Diagnosis vs. Distress: Reduced-Form Evidence on Absenteeism and Employment Selection

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Abstract

Using 2010–2014 MEPS data, I estimate how diagnosed mental illness and time-varying psychological distress relate to own-health absenteeism and why accounting for selection into employment matters. I model annual sick days with negative binomial regressions reporting average marginal effects, absorb time-invariant heterogeneity via correlated random effects, and address nonrandom employment using both a Heckman two-step and a semiparametric Gaussian-copula selection model. A diagnosis is associated with roughly one additional day of absence per year, on average, for men and women. Interacting diagnosis with a self-reported proxy for general psychological distress reveals a crossover: at low distress, diagnosed workers miss more days than undiagnosed peers, while at high distress diagnosed workers miss fewer days—consistent with diagnosis enabling access to care that averts the most severe productivity losses. Selection corrections indicate non-ignorable employment selection (stronger among women) and modestly attenuate some baseline magnitudes. Policy implications emphasize screening, access to effective care, and employer policies (paid sick leave and mental-health parity in benefits) that reduce extreme absenteeism without encouraging presenteeism.

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JEL Classification: *J24; I12; D91*

1 Introduction

Mental illness is among the most costly and prevalent health challenges facing the labor market. The World Health Organization (WHO, 2024) estimates that depression and anxiety account for nearly $1 trillion in lost productivity worldwide each year, and the National Institute of Mental Health (NIMH, 2024) reports that mental disorders are now a leading cause of disability and economic instability in the United States. These conditions affect not only individual well-being but also workplace outcomes, creating strong incentives for employers and policymakers to understand how mental health influences productivity.

This paper examines the relationship between mental illness and work absenteeism, with a focus on endogenous employment selection. Workers with the most severe symptoms are often those who exit employment, biasing downward standard estimates of the productivity costs of mental illness. Using the Medical Expenditure Panel Survey (MEPS), I quantify the link between mental illness and absenteeism at baseline, then account for within-individual heterogeneity using correlated random effects, and finally address selection on unobservables.

I show that a mental health diagnosis is associated with roughly one additional absence day per year, with similar effects for men and women. I then study dynamic effects by interacting diagnostic status with general psychological distress: diagnosis is linked to more absences at low distress but mitigates absenteeism at high distress, consistent with the hypothesis that timely intervention prevents the most severe productivity losses; this pattern is robust to a correlated random-effects specification. Finally, I show that models which assume away endogenous employment understate the productivity costs of mental illness, so ignorability should not be taken for granted in future work.

Taken together, these results reveal that the labor market burden of mental illness is larger than previously recognized, but also that early diagnosis and comprehensive coverage can reduce hidden productivity costs.

In the next section, I outline the theoretical framework. Section 3 presents the data, variable construction, and transformations. Section 4 details the econometric approach and baseline results. Section 5 extends the baseline with correlated random effects. Section 6 addresses endogenous sample selection and reports the corresponding estimates. Section 7 concludes.

2 Theoretical Framework: Absenteeism, Health Capital, and Implicit Contracts

Absenteeism as a short-run gap. Building on Becker's (1965) time-allocation model and Grossman's (1972) health capital model, let N^{req} denote contracted (required) hours and N_t^* the worker's feasible hours in period t given preferences, budget, and health. Define absenteeism as:

$$A_t \;=\; \max\{0,\; N^{\text{req}} - N_t^*\}.$$

Feasible hours depend positively on health capital, H_t, and negatively on symptom severity, S_t. Treating mental and physical health endowments as components of H_t, the interior comparative statics ($A_t > 0$) imply

$$\frac{\partial A_t}{\partial MH} < 0, \qquad \frac{\partial A_t}{\partial PH} < 0, \qquad \frac{\partial A_t}{\partial S_t} > 0.$$

This reduced-form interpretation aligns with the empirical specification in which absenteeism is modeled as a function of diagnosis, current health status, and controls.[1]

Diagnosis and symptomatology. In this framework, a clinical diagnosis is realized prior to the start of period t. Diagnosis is not time-dependent and is considered to partially define an individual's mental and physical health endowments ($MH, PH \in H_t$). Symptomatology associated with diagnosed conditions and with other health shocks varies over time. I empirically examine how diagnosis and symptoms interact to influence N_t^* (through the channel of H_t), thus influencing absenteeism.

[1]A simple structural version sets $N^{\text{req}} = d(w, N_{\min}, B)$ with $d(\cdot)$ a function of wage, minimum labor supply needed to do a job well, and benefit package features, and $N_t^* = n(C_t, H_t)$ from the time/budget problem. Health production is a function of time, market inputs, health endowments at baseline, and efficiency of health production: $H_t = f_h(T_{h,t}, x_{h,t}; MH, PH, e_h)$. Under $n_H > 0$ and $f_{h,MH}, f_{h,PH} > 0$, the interior derivatives yield $\partial A_t/\partial MH < 0$ and $\partial A_t/\partial PH < 0$. The main text remains reduced-form to match the empirical design.

Econometric implications. Two challenges follow from the theory. First, unobserved heterogeneity in health preferences/efficiency (Grossman, 1972) can bias reduced-form estimates; I address this with correlated random effects (Mundlak, 1978; Wooldridge, 2019). Second, selection into employment (a Beckerian margin) means the most severely limited workers may exit work; estimating absences only among the employed can understate productivity losses. I therefore complement baseline negative binomial models with selection-corrected specifications (Heckman, 1979; Wyszynski and Marra, 2017).

3 Data, Sample Construction, and Variables

Sources. I use the Medical Expenditure Panel Survey (MEPS), a nationally representative panel of the U.S. civilian non-institutionalized population, covering demographics, employment, health care utilization, and health status. Three public-use files are linked at the person-year level: the Full-Year Consolidated Data File (FYCD), the Medical Conditions File (MCF), and the Jobs File (JF). I also take data on monthly unemployment rates by region from the U.S. Bureau of Labor Statistics. The study period is 2010–2014.

Panel structure and calendar-year alignment. MEPS follows individuals over two consecutive calendar years across five interview rounds. Round 3 straddles the two years. For variables MEPS already assigns to a calendar year, I use those assignments. For remaining round-specific measures, I construct calendar-year values by weighting each round's value by the number of days within that round's reference period (e.g., splitting round 3 exposure across the two years using round start/end dates).

Sample construction. The analytic population is U.S. adults who are employed for a positive number of days in a given calendar year. Students, military personnel, and institutionalized persons are excluded. Observations reporting 'employed as of interview' with a job start date equal to the interview date are retained only if positive days worked are observed in at least one other round that year; otherwise, they are dropped because the reference period contains no work exposure. Individuals who have ever retired or who have a functional disability that precludes work are excluded. When respondents report a job change between rounds, absence reports and other time-varying variables are matched to the main job, which is defined as the job linked to the most days worked during the year. Job traits are taken from this main job within the reference window.

Handling unbalanced panels and attrition. Because persons may be observed in one or both calendar years, I pool person-years and compute cluster-robust standard errors at the individual level. To proxy for attrition mechanisms, I include indicators for whether the individual participated in both years of the MEPS whose first or second year of participation is not observed as well as indicators for whether an individual entered the sampled household late and whether a person moved during the year (Nijman and Verbeek, 1992).

Round and job start/end dates are used to approximate days employed in the year, accommodating heterogeneity in exposure to absence risk.

The final sample represents adults who were employed for a positive number of days during the respective calendar year and consists of 31,929 observations.

3.1 Variables

Table 11 in the appendix reports variable definitions and descriptive statistics for the study sample. Also in the appendix are tables that present summary statistics of analytical variables by sex (Table 12) and by sex and presence of diagnosed mental illness (Table 13). Categories of variables used in the analysis are discussed below.

Dependent Variable (A_i): The dependent variable of interest is a count variable ($sickdays$) representing absences from work due to the respondent's *own* physical or mental illness (from the MEPS FYCD). The MEPS includes a separate variable for days absent from work due to another person's illness, enabling more precise analysis of responses to health shocks.

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 generated using diagnostic codes in the Medical Conditions File (MCF). Diagnostic status is measured at the start of the year to ensure it is predetermined relative to the absenteeism outcomes examined.

To complement diagnosis, I measure time-varying symptoms using the Kessler–6 (K–6) psychological distress scale constructed from the Self-Administered Questionnaire (SAQ) located in the FYCD. The scale ranges from 0–24, with higher values indicating greater distress; scores of 9–12 are commonly interpreted as mild–moderate distress and scores greater than 12 as probable serious mental illness (Kessler et al., 2003; Ashwood et al., 2016). This variable is collected in Round 2 and references the prior 30 days; I therefore treat it as a time-varying proxy for symptomatology within the calendar year.[2] I denote this measure by $distress$ in the analysis.

General (Physical) Health (PH_i): I use self-reports of physical health (from the FYCD) collected in each MEPS interview round to create an index of poor physical health, named $physhlth$, with a range of 1–13 and higher levels indicating poorer perceived health. The second analytical variable in this category, named $prtycnds$, counts the number of priority conditions an individual has. These conditions are defined in the MEPS FYCD documentation and listed in the appendix.

Other noteworthy variables in this category include binary variables indicating an injury or illness in the past year that required immediate medical help ($injury$) and receiving

[2] Appendix A.3 provides construction details, timing discussion, and additional background on within- and between-disorder heterogeneity motivating the joint use of diagnosis and symptoms.

a routine checkup in the past year ($routine$), from the FYCD. These serve as proxies for lagged acute events and preventive care, respectively. Because they do not co-occur with current-year absenteeism, they reduce simultaneity concerns relative to other contemporaneous health variables. Additional variables controlling for other health behaviors are defined in the Appendix.

