INTEGRATED BENEFITS INSTITUTE

Snapshot 2.0 Technical Appendix

Contents

I. Overview 1

II. Lost time dependent variables 1

1. Hours worked 1
2. Job performance 2

III. Chronic conditions and co-morbidities 2

1. Chronic condition inventory 2
2. Other co-morbidities 3

IV. Demographic and other variables 3

1. Age 3
2. Sex 4
3. Occupation 4
4. Expected hours 4
5. Full-time status 4
6. Data source 5

V. Excluded cases 5

VI. Equations 5

1. Chronic conditions and treatment status 5
2. General note on modeling co-morbidities 6
3. Hours worked and job performance 7
4. Number of chronic conditions 7

VII. User inputs and default values 8

1. Occupations 9
2. Average daily wages and benefits 10
3. Expected hours worked 10
4. Lost productivity multipliers 11

VIII. Reporting lost/gained time for chronic conditions 11
1. Prevalence of chronic conditions 11
2. Per-person impacts 11
i. Hours worked 11
ii. Job performance/presenteeism 12
3. Workforce impacts 13
i. Hours worked 13
ii. Presenteeism 13
IX. Monetizing lost/gained time 13

I. Overview

The Health and Productivity Snapshot uses data obtained through the Health and Productivity Questionnaire (HPQ) – a modified version the World Health Organization's Health and Work Performance Questionnaire – to provide estimates of lost work time (and associated costs) independently attributable to employees' chronic health conditions. It is designed to eliminate the time, resources and analytic expertise required to develop an organization's initial cost estimate by providing an answer for multiple chronic conditions "on average" and simulating outcomes from the underlying results.

Snapshot estimates lost work time of two different types:

1. Reduced hours worked for employees with a given chronic health conditions relative to employees without that condition
2. The proportion of the work day lost to underperformance for employees with a given chronic health conditions relative to the typical performance of employees without that condition (i.e., "presenteeism")

The original survey was developed by Dr. Ronald Kessler of the Harvard Medical School, who collaborated with IBI to develop a modified version and provided IBI with data collected from nine employers (almost 40,000 employee surveys in all). IBI has subsequently administered the survey to additional employers, and periodically adds this information to the HPQ data. As of this writing, data for 55 employers (supplied from a single vendor, and referred to throughout this document as "supplemental employers") have been added, bringing the total number of employee surveys to almost 140,000.

For the purposes of Snapshot reporting, the HPQ contains three relevant sections: 1) work attendance and job performance, 2) chronic illnesses, and 3) demographic information. The remainder of this document describes the variables used in the analysis, the preparation of cases for inclusion in the models, the estimating equations, and guidelines for interpreting the results in terms of lost time and associated costs.

II. Lost time dependent variables

1. Hours worked

The HPQ asks the following question:

About how many hours altogether did you work in the <u>past 4 weeks</u> (28 days)? Examples for Calculating Hours Worked in the Past 4 Weeks:

- 40 hours per week for 4 weeks = 160 hours
- 35 hours per week for 4 weeks = 140 hours

- 40 hours per week for 4 weeks with 2 8-hour days missed = 144 hours
- 40 hours per week for 4 weeks with 3 4-hour partial days missed = 148 hours
- 35 hours per week for 4 weeks with 2 8-hour days missed and 3 4-hour partial days missed = 112 hours

We retain the original response, but count as missing information any responses higher than 392 (i.e., 14 hours per day for 28 consecutive days).

2. Job performance

The HPQ asks the following question:

On a scale from 0 to 10 where 0 is the worst job performance anyone could have at your job and 10 is the performance of a top worker … how would you rate your overall job performance on the days you worked during the past 4 weeks (28 days)?

We retain the original response.

III. Chronic conditions and co-morbidities

1. Chronic condition inventory

Respondents are asked if they have any of the following medical conditions, and if yes, to indicate if they never received, previously received, or currently receive treatment supervised by a health professional. If they were unsure whether they have a condition, they are instructed to respond NO.

