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# Absenteeism and Presenteeism Among American Workers

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## Abstract

Recent policy proposals for early intervention argue that health and workplace supports may be more effective if they are provided soon after the onset of a disabling condition, before an individual has completely stopped working. One challenge in developing effective early intervention programs, however, is identifying workers who may benefit from this type of assistance. Chronic absence from work or presenteeism (working while sick) could signal a worker has begun transitioning out of the labor force and may benefit from early intervention. We analyze the relationship between absences, presenteeism, and work outcomes using data from the American Working Conditions Survey. We find absences and productivity losses when working while sick are quite low on average, and absenteeism and presenteeism are highly positively correlated. We find no relationship between subsequent work outcomes and either absences or presenteeism *except* for individuals in the extreme right tail (95th percentile) of the absence distribution, who also engage in presenteeism. Those workers with extremely high absence rates and presenteeism have an 80% higher probability of labor force exit 3 years later. Our findings suggest that workers with many absences could be a useful group to target for early interventions and accommodations.

## Keywords

absence rates, absenteeism, presenteeism, labor force transitions

Approximately one in 10 working-age adults in the United States currently have a disability (Erickson et al., 2019), and individuals with disabilities who do not return to work quickly are more likely to enter and remain on disability programs (e.g., Autor et al., 2017; Hill et al., 2016; Kostol & Mogstad, 2014). As a result, there has been growing policy interest in early intervention, which provides supports such as targeted medical assistance, workplace accommodation, or training to workers with chronic conditions to improve their health and extend their working years. One challenge in developing effective early intervention programs, however, is identifying workers who may benefit from this type of assistance. Ideally, early interventions would target individuals at the onset of a chronic condition, while they are still in the labor force. Although it is difficult to directly observe the onset of a chronic condition, other changes in work-related activity may provide relevant information.

Labor force exit due to disability is often preceded by a gradual decline in health (van Rijn et al., 2014). If labor force exit is preceded by increased rates of absence from work or presenteeism (working while sick), then absence and presenteeism rates could serve as useful, objective signals that a worker is at risk of leaving the labor force (Johns, 2010). Such indicators could be used to target interventions to help the worker remain in the labor force, to provide access to needed medical assistance, or to anticipate the future need for support from federal programs such as Social Security Disability Insurance or Medicare. In this article, we use a novel data source to assess the predictive relationship between absences, presenteeism, and changes in employment to better understand whether or how these indicators can serve as a useful signal of future changes in employment or need for other health or workplace supports.

High absence rates and presenteeism need not be correlated with labor force exit. In some cases, a new pattern of chronic absence may serve as an early indicator of a condition that is expected to worsen and could eventually lead to labor market exit. In other cases, an individual may frequently be absent from work for medical appointments or other treatment-related activities, but these absences may actually *enable* the worker to manage their health condition

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and, therefore, maintain their employment. In the latter cases, telework or flexible work schedules could allow workers to schedule their work around necessary appointments without increasing absence rates at work. As a result, relationships between absences, poor health, and current and future labor force participation can be complex, and warrant careful study.

In this study, we analyze the relationship between absenteeism, presenteeism, and later work outcomes using a nationally representative, longitudinal sample of U.S. workers from the American Working Conditions Survey (AWCS), fielded in the RAND American Life Panel (ALP). We first establish baseline trends in absenteeism and presenteeism, and examine the relationship between absenteeism and presenteeism. We then relate absenteeism, presenteeism, and the interaction between absenteeism and presenteeism to labor force outcomes 3 years later to analyze the extent to which high absence rates or working while sick may be indicative of future changes in labor force activity. Rather than trying to estimate the causal effect of absenteeism on labor force exit, we are interested in understanding whether long absence spells, with or without presenteeism, can identify those workers at risk of labor force exit.

