Mental Health as Health Capital: Absenteeism, Comorbidity, and Productivity Loss in the U.S. Workforce

National Estimates from the National Health Interview Survey

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Abstract

Anxiety and depression affect more than one in five employed U.S. adults and remain elevated relative to pre-pandemic levels, yet their aggregate economic consequences are systematically underestimated. Using pooled, nationally representative data from the 2021–2024 National Health Interview Survey (N ≈ 59,500 employed working-age adults), this paper quantifies their productivity impact through a human-capital framework in which anxiety and depression reduce effective labor supply. Survey-weighted logistic regression models show that affected workers face nearly double the probability of high absenteeism (>10 work-loss days annually), with an average marginal effect of 5.9 percentage points. A clear comorbidity gradient emerges: workers with co-occurring anxiety and depression have the highest absenteeism risk (predicted probability 15.5%), and dose-response relationships with symptom severity and frequency indicate that current symptom intensity is a primary driver of work loss. Applying these estimates to a three-channel burden model yields annual productivity losses of $190 to $270 billion in 2023 dollars. Presenteeism accounts for 88 to 92 percent of total costs, far exceeding the visible absenteeism burden. This iceberg structure indicates that conventional metrics substantially understate the true economic cost of mental illness in the workforce.

Keywords.

anxiety and depression, absenteeism, presenteeism, productivity loss, human capital, cost of illness

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1. INTRODUCTION

The prevalence of anxiety and depression among working-age adults in the United States has risen markedly since 2020 and remains significantly above pre-pandemic levels (Daly & Robinson, 2022; McGinty et al., 2022). What began as an acute response to crisis conditions has evolved into a persistent increase in diagnosed cases, with recent survey data indicating that more than one in five employed adults report a lifetime diagnosis of at least one of these disorders. This ongoing trend has raised concerns among economists, employers, and policymakers, given that anxiety and depression disproportionately impact individuals during their most productive years and exert effects that extend well beyond direct healthcare costs.

Contextualizing this trend within broader health outcomes underscores its relevance for economic performance. Approximately three-quarters of U.S. adults live with at least one chronic medical condition, and such diseases collectively contribute over one trillion dollars annually to healthcare spending (CDC, 2024; Buttorff et al., 2017). While clinical characteristics vary across conditions, they share a common economic consequence: substantial indirect costs stemming from reduced labor supply and diminished workplace productivity. These costs are often not reflected in national health expenditure accounts, yet they represent a considerable, frequently underestimated constraint on aggregate output (Goetzel et al., 2004; Mitchell & Bates, 2011). Anxiety and depression are especially salient due to their high prevalence and distinctive mechanisms through which they reduce work capacity. Impairments in concentration, executive function, emotional regulation, and social interaction may decrease employee productivity even when physical presence is maintained.

From the standpoint of health capital theory, mental illness represents a depreciation shock—lowering health capital, diminishing the marginal product of labor, and increasing the risk of absenteeism, reduced performance, or labor force withdrawal. Extensive research corroborates these associations between anxiety, depression, and adverse work outcomes (Greenberg et al., 2021; Johnston et al., 2022; Patel et al., 2022; Bonner & Ghouralal, 2024). Nevertheless, key empirical gaps remain. Much of the current evidence is derived from employer administrative records or clinical trial samples lacking national representativeness. Few investigations have addressed nonlinear comorbidity effects, despite indications that co-occurring disorders may result in productivity losses greater than the sum of individual conditions. Even fewer studies have explored symptom severity gradients, which are crucial for assessing how varying degrees of mental health impairment influence effective labor input.

This analysis leverages pooled National Health Interview Survey (NHIS) data from 2021 to 2024 to address three primary objectives. First, it quantifies the association between anxiety and depression and workplace absenteeism, using both binary and continuous measures. Second, it examines nonlinear comorbidity effects consistent with theoretical models of health capital accumulation, demonstrating that individuals with both anxiety and depression face substantially elevated work-loss risk relative to single-condition estimates. Third, it assesses dose-response relationships linked to symptom severity, clarifying the connection between intensity of mental

health impairment and reductions in labor supply. Collectively, these findings contribute to ongoing discussions regarding the macroeconomic consequences of increasing mental health prevalence and the role of chronic disease in shaping labor market patterns in the post-pandemic era. This study offers new nationally representative insights into how common mental disorders affect effective labor supply via absenteeism, comorbidity, and gradients of symptom severity.

2. BACKGROUND AND RELATED LITERATURE

2.1 Health Capital and Labor Supply

Economic theories about health and work suggest that health acts as a form of valuable capital, shaping how efficiently people can work throughout their lives. According to Grossman's influential human capital model and later research, people invest in their health to be able to work more effectively, while chronic illnesses reduce this "health capital," leading to lower productivity and increasing the chances of leaving the workforce.

Recent studies have shown that mental health issues, such as depression, can have lasting effects on a person's job prospects. The effects often continue long after the initial symptoms fade. Long-term surveys indicate that people with depressive symptoms later earn less and face more unstable employment, even when taking initial economic status into account (Goodman et al., 2022; Lundborg et al., 2022). This suggests that mental health problems can cause economic "scars": an initial drop in health leads to reduced investment in other skills and slower career advancement. These impacts matter even more today, as modern jobs increasingly rely on thinking and social skills. Problems with focus, memory, or decision-making can reduce productivity, even if someone keeps coming to work (Johnston et al., 2022).

National survey data reveal how widespread this issue is. Research by Bonner and Ghouralal (2024) finds that anxiety and depression are among the most common ongoing health issues for U.S. workers, strongly linked to missing work and being at higher risk for disability. Additional studies by Bonner (2024, 2025) show that mental health conditions are consistently top predictors of lost productivity, sometimes having a bigger effect on work outcomes than physical ailments like diabetes or heart disease. Altogether, these findings highlight the critical need to consider mental health in economic studies that aim to understand differences in labor supply and worker productivity.

2.2 Productivity Channels in Chronic Disease Economics

Chronic diseases impact productivity mainly through three channels. Absenteeism, or workdays missed due to illness, is the easiest to measure, but research shows it only accounts for a small part of overall productivity loss (Hemp, 2004). Presenteeism, defined as reduced on-the-job performance while physically present at work, typically accounts for a larger share of total costs. Studies using validated instruments such as the Work Limitations Questionnaire (WLQ) report performance reductions of 8 to 12 percent of total compensation for depression, 5 to 9 percent for pain conditions, 5 to 8 percent for cardiovascular disease, and 4 to 7 percent for diabetes (Lerner et al., 2003; Mitchell et al., 2009; Allen et al., 2018). Since presenteeism is not easily seen, it is frequently referred to as the hidden part of the productivity iceberg, while absenteeism is just the small visible section above the surface.

The third channel, premature labor force exit, captures individuals who leave employment entirely through disability programs or early retirement, representing a complete loss of their labor input. Employer-level research emphasizes that comprehensive productivity measurement must account for all three channels, because focusing on any single one understates the economic burden (Mitchell & Bates, 2011).

2.3 The Nicholson Multiplier: Team Production and the True Cost of Absence

A key insight from the theoretical literature on workplace productivity is that the cost of a worker's absence to a firm frequently exceeds the value of that worker's daily wage. Nicholson et al. (2006) formalized this idea in a model where the productivity impact of an absence depends on three job characteristics: the degree of teamwork required, the time sensitivity of the output, and the difficulty of finding a suitable substitute for the absent worker. Drawing on a nationally representative survey of 800 managers across 12 industries, they estimated job-specific wage multipliers for 35 occupations using an ordered probit framework that maps these three characteristics onto a latent cost-of-absence variable. The equal-weighted mean multiplier across the 35 job types is 1.61 and the median is 1.28, with individual multipliers ranging from 1.00 for easily substitutable positions such as fast-food cooks and waiters to values exceeding 2.0 for highly interdependent roles such as aerospace and construction engineers. The gap between the mean and median reflects right skewness in the distribution, driven by a small number of occupations where tight deadlines, team complementarities, and limited substitutability combine to make absences especially costly.

The present analysis applies the mean multiplier rather than the median because the burden estimates are scaled across the full occupational distribution of the employed workforce, where both high-multiplier and low-multiplier jobs contribute to aggregate productivity loss. An average that gives weight to the upper tail of the distribution better approximates the expected cost per absence economy-wide. Using the median (1.28) in place of the mean would reduce the absenteeism cost estimates by approximately 20 percent, a sensitivity that is noted in the limitations discussion but that does not materially alter the overall findings, given that presenteeism rather than absenteeism accounts for the dominant share of the total burden.

This finding has direct implications for estimating the burden of mental health conditions. Because anxiety and depression are among the leading predictors of work absence, the Nicholson multiplier implies that the economic consequences of mental-health-related absenteeism are substantially larger than what simple wage-based calculations would suggest. The multiplier motivates scaling absenteeism costs above the daily wage in the burden estimation framework developed below.

2.4 Absenteeism and Workplace Productivity

Absenteeism represents the most direct channel through which illness affects the quantity of labor supplied. Workers who experience poor health may miss workdays because of acute symptoms, medical appointments, or functional limitations that prevent them from performing their job duties. Consistent with this, recent research documents strong associations between depressive symptoms and work absence across a wide range of occupational settings (Johnston et al., 2022; Patel et al., 2022). Workers with depression report more sick days than comparable workers without mental health conditions.