Job Traits (J_i): I control for fringe benefits offered by employers (see appendix) because they are likely to influence absence behavior. For example, paid sick leave mitigates the cost of being absent after a negative health shock. Additional job-related controls include job tenure, labor union membership, seasonal and part-time jobs, public sector jobs, firm size, and occupational categories.

Health Insurance (I_i): I control for characteristics of health insurance because health insurance affects access to care and therefore impacts health outcomes. A set of variables indicates a person's source of insurance with uninsured individuals serving as the reference category. Another variable proxies valuation of insurance and indicates whether the respondent agrees strongly or somewhat strongly with the prompt, 'Health insurance is not worth its cost'.

Demographics (X_i): Demographic controls include age, education, race, Hispanic ethnicity, U.S. nativity, number of young children, marital status, and socioeconomic status.

Other Control Variables (C_i): Regional indicator variables combined with monthly regional unemployment data from the U.S. Bureau of Labor Statistics for years 2010-2014 are used to estimate the average unemployment rate faced throughout the year ($unemp\_rt$). For persons that move to a different region during the year of interest, reference period start and end dates are additionally used in this calculation–unemployment rates are averaged over the months an individual resided in a given region and then averaged across regions occupied during the year. This variable controls for macroeconomic heterogeneity across regions.

Finally, I use information on interview start and end dates as well as job start and end dates and employment status to calculate the maximum number of days employed at the main job during the year to control for differences in exposure to the risk of absence ($empUB$). A full list of other control variables and definitions is located in the appendix.

The next section defines econometric models and estimation procedures.

4 Conditional Mean Function of Absenteeism

The dependent variable in the analysis is a count of the number of days absent from work due to the respondent's own physical or mental illness over the span of one calendar year, denoted A_i for observation i. Because the outcome is a count, I model the conditional mean with an exponential link.

Using mathematical notation, the baseline conditional mean specification is defined as follows:

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

$\forall i = 1, \ldots, n$ observations. Equation (1) will henceforth be referred to as BM1. Matrices MH, PH, J, I, X, and C hold observed values of the corresponding explanatory variables $\forall i = 1, \ldots, n$ observations.[3] 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 $l \in \{MH, PH, J, I, X, C\}$. In a similar fashion, each β^l for $l \in \{MH, PH, J, I, X, C\}$ is a $k_l \times 1$ vector of parameters.[4]

Define $ME_i^{MH_1}$ as the marginal effect of a diagnosed mental illness on the expected number of annual illness-induced absence days:

$$E[ME_i^{MH_1}] = E[A_i|keyMHdis_i = 1] - E[A_i|keyMHdis_i = 0] \\ = \exp(\beta^{MH_1} + \sum_{l \neq MH_1} x_{i,l}\beta^l) - \exp(\sum_{l \neq MH_1} x_{i,l}\beta^l) > 0, \tag{2}$$

where β^{MH_1} is the coefficient on $keyMHdis$. Matrix x_l holds observed values for every other explanatory variable $l \neq MH_1$, and β^l is the coefficient corresponding to explanatory variable l. In words, I hypothesize that diagnosed mental illness results in higher annual absences.

I expect other measures of health to exhibit similar impacts on absenteeism. Similarly define $ME_i^{MH_2}$ as the marginal effect for variable $distress$, $ME_i^{PH_1}$ as the marginal effect for variable $physhlth$, and $ME_i^{PH_2}$ as the marginal effect for variable $prtycnds$. I hypothesize the following:

$ME_i^{MH_2} > 0,$ a one-point increase in the $distress$ scale results in higher absenteeism.

$ME_i^{PH_1} > 0,$ a one-point increase in the poor health index ($physhlth$) increases absenteeism.

$ME_i^{PH_2} > 0,$ an additional health condition (an increase in $prtycnds$) increases absenteeism.

4.1 Estimation Strategy

Due to the count nature of the dependent variable, I examine the fit of two model specifications: Poisson and negative binomial II (NB2). The negative binomial specification is more flexible as it accounts for overdispersion and nests the Poisson specification when the overdispersion parameter tends to zero. I present Q–Q plots comparing Poisson and NB2 in the appendix.

Given persistent gender differences in labor market behavior (Jia and Vatto, 2021), I estimate models separately for men and women. For space, I report estimates for a subset of regressors; all variables in Table 11 are included unless otherwise noted.

[3]See appendix.

[4]For example, $\beta^{MH} = \{\beta^{MH_1}, \beta^{MH_2}, \beta^{MH_3}\}$ for MH_1 = $keyMHdis$, MH_2 = $distress$, MH_3 = $adhd$ (see appendix for variable definitions grouped by category).

Coefficients are not directly interpretable in nonlinear models, especially if the goal of research is to form policy implications (Braumoeller, 2004; Buis, 2010; Ai and Norton, 2003; Long and Freese, 2006; Williams, 2009). Instead, I use average marginal effects (AME) to test hypotheses (Wooldridge, 2010, *Econometric Analysis of Cross Section and Panel Data*, 737).

The MEPS follows a one-stage cluster random sampling design starting with the random selection of households from the total pool of household participants of the most recent National Health Interview Survey (NHIS). Data is then collected for each member of selected households. Further, the MEPS follows individuals who move out of the original sample household and begins following individuals who move into an originally sampled household starting at the next round. Standard errors are therefore two-way clustered by household and individual (Wooldridge, 2010; Mundlak, 1978; Cameron and Trivedi, 1986). The delta method is used to compute final standard errors for AME estimates.

4.2 Baseline Model AME Results

After estimating the model by MLE, the estimated dispersion parameters are 0.21 for men and 0.28 for women. The statistical significance of these estimates further supports the choice of the negative binomial II model. Table 1 reports average marginal effect estimates (AMEs) and two-way cluster-robust standard errors computed with the delta method. Pseudo-R^2 values are also reported.

Both men and women with a diagnosed mental illness exhibit a higher number of days absent, on average, compared to their counterparts without a diagnosed mental illness, consistent with the hypotheses. This pattern is also consistent with the literature on mental health and worker productivity.[5]

AME estimates for $keyMHdis$ are significant at the 1% level for both sexes. Men with a diagnosed mental disorder are estimated to report 1.11 additional absences per year, on average, relative to counterparts without a diagnosed mental disorder. Women in the sample are expected to report 0.92 additional absences per year when diagnosed with a mental illness. These estimates are robust to excluding $distress$ from the model for each sex. Estimates for the other three variables reported in Table 1 are highly statistically significant at the 1% level for both sexes. A marginal increase in general distress is estimated to increase days of absence by an average of 0.11 days per year for men and 0.15 days per year for women.[6]

On average, 0.37 additional days of absence occur annually for men after a marginal increase on the poor-health scale and 0.55 additional days annually for women. This discrepancy could reflect differences in how men and women define physical health, greater self-criticism among women, or greater responsiveness to perceived health changes, which may increase the likelihood of taking leave, though none of these mechanisms are identi-

[5] See Ashwood et al. (2016), Bubonya et al. (2017), Cseh (2008), Fletcher (2013), French & Zarkin (1998), Goetzel et al. (2002), Jones et al. (2010), Kohn et al. (2004), Rosenheck et al. (1999).

[6] Caution is warranted: the distress measure is collected only in round 2 of each survey year and refers to the prior 30 days (the last month of the round 1 reference period), so timing could influence these estimates.

fied in this research. For $prtycnds$, men exhibit 0.67 additional days of absence per year on average, and this is significant at the 1% level. For women, estimates indicate 0.69 additional days per year (significant at the 1% level).

Taken together, the results suggest sex differences in how health shocks affect daily labor supply.The higher impact of diagnosed mental illness observed for men is consistent with longer delays in seeking treatment. Longer delays to diagnosis are associated with worse outcomes in the labor market (Fletcher, 2013; Kohn et al., 2004; Krumm et al., 2017). Although the AME difference for $distress$ is small, it aligns with evidence on mental health stigma: if stigma affects self-reports, men may be less likely to disclose symptoms, attenuating the $distress$ AME for men (Krumm et al., 2017).

Men and women exhibit relatively equal impairments from an additional priority condition, yet men exhibit a lower AME estimate for the self-reported poor-health index; women's AMEs for these two measures are closer. Future research should examine whether men self-report poor health less often or whether differential prevalence rates of specific conditions drive these patterns.

4.3 Diagnosis–Distress Interaction

I now include an interaction term between $keyMHdis$ and $distress$ in the baseline negative binomial model to examine how diagnosed mental illness and time-varying mental distress jointly relate to absenteeism. The diagnosis variable does not pose the timing risk that $distress$ does–diagnostic status is measured at the start of the calendar year, so it is predetermined relative to the absenteeism outcomes. Because $distress$ is measured mid-year, I interpret the diagnosis $\times$ distress patterns as suggestive, not causal.

Figures 1 and 2 plot predicted absences against general psychological distress ($distress$) for men and women, respectively. At low levels of $distress$, diagnosed individuals with mental illness have more predicted absences than undiagnosed peers. At moderate and high levels of $distress$ (Kessler et al., 2003), the pattern reverses: at high distress, workers with diagnosed mental illness miss fewer days than undiagnosed peers. This is consistent with diagnosis enabling earlier access to care and preventing the most severe productivity losses.