Prior studies have measured the overall distribution of absenteeism or presenteeism in the United States (e.g., Ahn & Yelowitz, 2016; Davis et al., 2005; Gifford & Jinnett, 2014; Susser & Ziebarth, 2016), and other studies that relate absenteeism patterns to future disability benefit take up for manufacturing workers in the United States (Harrati et al., 2018) and for the overall workforce in Scandinavian countries (Andren, 2007; Gjesdal & Bratberg, 2003; Wallman et al., 2009). However, data limitations have prevented a comprehensive analysis of how absenteeism and presenteeism interact over the course of a year, and how these behaviors affect future labor force transitions in the overall U.S. population. This study is the first to our knowledge that fills this gap. Our unique panel data allow us to measure absence and presenteeism rates *and* to link this information to future labor force participation for the same nationally representative U.S. sample, while also taking into account the impact of health conditions.

Our study provides several contributions to the current understanding of the relationship between absenteeism, presenteeism, and labor force activity. Our survey provides a picture of these patterns in a longitudinal, nationally representative sample of working adults. We collect data on presenteeism and absenteeism using methods for eliciting this information that are standard in the field, allowing us to both validate prior measures of absenteeism and presenteeism rates and then relate these patterns to future labor force activity. Finally, the survey allows us to examine how absenteeism and presenteeism patterns vary for workers in different types of jobs, with different amounts of paid sick leave, and with different health conditions.

We present several key findings. First, we find that baseline absence rates are quite low in the overall population. The median worker takes only one absence day per year; workers in the 90th percentile take seven absences per year. Although nearly two thirds of the population reports working while sick at least once in the past year, productivity losses from working while sick are moderate, averaging around 20%. Second, absenteeism and presenteeism are highly correlated. Workers who report ever engaging in presenteeism are 36% more likely to have a high absence rate, and workers with a high absence rate are 13% more likely to report ever engaging in presenteeism. Workers with a high absence rate are nearly 50% more likely to report productivity losses in the top quartile of the loss distribution. Finally, we find no relationship between labor force outcomes and either absence rates or presenteeism *except* for workers with very high absence rates. We find that individuals with absence rates in the right tail of the distribution—individuals with absence rates above the 95th percentile (10 days/year)—who *also* engage in presenteeism have an 80% higher probability of exiting the labor force within 3 years. These findings suggest it could be useful to target individuals with significant deviations from the normal patterns of absence for early intervention.

## Background

Before analyzing patterns in absenteeism and presenteeism, we first define some key terms. We define a worker's *absence rate* as the number of days that he or she missed work over a given period of time. We use the term *absenteeism* to indicate a prolonged series of absences, which can be measured by a high absence rate. *Presenteeism*, however, occurs when an individual goes to work while sick. Finally, the extent to which presenteeism impairs work performance can be measured by the degree of *productivity loss* due to working while sick.

Measuring absences and presenteeism in existing data can be challenging due to the fact that this information is not captured consistently for all workers, and is often measured differently (or not at all) in employer databases and survey data. Both presenteeism and productivity loss are typically measured in self-reported survey data, whereas absence data can be collected in self-reported surveys or administrative data from employers. In practice, existing studies present different measures of absences and presenteeism based on different survey questions (e.g., asking about days of work missed for any reason or due to illness specifically), data sources, and time frames (e.g., days missed over the last 2 weeks vs. over the last year).

As a result of these measurement challenges, the existing literature on absenteeism and presenteeism is somewhat piecemeal. Existing studies tend to focus on subpopulations where data are available, for example, by analyzing trends in absenteeism for workers with a particular health condition,

or analyzing the effects of absenteeism in a particular workplace (e.g., Anesetti-Rothermel & Sambamoorthi, 2001; Boles et al., 2004; Burton et al., 2005; Callen et al., 2013; Cohen et al., 2015; Howard & Potter, 2014; Kessler et al., 2001; Muchmore et al., 2003; Pelletier et al., 2009). For a comprehensive discussion of the prior literature on absenteeism and presenteeism, see Halbesleben et al. (2014), Johns (2010), and Mullen and Rennane (2017).

