ represents the output generated by a worker supplying N hours of labor, with $F' > 0$ and $F'' < 0$. After a negative shock to mental health, the optimal amount of labor supply falls from some level N^H to a lower level N^L. However, if the individual chooses to supply this lower level of labor, N^L, then potential lost income rises proportionally to the difference between Y and $F(N^H)$ and Y and $F(N^L)$. To avoid the rise in potential lost earnings, the worker may prefer to increase market inputs (x_h) in health production to mitigate the impact of the health shock over increasing time inputs (T_h). I therefore theorize that the potential to earn bonus pay will mitigate some of the change in labor supply induced by poor mental health.

Finally, consider how a fringe benefit such as health insurance might impact the behavior of individuals in poor mental health. Healthcare service utilization takes both market and time inputs, so that T_h and x_h are complements in this setting. To simplify the discussion, assume that T_h and x_h are perfect complements so that the consumption of one additional unit of the healthcare market good (the care received) is paired by an additional unit of time spent on producing health. The marginal cost of utilizing one additional unit of healthcare is $(1 - c)p_h b_h + wt_h$ when covered by insurance at rate $0 < c \leq 1$, and $p_h b_h + wt_h$ when the individual is uninsured ($c = 0$). It directly follows that health insurance coverage incentivizes individuals to utilize healthcare services at higher rates to improve health.

When in poor mental health, health production is less efficient and requires more inputs per-unit to obtain some level of optimal health. Health insurance premiums as well as cost-sharing between individuals and insurers both work to incentivize individuals to utilize healthcare services when ill. In the particular case of poor mental health, health insurance acts as a mechanism toward professional intervention and possibly treatment. Since this type of service utilization requires both time and market inputs and health insurance supplements the cost of the latter, but does not directly supplement the former, poor mental health will induce higher degrees of absenteeism among workers with any health insurance coverage compared to uninsured workers facing poor mental health in the current theoretical framework in which decisions on utilization (and thus, absenteeism) are made on a daily basis would be made. Over a longer term perspective, if insurance induces the treatment of mental health symptoms, health improves over time and it may be that one's efficiency of health production in general increases. That is, compounding treatment effects may close the gap between optimal labor supply and contracted hours even if requiring additional time allotments to utilize treatment.

3 Data-Generating Process

3.1 Refinements to the Medical Expenditure Panel Survey

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 measures of health and well-being at the individual level. Table 1 provides a description for each of the variables included in analysis along with summary statistics. Each panel of the MEPS consists of five rounds spanning across two consecutive years. I utilize three public-use data files from the MEPS: the Full Year Consolidated Data File (FYCD), Medical Conditions File (MCF), and the Jobs File (JF). These files are merged into a single dataset describing calendar-year-specific health, insurance, and employment information at the individual level for years 2010 to 2014. After 2014, variables measuring health-related absence from work at each interview round in a given calendar year are replaced by a single variable measuring annual health-related work absences that is right-censored at an upper-bound of 60 days. Hence, including more recent years in the dataset would come at the cost of reliability of estimates due to differences in the nature of absenteeism measures. Additionally, using censored data comes at the risk of a range of econometric issues.

Upon consolidating the data sources, some persons are observed once for a single calendar year while other individuals are observed twice – once for each calendar year they participate in the survey. It should be noted that the reference period for the third interview round of the survey spans across the two consecutive calendar years; fortunately, the data sources used in the analysis ascribe round three data to the appropriate calendar year so that this does not cause a problem. Responses to most of the MEPS interview questions are reported separately for each of the three rounds per year (with the first year's round three variables pertaining to the start of round three up until the end of the calendar year and the next year's round three variables reference the time spent in round three after the start of the new year) so that FYCD annual data files contain three variables per interview prompt. I use several procedures to consolidate variables appearing in groups of three into new variables that are representative of the full year in which the individual is observed, so that rather than having three variables representing responses to a particular interview prompt, there is a single annual variable for each relevant prompt.

The MEPS collects information on each individual in a surveyed household. While late entry of *households* into the survey is not permitted, *individual* participants may enter the survey late if they enter a participating household during the survey period. For example, late entry may be observed for a newly married individual who moves into the residence of his or her spouse, who is a current MEPS participant. A dummy variable indicating whether an individual moved into a participating household during the survey period is therefore utilized as a control variable in the analysis. Aside from the possibility of the late entry of individual participants, the length of each reference period round may vary across individuals due to extenuating circumstances that interfere with an individual's availability on the originally scheduled interview date for a particular round. In such a case, the interview may be rescheduled to occur at an earlier or later date; in the former instance, an individual may exhibit fewer reference period days than the average participant and in the latter, may exhibit a greater than average number of days included in the particular survey round. Information on individual-specific reference period start and end dates for each of the three rounds occurring in a given year is utilized to generate control variables that account for heterogenous exposure to survey prompts.

After compiling each data source into a single dataset for the years of interest, only observations reporting employment at one or more of the three interview dates are kept. Some observations report employment as of a particular interview date and a job start date equal to said interview date. This may occur in the instance that an individual has been hired but has not yet started working as of the interview, and thus, did not work during the corresponding reference period. These observations are omitted *if* unemployment is reported at both of the other two interview rounds as any reports of missed work days due to illness may be in reference to work around the house only for these individuals and thus, may impact the validity of estimates if left in the sample. The FYCD documentation files support this consideration and explain that the portion of the survey collecting work-loss information is independent of the portion pertaining to employment information[5].

[5]Codebook Source: MEPS-HC Panel Design and Collection Process, Agency for Healthcare Research and Quality, Rockville, Md. https://meps.ahrq.gov/mepsweb/survey_comp/hc_data_collection.jsp.

Observations indicating job changes occurring between interview rounds are utilized to match the proper job characteristics to absenteeism reports relevant to the correct time period. Observations indicating a job change at some point between interview rounds are omitted to mitigate the risk of matching reported work absences to characteristics of the wrong job. Self-employed individuals[6], individuals who have ever retired, dependents, military personnel, and observations with non-response to any of the main variables of interest are removed from the sample.

3.2 Variables

Dependent Variable (A_i): The dependent variable of interest is a count variable (*sickdays*) representing absences from work due to an injury or physical or mental illness or ailment.

Mental Health (MH_i): The main explanatory variable of interest in this study is a binary variable indicating diagnosed mental illness (*keyMHdis*). This variable is based on responses reported in the Medical Conditions File (MCF) which provide condition-specific codes for various forms of mental illness. This variable is equal to one for individual's reporting diagnosis(es) of mood, anxiety, personality, or psychotic disorders[7]; I henceforth refer to these categories of mental illness as "key disorders." If an individual indicates a diagnosis of one or more of these key disorders, *keyMHdis* equals one and is zero otherwise.