The interaction between diagnosis and distress implies a threshold above which diagnosis mitigates severe absence. In the sample of men, predicted absences for diagnosed and undiagnosed workers are equal at $distress \approx 11$; above this level, diagnosed men miss fewer days. In the sample of women, the crossover occurs at $distress \approx$ 14–15, with an analogous reversal. These thresholds, together with narrow confidence bands around the curves, suggest that diagnosis may attenuate extreme productivity losses at high symptom severity even if average absences rise at low severity.

Because the interaction term alters the slope of $distress$, I evaluate conditional average marginal effects (CAME) of diagnosis at representative $distress$ values (5, 11, 15) and visualize predicted absences by diagnosis across the observed $distress$ range. Results appear in Table 2 along with the interaction coefficient. At $distress = 5$, the AME of diagnosis is positive and statistically significant; at $distress$ = 11 (the intersection) and 15, it is not statistically significant. Although the interaction coefficient is not directly interpretable in levels, its statistical significance supports a meaningful association between the interaction and absenteeism for men.

A similar pattern is observed for women in Figure 2. The curves intersect at a slightly higher level of $distress$ (approximately 14-15), but the relationship between $distress$ and $keyMHdis$ and its impact on predicted absences mirrors the men's pattern. At lower $distress$, diagnosed women have higher predicted absences than undiagnosed women; at higher $distress$, the difference is not statistically significant. The interaction coefficient is statistically significant at the 5% level (Table 2).

Taken together, the men's and women's results suggest that moderate-to-severe psychological distress is associated with larger productivity losses among undiagnosed workers. The high-distress reversal is consistent with diagnosis facilitating earlier and more effective care—reducing extreme absence—though I interpret this as suggestive rather than causal.

Similar patterns for physical health variables are shown in the appendix. Recognizing potential unobserved heterogeneity, I next apply correlated random effects in the negative binomial model.

I escalate from pooled NB to CRE and then to explicit selection because these steps address different sources of bias. The CRE absorbs time-invariant unobserved heterogeneity induced by factors such as baseline health capital, preferences for time off, contractual specifications, and other factors that are correlated with diagnosis, insurance, and distress.

5 Correlated Random Effects

Symptomatology can shape day-to-day labor supply differently across people, even within the same diagnostic group. If stable, individual traits (e.g., tolerance for symptoms, preferences, baseline health efficiency) are correlated with regressors, pooled models can suffer from omitted variable bias. To address time-invariant heterogeneity, I estimate correlated random-effects (CRE) negative binomial models using the Mundlak device (Mundlak, 1978; Wooldridge, 2019).[7]

I use the methodology defined in Wooldridge (2019)–individual-specific means are calculated for every variable for each individual observed in the sample. Formally, let y_{it} denote illness-induced absence days for individual i in year t, and x_{it} the vector of time-varying regressors. The following conditions persist in the CRE framework:

$$y_{it} \mid x_{it}, \alpha_i \sim \text{NegBin}(\mu_{it}, \theta), \qquad \mu_{it} = \exp\big(x_{it}'\beta + \alpha_i\big),$$

where α_i captures person-specific, time-invariant heterogeneity.

[7] Wooldridge (2019) extends the Mundlak approach to nonlinear models and unbalanced panels.

The CRE parameterization specifies

$$\alpha_i \;=\; \bar{x}_i'\xi \;+\; u_i, \qquad E[u_i \mid x_i] = 0,$$

with $\bar{x}_i$ the vector of person-specific means of the time-varying regressors (computed over observed periods; valid for unbalanced panels). Substituting yields a likelihood equivalent to estimating a NB2 model that augments x_{it} with $\bar{x}_i$:

$$E[y_{it} \mid x_{it}, \bar{x}_i] = \exp\bigl(x_{it}'\beta \;+\; \bar{x}_i'\xi\bigr).$$

Intuitively, $\bar{x}_i$ absorbs correlation between time-invariant unobservables and the regressors; identification then comes from within-person deviations of x_{it} around $\bar{x}_i$.

5.1 BM1 and CRE Results & Comparisons

I estimate an NB2 model with the set of variables $\{x_{it}, \bar{x}_i\}$ and report average marginal effects (AMEs) in days.

Tables 3 and 4 present results for men and women, respectively. Columns labeled 'BM1' reproduce AMEs from the baseline specification (Table 1) alongside coefficients; columns labeled 'Correlated RE' add the person-means $\bar{x}_i$.

The CRE estimates are broadly consistent with the baseline (BM1), with economically similar AMEs and unchanged signs. Confidence intervals tighten after adding person-means, indicating that time-invariant heterogeneity explains part of the residual variation. The largest change is for variable $keyMHdis$: for men, the AME declines from 1.11 days (BM1) to 0.95 days (CRE) while remaining statistically significant. This modest attenuation for $keyMHdis$ indicates part–but not all–of the baseline association reflected time-invariant traits.

For women, AMEs are stable across BM1 and CRE for $keyMHdis$ and $distress$; significance levels are unchanged. Relative to men, the 95% confidence intervals contract more under CRE, suggesting a greater role for time-invariant heterogeneity in the subsample of women. Overall magnitudes remain similar, reinforcing the baseline conclusions.

The CRE estimator tackles *time-invariant* unobserved heterogeneity by decomposing the individual effect as

$$\alpha_i \;=\; \bar{x}_i'\xi \;+\; u_i,$$

where $\bar{x}_i$ are person-specific means of the time-varying regressors. This permits correlation between individual person-specific, time-invariant heterogeneity, α_i, and x_{it} through $\bar{x}_i$. The remaining component u_i is assumed mean-independent of x_i conditional on $\bar{x}_i$ (i.e., $E[u_i \mid x_i] = 0$); it still enters the model as a random intercept (and thus affects the mean) but is not correlated with regressors once $\bar{x}_i$ are included.

Identification further relies on strict exogeneity of the time-varying regressors—this where the employment-selection problem comes into play: absenteeism is observed only when an individual is employed, and the employment decision is itself influenced by unobservables (e.g., magnitude and type of health shock (e.g., long-term/chronic illness vs. acute viral illness, underlying severity) that are correlated with the absenteeism error. If high-propensity absentees exit employment, baseline and CRE models estimate absenteeism on a positively selected sample, attenuating effect estimates.

6 Considering Selection on Unobservables

The decision not to work may relate to the factors that affect absenteeism. To determine whether sample selection significantly impacts estimates when ignored, I use a classic two-step sample selection model (Heckman, 1979), followed by a semiparametric, copula-based approach rarely cited in the literature.

6.1 Extended Samples and Exclusion Restrictions

The first-stage model estimates the probability of employment—employment is the state for which illness-related work absenteeism is observable. Therefore, additional observations must be added to the original sample for the analysis.

The first sample adds unemployed people. The resulting sample includes adults in the labor force. For consistency, the same data-generating processes are used to obtain the unemployed sample, excluding individuals who have ever retired, military personnel, disabled individuals reporting significant difficulty completing activities of daily living, and students. The inclusion of unemployed individuals yields a full sample size of 23,093 for women and 19,823 for men. The logic behind assessing a labor force sample on its own is in recognition that individual's with poorer health may wait until they find a job that offers certain benefits, thus selecting into employment. On the other hand, individuals with poorer health that inhibits productivity may be more likely to be unemployed.

The logic

As a final comparison, I consider working-age individuals outside the labor force who remain in the sample after excluding individuals who have ever retired, military personnel, disabled individuals reporting significant difficulty completing activities of daily living, and students. The extended sample for men consists of 24,562 observations; for women, there are 29,947 observations.

Although the model can be estimated with the same regressors in the first-stage and second-stage equations, identification and precision improve when the selection equation includes variables not in the outcome equation. I propose two exclusion restrictions.

Exclusion Restrictions (ER_i): A person's health, and thus, absenteeism, is linked to the health of other household members (e.g., communicable disease). In contrast, the health of family members that live outside of the household are unlikely to affect daily health-related labor supply decisions. The first exclusion restriction ($depout$) is a binary variable indicating whether a person has dependents living outside the household, such as college students, noncustodial children, or elderly parents in assisted care. I argue that $depout$

increases the probability of employment due to higher income needs but is not directly related to health-related absenteeism.

A binary variable equal to one if a person's spouse is employed, $spou\_emp$, is also considered as an exclusion restriction. Spousal employment likely affects an individual's employment status but should not directly influence absence decisions after a health shock. While caregiving responsibilities could link spousal employment to absenteeism, MEPS separately identifies absences due to one's own health versus someone else's need for care.[8]

6.2 Heckman Specification

I estimate the classic Heckman sample selection model (Heckman, 1979) even though the absenteeism outcome is a count. This sacrifices the discrete/overdispersed nature of A_i in the outcome stage but gains interpretability and a direct correction term (the inverse Mills ratio, IMR).

The first–stage probit includes all baseline regressors *except* job characteristics (category J), plus the two exclusion restrictions described earlier. The dependent variable is EMP_i, equal to one if individual i is employed and zero otherwise:

$$\begin{aligned} P\big(EMP_i = 1 \,\big|\, \{MH_i, PH_i, I_i, X_i, C_i, ER_i\}\big) \;&=\; \Phi\big(\beta_0 + MH_i\beta^{MH} + PH_i\beta^{PH} \\ &\qquad + I_i\beta^{I} + X_i\beta^{X} + C_i\beta^{C} + ER_i\beta^{ER}\big), \end{aligned}$$

for all $i = 1, \ldots, n$, where $\Phi(\cdot)$ is the standard normal CDF. Each regressor matrix has dimension $n \times k_\ell$ for $\ell \in \{MH, PH, I, X, C, ER\}$, with β^ℓ a $k_\ell \times 1$ parameter vector. The matrix ER contains the exclusions $depout$ and $spou\_emp$.