- Arthritis or rheumatism
- Chronic back/neck pain
- Migraine headaches
- Other frequent or severe headaches
- Any other chronic pain
- High blood pressure or hypertension
- Congestive heart failure
- Coronary heart disease
- High blood cholesterol
- An ulcer in your stomach or intestine
- Irritable bowel disorder
- Chronic heartburn or GERD
- Seasonal allergies or hay fever
- Asthma
- Chronic bronchitis or emphysema
- Chronic Obstructive Pulmonary Disease
- Urinary or bladder problems
- Diabetes
- Obesity
- Chronic sleeping problems

- Chronic fatigue or low energy
- Osteoporosis
- Skin cancer
- Any other kind of cancer
- Anxiety disorder
- Depression

2. Other co-morbidities

To capture the effects of interactions between a chronic conditions and other conditions a respondent may have (i.e., co-morbidities), we follow a co-morbidity measurement and modeling method described by Alonso et al. (2010).[3] We first create a dummy variable for each chronic condition. If a respondent indicated they had a condition (regardless of treatment status), they were coded as a 1 and as a 0 if they did not have the condition (respondents that did not answer the question are excluded from the calculation).

For each respondent that provided a non-missing response to all 26 chronic condition questions, we then create a linear measure of chronic conditions by summing all the 0 and 1 responses for the dummy variables. To create the condition-specific measure of other comorbidities, we multiply the dummy variable for each condition by the difference between the linear measure and the dummy variable.

For example, if a person had migraines and diabetes, but not asthma (nor any other conditions), their values on the migraine, diabetes, and asthma dummy variables would be:

- Migraines = 1
- Diabetes = 1
- Asthma = 0

The linear measure of total chronic conditions is 2 (Migraines + diabetes + asthma = 2); the number of other conditions comorbid with migraines = 1 (Migraines × [linear conditions – migraines] = 1 × [2 – 1] = 1); the number of other conditions comorbid with diabetes = 1 (Diabetes × [linear conditions – diabetes] = 1 × [2 – 1] = 1); and the number of other conditions comorbid with asthma = 0 (Asthma × [linear conditions – asthma] = 0 × [2 – 0] = 0).

IV. Demographic and other variables

1. Age

The original age variable is recoded ordinally into three age categories:

[3] Alonso, Jordi, Gemma Vilagut, Somnath Chatterji, et al., 2010, "Including information about comorbidity in estimates of disease burden: Results from the WHO World Mental Health Surveys," *Psychological Medicine*, 41(4):873-886.

- 18 to 34 years
- 35 to 54 years
- 55 to 85 years

Values less than 18 or greater than 85 are coded as missing.

2. Sex

The nominal variable “gender” is recoded dichotomously into a variable indicating female, where males are coded 0 and females are coded 1.

3. Occupation

The HPQ asks the following question:

Please choose the category that best describes your main job. If none of the categories fits you exactly, please respond with the closest category to your experience. (Select only one.)

1. Executive, administrator, or senior manager - (e.g., executive, management, administration)
2. Professional - (e.g., finance, legal, corporate support)
3. Technical support - (e.g., data analyst, paralegal)
4. Sales - (e.g., reservations, marketing, customer care)
5. Clerical and administrative support - (e.g., secretary, billing, administrative assistant, office supervisor)
6. Service occupation - (e.g., in-flight crew, flight operations, flight dispatchers)
7. Precision production and crafts worker - (e.g., maintenance, technical operations, engineer)
8. Operator or laborer - (e.g., ACS, air logistics/cargo)

We combine the occupational categories into four nominal groups:

- Executive and professional (categories 1 and 2)
- Technical and crafts (categories 3 and 7)
- Sales and office (categories 4 and 5)
- Service (categories 6 and 8)

4. Expected hours

The HPQ asks the following question:

How many hours does your employer expect you to work in a typical 7-day week? (If it varies, estimate the average. If more than 97, enter 97.)