It should be noted that diagnoses of other classes of mental illness are also reported in the MCF, such as sexual disorders, conduct disorders, and developmental disorders. I choose not to indicate these diagnosis categories with *keyMHdis* due to the differing nature of the diagnostic criteria associated with these groups of disorders according to the *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.; DSM–5; American Psychiatric Association, 2013). Sexual and conduct disorders are often times underreported and symptoms associated with these disorders are often external in nature. Developmental disorders are associated with highly heterogenous symptoms that may be internalized or externalized and that have a broad range of the degree of limitations associated with symptoms. The MEPS separately categorizes one form of developmental disorder, Attention Deficit/Hyperactivity Disorder (ADHD), "because of [its] relatively high prevalence, and because generally accepted standards for appropriate clinical care have been developed." As ADHD is technically a developmental disorder, the nature of its symptoms are less clear than the symptoms associated with the diagnostic categories included in the formation of *keyMHdis*; however, ADHD is highly comorbid with the diagnoses considered as "key" disorders in this paper so that I decide to include a dummy variable equal to one for individuals with ADHD as a control in the analysis.

It is important to further stress that the *keyMHdis* variable represents only *diagnosed* mental illness across the sample so that mental disorder prevalence rates illustrated by the sample may not be representative of actual population prevalence rates in the US. That is, individuals may exhibit symptoms of mental illness even without a formal diagnosis. There is also likely variation in the degree of symptom severity associated with a specific disorder across individuals and failing to account for this possibility may bias the estimated effect of diagnosed mental illness. The consideration of potential homogenous symptoms between individuals with and without a given diagnosis, as well as heterogenous symptoms across individuals within a particular diagnostic category are highlighted in the DSM-5, which separates itself from earlier DSM editions by its focus on a spectral approach to mental illness. DSM-5 states: "Earlier editions of DSM focused on excluding false-positive results from diagnoses; thus its categories were overly narrow, as is apparent from the widespread need to use NOS [not otherwise specified] diagnoses. Indeed the once plausible goal of identifying homogenous populations for treatment and research resulted in narrow diagnostic categories and did not capture clinical reality, symptom heterogeneity within disorders, and significant sharing of symptoms across multiple disorders". In acknowledgement of within-disorder heterogeneity and that mental health may be, to some degree, independent of a particular diagnosis, I utilize an index variable from the FYCD that measures one's general level of emotional distress over the last 30 days on a Kessler-6 scale with scores ranging from 0-24 and higher values indicating more psychological distress (Kessler et al., 2003; Ashwood et al., 2016). This information is collected as part of the MEPS Self-Administered Questionnaire (SAQ) which is collected at rounds 2 and 4 of the MEPS survey only.

[6] Other research may want to include self-employed individuals in a sample; due to the difference in survey prompts for self-employed individuals in the MEPS, reliable reports of illness-induced absenteeism is not available for such individuals in the current framework.

[7] These categories of mental illness are chosen due to population prevalence, standard treatment protocols, and comorbidity hazards among them.

General (Physical) Health (PH_i): The theoretical framework previously defined labor supply as a function of both mental health and physical health. The MEPS has numerous physical health markers. The FYCD files of the MEPS provide self-rated general health scores for each of the three interview rounds of the respective calendar year. Responses in each round range from 1-5 with higher values indicating *worse* perceived general health. These three variables are summed to create an annual index of general health originally with range 3-15; the index is rescaled by subtracting two from each observation, yielding a poor-health index (*physhlth*) ranging from 1-13 that acts as the main measure of general health.

As the variables just described may be prone to attenuation bias because they are based on self-perceptions of health, various other measures of health are utilized in the analysis. The second analytical variable in this category, named *prtycnds*, represents the number of diagnosed priority conditions as defined by the MEPS. The priority conditions specified by the FYCD are cancer, heart conditions, asthma, stroke, chronic bronchitis, emphysema, high cholesterol, high blood pressure, diabetes, arthritis, joint pain and ADHD. ADHD is not counted in *prtycnds* because it is psychological in nature; instead a dummy variable indicating diagnosed ADHD is utilized as a separate control. The MEPS singles out these priority condition categories "because of their relatively high prevalence, and because generally accepted standards for appropriate clinical care have been developed."

A dummy variable equal to one if an individual has experienced any kind of activity limitation in the past year due to a disability (*actlim*) acts as a control variable along with a binary variable equal to one if an individual has suffered an injury or illness (*injury*) in the past year that required immediate medical help; these aim to account for heterogeneity of absences induced by more severe or unanticipated injuries or illnesses. A dummy variable equal to one for individuals that exercise at least three days a week (*exercise*) as well as a dummy variable identifying smokers (*smoke*) are also utilized as controls to mitigate the impact of attenuation bias that may be associated with the poor-health index variable. For the subsample of women, a variable indicating pregnancy at any time in the year acts as an additional control, as pregnant women likely exhibit more absences. Similar to the *distress* variable previously defined, variables *injury*, *smoke*, and *exercise* are derived using information collected from the MEPS SAQ, and thus, are collected at rounds 2 and 4 of the MEPS calendar year only.

Job Traits (J_i): Variables indicating the fringe benefits offered to an individual by their employer such as paid sick leave (*sickpay*) and bonuses (*bonus*) are utilized as analytical variables in analysis as these factors likely influence an individual's decisions on short-run labor supply. It should be noted that binary variables indicating whether one receives paid vacation time and whether one receives paid leave to visit the doctor are also analyzed, but are determined to induce issues of collinearity with the *sickpay* variable. In addition, the inclusion of either of these binary variables does not significantly improve model fit so that they are excluded from analysis and I instead only focus on the analytical variable *sickpay*.

The decision making process on whether to go to work when facing illness is very likely to depend on the length of time for which an individual has been at their job; for example, an employee who has only worked at a firm for a year might be more averse to absence when ill than an equivalent worker who has worked at a firm for 15 years because less job-specific experience might make the newer employee relatively more expendable; there may also be varying degrees of rapport between the the firm and the employee based on the length of the worker's tenure, another channel through which tenure may impact labor supply decisions. A variable measuring an individuals job tenure in years (*tenure*) is created using information on job start and end dates provided by the MEPS.

Additional job-related controls include indicators for labor union membership (*union*) and dummy variables identifying seasonal workers (*ssnl*), temporary contracts (*temp*), and part-time employees (*parttime*), with individuals that typically work less than 35 hours per week considered part-time. Other job controls include indicator variables for public sector positions (*pubsect*), industry and occupational categories (see Table 1), and firm size (represented by variables $1to19$, $20to99$, $100to499$, and $500plus$ based on sample quartiles).

Health Insurance (I_i): The FYCD provides a copious amount of information on individuals' health insurance characteristics. An imputed variable that indicates the category of insurance the individual reported for the majority of the calendar year (categories are private, public, and uninsured) as well as variables reporting whether one held insurance through their employer from the raw FYCD files are used to derive dummy variables representing one's source of health insurance. The dummy variable equal to one for individuals who have insurance through their job (*jobins*) is included in the estimation of Baseline Model 1 ($BM1$) described later. Variables indicating uninsured individuals (*unins*), individuals insured privately through a source other than their employer (*otherins*), and individuals with a public source of health insurance (*pubins*) are created and the group of uninsured individuals acts as the reference category. A categorical variable from the FYCD is utilized to create a binary variable (*inscostly*) equal to one for individuals who either somewhat agree or strongly agree to the survey prompt, "health insurance is not worth its cost". Variable *inscostly* acts as a proxy of health insurance generosity.