Among the employed ($EMP_i = 1$), the outcome equation is estimated by OLS and includes J and the IMR:

$$\begin{aligned} E\big[A_i \,\big|\, EMP_i = 1; \{MH_i, PH_i, J_i, I_i, X_i, C_i\}; \lambda_i\big] &= \alpha_0 + MH_i\alpha^{MH} + PH_i\alpha^{PH} \\ &\qquad + J_i\alpha^{J} + I_i\alpha^{I} + X_i\alpha^{X} + C_i\alpha^{C} + \lambda_i\alpha^{bias}, \end{aligned}$$

for all $i = 1, \ldots, n$. Here, λ_i is the inverse Mills ratio and $\lambda_i\alpha^{bias}$ captures the selection correction. Each regressor matrix is $n \times k_m$ and each α^m, $m \in \{MH, PH, J, I, X, C, \lambda\}$, is a $k_m \times 1$ vector.

6.3 Heckman Results

Table 5 reports first–stage probit estimates and, from the outcome, OLS coefficients (in days) for a selected set of variables for men. Table 6 reports analogous results for women.[9]

[8] It may be argued that if a spouse is unemployed, a worker will be less likely to be absent when ill to ensure job security. However, such decisions depend on the severity of the health shock and the individual's ability to report to work—factors that are highly individual specific.

[9] Placebo check (employed subsample): adding $depout$ and $spou\_emp$ to the own–absence NB2 yields no significant effects and joint tests fail to reject $H_0: \beta_{depout} = \beta_{spou\_emp} = 0$.

Men. Relative to the NB2 AMEs (Table 1), Table 5 shows the $keyMHdis$ coefficient is about 0.10 smaller than the corresponding AME; the $physhlth$ coefficient is smaller by a similar magnitude. By contrast, the $distress$ coefficient is roughly twice the AME, while the $prtycnds$ coefficient is smaller than its AME. In the selection equation, both $depout$ and $spou\_emp$ are positive and significant at 5%, indicating higher employment probabilities for those with external dependents and with employed spouses.

In the extended–sample Heckman model (including those outside the labor force), the IMR remains significant but switches sign to positive. Health index and distress variables enter the selection equation with smaller magnitudes, whereas $keyMHdis$ and $prtycnds$ are more robust in the employment equation. In the outcome equation, $keyMHdis$ becomes insignificant. A sign change in the IMR across samples is plausible if the extended sample alters the composition of nonworkers in ways that flip the correlation between unobservables in the selection and outcome equations.

Women. For women (Table 6), the $keyMHdis$ coefficient is slightly larger than the NB2 AME and remains robust; the $distress$ coefficient is higher by about 0.10 and remains significant. Both $depout$ and $spou\_emp$ are positive and significant at 5% in the selection equation. The IMR is highly significant and negative—similar in sign to men's labor force sample but larger in magnitude—indicating a stronger selection correction for women. In the extended women's sample that includes those outside the labor force, the IMR is not significant.

6.4 Semiparametric Model

To relax the normality assumption in the selection framework, I also estimate a semiparametric selection model based on a Gaussian copula with penalized maximum likelihood. This approach models the dependence between the selection and outcome equations while allowing a negative binomial outcome in the second stage. This serves as a check of the validity of claims that there is evidence of sample selection on unobservables given the discrete and overdispersed nature of the dependent variable.

Dependence parameters (Kendall's τ and the copula parameter θ) and regression coefficients are estimated via penalized maximum likelihood.[10]

6.5 Semiparametric Results & Implications

In the copula model, dependence between the selection and outcome equations is summarized by Kendall's τ and θ. Table 7 reports estimates for men in the labor force (including the unemployed); Table 8 extends the men's sample to include those outside the labor force. Analogously, Tables 9 and 10 report estimates for women in the labor force and for the extended women's sample, respectively.

[10] The R package `SemiParSampleSel` functionality was rebuilt locally to enable estimation of the selection equation together with a negative binomial outcome.

For men, Kendall's τ is 0.124 (95% CI: 0.05–0.20) and θ is 0.194 (95% CI: 0.08–0.31). For women, the corresponding estimates are Kendall's τ of 0.15 (95% CI: 0.07–0.24) and θ of 0.24 (95% CI: 0.104–0.37). These positive values are consistent with a moderate degree of dependence between the employment and absence processes. Estimates in the extended samples (Tables 8, 10) are broadly similar to their labor–force counterparts.

Sample Selection Summary. Overall, the Heckman (1979) and semiparametric copula approaches reach qualitatively similar conclusions about the presence of selection, while differing in precision and assumptions. For the labor-force samples, the significant (negative) IMR indicates non-ignorable selection: models that ignore selection understate expected absenteeism and attenuate key health effects. This reflects nonrandom employment rather than distributional issues like overdispersion or excess zeros.

Comparing the copula–based and Heckman results highlights different trade–offs. The Heckman model provides a direct, interpretable correction via the IMR under its parametric assumptions. The semiparametric copula model flexibly captures the dependence structure and accommodates a negative binomial outcome, but the confidence intervals for Kendall's τ and θ are wider, indicating less precise dependence estimates in this application. Taken together, the two approaches offer complementary evidence about selection.

7 Concluding Remarks

7.1 Limitations

Several limitations merit caution in interpreting the results. First, mental-health measures are noisy: diagnosis is observed at baseline but may reflect care access and help-seeking, and $distress$ is a midyear proxy (collected in MEPS Round 2, referencing the prior 30 days). Accordingly, I interpret the relationship between $keyMHdis \times distress$ and absenteeism as suggestive rather than causal. Second, health and diagnosis are self-reported and subject to misclassification; unobserved severity and treatment adherence may vary within diagnoses.

Third, although correlated random effects and two-way clustering address important sources of unobserved heterogeneity and within-household dependence, residual confounding cannot be ruled out. Fourth, the Heckman correction imposes linearity and normality in the second stage, and the semiparametric copula approach, while flexible, yields wider confidence intervals; both rely on exclusion restrictions whose identifying strength, though supported empirically, is ultimately untestable. Fifth, job-policy detail (e.g., firm attendance rules, supervisory lenience) is limited, so J may not fully capture institutional drivers of absence. Finally, external validity is bounded by the study period and sample composition; effects may differ with changing labor markets, insurance environments, or mental-health care availability.

7.2 Conclusion

This paper quantifies how mental illness and symptomatology relate to labor supply at the daily margin and shows why accounting for selection into employment matters. Using MEPS, I find that a diagnosed mental illness is associated with roughly *one additional day* of own-health absence per year, on average, for both men and women. Interacting diagnosis with time-varying psychological distress reveals a clear pattern: at low distress, diagnosed individuals miss more days than undiagnosed peers, whereas at high distress, diagnosed workers miss fewer days—consistent with diagnosis enabling earlier treatment and preventing the most severe productivity losses. Ignoring employment selection understates these costs: both a Heckman correction and a semiparametric copula model indicate nonrandom selection (with a stronger correction among women) and yield meaningful changes in the magnitudes and significance of key health coefficients.

Policy implications follow directly. Lowering frictions to screening and diagnosis, and ensuring timely access to effective care, can reduce extreme absence at high distress levels even if average absences rise with formal recognition of illness. Employer policies that complement access to care—such as paid sick leave and flexible scheduling—may mitigate costly spikes in absenteeism without relying on underreporting or presenteeism. Future work should (i) incorporate richer employer-policy data and administrative absence records, (ii) use designs that sharpen identification of diagnosis and treatment effects (e.g., benefit or parity shocks, network-based instruments, or event-study timing), (iii) measure productivity on and off the job jointly to capture presenteeism, and (iv) study dynamic adjustment in symptom severity and care over the year. Together, these steps would refine estimates of the productivity costs of mental illness and inform interventions that stabilize labor supply while improving health.

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Tables

Table 1: Baseline AME Estimates

Dependent variable: sickdays	AME & Delta SE[1]	
Variable Name	Men	Women
$keyMHdis$	1.11 (0.35)***	0.92 (0.31)***
$distress$	0.11 (0.06)***	0.15 (0.03)***
$physhlth$	0.37 (0.05)***	0.55 (0.06)***
$prtycnds$	0.67 (0.09)***	0.69 (0.09)***
Observations	15,713	16,216
Pseudo R^2:	0.164	0.198
		*p<0.1; **p<0.05; ***p<0.01

[1] Values in parentheses are delta method standard errors after two-way clustering (household-level, individual-level).

Table 2: Conditional AME of Diagnosed Mental Illness by Distress Scores

Dependent Variable sickdays				
Sample	Variable	Conditioning Level	CAME[1]	Interaction Coefficients[2]
Men	$distress$	5	1.08 (0.35)***	-0.05 (0.02)***
		11	0.18 (0.68)	
		15	-0.70 (1.13)	
	Pseudo R^2: 0.177			
	LR Test[3] (H0: $BM1$, HA: $I1$): ***			
Women	$distress$	5	0.92 (0.32)***	-0.03 (0.01)**
		15	-0.11 (1.00)	
		20	-0.98 (1.72)	
	Pseudo R^2: 0.208			
	LR Test[4] (H0: $BM1$, HA: $I1$): ***			
				Note: *p<0.1; **p<0.05; ***p<0.01

[1, 2] Values in parentheses are two-way cluster-robust standard errors.
For conditional average marginal effects, standard errors are computed via the delta method.
[3, 4] Though LR Tests indicate that models with the interaction perform better,
the unconditional AME estimates are robust in significance and magnitude across models.