## Data and Method

Our analysis utilizes the AWCS. The AWCS was administered in July 2015 to RAND ALP respondents who were aged 18 to 70 years. The ALP is a nationally representative panel of adults designed for scientific research. The panel has been running since 2006 with periodic refresher samples. Recruitment is probability based and recruitment methods include in-person contact, by telephone, and by mail, providing opportunities to include individuals with a variety of impairments (e.g., an individual who is hearing impaired may be initially contacted in person or by mail). Panel members answer surveys on a wide variety of social science research topics and receive payment for each survey they complete. The amount of the payment varies with the duration of the survey, but is generally less than US$50 per survey. The ALP ensures the panel is representative of all adults (and not just those with internet access) by providing appropriate technology to those who need it. About 3% of panel members are provided a laptop/tablet and internet access to participate. ALP surveys meet Web Content Accessibility Guidelines and are Section 508–compliant to ensure that surveys are broadly accessible to the population of individuals with disabilities. See Pollard and Baird (2017) for more information on ALP survey methodology.

The AWCS asked 3,131 respondents (response rate 64%) about health conditions, workplace characteristics and preferences, labor market activity, occupation, income, work absences, and presenteeism. Just more than 2,000 respondents were working for pay and, therefore, were eligible to receive questions about absences and presenteeism. Use of sample weights in the AWCS ensures that the sample is nationally representative when estimating population statistics. As discussed in Maestas et al. (2017), the survey weights target the July 2015 Current Population Survey Outgoing Rotation Group, and the weighted AWCS matches the Current Population Survey (CPS) well on age, education, race/ethnicity, and a variety of labor force measures.

Data sets from all ALP surveys are publicly available and can be linked to one another using a fixed respondent identification number. In addition to the researcher-driven surveys, the ALP panel completes a demographic update survey on a quarterly basis. Importantly, these quarterly updates ask questions about respondents' current labor force participation. To analyze labor market outcomes 3 years later, we match the 2015 AWCS to the spring 2018 quarterly ALP demographic update module. Approximately 70% of respondents in the 2015 AWCS also responded to the 2018 ALP demographic update.

### *Key Variable Definitions*

We measure worker demographics (age, gender, household income, education), job characteristics (occupation, industry, part time vs. full time status, access to sick leave), and health (persistent health problems, muscle/back problems, and depression) from the AWCS survey in 2015, at the time in which we measure absences and presenteeism.

To measure absences, the AWCS asked respondents how many days in total they were absent from work for health-related reasons during the past 12 months. To measure presenteeism, the survey asked whether respondents worked when they were sick over the past 12 months, and if they did, we asked them to rate on a scale from 0% to 100% how much they think their productivity was affected while working sick. The presenteeism question in the AWCS is a slight modification on Question 5 in the Work Productivity and Activity Impairment (WPAI) Questionnaire, which asks workers to rate the extent of their productivity loss on a scale from 1 to 10 (see Goetzel et al., 2004, for a review of survey instruments for measuring productivity losses, including the WPAI). The main difference between the AWCS question and the WPAI is the difference in scale. Although a self-reported measure of productivity is not the optimal measure, objective measures of productivity are exceptionally difficult to develop, even in more general settings. As a result, self-reported productivity measures reflect the current state of presenteeism measures in the literature. Johns (2010) identifies 14 instruments for measuring presenteeism, all of which rely on self-reports of worker's health and/or productivity at work.

We measure labor force participation 3 years after the baseline survey based on the current labor force status variable in the 2018 ALP demographic update. Respondents are asked to indicate whether they are working, unemployed, temporarily laid off, disabled, retired, a homemaker, or a student at the time of the survey. However, these categories are not mutually exclusive: Some respondents report being both unemployed and disabled, for example. Overall, approximately 10% of respondents select multiple labor force participation categories. Approximately half of this group reports working and some other activity, and approximately half reports being retired and some other activity. We create mutually exclusive labor force participation categories by imposing a hierarchy among the possible multiple responses. If respondents report that they are working, we code them as working, regardless of what other activities they select. We place unemployment in the second level of the hierarchy, followed by retired, disabled, and then we group students and homemakers together in an "other" category.