($\tilde{I}_i$): A model specification henceforth referred to as Baseline Model 2 (*BM*2) replaces *jobins* with a group of three dummy variables, *plnchoic*, *nochoic*, and *NR.choic*. Variable *plnchoic* identifies individuals with a choice between multiple insurance plans offered by an employer and variable *nochoic* identifies the individuals that receive insurance through their employer but are only offered one plan option. Variable *NR.choic* indicates observations that report having insurance through an employer but have missing values for prompts on whether or not the employer offers an array of plans to choose from. The variables *pubins* and *otherins* variables remain present in the *BM*2 specification so that uninsured individuals still act as the reference group. The variable *inscostly* discussed above still remains as another insurance characteristic variable in the *BM*2 specification.

The analysis that utilizing the broader variable, *jobins*, aim to consider the impact of the general fringe benefit of health insurance on employee absence. Replacing this variable with *plnchoic*, *nochoic*, and *NR.choic* in the second model specification is a means to analyze the impact of benefit offering designs that allow for self-selection into insurance plans relative to more stringent benefit package designs. I anticipate that there may be a significantly larger impact of *plnchoic* on absenteeism than that observed for *nochoic* because of potential differences in healthcare utilization rates resulting from the ability to select into a preferred plan.

Demographics (X_i): One's highest level of educational attainment is controlled for using a group of dummy variables (*belowhs*, *hsdeg*, *somecoll*, *bachdeg*, *bachplus*). Other variables control for race (*black* and *asian*), Hispanic ethnicity (*hispanic*), native-status (*bornus*), age (*age*), family size (*famsz*), the number of young children in the household (*yngchldrn*), marital status (*married*), and socioeconomic status (*poor*, *lowinc*, *midinc*,*highinc*).

Other Control Variables (C_i): Regional indicator variables (*NE*, *MW*, *W*, *S*) are generated using FYCD variables indicating one's region of residence for the majority of the calendar year. Monthly data from the U.S. Bureau of Labor Statistics on regional unemployment rates is utilized to estimate the average unemployment rate faced by an individual (*unemp.rt*). Reference period start and end dates are used to generate these estimates for individuals that move to a different region during the year of interest; the unemployment rates are averaged across the months for which an individual reported a certain region of residence, then the average is taken across each of the regions that one resided in during the year. This measure of the average unemployment rate faced by an individual in a particular year provides the benefit of controlling for heterogeneity induced by macroeconomic features of the regional economy.

It is assumed that the decision-making process on work absence is only faced on the days that an individual is employed. Thus, differences in exposure to this decision-making process across individuals should be accounted for. I use information on interview start and end dates as well as job start and end dates and employment status to generate an estimate of the number of days employed during the respective calendar year (*empUB*). This is utilized as an offset variable in the econometric methodology that accounts for the discrepancy in exposure to the decision that I am trying to observe (i.e., decision to be present or absent given observed health status).

Persons observed for a single year are split into two categories to indicate which of the two years of participation in the panel that they are observed for. Two dummy variables indicate these two sub-groups of individuals, one indicates that the individual is observed in his or her first year of participation (*yearone*). The second identifies individuals observed in the second (*yeartwo*) year of participation. Sample statistics for a third variable, *bothyears*, for individuals observed in the sample for both years in which their household participated, are included in Table 1, but it should be noted that *bothyears* acts as a reference variable in the empirical analysis.

I control for other outside factors that might impact absence decisions such as a move from one region of the US to another at some point in the calendar year (*moved_US*) and a move from one participating household to another (*moved_RU*). A dummy variable equal to one for individuals responding on their own behalf (*refpers*) acts to capture heterogeneity induced by varying levels of accuracy in the information reported on one's own behalf versus on the behalf of a family member. This consideration is especially important because of the inclusion of subjective measures in the analysis, particularly perceived health status (represented by variable *physhlth*). Finally, dummy variables indicating each observation's respective calendar year (2010 - 2014) are used to account for year fixed effects.

4 Empirical Modeling

To obtain appropriate parameter estimates for the hypothesis tests, it is important to use an econometric model that correctly describes the distribution of the dependent variable. The fact that the count of work absences cannot be negative rules out the use of linear modeling[8]. On the other hand, nonlinear models ensure that fitted values are not negative but forgo some degree of reliability when using random effects or fixed effects estimation with panel data. Roughly half of the individuals in the sample are observed twice, once in each year they participate in the survey while the remainder are observed only once after I edit the sample.There is no clear consensus on the best way to conduct panel analysis in nonlinear count models (Cameron and Trivedi, 2004; Cameron and Trivedi, 1986; Mundlak, 1978; Greene, 2002) and cutting the sample to include only individuals observed in both years comes at the cost of possible efficiency loss (Cameron and Trivedi, 2004); thus, I keep individuals observed only one in the sample rather than deleting them and utilize cluster-robust inference at the individual level. I include multiple control variables that identify possible sources of attrition for individuals observed once, including variables indicating which year of participation (first year or second) in the MEPS these individual's are observed for and whether these individuals participated for both years of MEPS and thus are observed once as a result of my own data-generating process. The inclusion of these variables is inspired by strategies proposed by Verbeek and Nijman (1992) to roughly control for some of the attrition bias induced by the unbalanced sample design.

4.1 Baseline Econometric Models

The dependent variable used in each of the analysis is a count of the number of days absent from work due to *one's own* physical or mental illness over the span of one calendar year, A_i for observation i. Due to the count nature of dependent variable A_i, I specify an exponential conditional mean function.

I specify two separate baseline specifications of the conditional mean of absence days. The first baseline conditional mean specification is defined as follows:

$$E[A_i|MH_i,PH_i,J_i,I_i,X_i,C_i] = \exp(\beta^0_{BM1} + MH_i\beta^{MH}_{BM1} + PH_i\beta^{PH}_{BM1} + J_i\beta^{J}_{BM1} + I_i\beta^{I} + X_i\beta^{X}_{BM1} + C_i\beta^{C}_{BM1}), \tag{22}$$

for every observation, $i = 1,...,n$. Equation (22) will henceforth be referred to as $BM1$ (baseline model one). MH, PH, J, I, X, and C are matrices holding observed values of the corresponding explanatory variables for all i = 1, ..., n observations. Section 4.2 discussed the explanatory variables included in each of these matrices and Table 1 also groups explanatory variables in terms of these matrices and provides definitions. Each matrix of explanatory variables is of dimension $n \times k_l$ where n is the total number of observations in the sample and k_l is an integer equal to the number of explanatory variables in corresponding matrix l for $l = \{MH,PH,J,I,X,C\}$. In a similar fashion, each β^l for $l = \{MH,PH,J,I,X,C\}$ is a $k_l \times 1$ vector of parameters[9].