Correlated Random Effects

Table 3: Estimates for Pooled Negative Binomial and Correlated Random Effects Negative Binomial: Men

Dependent variable:	AME		Coefficients	
$sickdays$	$BM1$	Correlated RE[1]	$BM1$	Correlated RE[2]
$keyMHdis$	1.11***	0.95***	0.37***	0.33***
	(0.43, 1.77)	(0.39, 1.51)	(0.10)	(0.11)
$distress$	0.11***	0.10***	0.04***	0.03***
	(0.06, 0.16)	(0.05, 0.14)	(0.01)	(0.01)
$physhlth$	0.37***	0.35***	0.12***	0.12***
	(0.27, 0.46)	(0.27, 0.43)	(0.01)	(0.01)
$prtycnds$	0.67***	0.62***	0.22***	0.21***
	(0.50, 0.84)	(0.48, 0.75)	(0.02)	(0.02)
Observations		15,713		
				*p<0.1; **p<0.05; ***p<0.01

[1,2] Correlated random effect estimates are computed using the model proposed by Wooldridge (2019). Values in parentheses are upper- and lower-bounds for 95% CI; for coefficients, these values are two-way cluster-robust robust standard errors. AMEs are in days per year.

Table 4: Estimates for Pooled Negative Binomial and Correlated Random Effects Negative Binomial: Women

Dependent variable:	AME		Coefficients	
$sickdays$	$BM1$	Correlated RE[1]	$BM1$	Correlated RE[2]
$keyMHdis$	0.92**	0.91***	0.21***	0.21***
	(0.33,1.54)	(0.35, 1.46)	(0.07)	(0.06)
$distress$	0.15***	0.14***	0.03***	0.03***
	(0.09, 0.21)	(0.09, 0.20)	(0.01)	(0.01)
$physhlth$	0.55**	0.53***	0.12***	0.12***
	(0.44, 0.66)	(0.43, 0.64)	(0.01)	(0.01)
$prtycnds$	0.69***	0.66***	0.16***	0.15***
	(0.52, 0.88)	(0.49, 0.82)	(0.02)	(0.02)
Observations		16,216		
				*p<0.1; **p<0.05; ***p<0.01

[1,2] Correlated random effect estimates are computed using the model proposed by Wooldridge (2019). Values in parentheses are upper- and lower-bounds for 95% CI; for coefficients, these values are two-way cluster-robust robust standard errors. AMEs are in days per year.

Heckman Estimates

Table 5: Employment and Outcome Equation Estimates, Men

	In Labor Force[1]		Extended Sample[2]	
	Probit	Outcome	Probit	Outcome
$keyMHdis$	-0.27*** (0.04)	0.91*** (0.15)	-0.40*** (0.05)	0.22 (0.29)
$distress$	-0.56*** (0.05)	0.33** (0.12)	-0.01** (0.004)	0.09*** (0.02)
$physhlth$	-0.92** (0.04)	0.25** (0.20)	-0.03** (0.01)	0.35** (0.03)
$prtycnds$	-0.05*** (0.01)	0.51*** (0.01)	-0.05*** (0.01)	0.62*** (0.06)
$depout$	0.45*** (0.06)		0.85** (0.10)	
$spou.emp$	0.19*** (0.03)		0.21*** (0.04)	
Inverse Mills Ratio	-1.32*** (0.37)		0.81*** (0.16)	
Observations	19,823[3]	15,713	24,562[4]	15,713
				*p<0.1; **p<0.05; ***p<0.01

[1, 2] Values in parentheses are two-way cluster-robust standard errors.

[3] Sample includes employed men and unemployed men in the labor force.

[4] Sample includes employed men, unemployed men, and men outside of the labor force.

Table 6: Employment and Outcome Equation Estimates, Women

	In Labor Force[1]		Extended Sample[2]	
	Probit	Outcome	Probit	Outcome
$keyMHdis$	-0.02 (0.03)	0.95*** (0.15)	-0.34 (0.03)	0.68** (0.26)
$physhlth$	-0.79*** (0.03)	0.91*** (0.14)	-0.01 (0.01)	0.49*** (0.04)
$distress$	-0.12*** (0.04)	0.25** (0.20)	-0.01** (0.003)	0.14*** (0.02)
$prtycnds$	-0.03*** (0.01)	0.52*** (0.03)	-0.06*** (0.01)	0.52*** (0.07)
$depout$	0.44*** (0.05)		1.12*** (0.15)	
$spou.emp$	-0.46*** (0.02)		0.21*** (0.03)	
Inverse Mills Ratio	-1.85** (0.80)		0.54 (0.40)	
Observations	23,093[1]	16,216	29,947[2]	16,216
				*p<0.1; **p<0.05; ***p<0.01

[1, 2] Values in parentheses are two-way cluster-robust standard errors.

[3] Sample includes employed women and unemployed women in the labor force.

[4] Sample includes employed women, unemployed women, and women not in the labor force.

Semiparametric Estimates

Table 7: Estimates for Each Stage of Semiparametric Selection Model: Men

	Probit		Outcome (Negative Binomial)	
Variables	Coefficients	Standard Errors[1]	Coefficients	Standard Errors[2]
$keyMHdis$	-0.15***	(0.04)	0.41***	(0.11)
$physhlth$	-0.70***	(0.04)	0.14***	(0.01)
$distress$	-0.81***	(0.10)	0.03***	(0.01)
$prtycnds$	-0.09***	(0.01)	0.20***	(0.02)
$depout$	0.57**	(0.06)		
$spou.emp$	0.28**	(0.03)		
Sample Size	19,823[1]		15,713	
Kendall's τ		0.124 (0.05,0.20)		
θ		0.194 (0.08,0.31)		
				*p<0.1; **p<0.05; ***p<0.01

[1, 2] Values in parentheses are two-way cluster-robust standard errors.

[3] Sample includes employed men and unemployed men in the labor force.

Table 8: Estimates for Each Stage of Semiparametric Selection Model: Men – *Including men out of the labor force*

	Probit		Outcome (Negative Binomial)	
Variables	Coefficients	Standard Errors[1]	Coefficients	Standard Errors[2]
$keyMHdis$	-0.15***	(0.04)	0.35***	(0.05)
$physhlth$	-0.73***	(0.04)	0.14***	(0.01)
$distress$	-0.52***	(0.06)	0.03***	(0.01)
$prtycnds$	-0.09***	(0.01)	0.20***	(0.02)
$depout$	0.55***	(0.06)		
$spou.emp$	0.25***	(0.03)		
Sample Size	24,562[1]		15,713	
Kendall's τ		0.126 (0.04,0.20)		
θ		0.197 (0.07,0.31)		
				*p<0.1; **p<0.05; ***p<0.01

[1, 2] Values in parentheses are two-way cluster-robust standard errors.

[3] Sample includes employed men, unemployed men, and men not in the labor force.

Table 9: Estimates for Each Stage of Semiparametric Selection Model: Women

	Probit		Outcome (Negative Binomial)	
Variables	Coefficients	Standard Errors[1]	Coefficients	Standard Errors[2]
$keyMHdis$	-0.10***	(0.02)	0.28***	(0.11)
$physhlth$	-0.64***	(0.06)	0.09***	(0.01)
$distress$	-0.70***	(0.10)	0.06***	(0.01)
$prtycnds$	-0.03**	(0.01)	0.18***	(0.02)
$depout$	0.45**	(0.06)		
$spou.emp$	-0.12**	(0.03)		
Sample Size	23,093[1]		16,216	
Kendall's τ		0.154 (0.07,0.24)		
θ		0.24 (0.104,0.37)		
				*p<0.1; **p<0.05; ***p<0.01

[1, 2] Values in parentheses are two-way cluster-robust standard errors.

[3] Sample includes employed women and unemployed women.

Table 10: Estimates for Each Stage of Semiparametric Selection Model: Women – *Including women out of the labor force*

	Probit		Outcome (Negative Binomial)	
Variables	Coefficients	Standard Errors[1]	Coefficients	Standard Errors[2]
$keyMHdis$	-0.28***	(0.04)	0.33***	(0.05)
$physhlth$	-0.94***	(0.04)	0.09***	(0.01)
$distress$	-0.76***	(0.06)	0.06***	(0.01)
$prtycnds$	-0.03**	(0.01)	0.18***	(0.02)
$depout$	0.47***	(0.06)		
$spou.emp$	-0.15***	(0.03)		
Sample Size	29,947[1]		16,216	
Kendall's τ		0.139 (0.05,0.21)		
θ		0.217 (0.08,0.33)		
				*p<0.1; **p<0.05; ***p<0.01

[1, 2] Values in parentheses are two-way cluster-robust standard errors.

[3] Sample includes employed women, unemployed women, and women not in the labor force.