Values less than 20 or greater than 97 are coded as missing.

5. Full-time status

Responses to the expected hours question are recoded to indicate whether an employee works full-time. We use the Bureau of Labor Statistics Current Population Survey definition to classify persons who work 35 hours or more per week as full-time, and persons who work less than 35 hours per week as part-time. We create a dichotomous variable where responses between 20 and 34 are coded 0, and responses between 35 and 97 are coded 1.

6. Data source

We create a nominal variable to indicate the administrative source of the data. Cases from the original nine employers are considered Source 1, and cases from the supplemental employers are considered Source 2. For analysis, we create a dichotomous variable where Source 1 cases = 1 and Source 2 cases = 0.

V. Excluded cases

The regression models exclude cases in a listwise fashion; i.e., cases are excluded when they have missing values on any of the variables used in a regression model.

The number of listwise-excluded cases varies from model to model. The main models of lost time and job performance include about 127,000 cases, roughly 91% of the cases from the combined sources.

VI. Equations

1. Chronic conditions and treatment status

We use multinomial logistic regression analysis to estimate the likelihood that an employee has a specific chronic condition and either (1) has never received treatment for it, (2) received treatment for it only in the past, or (3) is currently receiving treatment for it, relative to not having the condition at all.[4]

Multinomial logistic regression uses a maximum likelihood estimation procedure to predict the log of the odds that the outcome of a categorical dependent variable takes on one of three or more possible values for each *i*th case. For multinomial logistic regression with a categorical dependent variable that has *m* outcomes and where *m*>2, one category of *m* is arbitrarily designated as the reference category (*r*) to which all other categories are compared. By definition, the log odds of the reference category equals zero (because the relative odds of an outcome compared to itself equals 1). This reduces the estimation of the remaining probabilities to *m*-1 equations of the following form:

$$Pr(Y_i = m|r) = \frac{exp^{X\beta m|r}}{\sum exp^{X\beta z|r}} \text{ for } m = 1 \text{ to } z \text{ categories}$$

Equation 1

where $X\beta m|r$ represents the model coefficients for each outcome of *m* relative to the reference category *r*, and $X\beta z|r$ represents the model coefficients for all *z* outcomes relative to *r*. Although only

[4] For a general discussion of multinomial logistic regression, see Long, J. Scott and Jeremy Freese, 2006, *Regression Models for Categorical Dependent Variables Using Stata*, College Station, TX: Stata Press.

m-1 equations are estimated, the probability of an outcome in the reference category can be solved by subtracting the probabilities of all other outcomes from 1 (since the sum of all probabilities must equal 1).

We estimate multinomial logistic equation models for each of 26 different chronic conditions separately. The models include variables for sex, age category, occupation, and a dummy variable indicating the data source.

2. General note on modeling co-morbidities

In keeping with Snapshot's intent to provide timely, robust, and cost-effective estimates of specific chronic illnesses' toll on productivity, we use fully saturated regression models with all chronic conditions included simultaneously rather more expensive or computationally intensive methods (such as administering new surveys or weighting the underlying data and recalculating results anew for each user).

Several tests indicated that modeling outcomes with fully saturated chronic conditions underestimated outcomes compared to a model with a single dummy variable for having at least one chronic condition. Since these models produced very similar job performance estimates among employees with <u>no</u> chronic conditions, un-modeled interactions between conditions was a likely explanation.

This was substantiated when a dummy variable for "any chronic" was added to the fully saturated model, which reduced the dissimilarity substantially. However, adding the "any chronic" dummy as a placeholder for co-morbidities is an imperfect solution because it does not help calculate the marginal lost time for each condition. In effect, when solving the equation to estimate hours worked or job performance, condition-specific lost work days would be underestimated because the co-morbid lost time would have a value as its own, non-interpretable (but arithmetically correct) category of chronic illness-related lost time.