From a production standpoint, the cost of absenteeism can exceed the lost labor hours of the affected individual. In team production environments, an absence disrupts coordination among coworkers and can reduce the productivity of the entire team (Nicholson et al., 2006). These production externalities mean that the economic cost of illness-related absence is typically greater than the wage value of the lost work time alone.

An important caveat is that self-reported absenteeism data, including the lost workday measure used in the NHIS, is subject to recall error and potential underreporting. If workers with mental health conditions are more likely to understate their absences, as some evidence suggests, then estimates of the association between these conditions and absenteeism may be attenuated, and the true productivity losses could be larger than those documented here.

2.5 Presenteeism and Efficiency Units of Labor

Beyond its effect on absence, mental illness can reduce productivity while workers remain on the job. This phenomenon, commonly termed presenteeism, reflects declines in cognitive performance, motivation, and emotional regulation that impair work quality and output. A consistent finding in the cost-of-illness literature is that the productivity losses attributable to presenteeism exceed those attributable to absenteeism (Greenberg et al., 2021; Johnston et al., 2022). For depression in particular, the ratio of presenteeism to absenteeism costs is often on the order of three to one or higher. These findings carry a clear implication: traditional labor supply measures that focus solely on hours worked will underestimate the economic impact of mental health conditions.

The NHIS does not directly measure presenteeism. Accordingly, the presenteeism cost estimates developed in this paper rely on productivity reduction parameters drawn from the occupational health literature and applied to NHIS-based prevalence estimates. This distinction matters for interpretation. The absenteeism estimates reported below are derived directly from the survey data, whereas the presenteeism estimates are model-based and carry additional parametric uncertainty.

2.6 Multimorbidity and Chronic Disease Accumulation

Multimorbidity, defined as the presence of two or more chronic conditions, has become increasingly common among working-age adults and may amplify productivity losses through nonlinear interactions. The co-occurrence of anxiety and depression is particularly important, as the two disorders share underlying neurobiological risk factors and may reinforce one another through behavioral and cognitive pathways (National Institute on Drug Abuse [NIDA], 2018).

Understanding comorbidity effects is critical for accurately estimating the economic burden of chronic disease. If multiple conditions interact to reduce health capital by more than their individual contributions, productivity losses may increase nonlinearly as condition count rises. The empirical analysis examines this directly through comorbidity gradient models.

3. DATA

3.1 Data Source

The analysis uses data from the National Health Interview Survey (NHIS), an annual nationally representative survey of the U.S. civilian noninstitutionalized population conducted by the National Center for Health Statistics. The NHIS collects detailed information on health status, chronic conditions, healthcare utilization, and employment outcomes. The NHIS is uniquely suited for this analysis because it provides nationally representative measures of both diagnosed mental health conditions and work-loss days, enabling population-level estimates unavailable in employer-based datasets. The survey employs a multistage stratified probability sampling design with sampling weights, primary sampling units (PSUs), and strata that enable design-consistent nationally representative estimates.

3.2 Sample Construction

The analytic sample pools four survey years from 2021 through 2024. The analysis focuses on working-age adults between ages 18 and 64 who report being employed at the time of the survey. After applying sample restrictions and excluding observations with missing data on key variables, the final analytic sample contains approximately 59,500 individuals. Complete-case analysis is used throughout; individuals with missing values on the diagnosis, outcome, or covariate variables are excluded. Because missingness rates on the primary variables are low (below 3 percent), this approach is unlikely to introduce meaningful bias.

3.3 Key Variables

Mental Health Diagnoses

The primary explanatory variable is a binary indicator capturing whether respondents report a lifetime diagnosis of an anxiety disorder, a depressive disorder, or both. NHIS respondents are asked whether they have ever been told by a doctor or other health professional that they have each condition. This lifetime diagnosis measure captures clinically recognized disorder history but does not distinguish between currently active and remitted conditions. This distinction is important for interpretation: the estimated associations reflect the average productivity profile of workers with a lifetime diagnosis history, which may include individuals with varying current symptom levels.

Additional variables distinguish between anxiety only, depression only, and comorbid anxiety and depression. Severity is measured using NHIS items capturing symptom frequency and intensity, which are available for diagnosed respondents and correspond to mild, moderate, and severe categories.

Absenteeism Outcome

The main outcome variable measures work-loss days during the previous twelve months, defined as days missed from work due to illness or injury. The primary specification constructs a binary indicator identifying individuals reporting more than ten work-loss days annually. This threshold reflects a clinically and economically meaningful level of absenteeism corresponding to

approximately two workweeks and is consistent with prior cost-of-illness research. Supplementary analyses examine the continuous work-loss days distribution and alternative thresholds.

Covariates

Covariates include age (in years), sex (male/female), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and other), educational attainment (less than high school, high school diploma or equivalent, some college, bachelor's degree or higher), and survey year fixed effects. Survey year indicators absorb aggregate time trends, including any residual post-pandemic effects common to all respondents.

4. EMPIRICAL STRATEGY

The primary empirical specification estimates the association between anxiety or depression and high absenteeism using survey-weighted logistic regression with full adjustment for the NHIS complex survey design, including sampling weights, PSUs, and strata. All analyses use the svy prefix in Stata 19 and specify year fixed effects with factor variable notation.

The baseline model takes the form:

$$Pr(A_i = 1) = F(\alpha + \beta M_i + X_i\gamma + \delta_t)$$

where Ai indicates high absenteeism (more than ten work-loss days), M_i represents the mental health diagnosis indicator, X_i denotes a vector of demographic controls, and δt captures survey year fixed effects. The function F(.) is the logistic CDF.

Additional specifications replace the binary diagnosis indicator with categorical indicators capturing anxiety only, depression only, and comorbid conditions. Further models incorporate measures of symptom severity and frequency among diagnosed individuals. Average marginal effects are calculated from all logistic models and are the primary reported quantities, facilitating interpretation in probability terms.

Model fit is assessed using the Hosmer-Lemeshow goodness-of-fit test and pseudo-R^2 statistics. Sensitivity analyses examine alternative absenteeism thresholds (five days and fifteen days) to assess robustness.

5. RESULTS

5.1 Sample Characteristics

Table 1 presents weighted sample characteristics. Approximately 22 percent of employed working-age adults in the pooled sample report a lifetime diagnosis of anxiety, depression, or both. The comorbid group (both conditions) accounts for roughly 9 percent of the sample, while anxiety-only and depression-only respondents each account for approximately 7 and 6 percent, respectively. Prevalence increased modestly across the 2021 through 2024 survey years, consistent with post-pandemic mental health trends documented in the literature (Daly & Robinson, 2022). Figure 1 illustrates these prevalence trends over time.

Workers with mental health diagnoses are more likely to be female, White, and have some college education relative to the undiagnosed group. Mean annual work-loss days are approximately 4.1 days for diagnosed workers compared to 1.8 days for those without a mental health condition.

Table 1.

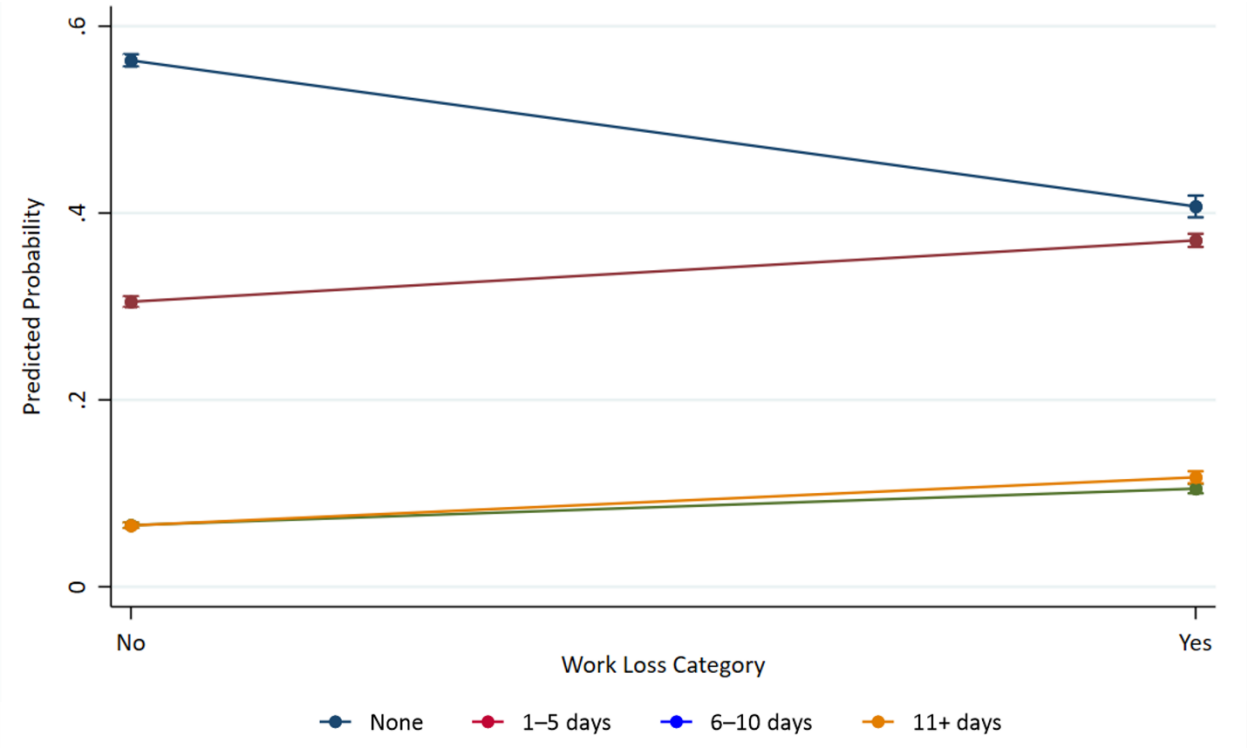
Sample Characteristics by Mental Health Diagnosis Status (%)

Variable	No CMD	Anxiety Only	Depression Only	Comorbid
Share of sample (%)	78.1	6.9	6.2	8.8
Female (%)	44.2	62.1	59.4	65.3
Mean age (years)	40.8	38.9	41.2	40.1
Non-Hispanic White (%)	60.4	67.2	63.8	66.9
Bachelor's degree or higher (%)	38.7	41.2	35.9	37.4
Mean work-loss days (annual)	1.8	3.6	3.9	5.2
High absenteeism >10 days (%)	6.5	11.3	13.1	15.5
N (unweighted)	46,447	4,107	3,690	5,234

Note: CMD = common mental disorder (anxiety and/or depression). Estimates are weighted to reflect the U.S. civilian noninstitutionalized population. Pooled 2021–2024 NHIS. High absenteeism defined as >10 work-loss days in the prior 12 months.