Figures

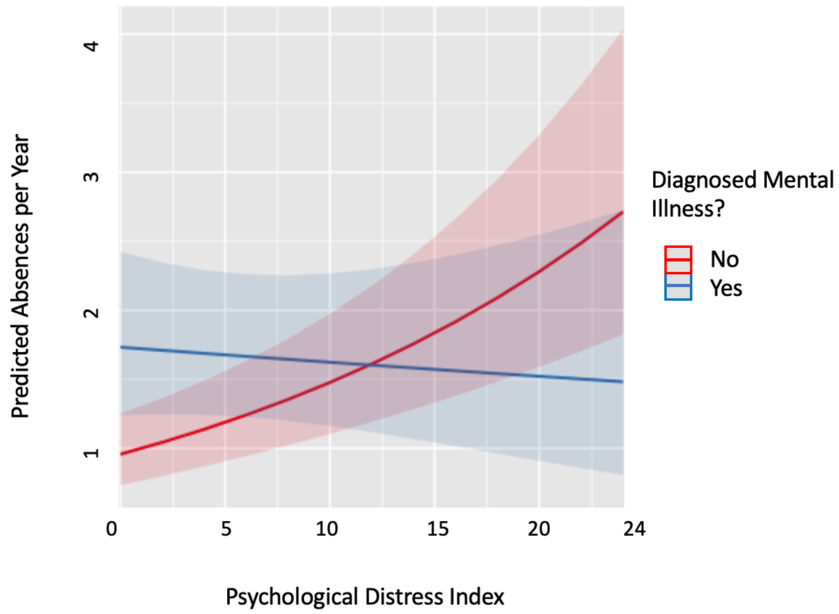

Figure 1: Between-Group Predicted Absences by General Distress: Men

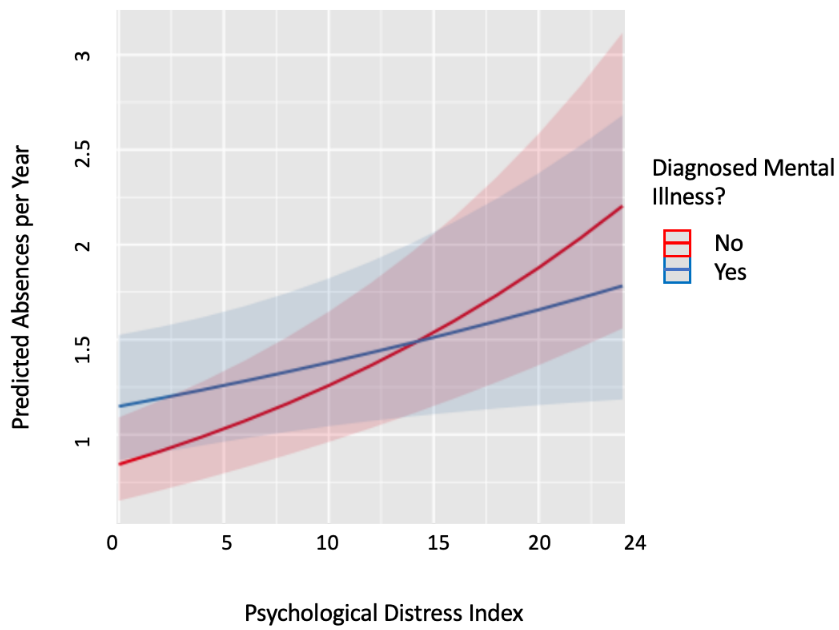

Figure 2: Between-Group Predicted Absences by General Distress: Women

A Data Appendix

A.1 Sources

MEPS-HC (Household Component Full-Year Files)

FYCD Full-Year Consolidated Data Files: HC-171 (Panel 18 only), HC-163, HC-155, HC-147, HC-138 (Panel 15 only)

MCF Medical Conditions File: HC-162 (Panel 18 only), HC-154, HC-146, HC-137 (Panel 15 only)

JF Jobs Files: HC-166 (Panel 18 only), HC-158, HC-150, HC-142, HC-133 (Panel 15 only)

BLS (United States Bureau of Labor Statistics)

- Unemployment Statistics by region and month from Jan. 2010 to Dec. 2014

A.2 Diagnosed Mental Illness Variable

`keyMHdis` is composed using the following values of `CCCODEX` from MEPS MCF

657 Mood Disorders — subcategories: bipolar disorders, depressive disorders.

658 ersonality Disorders.

659 Schizophrenia and other psychotic disorders.

663 Screening and history of mental health and substance use disorders — *mental-health–related codes only*[11]

A.3 Kessler–6 Distress Scale and Diagnostic Heterogeneity

Construction. The Kessler–6 (K–6) is computed from six SAQ items (FYCD) on the frequency of nervousness, hopelessness, restlessness, depression, effortfulness, and worthlessness over the past 30 days (0=none of the time to 4=all of the time), summed to a 0–24 index (Kessler et al., 2003). In MEPS, K–6 is fielded in Round 2; I align it to the calendar year by treating it as a time-varying symptom proxy within-year.

Interpretation. Conventional cut points treat 9–12 as mild–moderate distress and ≥ 13 as probable serious mental illness (Kessler et al., 2003; Ashwood et al., 2016). I use the continuous index in baseline models and, where noted, report results by cut-point categories as a robustness check.

[11] These individuals are included in the diagnosed dummy variable under the assumption that mental health disorders are chronic conditions. The potential for this code to influence the relative effect of mental illness was considered, and results were robust to leaving them out.

Timing and measurement error. Because K–6 references the last 30 days of Round 2, it does not perfectly align with annual absences. This timing mismatch can attenuate coefficients toward zero if symptoms vary within year. I therefore (i) report models that use $distress$ continuously and (ii) include sensitivity checks (not shown) that interact $distress$ with interview timing.

Why use diagnosis and symptoms jointly. DSM-5 emphasizes substantial within- and between-disorder heterogeneity of symptom profiles. As stated:

> 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 homogeneous 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.

This motivates including both a diagnosis indicator ($keyMHdis$) and a symptom index ($distress$).

Prior to estimation, I consider the possibility of harmful collinearity induced by including both $keyMHdis$ and $distress$ in the models. I perform an initial fit of the preferred baseline models which include both $keyMHdis$ and $distress$ and then conduct a VIF test for each sex separately. The results of the VIF tests indicate that there is no evidence of significant multicollinearity induced by either measure of mental health when controlling for other explanatory variables. I additionally perform a likelihood ratio test of the null hypothesis that a model specification excluding the scale variable, $distress$, provides the best fit, and reject the null hypothesis in favor of the unrestricted model at the 0.1 percent level.

A.4 Priority Conditions of MEPS FYCD:

- High blood pressure (HIBPDX)
- Heart disease (CHDDX, ANGIDX, MIDX, OHRTDX)
- Stroke (STRKDX)
- Emphysema (EMPHDX)
- Chronic bronchitis (CHBRON31, CHBRON53) — counted if the person responds "yes" in either survey round.
- High cholesterol (CHOLDX)
- Cancer (CANCERDX)
- Diabetes (DIABDX)
- Joint pain (JTPAIN31, JTPAIN53) — counted if "yes" in either survey round.

- Arthritis (ARTHDX)
- Asthma (ASTHDX)
- ADHD (ADHDADDX) — not counted in the analytic variable $prtycnds$ due to psychological nature; used as a separate control.

MEPS documentation states that these conditions are chosen "because of their relatively high prevalence, and because generally accepted standards for appropriate clinical care have been developed."

Presentation and comorbidity. Symptom profiles and functional impacts vary widely across disorders, and comorbid conditions can interact in ways that differ by disease pairing. While $prtycnds$ captures the *count* of priority conditions, it does not identify *which* conditions co-occur, so heterogeneity in comorbidity patterns is not fully observed. The correlated random–effects (CRE) specification mitigates bias from time-invariant unobservables, but residual confounding from unmeasured comorbidity composition and severity likely remains. Interactions among specific conditions and richer disease taxonomies are promising targets for future work.

A.5 Variable Descriptions and Sources

Table 11: Total Sample Summary Statistics (MEPS references added)

Variable	Description	Mean	Min	Max	MEPS name	Source
Dependent Variable (A)						
`sickdays`	Count of total days absent from work due to own illness/injury (past year).	3.18	0	160	`DDNWRK31/42/53` (annual sum)	FYCD
Mental Health (MH)						
`keyMHdis`	=1 if diagnosed mental disorder of interest, =0 otherwise.	0.10	0	1	*Constructed from* mental condition flags	FYCD/MCF
`distress`	K6 psychological distress (0–24; higher=worse).	2.60	0	24	`K6SUM42`	FYCD (SAQ)
`adhd`	=1 if ADHD diagnosis reported, =0 otherwise.	0.01	0	1	*Constructed:* `CCCODEX`=652	MCF
Physical Health (PH)						
`physhlth`	Discrete scale (1–13; higher=worse general health).	4.66	1	13	`RTHLTH31/42/53` (harmonized)	FYCD
`prtycnds`	Number of priority condition diagnoses.	1.31	0	9	*Constructed from priority-condition flags*	FYCD
`routine`	=1 if routine medical evaluation in past year, =0 otherwise.	0.03	0	1	`CHECK53` $\leq$ 12 months (binary)	FYCD (SAQ)
`injury`	=1 if injury/illness required immediate care (past year), =0 otherwise.	0.24	0	1	`ADILCR(2/4)`	FYCD (SAQ)
`smoke`	=1 if currently smokes, =0 otherwise.	0.17	0	1	`ADSMOK42`	FYCD (SAQ)
`exercise`	=1 if exercises $\geq$3 times/week, =0 otherwise.	0.53	0	1	`PHYEXE53` (binary)	FYCD (SAQ)
`pregnt`	*Women only.* =1 if pregnant at any point during year.	0.03	0	1	`PREGNT31/42/53`	FYCD
Job Traits (J)						
`selfemp`	=1 if self-employed, =0 otherwise.	0.13	0	1	`SLFCM31/42/53`	JF/FYCD
`one4`	Tenure 1–4 years (benchmark).	0.37	0	1	*Constructed from job start date $\to$ tenure*	JF
`five14`	Tenure 5–14 years.	0.35	0	1	*Constructed from job start date*	JF
`fifteen24`	Tenure 15–24 years.	0.11	0	1	*Constructed from job start date*	JF
`25plus`	Tenure $\geq$25 years.	0.06	0	1	*Constructed from job start date*	JF

Continued on following page.