A second specification of the conditional mean of A_i that I reference as $BM2$ (baseline model two) throughout the rest of the paper is defined in a similar manner to (22). $BM2$ is identical to specification $BM1$ *except* that matrix $\tilde{I}$ replaces matrix I for the $BM2$ specification. As discussed previously in section 4.2, $\tilde{I}$ in $BM2$ holds variables $inscostly$ and the set of dummy variables *nochoic*, *plnchoic*, $NR.choic$, *pubins*, and $otherins$, with *unins* acting as the reference category variable. Variables *plnchoic*, *nochoic*, and $NR.choic$ further break down the variable *jobins* which is included in the $BM1$ specification in place of those three variables. The purpose of this break down is to analyze and compare how the implementation of different types of benefit package designs influence employee absence behavior. The $BM2$ specification takes the form

$$E[A_i|MH_i,PH_i,J_i,\tilde{I}_i,X_i,C_i] = \exp(\beta^0_{BM2} + MH_i\beta^{MH}_{BM2} + PH_i\beta^{PH}_{BM2} + J_i\beta^{J}_{BM2} + \tilde{I}_i\beta^{\tilde{I}} + X_i\beta^{X}_{BM2} + C_i\beta^{C}_{BM2}), \tag{23}$$

[8]Linear regression models pose the risk of generating negative values of estimated outcomes for some combinations of explanatory variable values.

[9]For example, β^{MH}_{BM1} is a 3×1 vector holding parameter values for the three explanatory variables represented in matrix MH, which are $keyMHdis$, $distress$, and $adhd$.

where each β^j for $j = \{MH, PH, J, \tilde{I}, X, C\}$ is a $k_j \times 1$ vector of parameters, where k_j is an integer equal to the number of explanatory variables held in corresponding matrix j. Thus far, I have used notation that assigns parameter subscripts that indicate the specific baseline specification in order to highlight that coefficient estimates may differ between $BM1$ and $BM2$. For notational efficiency I henceforth drop these subscripts and work within a more general framework.

Coefficients are typically not directly interpretable in nonlinear models, especially if the goal of research is to form policy implications (Ai and Norton, 2003; Long and Freese, 2006; Williams, 2009; Braumoeller, 2004; Buis, 2010). Coefficients represent the marginal change in the *log* of the conditional mean outcome and thus are not very valuable in addressing the main research questions presented in this paper. Instead, I prefer to test hypotheses on the difference in the conditional mean expectation of absences resulting from a discrete change in an explanatory variable; this will allow for more intuitive inference (Wooldridge, 2010, *Econometric Analysis of Cross Section and Panel Data*, 737).

Define ME_i as the effect of a diagnosed mental illness on the expected value of annual illness-related work absences, which is equal to the change in expected absences when the binary variable *keyMHdis* changes between zero and one. Referring back to the context of the theoretical framework proposed in section 3, consider an individual endowed with a low level of mental health who faces the same time constraints, budget constraints, and preferences over health and conglomerate consumption as a second individual endowed with a higher level of mental health. The former individual will, in theory, exhibit the same optimal level of health production, H^*, as the latter individual; however, the former individual will require more time and market inputs to reach or maintain level H^* compared to the latter individual due to the less-efficient health production process imposed by the low health endowment. It follows that the individual with the lower endowment of mental health will exhibit a lower optimal level of labor supply relative to the individual with high mental health endowment. This result can easily be used to form a testable empirical hypothesis defined as follows:

$$\begin{aligned} E[ME_i] &= E[A_i|keyMHdis_i = 1] - E[A_i|keyMHdis_i = 0] > 0 \\ &= \exp(\beta^{MH_1} + \sum_{l \neq MH_1} x_{i,l}\beta^l) - \exp(\sum_{l \neq MH_1} x_{i,l}\beta^l) > 0, \end{aligned} \tag{24}$$

where β^{MH_1} is the parameter corresponding to the first variable in vector MH, which is assumed to be binary variable *keyMHdis*. Matrix x_l holds observed values for every other explanatory variable $l \neq MH_1$[10], and β^l is the coefficient corresponding to explanatory variable l. In words, I hypothesize that diagnosed mental illness is associated with higher expected annual absences.

In what follows, I consider how the magnitude of (24) may change across levels of various job, health insurance, and health variables. While this would require the use of the appropriate interaction terms if utilizing a linear model, in nonlinear models of exponential form, the effect of one variable (*keyMHdis*, in this application) may vary with the value of a second variable without the additional consideration of an interaction term between the two variables. Aspects of employment contracts and health insurance coverage are theoretically different in nature than variables characterizing one's mental health endowment because of the different channels through which each of these types of factors influence absence behavior (e.g., sick leave and health insurance generosity influence choices of time and market inputs in health production, while mental illness is tied to an efficiency factor. See section 3 for more detailed discussion). Thus, I decide that conditional marginal effects, where job and insurance characteristics act as the conditioning variables, may be more useful in forming testable hypotheses compared to the use of explicit interaction terms (Karaca-Mandic et al., 2012). On the other hand, I argue that there is likely to be a clear interaction between diagnosed mental illness and other measures of health that explicitly influence individual absence behavior. In consideration of this, I later define extended model specifications that include interaction terms between *keyMHdis* and other variables measuring health and form hypotheses on the sign of these terms.

4.2 Mental Illness, Fringe Benefits, Health Insurance, and Absenteeism

Mental illness is anticipated to impose higher discrepancies between contracted hours and short-term labor supply decisions (i.e., higher absenteeism). It is of interest to consider how this discrepancy may be exacerbated or mitigated

[10] Note that $x_{i,l}$ is a generalization for notational efficiency. In practice, $E[ME_i]$ will be estimated for both $BM1$ and $BM2$ specifications so that the explanatory variables in matrix x_l for $l \neq MH_1$ will be different based on the model specification used.

in different "states" of employment contracts and in different "states" of access to care. Consider a binary moderating variable with each level of the variable representing a different state. In particular, for a binary fringe benefit variable, a value of zero represents state "not offered" and a value of one represents state "offered". For health insurance source variables, there are states "enrolled" and "uninsured" for levels one and zero, respectively. I form testable hypotheses on the relative magnitude of the change in expected absences occurring when *keyMHdis* changes from zero to one at each level (state) s of a binary fringe benefit or health insurance variable. For arbitrary moderating variable, *mod*, the conditional marginal effect of mental illness on expected absence days is

$$E[ME_i|mod_i = s] = \exp(\beta^{MH_1} + s\beta^{mod} + \sum_{l \neq mod, MH_1} x_{i,l}\beta^l) - \exp(s\beta^{mod} + \sum_{l \neq mod, MH_1} x_{i,l}\beta^l), \tag{25}$$

for each value of $s = \{0,1\}$.The moderating effect of *mod* on the association between mental illness and absenteeism is defined as

$$\begin{aligned} E[ME_i|mod_i = 1] - E[ME_i|mod_i = 0] = \\ &\{E[A_i|keyMHdis_i = 1, mod_i = 1] - E[A_i|keyMHdis_i = 0, mod_i = 1]\} \\ &- \{E[A_i|keyMHdis_i = 1, mod_i = 0] - E[A_i|keyMHdis_i = 0, mod_i = 0]\}. \end{aligned} \tag{26}$$

I first consider moderating effects of fringe benefits that supplement time off from work. The MEPS provides information on whether or not individuals receive paid sick leave and paid vacation time at their job. Unfortunately, including both of these factors in a model induces issues of collinearity because only a small portion of the sample has one of these benefits but not the other. As paid sick leave seems more relevant to the context of this paper, I choose to omit information on whether workers receive paid vacation time and instead focus on hypotheses regarding paid sick leave only. Paid sick leave supplements some of the lost wages associated with illness-related work absence and thus acts as a mechanism to reduce the opportunity cost of missing work when ill. This leads to the hypothesis that $E[ME_i|sickpay = 1] > E[ME_i|sickpay = 0]$, i.e., I anticipate that the moderating impact of paid sick leave on the level of additional expected absence days associated with mental illness will be positive.