Because there are over 67 million combinations of 26 conditions (including all conditions and no conditions), specific interactions are not feasible. Instead, we first modeled co-morbidities as a linear measure and as dummies for numbers of chronic conditions. The linear measure is not feasible because it over-saturates the model, which makes the standard errors unreliable without complicated bootstrap re-estimates. Dummies for each number of chronic conditions have the same drawback as a single dummy for "any chronic" condition.

Alonso et al. (2010) found that compared to models that include additive effects of comorbidity or dummy variables for the number of co-morbidities, allowing the effects of a condition to vary as a linear function of the number of other conditions produced a good fit for predicting perceived health on a visual analog scale. As described above in Section III, following Alonso, for each chronic condition, we created an interaction term by multiplying the chronic dummy by the number of **<u>other</u>** conditions an employee had. This saturated co-morbid model fully accounts for the chronic-illness related hours worked and job performance at the aggregate level, and permits an appropriate allocation of lost time for each condition. These co-morbidity measures are included in the models of hours worked and job performance.

3. Hours worked and job performance

We estimate hours worked using ordinary least squares (OLS) regression. Included are dummy variables for all chronic conditions and interaction variables for each condition and co-morbidities (i.e., the number of other conditions). The OLS model takes the form:

$$\begin{aligned}\widehat{Hours\ worked} &= \alpha + \beta_1 Expected\ hours\ worked + \beta_2 Conditions_{1\ through\ 26} \\ &+ \beta_3 (Conditions_{1-26} \times Number\ of\ other\ conditions) + \beta_4 Demographics + \varepsilon\end{aligned}$$

Equation 2

Demographics include sex, age category, occupation, and a dummy variable indicating the data source.

Job performance is also estimated using OLS, and similarly includes chronic condition dummy variables and co-morbidity interactions. Because we calculate presenteeism for each condition based on job performance for a given number of hours worked, we include the predicted hours from equation 1 in the model predicting job performance (using a two-stage least squares method). The model takes the form:

$$\begin{aligned}Job\ performance &= \alpha + \beta_1 \widehat{Hours\ worked} + \beta_2 Conditions_{1\ through\ 26} \\ &+ \beta_3 (Conditions_{1-26} \times Number\ of\ other\ conditions) + \beta_4 Demographics + \varepsilon\end{aligned}$$

Equation 3

Demographics include sex, age category, occupation, full-time status, and a dummy variable indicating the data source.

4. Number of chronic conditions

Although the results do not contribute to estimates of costs, the Snapshot provides estimates of the proportions of employees with multiple chronic conditions. The results are obtained using ordinal logistic regression to predict the number of chronic conditions an employee has – "none," "only one," "exactly two," and so on up to "eight or more."

Ordinal logistic regression[5] estimates the log of the odds that for a dependent variable with *m* sequential categories (i.e., the magnitude of the scores assigned to each category are irrelevant, but the higher value scores correspond to logically "higher" outcomes), an outcome is less than *m*, relative to greater than or equal to m, for a one-unit change in a variable *X*. This is expressed by the equation:

$$\widehat{Ln}\left(\frac{Pr(Y_i > m)}{Pr(Y_i \leq m)}\right) = \alpha_m + \sum \beta_i X_{ij} \quad \text{for } m = 1 \text{ to } z \text{ categories}$$

Equation 4

[5] The discussion in this section draws primarily from Long and Freese (2006).

Where *Y* is the ordinal dependent variable outcome for the *i*th case, β is the regression coefficient for the *j*th variable *X* and α is a constant value for dependent variable category *m*. This equation is then solved to obtain the probabilities that $Y_{1\ to\ z-1}$=1 (the probability for the remaining category is solved by subtracting the cumulative probabilities from 1.0). For example, for a dependent variable with three ordinal categories:

$$Pr(Y_1 = 1) = \frac{1}{exp^{a_1+\sum \beta X}}$$

$$Pr(Y_1 = 2) = \frac{1}{exp^{a_2+\sum \beta X}} - Pr(Y_1 = 1)$$

$$Pr(Y_1 = 3) = 1 - Pr(Y_1 = 1) - Pr(Y_1 = 2)$$

Equation 5

It is assumed that the magnitude of the change in the log odds of *Y* given a change in *X* is uniform across the dependent variable categories.