Variable	Description	Mean	Min	Max	MEPS name	Source
temp	=1 if temporary contract, =0 otherwise.	0.05	0	1	TEMPJB31/42/53	JF
parttime	=1 if works $\geq$35 hours/week (doc's coding label retained) , =0 otherwise.	0.17	0	1	HOURW31/42/53 ≥ 35 (binary)	JF
union	=1 if union member, =0 otherwise.	0.13	0	1	UNION31/42/53	JF
ssnl	=1 if main job is seasonal, =0 otherwise.	0.05	0	1	SSNLJB31/42/53	JF
pubsect	=1 if public-sector job, =0 otherwise.	0.18	0	1	JBORG31/42/53 $\in \{2, 3\}$	JF
occ1	Management, business, financial operations.	0.13	0	1	OCCUPN major group	JF
occ2	Professional and related.	0.22	0	1	OCCUPN major group	JF
occ3	Service occupations.	0.19	0	1	OCCUPN major group	JF
occ4	Sales and related.	0.08	0	1	OCCUPN major group	JF
occ5	Office and administrative support.	0.14	0	1	OCCUPN major group	JF
occ6	Farming, fishing, forestry.	0.01	0	1	OCCUPN major group	JF
occ7	Construction, extraction, maintenance.	0.08	0	1	OCCUPN major group	JF
occ8	Production, transportation, material moving (benchmark).	0.15	0	1	OCCUPN major group	JF
occ9	Unclassifiable occupation.	0.004	0	1	OCCUPN	JF
1to19	Firm size: 1–19 employees.	0.30	0	1	NUMEMP31/42/53 or NMEMP*	JF
20to99	Firm size: 20–99.	0.33	0	1	NUMEMP31/42/53 or NMEMP*	JF
100to499	Firm size: 100–499.	0.21	0	1	NUMEMP31/42/53 or NMEMP*	JF
500plus	Firm size: 500+ (benchmark).	0.16	0	1	NUMEMP31/42/53 or NMEMP*	JF
NRunemp	Missing/nonresponse on firm size.	0.05	0	1	*Constructed:* missing in NUMEMP/NMEMP	JF
Health Insurance (I)						
inscostly	=1 if "health insurance not worth the cost", =0 otherwise.	0.28	0	1	ADINSB42	FYCD (SAQ)
jobins	=1 if insured through own job, =0 otherwise.	0.63	0	1	CMJHLD31/42/53 (linked)	PRPL→FYCD

Continued on following page.

Variable	Description	Mean	Min	Max	MEPS name	Source
otherins	Private insurance via non-job source.	0.13	0	1	PRPL (holder ≠ respondent; other private)	PRPL
pubins	Public coverage.	0.07	0	1	PUBCOV (or equivalent)	FYCD
unins	Uninsured (benchmark).	0.17	0	1	INSURCOV recode	FYCD
Demographics (X)						
poor	Poverty status: poor/near-poor.	0.14	0	1	POVCAT recode	FYCD
lowinc	Low income.	0.16	0	1	POVCAT recode	FYCD
midinc	Middle income.	0.34	0	1	POVCAT recode	FYCD
highinc	High income (benchmark).	0.37	0	1	POVCAT recode	FYCD
married	=1 if married, =0 otherwise.	0.55	0	1	MARRY31/42/53 (harmonized)	FYCD
yngchldrn	Number of children age ≤6.	0.38	0	6	*Constructed from household roster*	FYCD
age	Age in years.	41.86	18	84	AGE12X (or round-specific AGE31/42/53)	FYCD
belowhs	Less than high school.	0.13	0	1	EDRECODE	FYCD
hsdeg	High school/GED (benchmark).	0.32	0	1	EDRECODE	FYCD
somecoll	Some college/AA.	0.25	0	1	EDRECODE	FYCD
bachdeg	Bachelor's degree.	0.20	0	1	EDRECODE	FYCD
bachplus	More than bachelor's.	0.10	0	1	EDRECODE	FYCD
hispanic	Hispanic.	0.28	0	1	HISPANX	FYCD
black	Black.	0.18	0	1	RACETHX/RACEV1X	FYCD
asian	Asian.	0.08	0	1	RACETHX/RACEV1X	FYCD
bornus	Born in the U.S.	0.65	0	1	BORNUSA	FYCD
Other Controls (C)						
unemp_1	Unemployed in exactly one interview round.	0.07	0	1	*Constructed from* EMPST31/42/53	FYCD
unemp_2	Unemployed in exactly two interview rounds.	0.06	0	1	*Constructed from* EMPST31/42/53	FYCD
partialemp	Unemp. in one round but worked part of prior ref. period.	0.04	0	1	*Constructed (employment spells)*	FYCD
empUB	Total days employed during year.	338	28	365	*Constructed (job spells/calendar)*	FYCD
moved_US	Moved within U.S. during calendar year.	0.03	0	1	*Mover indicator*	FYCD
moved_RU	Joined a new reference unit during year.	0.01	0	1	*New RU indicator*	FYCD
NE	Region: Northeast.	0.16	0	1	REGION31/42/53	FYCD
MW	Region: Midwest.	0.20	0	1	REGION31/42/53	FYCD

Continued on following page.

Variable	Description	Mean	Min	Max	MEPS name	Source
W	Region: West.	0.28	0	1	REGION31/42/53	FYCD
S	Region: South (benchmark).	0.37	0	1	REGION31/42/53	FYCD
unemp_rt	Avg. annual unemployment rate faced.	8.05	5.5	10.9	*Merged: BLS LAUS + MEPS region-by-round*	BLS + FYCD
yearone	Observed only in first panel year.	0.26	0	1	*Panel participation flag*	FYCD
yeartwo	Observed only in second panel year.	0.20	0	1	*Panel participation flag*	FYCD
bothyrs	Observed in both panel years (benchmark).	0.54	0	1	*Panel participation flag*	FYCD
Exclusion Restrictions (*ER*)						
depout	Dependants outside the household.	0.04	0	1	DPOTSDX	FYCD
spou_emp	Spouse employment status.	0.84	0	1	*Constructed using marital status, employment status, family IDs*	FYCD + JF

B Sample (Employed) Summary Statistics

Table 12: Means of Analytical Variables by Sex

Category	Variable	Men	Women	T-Stat
Dependent Variable (A)	$sickdays$	2.50	3.85	-12.11***
Mental Health (MH)	$keyMHdis$	0.07	0.14	-22.00***
	$distress$	2.30	2.90	-15.02***
Physical Health (PH)	$physhlth$	4.44	4.87	-16.01***
	$prtycnds$	1.26	1.35	-5.57***
Health Insurance Characteristics (I, $\tilde{I}$)	$inscostly$	0.30	0.26	7.69***
	$jobins$	0.66	0.61	9.38***
	$plnchoic$	0.34	0.34	-0.30
	$nochoic$	0.26	0.22	8.76***
	$otherins$	0.11	0.15	-12.01***
	$pubins$	0.05	0.09	-14.71***
	$unins$	0.19	0.15	8.57***
Observations		15,713	16,216	

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

Table 13: Means of Analytical Variables by Sex and Presence of Mental Illness

	Men			Women		
Variable	***keyMHdis* =1**	***keyMHdis* =0**	**T-Stat**	***keyMHdis* =1**	***keyMHdis* =0**	**T-Stat**
$sickdays$	4.64	2.35	6.35***	6.14	2.48	9.02***
$distress$	5.33	2.09	20.53***	5.57	2.46	28.44***
$physhlth$	5.59	4.36	15.34***	5.78	4.72	18.50***
$prtycnds$	2.04	1.21	16.47***	1.96	1.25	19.24***
$inscostly$	0.27	0.30	-1.61	0.22	0.26	-4.96***
$jobins$	0.71	0.65	3.87***	0.63	0.60	2.70***
$plnchoic$	0.38	0.33	3.29***	0.36	0.33	2.87***
$nochoic$	0.27	0.26	0.47	0.24	0.22	1.63
$otherins$	0.10	0.11	-0.64	0.16	0.15	1.43
$pubins$	0.05	0.05	0.40	0.10	0.09	1.42
$unins$	0.14	0.19	-4.75***	0.11	0.16	-7.05***
Observations		15,713			16,216	