In contrast to a fringe benefit like paid sick leave, the ability to receive bonus pay at a job increases the opportunity cost of missing work (by increasing potential earnings lost).Thus, even though individuals with mental illness are anticipated to value time spent on nurturing health more than counterparts without mental illness, when given the opportunity to receive bonus pay, relatively higher levels of absenteeism come at a greater cost because, in addition to the opportunity cost of lost wags, absenteeism also hinders one's ability to receive bonus pay. I hypothesize that mental illness is associated with fewer additional expected absences when bonus pay can be earned relative to when bonus pay is not offered at a job ($E[ME_i|bonus = 1] < E[ME_i|bonus = 0]$). This translates to the hypothesis that the variable *bonus* will mitigate the degree of additional expected absences associated with the variable *keyMHdis* switching between zero and one.

Health insurance covers some of the cost of utilizing healthcare services so that it is likely that insured individuals with mental illness will be more likely to receive treatment or intervention services than uninsured mentally ill individuals[11]. The utilization of such services imposes a time cost. I thus hypothesize that mental illness is associated with a greater degree of additional expected absences over the baseline category of no mental illness when insured, regardless of the source, relative to the degree of this association when uninsured. That is, I anticipate the moderating effect of health insurance to be positive. Finally, I theorize that a more generous insurance plan will also have an amplifying impact on the positive change in expected absences associated with a change in *keyMHdis* from zero to one. The variable *inscostly* represents either somewhat or totally agreeing with the survey prompt "health insurance is not worth its cost" and acts as a proxy for insurance plan generosity. The argument for this is that individuals who agree with this prompt exhibit a marginal cost of receiving care under a plan that outweighs the marginal benefit of care. Such individuals may face financial and/or accessibility barriers under their health insurance plan (for the group of insured individuals), or may believe that the plans available to them would not benefit them anymore than if they remained uninsured so that the *inscostly* variable proxies exposure to "skimpy" health insurance plans. Thus, I hypothesize that $E[ME_i|inscostly = 1] < E[ME_i|inscostly = 0]$.

[11] The validity of this assumption will be tested in future research.

4.3 Diagnosed Mental Illness and Mental Distress

As a final analysis, I consider an extension of the $BM1$ specification in which an interaction effect between the diagnosed mental illness variable and the index variable measuring a participant's general level of psychological distress on a scale of zero to 24 I refer to this model as $I1$ henceforth. I choose to explicitly model this interaction due to highlight the distinction between diagnosis and symptomotalogy and how these factors interact to predict absenteeism. I define equation $I1$ as follows:

$$E[A_i|MH_i,PH_i,J_i,I_i,X_i,C_i] = \exp(\beta^0 + MH_i\beta^{MH} + PH_i\beta^{PH} + J_i\beta^J + I_i\beta^I + X_i\beta^X + C_i\beta^C + MH_{1i} \times MH_{2i}\beta^{MH_1 \times MH_2}), \tag{27}$$

where MH_1 is the first column of matrix MH and it holds values of $keyMHdis$ and MH_2 holds values of $distress$, the second variable present in matrix MH.

5 Econometric Strategy

Given the significant differences observed across men and women in the sample, I conduct analysis for men and women separately. I consider two conditional mean distributions: Poisson and negative binomial, which inherently account for the fact that A_i is restricted to non-negative values. The negative binomial distribution innately allows for overdispersion and includes the Poisson distribution as a special case, allowing for a more flexible specification. I thus choose to utilize a negative binomial model to estimate $BM1$ and $BM2$ conditional mean specifications[12]. Though estimates are only reported for a subset of explanatory variables for organizational purposes, it should be noted that no variables are dropped from any of these model specifications at any point in the estimation process. The MEPS design is such that information on every individual living within a household is collected. Thus, some individuals in my sample are from the same family unit. Due to possible correlation of unobservables within the same family unit, I cluster standard errors at the family level. Further, there is likely an individual-specific error component that will be correlated within individuals that have two observations in the sample leading to bias in variance estimates for these individuals. Thus, standard errors are additionally clustered at the individual level.

Unconditional average marginal effects (AME) of a subset of explanatory variables are estimated for both of the baseline model specifications. Conditional AME (CAME) estimates for $keyMHdis$ are estimated using the $BM1$ specification for conditioning variables *sickpay*, *bonus*, *jobins*, and $inscostly$. Estimated CAME for $keyMHdis$ conditional on variables *plnchoic* and *nochoic* are generated using the $BM2$ specification. CAME estimates of $keyMHdis$ given conditioning variables *pubins* and $otherins$ are estimated for each of the $BM1$ and $BM2$ specifications. Estimates of the moderating effect of each of the conditioning variables on the AME of $keyMHdis$ are calculated as the mean difference in conditional fitted value estimates across levels of the moderating variable and are based on manipulating the sample to assign a particular level of a variable to the entire sample; thus, the moderating effect estimates are based on counterfactual information. Standard errors for all AME, CAME, and moderating effect estimates are computed using the delta method.

6 Sample Characteristics

Summary statistics and definitions of each variable considered in the analysis are reported in Table 1 for the total sample. Half of the sample observations are men. The mean age exhibited by the sample is about 42 years old; the minimum age observed is 18 years and the maximum age is 84 years old. Sample statistics for the dummy variables representing household socioeconomic status suggest that a majority of observations in the sample are from high-income households. Individuals of Black, Hispanic, and Asian decent account for 18 percent, 28 percent, and eight percent of the sample, respectively. Individuals on average report three members in the household other than the self, with a minimum of zero (other than the self) and maximum size of 14 (other than the self). The maximum number of children aged six and under in sample households is six children. Of all individuals in the sample, 54 percent are

[12] I note that 65 percent of observations in the male sub-sample and 55 percent of observations in the female sub-sample report zero absences, suggesting that future researchers may wish to consider the use of a zero-inflated or hurdle model.

observed in both years for which they participated and 62 percent of the total observations in the sample represent individuals answering on their own behalf.