The model includes variables for sex, age category, occupation, and a dummy variable indicating the data source.

VII. User inputs and default values

Once the underlying equations are estimated, simulating lost time and costs results for organizations requires only providing the various values of *X*, solving for each βX, and applying values of per-unit labor and opportunity costs to the results. The components for these calculations include:

- # of employees
- % female
- % in each age category
- % in each occupational group
- % with full-time employment
- % receiving full pay for sick day absences
- Average daily wages and benefits
- Expected hours worked
- Opportunity costs multipliers for each FTE day of lost time

With the exception of opportunity cost multipliers and expected hours worked, users provide these values, either directly or in some easily calculable form (e.g., the number of employers and the number of females; total wages and benefits and the number of employees, etc.). When any of these components is not provided, it is estimated using averages from the U.S. workforce or the nearest industry average. Users initiate the Snapshot estimate by selecting a North American Industry Classification System (NAICS) industry at the 2-, 3, or 4-digit level; selecting no industry defaults to the U.S. workforce. The NAICS employs a hierarchical structure. For example, NAICS 1234 is a sub-industry of NAICS 123, which is itself a sub industry of NAICS 12, which is itself a subset of all U.S. industrial activity. This means that results for each level reflect the weighted average of the levels below it, and permits the substitution of higher-level for lower-level values when the latter are unavailable. With the exception of wages, benefits load, and number of employees, all estimates are keyed to the 2-digit NAICS code (regardless of whether a 3- or 4-digit industry is selected). Benefits load is keyed to the selected 2- or 3-digit industry, and wages and number of employees is keyed the selected level.

Sources for industry data are listed in the table below.

Table 1

Statistic	Source		Date
# of employees (industry total)	Bureau of Labor Statistics (BLS)	Occupational Employment Statistics	2011
Average Wage	BLS	Occupational Employment Statistics	2011
Benefits load	BLS	National Compensation Survey	March 2011
Eligibility for paid sick days	Centers for Disease Control and Prevention	National Health Interview Survey (NHIS)	2011
Full-time employees	BLS	Current Population Survey	March 2011
Occupational distribution	BLS	Occupational Employment Statistics	March 2011
Sex distribution	BLS	Current Population Survey	March 2011
Age distribution	BLS	Current Population Survey	March 2011

1. Occupations

The Bureau of Labor Statistics provides occupational employment using 7-digit Standard Occupational Classification (SOC) codes, which are then cross-walked to the following U.S. Equal Employment Opportunity Commission codes (which have a closer correspondence to the HPQ categories):

1. Officials and managers (EEOC1)
2. Professionals (EEOC2)
3. Technicians (EEOC3)
4. Sales workers (EEOC4)
5. Administrative support workers (EEOC5)
6. Craft workers (EEOC6)
7. Operatives (EEOC7)
8. Laborers and helpers (EEOC8)
9. Service workers (EEOC9)

Since these categories do not correspond perfectly with the HPQ response options, we aggregate the totals for the four HPQ occupational groups as follows:

- Executive and professional (EEOC1 and 2)
- Technical and crafts (EEOC3 and 6)
- Sales and office (EEOC4 and 5)
- Service (EEOC 6, 8, and 9)

Since an occupational category dummy is excluded from the regression models and the proportions for all categories must sum to 1.0, the Snapshot requires that users who wish to override the occupational distribution defaults provide percentages (including zero where appropriate) for all categories, and that the percentages must sum to 100. The same logic is applied for the age distribution.