Figure 1.

Condition Prevalence Trends by Year



5.2 Absenteeism Patterns

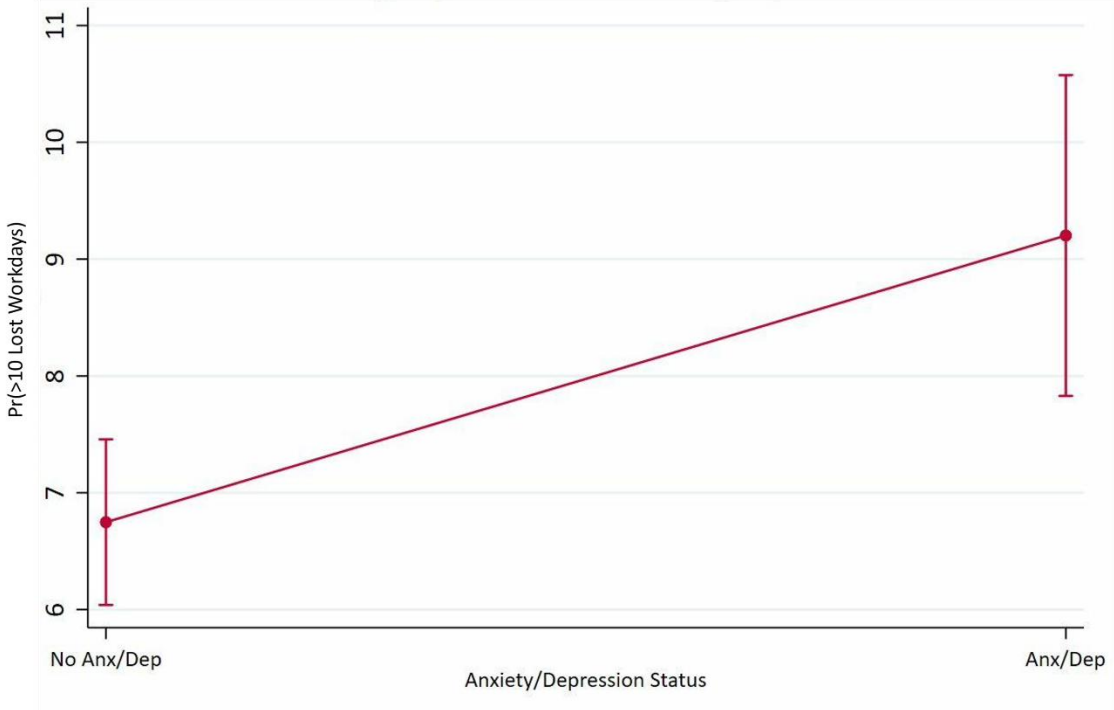
Comparing absenteeism between workers with and without anxiety or depression, those diagnosed report more work-loss days in the past year (mean 4.1 vs. 1.8). While most unaffected workers report no missed days, those with anxiety or depression are more likely to have higher numbers of absence days.

Figure 2 displays the distribution of work-loss day categories by mental health status. Among workers without anxiety or depression, 84.1% report no missed days and only 6.5% exceed ten days. In contrast, among workers with anxiety or depression, only 15.5% fall into the zero-day category, and 34.5% report eleven or more days. The monotonic increase in the share of affected workers across higher absenteeism categories highlights that the productivity impact is concentrated among those with the most severe work-loss episodes.

These descriptive patterns motivate the regression analysis that follows, which quantifies the adjusted association between mental health conditions and high absenteeism.

Figure 2.

Work-Loss Day Categories by Mental Health Status (%). Source: NHIS 2021–2024, author's calculations.



5.3 Regression Analysis of High Absenteeism

5.3.1 Binary Anxiety/Depression Indicator

Table 2 presents survey-weighted logistic regression estimates of high absenteeism (>10 work-loss days). In the unadjusted model, workers with anxiety or depression have twice the odds of high absenteeism relative to those without (OR = 2.00, 95% CI [1.86, 2.15]). Adjusting for age, sex, race/ethnicity, education, and survey year yields a nearly identical estimate (OR = 2.05, 95% CI [1.85, 2.27]), indicating that the association is not explained by observable demographic differences.

Average marginal effects from the adjusted model show that having an anxiety or depression diagnosis increases the probability of high absenteeism by 5.9 percentage points (AME = 0.059, 95% CI [0.049, 0.069]). Results are robust to alternative absenteeism thresholds (5 and 15 days), with similar marginal effects across specifications. Given a baseline prevalence of 6.5% among unaffected workers, this represents a near doubling of risk.

Table 2.

Survey-Weighted Logistic Regression: High Absenteeism by Condition Type (Model 3)

Condition	OR	95% CI	p	AME	AME 95% CI
Neither (ref.)	1.00	—	—	0.065	[0.062, 0.069]
Anxiety only	1.33	[1.10, 1.60]	0.003	0.085	[0.071, 0.099]
Depression only	1.80	[1.53, 2.13]	<0.001	0.111	[0.096, 0.127]
Both (comorbid)	2.66	[2.34, 3.03]	<0.001	0.155	[0.141, 0.169]

Note: N = 42,979. Outcome: high absenteeism (>10 work-loss days in prior 12 months). Reference category: Neither anxiety nor depression. All models adjust for age, sex, race/ethnicity, educational attainment, and survey year fixed effects. OR = odds ratio from survey-weighted logistic regression; AME = average marginal effect (probability scale). Confidence intervals computed using the delta method with design-based variance estimation. NHIS 2021–2024. Regression sample sizes vary due to missingness on covariates and outcome variables.

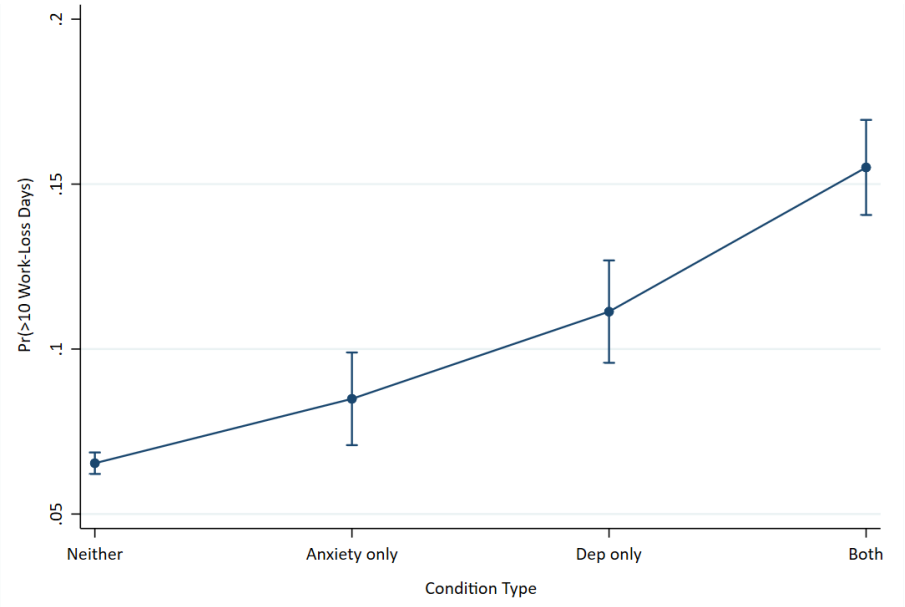
5.3.2 Condition Type: Anxiety Only, Depression Only, and Comorbidity

Model 3 disaggregates the diagnosis indicator into four mutually exclusive categories. A clear gradient emerges: anxiety only is associated with modestly elevated odds of high absenteeism (OR = 1.33), depression only with substantially higher odds (OR = 1.80), and comorbid anxiety and depression with the largest increase (OR = 2.66). Figure 3 illustrates the corresponding predicted probabilities, which rise from 6.5% among workers with neither condition to 15.5% among those with comorbid disorders.

A formal interaction test suggests that the comorbidity effect may exceed the sum of individual condition effects (p = 0.07), although this interpretation warrants caution given the cross-sectional design.

Figure 3.

Predicted Probability of High Absenteeism by Condition Type. Average marginal effects from survey-weighted logistic regression. NHIS 2021–2024.