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

C Supporting Figures

C.1 Q-Q Plots

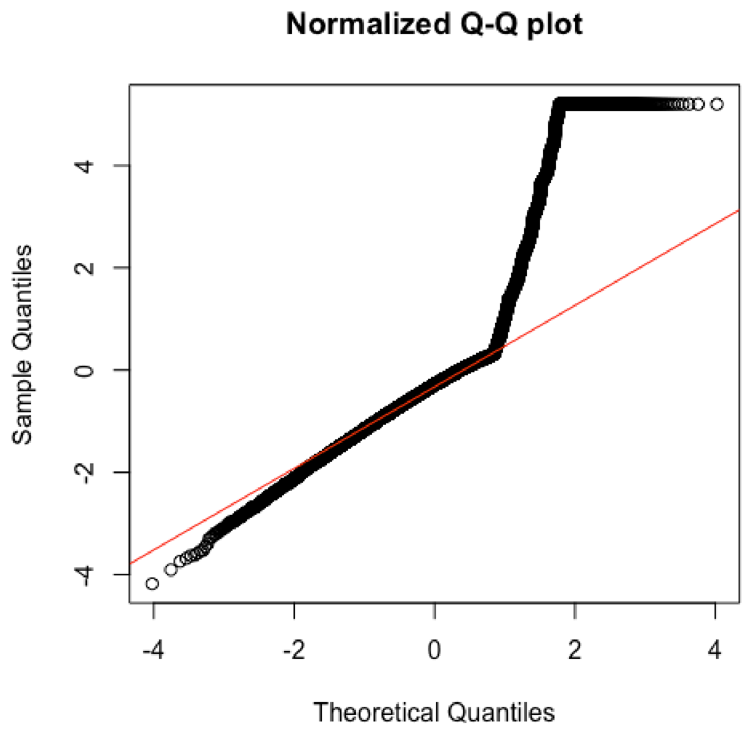

Figure 3: Poisson Distribution

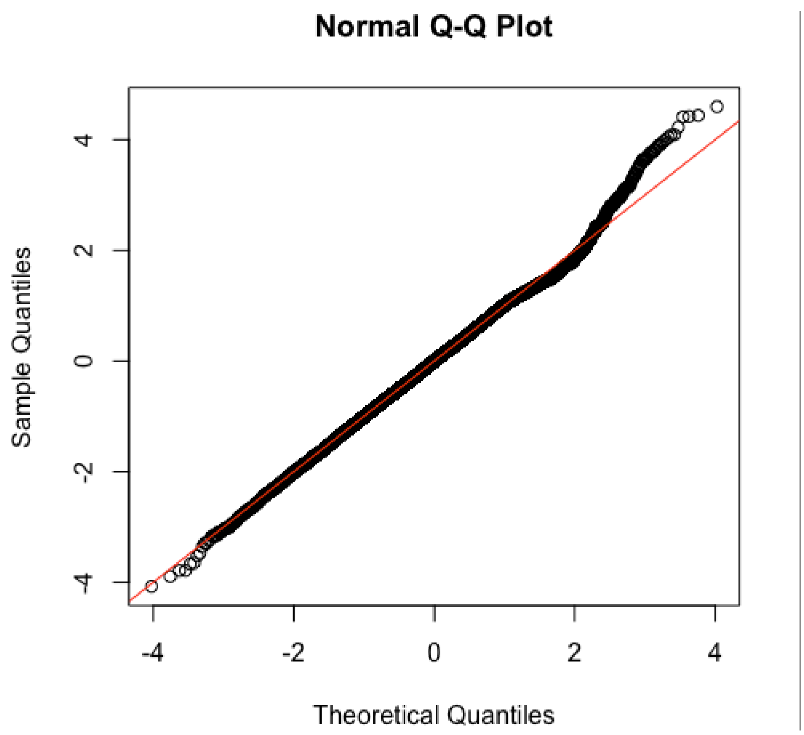

Figure 4: Negative Binomial II Distributions

Note: These plots are for the entire sample of 31,929 (employed) observations prior to splitting the sample by sex. I test a zero-inflated negative binomial as well as a hurdle model due to a majority of observations indicating zero absences. Neither are found to perform any better than a traditional negative binomial II.

C.2 Patterns of Absenteeism by Mental Illness and Physical Health Measures

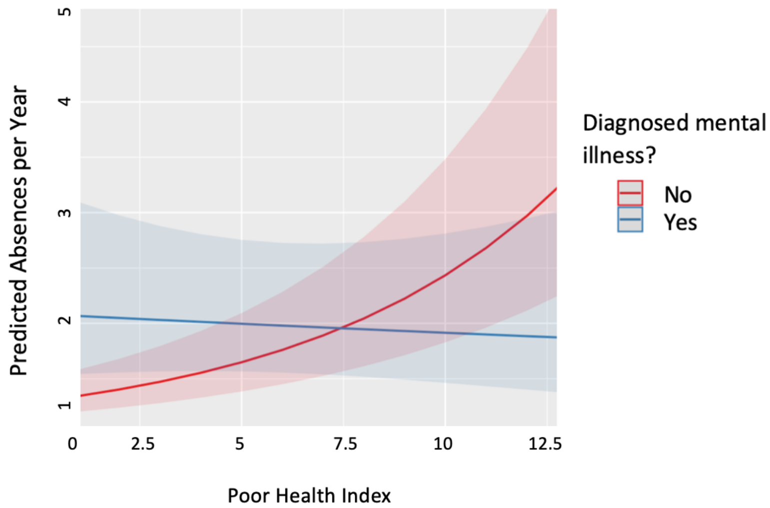

Figure 5: Between-Group Predicted Absences by Poor Health Index: Men

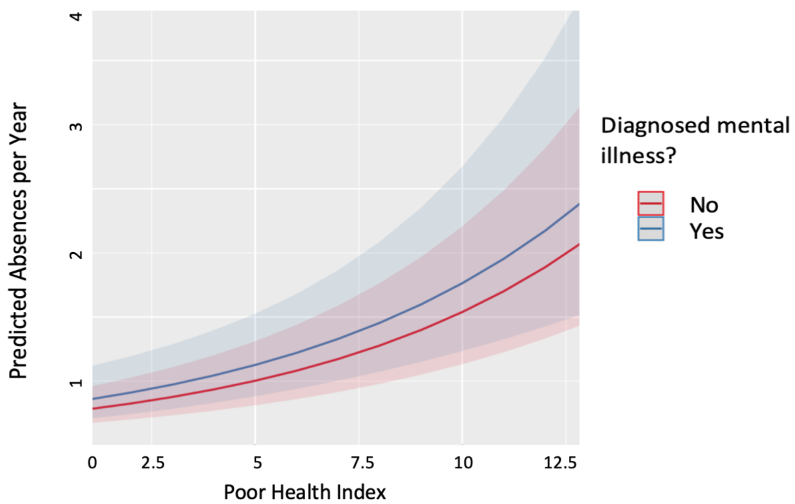

Figure 6: Between-Group Predicted Absences by Poor Health Index: Women

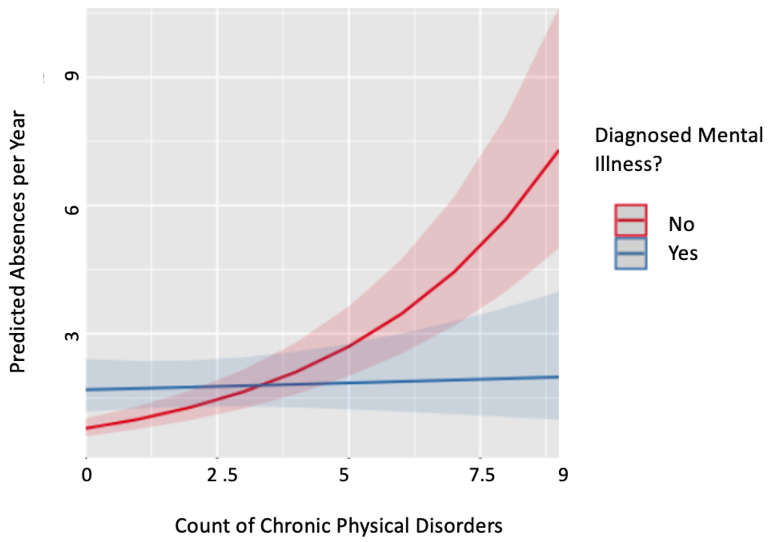

Figure 7: Between-Group Predicted Absences by Count of Conditions: Men

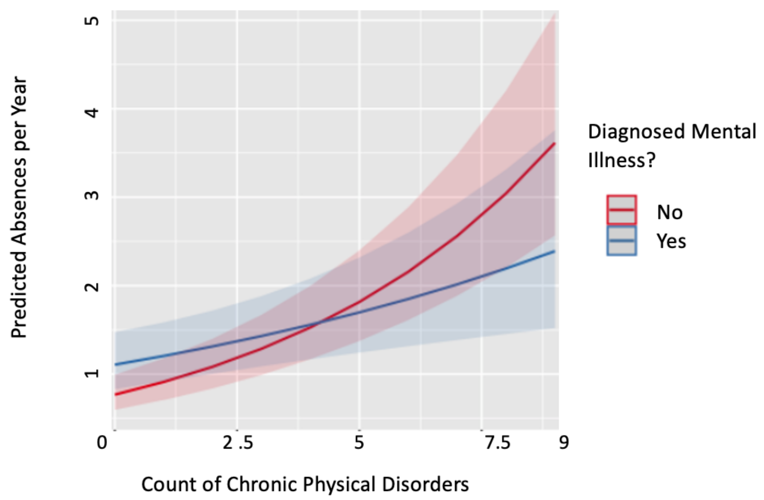

Figure 8: Between-Group Predicted Absences by Count of Conditions: Women