2. Average daily wages and benefits

If a user supplies the total wages average daily wage is the quotient of 1) total wages over 2) the product of (a) total employees and (b) 260 (i.e., annual workdays, assumed to be the product of five days per week for 52 weeks per year). If the BLS estimated average annual wage is used, we obtain the average daily wage by dividing by 260.

The costs of each missed day include not only wages paid to employees, but also the dollar value of taxes and benefits paid on their behalf. Users are asked to provide total wages and benefits (in which case average daily wages and benefits are calculated in the same manner as average daily wages), total wages only, or total wages and the total amounts of the following benefits categories:

- Paid leave: vacations, holidays and personal days (but not sick days)
- Insurance: life insurance, health insurance, STD and LTD insurance
- Retirement: defined benefit and defined contribution expenses
- Legal requirements: social security and Medicare contributions, federal and state unemployment insurance, and Workers' Compensation

When costs for a benefit category are not provided (or when no benefits costs are provided), we estimate using the industry average as a percent of wages, and apply this value to the calculated average daily wage.

3. Expected hours worked

We estimate the expected hours worked as the weighted average hours for full-time and part-time workers. For full-time workers, we assume they are expected to work 40 hours per 7 days; for part-time workers, we assume they are expected to work 27 hours per 7 days (the observed average for part-time workers in the data).

4. Lost productivity multipliers

The multipliers used to estimate the opportunity costs of each unit of absence are adapted from research by Dr. Sean Nicholson of Cornell University and his colleagues.[6] In brief, Nicholson and colleagues surveyed managers of employees in different occupations to determine the additional costs or lost sales (as a percentage of daily pay) that are incurred when a worker is absent or underperforming due to illness. They estimate this as a function of 1) the ease with which an absent employee can be temporarily replaced with a worker of similar quality, 2) whether they work in teams, and 3) the timeliness of their output, and generate an average cost per absence as a multiple of average daily wages.[7] Multipliers for the EEOC occupation groups have a range of 1.1 to 1.65 for absence and 1.0 to 1.74 for presenteeism.

To create absence and presenteeism multipliers for an organization, we use average multipliers calculated for each EEOC occupational group, weighted by the proportion of employees in each group.

VIII. Reporting lost/gained time for chronic conditions

1. Prevalence of chronic conditions

We estimate the prevalence of each chronic condition by solving equation 1 above with the user-provided or default X values. The percentage of employees estimated to have a condition (i.e., 1 minus the estimated proportion in the category of “no condition”) is used to solve the equations for hours worked and job performance.

2. Per-person impacts

i. Hours worked

Hours worked for a 28 day period are estimated by solving equation 2 above. The independent impact of a chronic health condition on hours worked is the sum of (1) the dummy coefficient (the main effect) and (2) the product of the interaction coefficient and the average number of other conditions (the co-morbid effect).

Coronary heart disease (CHD) serves as an example:

[6] Nicholson, S., Pauly, M.V., Polsky, D., Sharda, C., Szrek, H. and Berger, M.L. "Measuring the effects of work loss on productivity with team production." Health Economics. 2006;15(2):111-123. Pauly, Mark V., Sean Nicholson, et al. 2008. “Valuing Reductions in On-the-Job Illness: ‘Presenteeism’ From Managerial and Economic Perspectives.” *Health Economics*. 17(4):469-485.

[7] Readers interested in more detail on the method should refer to Nicholson, Pauly et al. (2006) and Pauly, Nicholson et al. (2008), or to the technical documentation for IBI’s [Full Cost Estimator].

Table 2

CHD main coefficient	-2.4
Coefficient for CHD co-morbid interaction	-0.5
CHD sufferers' avg. # of other conditions	4.8
Adjusted CHD coefficient	-2.4 + (4.8 × -0.5) = -4.8

In the above example, a person with CHD and no other chronic conditions works 2.4 hours fewer on average than a person without CHD; a person with CHD and the average number of other conditions works 4.8 hours fewer on average than a person without CHD.