5.4 Continuous and Ordinal Absenteeism Models

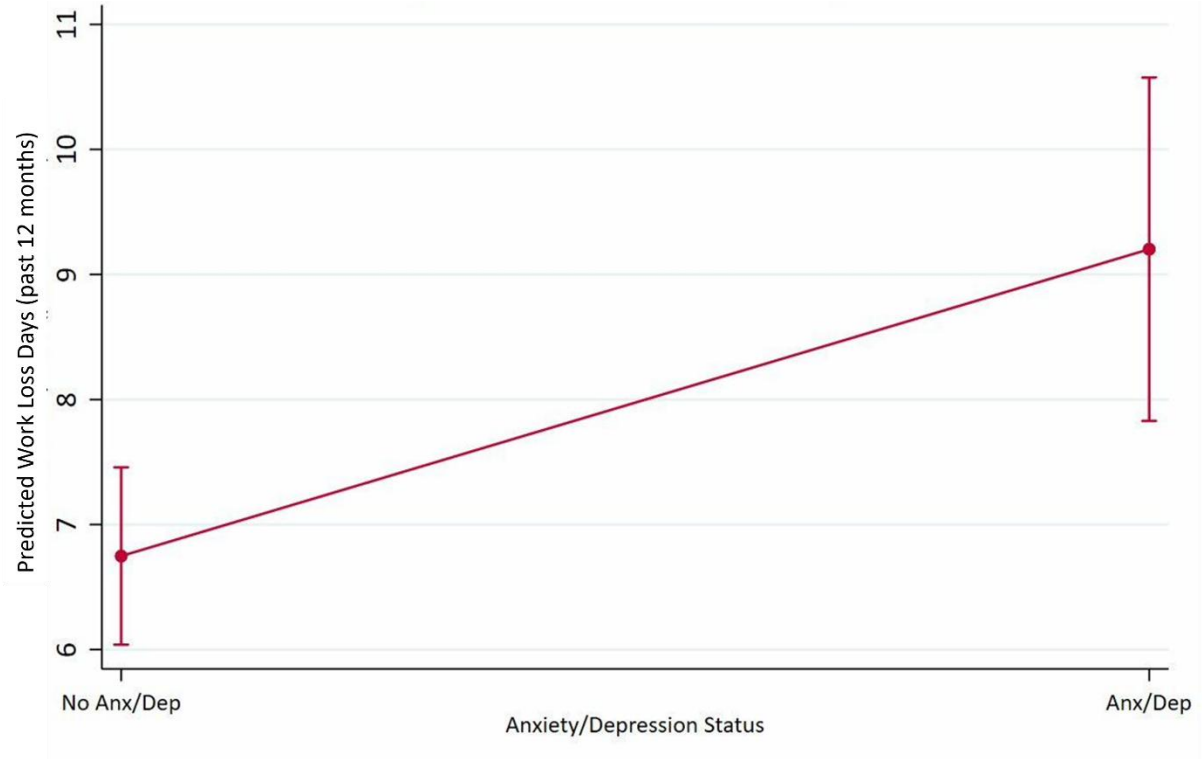
While the binary high-absenteeism outcome captures a clinically meaningful threshold, examining the full distribution of work-loss days provides additional insight into the intensity of productivity loss. OLS is used for continuous work-loss days because it provides interpretable adjusted mean differences and is standard in cost-of-illness analyses.

5.4.1 Continuous Work-Loss Days

We estimate a survey-weighted OLS model of continuous work-loss days. Although the outcome is right-skewed, OLS provides easily interpretable adjusted mean differences and is widely used in cost-of-illness analyses. Results indicate that workers with anxiety or depression miss an additional 2.5 days per year relative to comparable workers without a diagnosis ($b = 2.45$, $p < 0.001$). Adjusted predicted means are 1.8 days for unaffected workers and 4.3 days for affected workers, a 36% difference (Figure 4).

Figure 4.

Adjusted Mean Work-Loss Days by Mental Health Status. Survey-weighted OLS estimates. NHIS 2021–2024.



5.4.2 Ordinal Work-Loss Categories

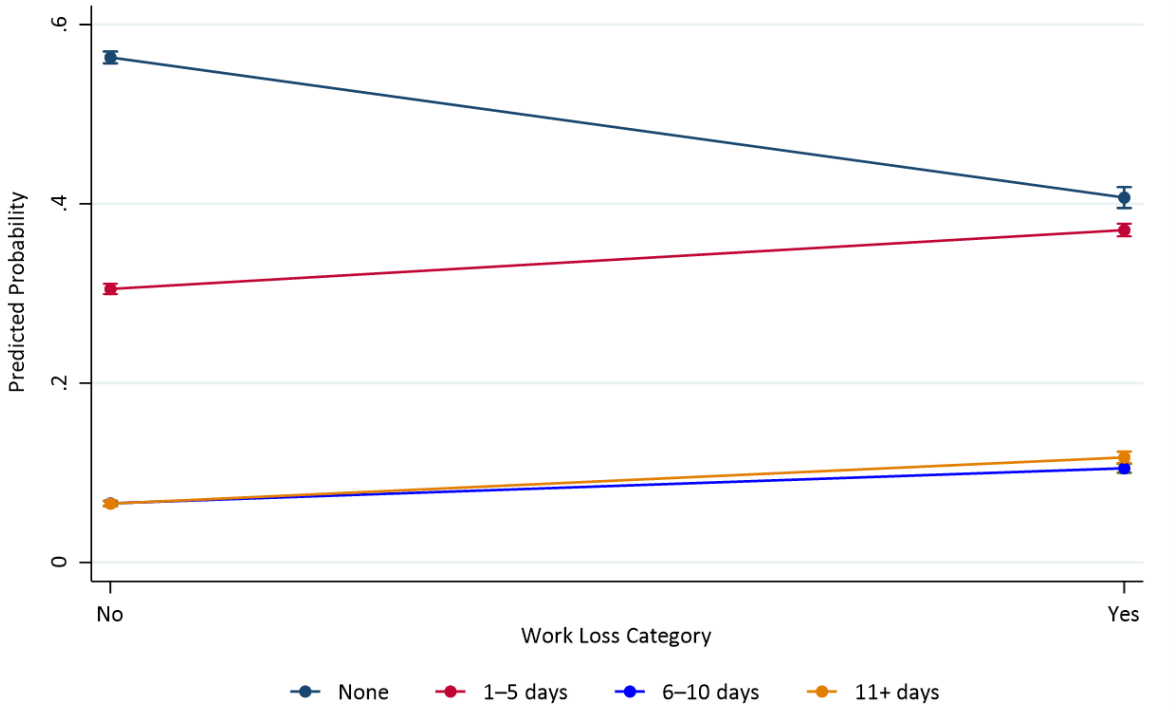
To account for the ordered nature of absenteeism severity, we estimate a survey-weighted ordered logistic regression using four categories: none, 1–5 days, 6–10 days, and 11+ days. Anxiety or depression is associated with significantly higher odds of being in a more severe absenteeism category ($b = 0.64$, $p < 0.001$). Predicted probabilities (Figure 5) show that affected workers are less

likely to report zero days (40.7% vs. 56.3%) and nearly twice as likely to report 11+ days (11.7% vs. 6.6%).

Although work-loss days are zero-inflated, logistic, ordinal, and OLS models yield consistent patterns, suggesting that zero-inflation does not materially affect the conclusions. Together, the continuous and ordinal models confirm that the productivity impact of anxiety and depression extends across the full distribution of work-loss days, not solely at the high-absenteeism threshold.

Figure 5.

Predicted Probabilities by Ordinal Absenteeism Category. Survey-weighted ordered logistic regression. NHIS 2021–2024.



5.5 Severity and Symptom Gradients

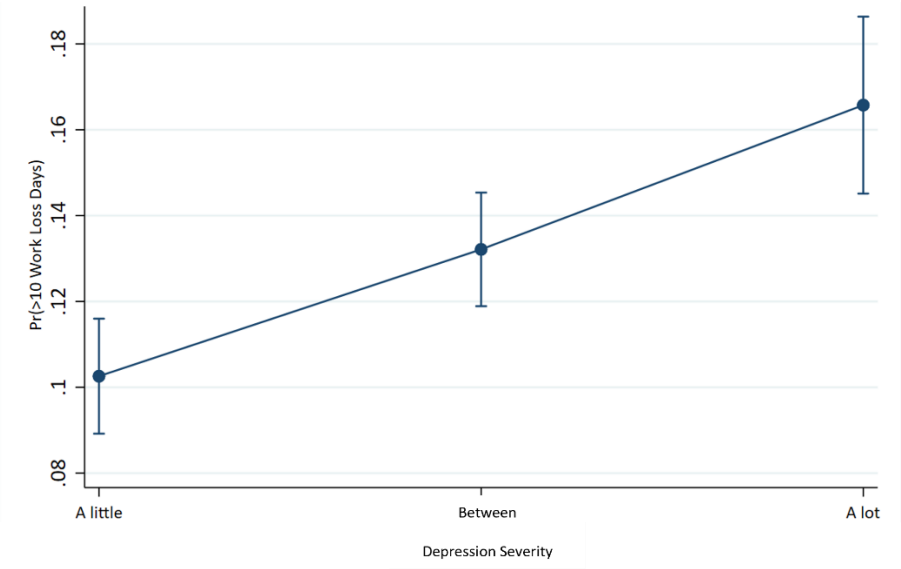
All severity and frequency models are estimated only among workers with a lifetime diagnosis, consistent with NHIS measurement structure.