Table 2 reports sample means for a subset of explanatory variables by sex. Sample T-Test statistics are also provided in Table 2 and highlight the differences in sample means of several determinants of labor supply across men and women. Table 2 reports that the prevalence rate of diagnosed mental illness is twice as high for the sample of women than for men. The difference in the percentage of observations with $keyMHdis = 1$ between men and women in the sample is about 7 percent. This is similar to the population discrepancy in the percentage of diagnosed mental illness by sex reported for the U.S. in 2017 (7.2 percent)[13]. Women in the sample report significantly more emotional distress and significantly poorer health compared to men in the sample. The sample of women additionally reports a higher average number of priority conditions ("priority" is as defined by the MEPS and represented by variable $prtycnds$).

Regarding insurance characteristics, Table 2 reports that fewer sampled women believe that health insurance is not worth its cost. This is reasonable, as the average woman in the U.S. exhibits higher rates of healthcare utilization than the average U.S. man, suggesting that exposure to care likely drives some of the discrepancy in means of $inscostly$ reported in Table 2.

Table 3 reports the sample means for a subset of variables by sex and by exhibited levels of $keyMHdis$. Men with a key diagnosed mental disorder report significantly higher absences, on average; the discrepancy in mean absences for women with and without a key disorder diagnosis is much larger. This may suggest that there are additional (or different) factors that influence the absence decisions of women with diagnosed mental illness compared to factors that drive the mentally ill absence decision for men; for example, symptoms may exhibit themselves in different manners between the sexes or women may put a higher degree of importance on nurturing their mental health so that they are more prone to illness-related absence.

As anticipated, average levels of general psychological distress are significantly higher for individuals with a diagnosed key mental disorder, regardless of sex. Discrepancies in mean values reported for $physhlth$ by $keyMHdis$ are interestingly very similar for both men and women. This is also the case for the discrepancy in mean values for $prtycnds$ by levels of $keyMHdis$. The magnitude of the within-sex discrepancy in means of these variables are highly statistically significant for both men and women, further suggesting significant correlations between mental illness and other measures of (physical) health.

Means for job characteristics suggest that for individuals with a diagnosed mental illness, one of the following phenomenons may occur: individuals with mental illness select into jobs that provide fringe benefits to supplement the extra time and income constraints necessary to achieve a certain level of health; or, for individuals diagnosed while on the job, fringe benefits that supplement time lost from work ($sickpay$) increase the likelihood of seeking care when experiencing symptoms of mental illness, thus increasing the likelihood of being diagnosed while on the job.

Regarding health insurance characteristics, Table 3 reports that 22 percent of women in the sample with a key mental disorder diagnosis believe that health insurance is not worth the cost, while 26 percent of women without any such diagnosis share this belief. This discrepancy in means is significant at the one percent level and can likely again be explained by differing rates of exposure to healthcare services. Finally of note, women and men in the sample who have a key diagnosis ($keyMHdis = 1$) report lower means for variable $unins$.

7 Baseline Model Estimates

Table 4 reports AME for a subset of right-hand side variables. Pseudo R^2 are also reported. AME estimates represent the expected change in the count of absence days per year in response to a unit change in the respective explanatory variable, on average. Estimates are robust across both $BM1$ and $BM2$ specifications. Both men and women with a diagnosed mental illness are expected to exhibit a higher number of absence days than counterparts without a diagnosed mental illness, on average. These estimates support the empirical hypothesis that the unconditional AME of $keyMHdis$ is positive and are consistent with the literature on mental health and worker productivity. AME estimates for $keyMHdis$ reported in columns 1 through 4 are all statistically significant at the one-percent level. Men with a

[13] Mental Health by the Numbers. (n.d.). Retrieved from https://www.nami.org/learn-more/mental-health-by-the-numbers From the National Alliance on Mental Illness.

diagnosed mental illness are estimated to report 1.11 days of additional absence, on average. The average sample female is expected to report about 0.92 additional annual absences after being diagnosed with a mental illness. This may suggest that women in the sample exhibit average levels of annual absences that are less sensitive to changes in diagnosis status.

On the other hand, AME estimates for one's level of general psychological distress are slightly larger for women, as are estimates of the AME of higher levels of poor health (for variable *physhlth*), suggesting that absenteeism for women in the sample may be more sensitive to measures of severity. A marginal increase in general distress is estimated to increase absences of sample males by an average of 0.11 days. AME estimates for women suggest that an increase in general distress is associated with an increase in work absence by a factor of 0.15 days, on average.

AME estimates regarding self-reported measures of general physical health suggest that poorer degrees of physical health are associated with higher absences from work, on average, as anticipated. A one-point increase in the rating of one's own degree of poor physical health is estimated to increase absences by under half a day for men (by a factor of about 0.37) on average, and over half a day (a factor of 0.55) for women in the sample, on average. AME estimates suggest that men and women respond similarly to an additional priority condition diagnosis, on average

Table 4 reports that AME estimates for variable *sickpay* are significant at the five-percent level both model specifications and for both men and women. On average, receiving compensation for health-related absence from work is anticipated to increase expected days absent by about half a day for the sample of men. Estimates reported in columns 3 and 4 suggest that women may be slightly more responsive to a fringe benefit that supplements time lost from work due to illness, on average. It should be noted that, while the survey prompt corresponding to the dependent variable of interest specifies that respondents should report only work absences due to *the individual's own* illness or health event, there may still be some degree of reporting error; as US law dictates that workers who are offered paid sick leave be able to use that time to care for a family member, if an individual were to misreport annual absences because they include the illness of the family member, the estimated degree of association between paid sick leave and illness-induced absence may be biased upward. Estimates for the variable *bonus* suggest that the potential to earn bonuses is not a statistically significant determinant of absenteeism. Interestingly, however, men exhibit negative AME estimates for *bonus*, which is consistent with the theoretical hypothesis derived in Chapter 3, while women do not, which might suggest further differences in preferences across genders.

Having health insurance through a job is estimated to have a highly significant, positive association with absenteeism. The magnitude of the AME estimates for *jobins* suggest that men substitute fewer units of time at work for time spent on improving health than women, on average, with men enrolled in health insurance through an employer reporting an average of 0.82 additional days of absence compared to the average of 1.23 additional expected absences estimated for women. women exhibit larger magnitudes of AME estimates compared to men when having a public source of insurance asa well as some other form of private insurance. This is not unusual considering that the empirical literature suggests that women have a greater propensity to utilize healthcare. Results for variable *pubins* suggest that having a public source of health insurance slightly amplifies expected absences, on average, relative to having insurance through a job. This phenomena might be partially driven by the association between poverty and health – low-income individuals who are eligible for public health insurance may face more health issues and thus require more time away from work; public health insurance may also be offered to individuals with debilitating health problems who require more time outside of work to receive care. Having a source of private insurance other than through an employer (*otherins*) is associated with a 0.65 or 0.68 day (for $BM1$ and $BM2$ specifications, respectively) increase in expected absence days over the uninsured reference category for men, on average, and these estimates are significant at the five-percent level for sample men. AME estimates for *otherins* are not statistically significant for women.