In solving the full hours worked equation for a person with a given condition, the estimated proportions of employees with each condition are used as *X* values for the other conditions in the model, and *X* values for workforce co-morbidities are calculated as the product of the average co-morbidities and the estimated proportion with a condition.

Depression serves as an example:

Table 3

Depression main coefficient	-2.3
Estimated proportion of employees with depression	.117
Coefficient for depression co-morbid interaction	-.09
Depression sufferers' avg. # of other conditions	5.0
Average contribution of depression to hours worked	(-2.3 × .117) + (5.0 × -0.09 × .117) = -0.322

ii. Job performance/presenteeism

Job performance for a 28 day period is estimated by solving equation 3 above. The independent impact of a chronic health condition on job performance is the sum of (1) the dummy coefficient (the main effect), (2) the product of the interaction coefficient and the average number of other conditions (the co-morbid effect), and (3) the product of the predicted hours coefficient and the marginal impact of the condition on hours worked (i.e., the calculated value in the last row of Table 3).

Coronary heart disease (CHD) serves as an example:

Table 4

CHD main coefficient	0.0
Coefficient for CHD co-morbid interaction	-0.02
CHD sufferers' avg. # of other conditions	4.8
Coefficient for predicted hours worked	-0.002
Adjusted CHD coefficient for hours worked (from Table 3)	-4.8
Adjusted CHD coefficient	0.0 + (4.8 × -0.02) + (-4.8 × -0.002) = -0.086

In the above example, a person with CHD and no other chronic conditions has the same performance as a person without CHD (i.e., the main coefficient is 0.0); a person with CHD and the average number of other conditions has performance -0.086 points lower on average than a person without CHD.

Net performance equivalent hours (i.e., presenteeism hours) are the quotient of the adjusted job performance coefficient (i.e., the calculated value in the last row of Table 5) over 10, multiplied by the estimated hours worked for employees with that condition.

Coronary heart disease (CHD) serves as an example:

Table 5

Adjusted CHD coefficient for job performance (from Table 5), divided by 10	-0.086 ÷ 10 = -0.0086
Estimated monthly hours worked for employees with CHD	144.6
Net performance equivalent hours	-0.0086 × 144.6 = -1.24

In the above example, a person with CHD and the average number of other conditions works the equivalent of 1.24 fewer hours per month than a person without CHD.

3. Workforce impacts

i. Hours worked

To obtain the total net hours worked over 28 days for all employees with a condition, we multiply the adjusted condition coefficient (i.e., the calculated value in the last row of Table 3) by the estimated prevalence of the condition and the total number of employees. We express this in full-time equivalent days by dividing by 8 (assuming eight hour workdays).

ii. Presenteeism

To obtain the total net performance equivalent hours worked over 28 days for all employees with a condition, we multiply the net performance equivalent hours per person (i.e., the calculated value in the last row of Table 6) by the estimated prevalence of the condition and the total number of employees. We express this in full-time equivalent days by dividing by 8 (assuming eight hour workdays).

IX. Monetizing lost/gained time

We estimate the costs of particular chronic health conditions as the product of 1) workforce net days, 2) average daily wages and benefits, and 3) the proportion of employees eligible for paid sick days. To this value we add the product of 1) workforce net days worked, 2) average daily wages and benefits, and 3) the fractional portion of the absence multiplier (i.e., multiplier – 1.0). We report the costs in annual dollars, and so multiply the 28-day totals by 13. This simplifies to the following formula:

$$Annual\ cost\ of\ net\ days\ = [(Monthly\ net\ days) \times (Sick\ pay + absence\ multiplier - 1)] \times 13$$

We calculate costs for net worked days and presenteeism separately, and then sum for the total costs. Since the Nicholson multiplier was developed to monetize absences rather than overtime, we have no basis for estimating the opportunity costs when a condition is associated with gained work time. Therefore when the net days are positive, we assume that the absence multiplier equals 1.0.

Additionally, for performance equivalent lost work days, we assume that the proportion of employees eligible for sick pay is 1.0.