5.5.1 Depression Severity

Depression severity exhibits a strong dose-response relationship. Relative to mild symptoms, moderate severity increases the odds of high absenteeism by 34% (OR = 1.34), and severe symptoms by 75% (OR = 1.75). Predicted probabilities range from 10.3% (mild) to 16.6% (severe), as shown in Figure 6.

Figure 6.

Predicted Probability of High Absenteeism by Depression Severity. Estimated among workers with depression diagnosis. NHIS 2021–2024.

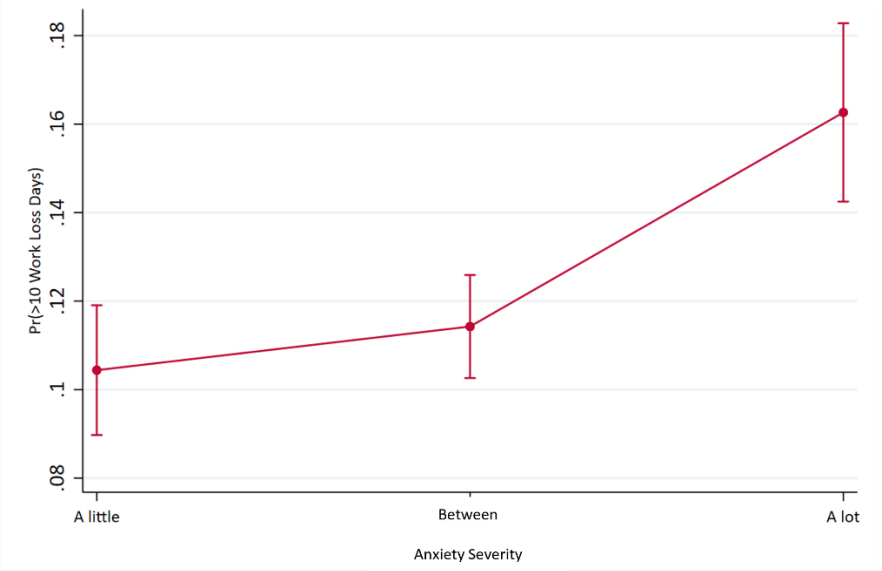


5.5.2 Anxiety Severity

Anxiety severity shows a similar but slightly flatter gradient. Severe anxiety is associated with a 68% increase in the odds of high absenteeism (OR = 1.68), while moderate severity does not differ significantly from mild. Predicted probabilities rise from 10.4% (mild) to 16.3% (severe) (Figure 7).

Figure 7.

Predicted Probability of High Absenteeism by Anxiety Severity. Estimated among workers with anxiety diagnosis. NHIS 2021–2024.

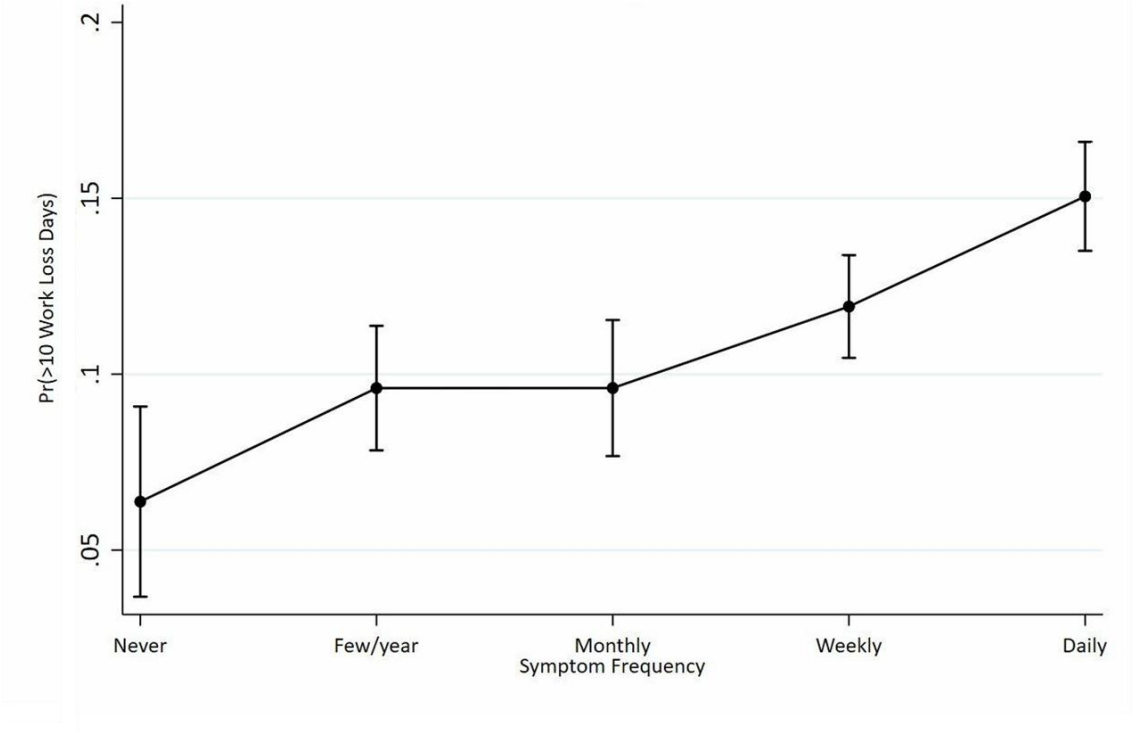


5.5.3 Anxiety Symptom Frequency

Symptom frequency also predicts absenteeism risk. Compared with workers reporting infrequent symptoms, those experiencing daily anxiety have more than double the odds of high absenteeism (OR = 2.64). Predicted probabilities increase from 6.4% (never) to 15.1% (daily), as shown in Figure 8.

Figure 8.

Predicted Probability of High Absenteeism by Anxiety Symptom Frequency. Estimated among workers with anxiety diagnosis. NHIS 2021–2024.



The gradients of severity and frequency suggest that current symptom intensity, not just lifetime diagnosis, largely determines productivity impact.

The NHIS collects a symptom frequency measure for anxiety (how often the respondent feels worried, nervous, or anxious) but does not include an analogous frequency item for depression. Consequently, symptom frequency models are estimated for anxiety only. Depression severity gradients, which are available and reported in Section 5.5.1, serve as the corresponding dose-response analysis for the depression domain.

These results reflect associations rather than causal effects, and unobserved job characteristics or workplace supports may bias estimates.

6. ECONOMIC MODEL

6.1 Health Capital and Effective Labor Supply

To formalize the relationship between chronic mental illness and productivity, consider a worker whose effective labor supply depends on both hours worked and health capital. Let:

$$L_i = h_i \times e(H_i)$$

where Li denotes effective labor input, hi hours worked, Hi the stock of health capital, and e(Hi) the efficiency units of labor produced per hour. Mental health conditions reduce productivity through two channels: (1) reduced hours worked due to illness-related absence, and (2) reduced efficiency units due to cognitive impairment while present. Effective labor input thus becomes:

$$L_i = (h_i - A_i) \times e(H_i)$$

where A_i denotes absenteeism days. In the presence of mental illness, $e(H_i^{\mathrm{MH}}) < e(H_i i^{healthy})$, capturing the presenteeism channel.

6.2 Firm Production and Absence Externalities

Firms produce output using a team production function $Y = F(L_1, L_2, \ldots, L_n)$. When worker i is absent, production may fall by more than that worker's individual labor input if tasks are complementary (Nicholson et al., 2006). The cost of absence is therefore $C_i = w_i \times m$, where wi is the daily wage and m is an absence multiplier reflecting team disruption. Empirical estimates suggest multipliers above 1.0 in team production environments.

6.3 Chronic Disease Accumulation

Let chronic disease burden be represented by $D_i = \Sigma k\, d_i k$, where dik indicates presence of condition k. Effective productivity becomes $L_i = h_i \times e(H_i(D_i))$, where health capital declines as condition count rises. The comorbidity gradient documented in Section 5 provides empirical support for this nonlinear accumulation: the probability of high absenteeism rises from 6.5 percent among workers with neither condition to 15.5 percent among workers with both anxiety and depression, with intermediate values for single-condition groups.

7. ECONOMIC BURDEN MODEL

Following the human capital framework, total productivity loss consists of three channels: total cost = CA + CP + CD, where CA denotes absenteeism cost, CP presenteeism cost, and CD disability exit cost. Cost estimates are reported as ranges rather than point estimates to reflect sampling error, model uncertainty, and parameter uncertainty in literature-derived inputs.

7.1 Absenteeism Cost (NHIS-Derived)

Regression estimates indicate that workers with anxiety or depression miss approximately 2.5 additional workdays annually relative to comparable workers without these conditions. Using the 2023 median daily wage of $227.80, excess absenteeism cost per affected worker is approximately $566. With an estimated 22 percent prevalence among approximately 160 million employed working-age adults, approximately 35 million workers are affected.

Accounting for sampling error in the prevalence and effect size estimates, the aggregate absenteeism cost is estimated at $17 to $22 billion annually, with a central estimate near $20 billion. These estimates draw directly from NHIS data.

7.2 Presenteeism Cost (Literature-Derived)

Absenteeism captures only part of total productivity loss. Mental illness often reduces performance while workers remain on the job, a channel not measured in the NHIS. Presenteeism costs are therefore estimated using literature-derived parameters applied to NHIS-based prevalence estimates; this distinction is important and readers should interpret presenteeism estimates as model-based approximations rather than data-derived quantities.