The $BM2$ specification yields AME estimates for variables *plnchoic*, *nochoic*, and *NR.choic* which are dummy variables that further break down the *jobins* variable into three additional types of insurance within the group of individuals enrolled through an employer-sponsored plan: employees that have a choice among multiple plans offered by their employer (*plnchoic*), employees with no choice between plans (only one plan offered by employer) (*nochoic*), and employees that report being enrolled in an employer-sponsored plan but fail to answer survey prompts on whether or not their employer offers multiple plans to choose from (*NR.choic*). Variable *NR.choic* is utilized as a necessary control so that the reference insurance source variable is still *unins* and thus, I omit estimates for this variable because they serve no real descriptive value.

Men with employer-provided insurance that were able to choose among multiple plans exhibit an average of 1.04

additional days absent relative to uninsured men on average, and this AME estimate is significant at the 0.1 percent level. AME estimates of the *plnchoic* variable for sample women are also significant at the 0.1 percent level and suggests that having the ability to choose among multiple employer plan options is associated with an average increase in expected absences of about 1.41 days compared to expected absences for the reference category. AME estimates of the additional absence days induced by employer-sponsored insurance when benefit package offerings are restricted to one insurance plan (*nochoic*) are smaller in magnitude and suggest that there may be a selection effect present if offered a choice among plans. If selection comes in the form of selecting into the most generous plan regardless of health status, this may suggest adverse selection, but this is difficult to say without fully characterizing the degree of an individual's need for health insurance.

There is, again, a consistent pattern of the magnitude of additional expected absences induced by certain sources of health insurance across both genders. AME estimates for both men and women suggest that the magnitude of the effect of each source is as follows (from largest to smallest): *plnchoic*, *pubins*, *nochoic*, and *otherins*. Again, the larger degree of additional absences associated with public sources of health insurance may be driven by individuals with debilitating conditions that qualifies one for government-funded insurance. Finally, AME estimates for variable $inscostly$ suggest that this variable may be a valid proxy for only having the option to be eligible to enroll in insurance plans that are sub-optimal in terms of benefit generosity, as these estimates are negative for both men and women. man estimates for $inscostly$ are significant at the five-percent level and suggest that the belief that health insurance is not worth its cost is associated with an average fall in expected absence days by a factor of about -0.43 compared to expected absences when disagreeing with this belief.

8 CAME Results: Job and Insurance Moderators

Table 5 reports CAME estimates separately for men and women. CAME estimates represent the average change in expected absence days associated with having a diagnosed mental illness in each "state" (each level of the binary moderating variable). The "Moderator" column lists the name of the conditioning explanatory variable. CAME estimates of a change in the value of the binary variable *keyMHdis* at each level of a moderating variable are presented in columns 1, 2, 4, and 5 along with delta method standard errors. Columns 3 and 6 report estimates of the moderator's effect on the AME of *keyMHdis* on expected absences and the corresponding standard errors computed using the delta method for men and women in the sample, respectively. The estimates in columns 3 and 6 are derived using counterfactual datasets and may be slightly different in magnitude than the discrete difference in the CAME estimates presented in columns 1 and 2 for men and 4 and 5 for women.

Table 5 reports that, conditional on having paid sick leave at a job, diagnosed mental illness is anticipated to increase expected annual absence by about 1.18 days for men and 0.98 days for women, on average. These estimates are larger by factors of about 0.7 and 0.6 days, respectively, than the unconditional AME estimates of diagnosed mental illness. Columns 3 and 6 suggest that, on average, the discrete difference in expected absences when sample men exhibit $keyMHdis = 1$ versus when sample men exhibit $keyMHdis = 0$ is larger by a factor of about 0.20 when conditioning on level $sickpay = 1$ compared to conditioning this discrete difference on $sickpay = 0$. This value is 0.14, on average, for sample women. This is a key finding considering that the unconditional AME estimate of $sickpay$ on expected absences reported in Table 4 is larger for women than for men, suggesting that the average additional absences induced by diagnosed mental illness may be less sensitive for women in the sample than additional absences estimated for men in the sample. The economic significance of the estimates reported in columns 3 and 6 for the moderator of paid sick leave is negligible, suggesting that paid sick leave is a means for increasing absenteeism regardless of whether one has a mental illness or not. A similar issue of economic significance is estimated for variable $inscostly$ as well.

When insured, sample men exhibit AME estimates of mental illness between 1.18 days and 1.09 days for the $BM1$ specification, and public sources of insurance are still anticipated to have the largest impact on absenteeism relative to the uninsured. In contrast, sample women report CAME estimates that are largest in magnitude for the $jobins$ variable, though almost identical in magnitude to CAME estimates conditional on levels of *pubins* for the $BM1$ specification. The relative magnitude of variable *pubins* on the AME estimates for $keyMHdis$ in $BM1$ specification may imply that state or federal sources of health insurance are held to higher oversight standards regarding mental health parity compared to private insurers so that there may be greater accessibility to mental healthcare, increasing healthcare service utilization even further over the group of the uninsured. Additionally, individuals with public sources of health insurance may be low income or have expensive health conditions. In the former case, individuals with low income at less lucrative jobs may not be offered certain benefits, especially more expensive offerings of fringe benefits such as health insurance; in the latter case, these estimates may suggest some form of selection bias based on necessity – individuals with a serious diagnosed mental illness associated with high treatment costs may not be eligible for employer mental health benefits, and thus might have the opportunity to receive a public source of mental health insurance. Though I control for age, this might also represent heterogeneity induced by the health of elderly persons who elect into Medicare Part B – those who opt-out may have a comprehensive source of primary health insurance through an employer, be more certain of future job security, and be in better health than counterparts of similar demographics.

CAME estimates for men suggest that when uninsured, mental illness is anticipated to increase predicted absences between 0.82 and 0.85 days, on average. CAME estimates for women reported in column 5 report an average of 0.72 to 0.73 additional absences induced by diagnosed mental illness when uninsured. women consistently report lower CAME estimates compared to men for the moderating variables listed in Table 5, as well as smaller estimated mean changes in predicted absences reported in column 6, suggesting that the additional absences associated with diagnosed mental illness are less sensitive to values of the moderating variables for women.

CAME estimates of mental illness on mean predicted absences given levels of the health insurance source moderating variables for the $BM2$ specification suggest that being enrolled in employer-provided health insurance and having the choice between multiple plans to enroll in is associated with about 1.20 additional absences when diagnosed with mental illness relative to this conditional effect when there is no diagnosis, on average for sample men, and about 1.01 additional absences over the baseline category of no diagnosed mental illness, on average, for sample women. These are the largest CAME estimates of diagnosed mental illness on expected absences reported for both genders, suggesting that the choice among plans may induce selection into plans that improve accessibility to care and time allotted to receiving care.CAME estimates for men additionally suggest that, conditional on being enrolled in an employer-sponsored health insurance plan that was assigned without selection on behalf of the employee (i.e., conditional on *nochoic* = 1), expected absences are greater by a factor of about 1.11 days, on average, which is identical to the estimated average unconditional effect of mental illness on sampled men, suggesting that diagnosed mental illness on predicted absences suggest that Compared to AME estimates of *keyMHdis* on expected absences conditional on variable *nochoic*, AME estimates conditional on *plnchoic* are higher by a factor of 0.9 for men and 0.7 for women. Results for conditioning variable *nochoic* also suggest that employer-sponsored plans that are not self-selected (i.e., only one plan offered) may be more restrictive and induce less health service utilization among the mentally ill than sources of public health insurance.