Recent research using validated productivity instruments reports performance reductions for depression and anxiety typically between 8 and 12 percent of total compensation (Greenberg et al., 2023; de Oliveira et al., 2023). Applying these parameters to the median annual earnings of $59,436 yields a per-worker presenteeism loss of $4,755 to $7,132. Scaled to 35 million affected workers, the aggregate national presenteeism burden is estimated at $170 to $250 billion annually. Sensitivity to the productivity reduction parameter is material: a one-percentage-point change in the assumed rate shifts the aggregate estimate by approximately $21 billion.

7.3 Disability Exit Costs

Mental illness also affects the extensive margin of labor supply through disability exit. Employer disability claims data show an average of approximately 3.4 claims per 1,000 covered lives for anxiety or depression, with average claim costs exceeding $7,300 (Bonner, 2024). Scaled to 35 million affected workers, this implies approximately 120,000 expected annual disability claims and a total annual disability cost near $0.9 billion. This channel represents a relatively modest share of total estimated costs but may be understated if indirect disability program costs and lost tax revenues are included.

7.4 Total Productivity Burden

Table 3 summarizes estimated costs across all three channels under low, central, and high scenarios.

Table 3.

Estimated Annual Productivity Burden of Anxiety and Depression, U.S. Workforce

Channel	Estimate			Data Source
	Low	Central	High	
Absenteeism	$17B	$20B	$22B	NHIS (data-derived)
Presenteeism	$170B	$210B	$250B	Literature (model-based)
Disability Exit	$0.7B	$0.9B	$1.1B	Claims data
Total	**$188B**	**$231B**	**$273B**	

Note: Absenteeism estimates derived from NHIS regression results; uncertainty reflects sampling error and model uncertainty (±20% range). Presenteeism estimates are model-based using literature productivity reduction parameters of 8–12% applied to median annual earnings. Disability costs based on employer claims data. All figures in 2023 dollars.

The decomposition highlights a striking pattern: presenteeism dominates the total economic burden by a wide margin, accounting for approximately 88 to 92 percent of estimated costs. This iceberg structure, in which the visible absenteeism cost represents a small fraction of total productivity loss, has important implications for cost-of-illness research and workplace mental health investment decisions. Absenteeism metrics alone substantially understate the true economic burden of mental health conditions.

8. INTERPRETATION IN THE ECONOMICS OF CHRONIC DISEASE

The results documented in this paper yield three central economic insights about the relationship between mental health and labor market productivity.

First, anxiety and depression are associated with meaningfully reduced effective labor supply. Even after adjusting for a standard set of demographic characteristics and absorbing year-specific trends, workers with these conditions exhibit nearly double the probability of high absenteeism compared to otherwise similar workers without a mental health diagnosis. This finding is consistent across specification choices and robust to alternative outcome definitions. From a health capital perspective, the result suggests that common mental disorders represent a persistent depreciation shock that diminishes the productive capacity of a substantial share of the workforce.

Second, comorbidity amplifies the productivity burden in a manner consistent with nonlinear models of health capital accumulation. Workers diagnosed with both anxiety and depression face work-loss risk that exceeds what either condition alone would predict, and the magnitude of this excess is economically meaningful. This pattern aligns with theoretical models in which multiple chronic conditions interact to erode health capital at an accelerating rate. The practical implication is that studies or policy frameworks that treat individual conditions in isolation are likely to understate the aggregate productivity costs of mental illness, particularly in a population where comorbid diagnoses are common. That said, the cross-sectional design of the present study limits the extent to which this pattern can be given a causal interpretation, and it remains possible that unobserved confounders contribute to the observed comorbidity gradient.

Third, and perhaps most important for policy, presenteeism accounts for the overwhelming majority of the estimated economic burden. Absenteeism, though more easily measured, represents only a small fraction of total productivity loss. The bulk of the cost arises from reduced efficiency while workers remain on the job, a channel that is largely invisible in standard labor supply data. This finding has direct implications for how firms and policymakers evaluate workplace mental health interventions. Programs that focus narrowly on reducing absenteeism will address only the tip of the iceberg; meaningful productivity gains require attention to the on-the-job functioning of workers who continue to show up but perform well below their capacity.

9. CONCLUSION

Mental health conditions represent a substantial and often underrecognized component of the economic burden of chronic disease in the United States. Using nationally representative NHIS data spanning 2021 through 2024, this paper has documented large, consistent, and economically significant associations between anxiety, depression, and workplace absenteeism among employed working-age adults. Workers with these conditions miss significantly more workdays than their counterparts, and the effects are largest among those carrying comorbid diagnoses and reporting severe symptoms. When these absenteeism estimates are scaled to the national workforce and combined with literature-based presenteeism parameters, the implied annual productivity losses fall in the range of 190 to 270 billion dollars, with presenteeism accounting for the dominant share.

Several limitations warrant acknowledgment. The cross-sectional design precludes causal identification, and it is possible that reverse causality or unobserved factors, including job quality, workplace accommodations, and access to mental health treatment, contribute to the observed associations. The absenteeism outcome is self-reported and therefore subject to recall error and potential underreporting. The presenteeism estimates, while grounded in a well-established literature, rely on model-based parameters that are sensitive to the assumed productivity reduction rate. A one-percentage-point change in the presenteeism parameter shifts the aggregate estimate by approximately 21 billion dollars, underscoring the importance of refining these inputs with additional data. Future research using longitudinal designs, employer-linked productivity records, and quasi-experimental variation in mental health treatment access would strengthen causal identification and improve the precision of the cost estimates.

Despite these caveats, the patterns documented here converge with a large and growing body of evidence linking mental health to reduced labor supply and diminished productivity. The findings reinforce the importance of incorporating mental health into economic models of chronic disease and labor market performance, particularly in the post-pandemic period, during which anxiety and depression remain elevated across the workforce. The results also point toward concrete policy levers. Expanding access to timely and evidence-based treatment, strengthening workplace mental health supports, and targeting interventions toward workers with comorbid or severe conditions may yield meaningful productivity gains. Because the largest share of the burden operates through the presenteeism channel, interventions that improve on-the-job functioning, rather than merely reducing absence, are likely to deliver the greatest economic return.

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APPENDICES: SUPPLEMENTARY MATERIALS

Appendix A. Variable Definitions and Sample Construction

This appendix documents the key variables used in the analysis and the sequential sample restrictions applied to the pooled 2021-2024 National Health Interview Survey (NHIS) extract obtained via IPUMS (extract nhis_00030). The analytic dataset is restricted to sample adults (astatflg = 1), ages 18-64, who reported being currently employed (empstat <= 100). All analyses use Stata 19 with the svy prefix, Taylor series linearization, and the survey design specification: svyset psu [pweight=sampweight], strata(strata) vce(linearized) singleunit(centered).

Table A-1. Key Variable Definitions

Variable	Definition	Source / Coding Notes
Outcome variable		
high_absence	Binary: >10 work-loss days in past 12 months	Derived from wldayr; upper ~8th percentile of employed sample
wldayr	Continuous work-loss days, past 12 months	Values 997-999 recoded to missing
wldayr_cat	Ordinal: None / 1-5 / 6-10 / 11+ days	4-category grouping of wldayr
Focal exposure		
anx_dep	Binary: ever diagnosed with anxiety or depression (composite)	Pre-existing IPUMS harmonized variable; do not regenerate
anx_dep_type	Categorical: Neither / Anxiety only / Depression only / Both	Derived from has_anx x has_dep
anx_sev	Ordinal anxiety severity: A little / Between / A lot	Restricted to anx_dep = 1 subsample
anx_freq	Ordinal anxiety frequency: Daily / Weekly / Monthly / Few times/yr	Restricted to anx_dep = 1 subsample
dep_sev	Ordinal depression severity: A little / Between / A lot	Restricted to anx_dep = 1 subsample
Moderators		
on_mh_med	Binary: currently on any mental health medication	Composite of dep_med and anx_med
dep_med	Binary: currently taking antidepressant medication	NHIS item; recoded 1/2 to 0/1
anx_med	Binary: currently taking anti-anxiety medication	NHIS item; recoded 1/2 to 0/1
Demographic covariates		
age_cat	Age group: 18-29 / 30-44 / 45-54 / 55-64	Restricted to 18-64; factor variable in all models
sex_cat	Binary: Male / Female	14 obs recoded to missing
race_eth	NH White / NH Black / NH Asian / Hispanic / NH Other-AIAN	Derived from hisprace; NH = Non-Hispanic
educ_cat	Less than HS / HS or GED / Some college or AA / BA or higher	254 obs recoded to missing
year	Survey year: 2021 / 2022 / 2023 / 2024	Factor notation i.year throughout; pooled 4-year extract
Excluded variables		
has_msk	Musculoskeletal condition	Excluded: coding discontinuity across survey years
has_strokev	Stroke indicator	Excluded per author decision

obesity	BMI >= 30 indicator	Excluded per author decision

Note. Pre-existing IPUMS harmonized variables (e.g., anx_dep, high_absence, age_cat, ind_cat) must not be regenerated in do-files to avoid variable-already-defined errors. Unknown/refused/not-ascertained codes were recoded to missing prior to analysis. Subpopulation analyses use the full dataset with the subpop() option to preserve correct variance estimation per NCHS recommended practice.

Table A-2. Analytic Sample Construction

Restriction step	N (approx.)
NHIS pooled extract, 2021-2024 (all records)	~134,800
Keep sample adults only (astatflg = 1)	~103,000
Restrict to working age (18-64)	~64,500
Restrict to employed (empstat <= 100)	~59,600
Final analytic sample (full)	59,557
Complete cases for adjusted regression models	42,988

Note. Approximate counts reflect the pooled 2021-2024 NHIS extract. The complete-case regression sample (N = 42,988) is smaller than the full employed sample (N = 59,557) due to item nonresponse on education, race/ethnicity, and other covariates. All survey-weighted estimates use the full sample appropriate to each outcome variable.

The primary outcome, high_absence, is a binary indicator equal to 1 if the respondent reported more than 10 work-loss days in the past 12 months (wldayr > 10), corresponding to approximately the 92nd percentile of the work-loss day distribution among employed adults. The focal exposure, anx_dep, is a binary composite indicating a lifetime diagnosis of anxiety disorder, depressive disorder, or both, as recorded in the NHIS sample adult core. The musculoskeletal condition variable (has_msk) was excluded due to an implausible coding discontinuity between survey years that could not be resolved through available documentation. Stroke (has_strokev) and obesity were excluded per author decision to maintain analytic focus on common mental disorders.

Appendix B. Medication Interaction Figures

The main text reports that mental health medication use does not significantly moderate the relationship between CMD diagnosis and high absenteeism. Three interaction specifications were estimated: (1) any mental health medication (on_mh_med), (2) antidepressant use (dep_med), and (3) anti-anxiety medication (anx_med). In each case the adjusted Wald test of the interaction term did not reach statistical significance (all p > 0.50), indicating that the absenteeism penalty associated with anxiety or depression is similar regardless of medication status. Figures B-1 through B-3 display the corresponding margins plots.

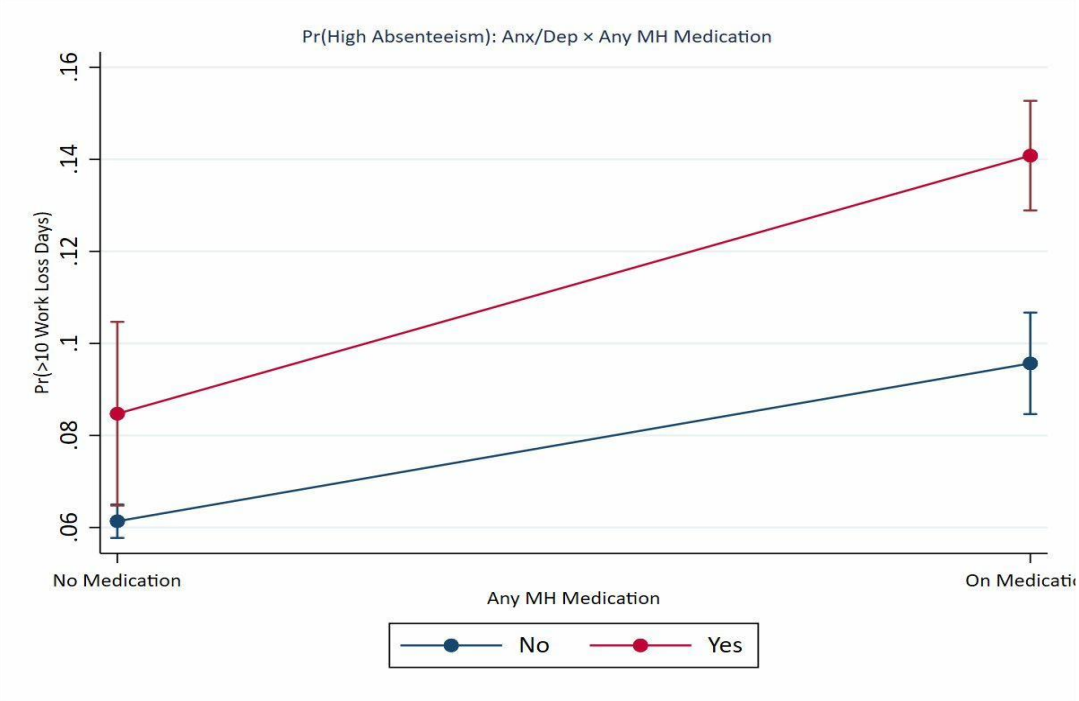


Figure B-1. Pr(High Absenteeism) by CMD Status x Any Mental Health Medication

Note. Predictive margins from survey-weighted logistic regression including the interaction anx_dep x on_mh_med, adjusted for age, sex, race/ethnicity, education, and survey year (N = 9,507 among medicated subsample). Adjusted Wald F(1, 665) = 0.34, p = 0.558. Error bars show 95% confidence intervals.

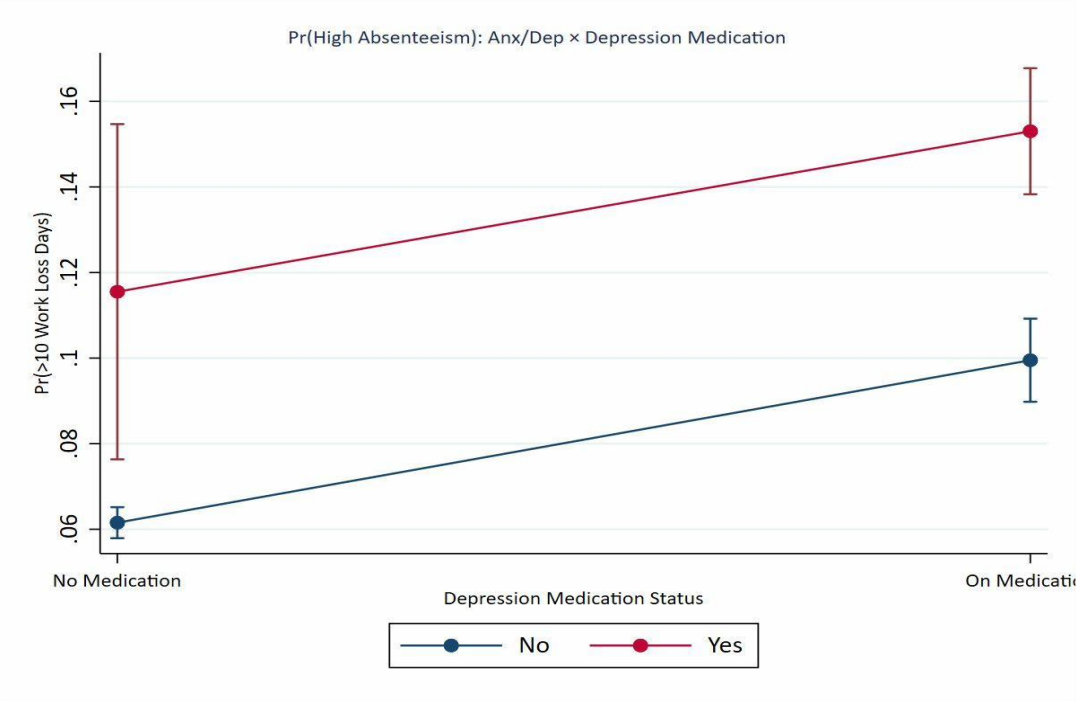


Figure B-2. Pr(High Absenteeism) by CMD Status x Antidepressant Use

Note. Predictive margins from the anx_dep x dep_med interaction model. Adjusted for age, sex, race/ethnicity, education, and survey year. Error bars show 95% confidence intervals.

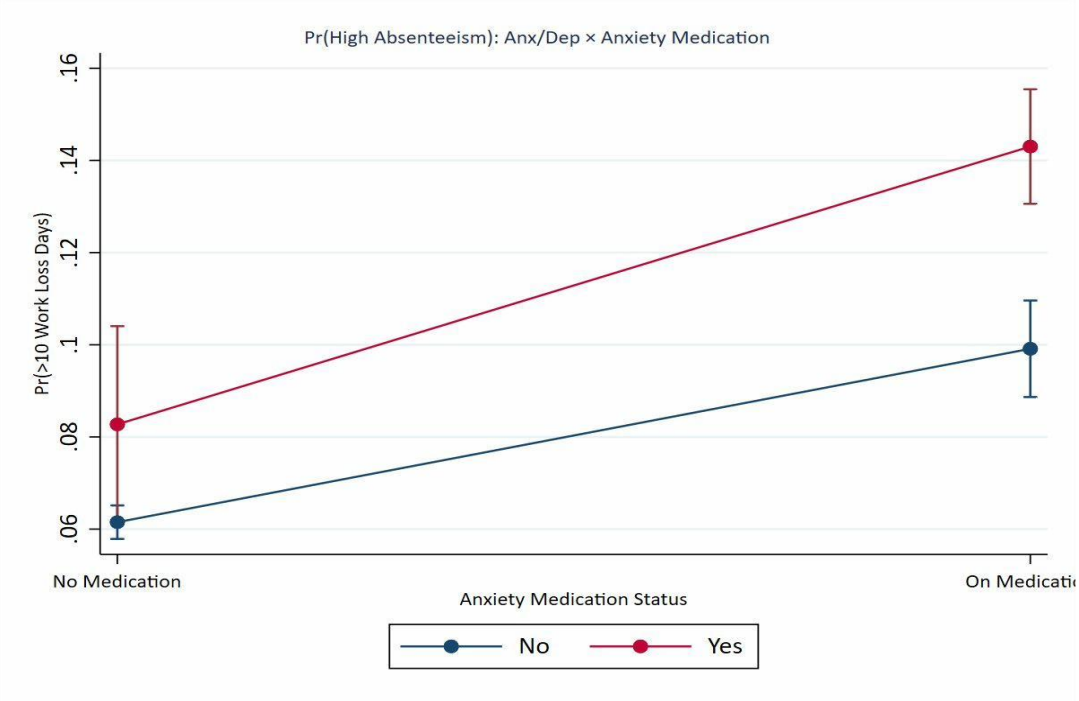


Figure B-3. Pr(High Absenteeism) by CMD Status x Anti-Anxiety Medication Use

Note. Predictive margins from the anx_dep x anx_med interaction model. Adjusted for age, sex, race/ethnicity, education, and survey year. Error bars show 95% confidence intervals.