9 Interactions Between Diagnosed Mental Illness and General Distress

This section serves to provide more insight into the relationship between the binary measure of mental illness, *keyMHdis*, and variable *distress*. I choose to graphically illustrate this relationship due to the indexing nature of the variable measuring distress. Each of the figures discussed hereafter plot predicted absences by the values of the interacted health index or continuous variable and distinct curves are plotted to represent this relationship at each level of variable *keyMHdis*. Blue curves illustrate the relationship between varaible *distress* and predicted absences when *keyMHdis* = 1 and red curves illustrate this relationship when *keyMHdis* = 0. After observing each plot, I estimate the AME of *diagnosed* mental illness (*keyMHdis*) at three distinct levels of the *distress* variable. These CAME estimates are reported in Table 6 along with coefficient estimates of the respective interaction term. Pseudo R^2 for the extended model specification and results of a likelihood-ratio test of the null hypothesis that the more restrictive $BM1$ specification produces a better fit than the $I1$ specification that includes the interaction term are also reported.

Figures 1 and 2 depict the relationship between general psychological distress (index variable *distress*) and predicted absences for men and women, respectively, by levels of *keyMHdis*. Figures 1 and 2 illustrate that, at lower levels of *distress*, men that have a mental illness are anticipated to see higher levels of absences than men without a mental illness. An intersection between the groups of men with and without a key mental disorder diagnosis is observed around a scale score of 11. A score of 11 is close to the upper-bound score of 12 that separates individuals from crossing over from category of "moderate evidence of psychological impairment" to the category of "evidence of severe impairment" (Kessler, Barker, et al. 2003). At this point of intersection, there is anticipated to be no statistically significant difference in expected absence days between the two groups. From this intersection onward, it appears that at higher levels of distress, men without a diagnosed mental illness are anticipated to exhibit higher levels of absence than men with a diagnosis.

After observing this pattern in Figure 1, I estimate the AME of *diagnosed* mental illness (*keyMHdis*) on expected absences at three distinct levels of the variable *distress* for men in the sample: 5, 11, and 15. These estimates are reported in Table 6 along with coefficient estimates for the interaction term $keyMHdis \times distress$. CAME results are consistent with the relationship suggested by Figure 1 – at a score of 5 on the *distress* index, the CAME of *keyMHdis* on expected absences is estimated to be positive and statistically significant; on the other hand, at a *distress* level of 11 which is approximately the point of intersection exhibited in Figure 1, this estimate is not statistically significant, nor is it at the higher index score of 15. Though the sign and magnitude of the coefficient on the interaction term is not directly interpretable here, the estimated degree of statistical significance of this coefficient is of value and illustrates that there is a distinct association between the interaction of diagnosed mental illness and general psychological distress and absenteeism for men in the sample.

A phenomenon similar to that exhibited for men can be observed in Figure 2 for women after adding an interaction between *distress* and *keyMHdis* to the $BM1$ specification. The point of intersection between the lines representing the marginal effect of *distress* on predicted absences at levels $keyMHdis = 0$ and $keyMHdis = 1$ occurs at slightly higher levels of *distress* for sample women compared to sample men (approximately between levels 14 and 15), but the pattern exhibited by the relationship between *distress* and *keyMHdis* and its impact on predicted absences more or less mimics that observed for sample men. At lower levels of general distress, women display a positive and significant difference in predicted absences between the group reporting diagnosed mental illness and the baseline group of women with no such diagnosis, while higher levels of *distress* suggest no statistically relevant difference in the absence behavior between the group of women with a diagnosed mental illness and no diagnosed mental illness.The coefficient estimate on the interaction term for the woman $I1$ specification is statistically significant at the five-percent level and is reported in Table 6.

10 Conclusions

Empirical findings highlight sex differences in the process of deciding when to go to work when ill. Sample men exhibit a higher magnitude of the impact of *diagnosed* mental illness on absenteeism compared to sample women; on the other hand, women may be more sensitive to current symptomatology. Baseline model estimates for various measures of health indicate a high degree of significance in predicting absenteeism.

Estimates of the moderating effects of certain variables suggest that there is a positive and significant moderating effect of paid sick leave on the impact of mental illness on absenteeism for men and women. Paid sick leave significantly increases absenteeism of men in the sample by just under half of a day, on average, and this result is significant at the one-percent level; for women, paid sick leave is estimated to increase absence by just under half a day, on average, and this estimate is significant at the one-percent level. These findings are consistent with theoretical hypotheses on how fringe benefits that supplement potential lost income induce a substitution away from occupational time to time spent on nurturing health.

Results regarding each of the dummy variables representing sources of health insurance imply that any source of health insurance increases absenteeism relative to the absence levels exhibited for uninsured individuals. The implications of this finding are intuitive – the higher the price of inputs in health production, the less time allotted to health production and the more time available to allot to occupational labor. Results suggest that health insurance impacts absence rates through two different channels: the substitution of labor time for time spent utilizing healthcare services (leading to an increase in absenteeism), and through the channel of mitigating the impact that mental illness has on absenteeism. The latter of the two cases is suggestive that being insured increases the likelihood of seeking treatment for mental illness so that the additional absences exhibited by individuals with mental illness are further amplified over counterparts without mental illness for both genders. This is further suggested by the estimated effects of the belief that one's health insurance is not worth the cost (*inscostly*).

Results for the interaction of diagnosed mental illness and general psychological distress suggest harmful impacts on labor productivity for individuals exhibiting symptoms of moderate-to-severe mental illness and whom do not report a diagnosis. It is plausible to conjecture that those with an official diagnosed mental illness will exhibit a greater propensity to seek intervention as psychological symptoms such as feelings of distress worsen (i.e., as their distress-index climbs) because they have knowledge of their diagnosis and mental health history. Thus, we might indeed see lower levels of absences attributed to extreme levels of distress across individuals with diagnosed mental illness compared to individuals without a diagnosis that may not have the same knowledge or resources to be proactive. Further study of a structural mental health production function would provide valuable insight as to the validity of this argument.

10.1 Limitations of Study

Shortcomings of the empirical methods of this paper should be noted. First, it is unclear whether the reduction in mental illness-induced absences imposed by certain fringe benefits is truly a benefit in the form of an improvement in the productivity of workers with mental illness. The inability to control for rates of presenteeism poses the issue of whether this is a true increase in productivity among these individuals, or if these individuals are more likely to exhibit presenteeism. This may be part of the reason we see significant and negative estimates of interaction effects for men, but no significance for women. That is – men may be more likely to exhibit presenteeism whereas women may be more likely to exhibit absenteeism. In order to refine the modeling of the relationships between job and insurance factors and mental health and how these relationships affect absenteeism, the use of a hurdle model may be preferred. For example, a binary measure of paid sick leave may influence the initial decision to be absent, but it may be the actual amount of the wages supplemented by this benefit that determines the number of positive days absent.

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