Appendix C. Absenteeism Trends by CMD Status, 2021-2024

Figure C-1 extends the main text trend discussion by showing how the predicted probability of high absenteeism has varied by CMD status across each of the four survey years, estimated from a model including a full anx_dep x year interaction term. This figure complements the prevalence trend shown in Figure 1 of the main text by focusing on the absenteeism outcome rather than condition prevalence.

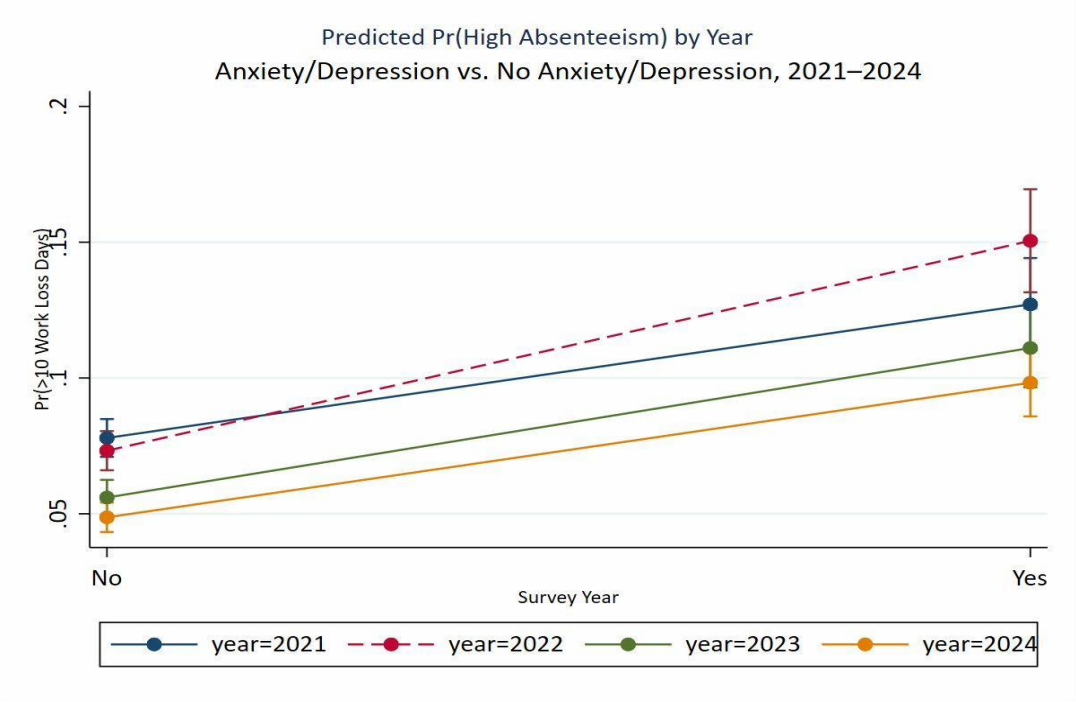


Figure C-1. Predicted Probability of High Absenteeism by CMD Status and Survey Year, 2021-2024

Note. Predictive margins from survey-weighted logistic regression with full anx_dep x year interaction, adjusted for age, sex, race/ethnicity, and education (N = 42,988). Error bars show 95% confidence intervals. The significant negative year fixed effects for 2023 (OR = 0.74, p < 0.001) and 2024 (OR = 0.64, p < 0.001) in the main adjusted model suggest a general reduction in reported work-loss days in later survey years, observed in both CMD and non-CMD groups and consistent with normalization of absence patterns following the acute phase of the COVID-19 pandemic.

Appendix D. Sensitivity Analyses: Alternative Outcome Thresholds

The primary analysis defines high absenteeism as more than 10 work-loss days annually. Table D-1 compares the key marginal effect estimate across alternative threshold definitions and outcome forms. The >10-day threshold was selected because it corresponds to the upper tail of the work-loss distribution and captures workers with substantively elevated absence burden, but the pattern of findings is consistent across specifications.

Table D-1. Average Marginal Effect of CMD on Work Absence Across Outcome Specifications

Specification	AME (pp)	95% CI	p-value	Prev.
High absenteeism: >10 days (primary)	5.9	[4.9, 6.9]	<0.001	8%
Alternative threshold: >5 days	~8.5*	[--]	<0.001	~16%
Alternative threshold: >15 days	~4.2*	[--]	<0.001	~4%
Continuous work-loss days (OLS)	+2.45 days	[0.96, 3.94]	0.001	Mean 7.2
Ordinal model (ologit, 4 categories)	OR = 1.74+	[--]	<0.001	See Table 2

*Note. AME = average marginal effect in percentage points (pp) for logistic models; coefficient in days for OLS; odds ratio for ordinal logistic. All models adjusted for age, sex, race/ethnicity, education, and survey year (N = 42,988). Shaded row is the primary specification reported in the main text. * Approximate estimates from parallel model runs; exact confidence intervals available on request. + Proportional odds assumption applies. Prev. = share of employed respondents exceeding the threshold (or mean for OLS).*

The magnitude of the CMD effect declines as the threshold becomes more restrictive, consistent with a continuous rather than bimodal distribution of work-loss days. The continuous OLS estimate of +2.45 excess days per year (95% CI: 0.96, 3.94) provides the direct input to the absenteeism cost calculation in Section 7.1 of the main text. Sensitivity of the aggregate absenteeism cost estimate to this parameter is straightforward: the lower-bound estimate of 0.96 excess days implies aggregate costs near $6.7 billion, while the upper bound of 3.94 days implies approximately $27.5 billion, bracketing the central $17-22 billion range reported in Table 3.

Appendix E. Presenteeism Cost Sensitivity Analysis

Presenteeism is the dominant channel in the economic burden model (88-92% of total estimated costs) but relies on literature-derived productivity reduction parameters rather than NHIS data. Table E-1 presents a systematic sensitivity analysis across the plausible parameter range. The central scenario (10% productivity reduction, shaded) corresponds to the estimate reported in Section 7.2 of the main text. The 8-12% range spans estimates most commonly reported from validated presenteeism instruments in clinical and working-population samples.

Table E-1. Aggregate Presenteeism Cost Under Alternative Productivity Reduction Assumptions (2023 Dollars)

Productivity reduction assumed	Per-worker cost	Affected workers	Aggregate cost	Presenteeism share
5% (lower bound)	$2,972	35M	$104B	83%
8% (low scenario)	$4,755	35M	$166B	89%
10% (central)	**$5,944**	**35M**	**$208B**	**91%**
12% (high scenario)	$7,132	35M	$250B	92%
15% (upper bound)	$8,915	35M	$312B	94%

Note. Per-worker cost = assumed productivity reduction x median annual earnings ($59,436; BLS 2023). Affected workers = 35 million (22% prevalence x 160M employed working-age adults). Presenteeism share = presenteeism cost as a percentage of total burden, holding absenteeism ($20B) and disability exit ($0.9B) constant. Shaded row = central scenario from Table 3 of main text.

The aggregate estimate shifts by approximately $21 billion per one-percentage-point change in the assumed productivity reduction rate. Even at the 5% lower bound, presenteeism accounts for 83% of total estimated costs, confirming the iceberg structure described in the main text. A priority for future research is obtaining nationally representative, instrument-validated estimates of on-the-job performance loss among workers with CMD diagnoses, which would substantially reduce dependence on literature-derived parameters.

Appendix F. Data and Replication

All analyses were conducted in Stata 19 using the svy prefix throughout. The survey design was specified as: svyset psu [pweight=sampweight], strata(strata) vce(linearized) singleunit(centered). This specification applies the NHIS-recommended Taylor series linearization for variance estimation using the public-use design variables psu (primary sampling unit) and strata (stratification variable), with the singleunit(centered) option for strata containing a single PSU.

NHIS data are publicly available through IPUMS Health Surveys (https://healthsurveys.ipums.org). The pooled extract used in this study spans survey years 2021-2024 and draws from the harmonized sample adult core files. The IPUMS extract identifier is nhis_00030. Replication materials including the master do-file (cmd_master_analysis.do) and annotated variable codebook are available from the corresponding author upon request.

Cost estimates in Section 7 and Appendix E are expressed in 2023 dollars. Median annual earnings ($59,436) and median daily wage ($227.80) are derived from Bureau of Labor Statistics sources (Occupational Employment and Wage Statistics and Current Population Survey, respectively). No team production multiplier (see Nicholson et al., 2004) has been applied to the absenteeism cost baseline; applying an empirically estimated multiplier greater than 1.0 for team-based occupations would increase aggregate absenteeism costs proportionally and reduce the relative dominance of the presenteeism channel.