We create several variables measuring various job demands that could affect absence rates or presenteeism. We structure these variables after the categorizations used in other AWCS analyses (Maestas et al., 2017). We characterize a worker's job as having high flexibility if the respondent reports that he or she has the option to telecommute or that he or she can modify working hours either entirely or within certain limits. A job is considered to be highly physical if the respondent reports that his or her job involves tiring or painful positions, lifting or moving people, carrying or moving heavy loads, or repetitive motions at least one quarter of the time. Finally, a job is determined to be highly cognitive if the respondent indicates all of the following: His or her job involves solving unforeseen problems on his or her own, complex tasks, learning new things; *and* that the worker is able to apply his or her own ideas most or all of the time.

### Method

We use these data to conduct several analyses. First of all, we estimate the baseline distribution of absence rates and presenteeism, and compare our estimates with the other measures of absenteeism and presenteeism in the literature. Next, we analyze cross-sectional data from the 2015 AWCS in a logistic regression framework to determine which characteristics are most predictive of having a high absence rate or high productivity loss, and to examine the relationship between absenteeism and presenteeism. We then link these cross-sectional data from the 2015 AWCS to the 2018 ALP demographic follow-up to assess the extent to which absenteeism and presenteeism predict various labor force outcomes 3 years later in a logistic regression framework of the following form:

$$Y_{it} = \frac{1}{1+e^{-(A_{it-3}\beta+P_{it-3}\delta+X_{it-3}\theta+\varepsilon_{it})}}$$

We measure various labor force outcomes $y$ (working, being unemployed, disabled or retired) for worker $i$ in year $t$ = 2018, and relate these to indicators for worker absences and presenteeism behavior in 2015 ( $A_{it-3}$ and $P_{it-3}$) as well as other worker characteristics in 2015 $(X_{it-3})$ including age, gender, education, access to sick leave, health, and job demands. We additionally consider whether the impact of absences on labor force outcomes varies depending on whether workers engage in presenteeism or not in an interaction model as follows:

$$Y_{it} = \frac{1}{1+e^{-(AP_{it-3}\gamma+X_{it-3}\theta+\varepsilon_{it})}}$$

where $AP_{it-3}$ denotes indicators for a full set of interactions between absenteeism and presenteeism in 2015. We present estimated marginal effects of absence rates and/or presenteeism on future labor force activity, which are easily interpreted as the effect of an incremental (one-unit) change in a given covariate on the outcome of interest for the average worker, while holding other factors constant.

## Results

### Summary Statistics

Table 1 shows summary statistics for the population of AWCS respondents who were working in 2015. Column 1 shows weighted statistics for the overall population and column 2 shows statistics for the subset of respondents who report no access to sick leave. Columns 3 to 5 are for respondents who have access to sick leave, organized by the amount of sick days they are allowed in a year. Finally, column 6 shows statistics for respondents who have access to sick leave, but did not indicate how many days of sick leave they were eligible to use in a year.

Overall, column 1 shows that the average respondent is in his or her mid-40s, slightly less than half of the population is female, 60% of the overall population works in a blue-collar occupation and two thirds have some level of education beyond a high school degree. Twenty-nine percent of the population reports having a health problem expected to last at least 6 months. Muscle and back problems (of any duration) are highly prevalent in the sample: 60% of respondents report having had muscle, joint, or back pains during the last 12 months. Finally, 37% the population reports having had depression during the last 12 months.

Absence rates in the overall population are quite low: Half of respondents report having missed work at least once in the past 12 months, and the mean and median days of absence (unconditional on missing any work) are 3 and 1, respectively. Even the conditional mean and median absence rates are low, at 6 and 3 days, respectively. The 90th percentile of absences over the past 12 months in the overall population is 7 days, and even among those with 11+ days of available sick leave, the 90th percentile is 10 days of absence. The low absence rate is consistent with other literature using survey data collected on absences in the past year. For example, Ahn and Yelowitz (2016) find that respondents from the National Health Interview Survey report approximately three absences per year on average, and Peng et al. (2016) find that respondents in the Medical Expenditure Panel Survey report an average of 3.5 absences per year. Bierla et al. (2013) and Garcia-Serrano and Malo (2014) find similarly low absence rates using European data sources.

However, presenteeism is quite common: 69% of respondents report going to work while sick at least once in the past year. Workers who do go to work while sick estimate that their productivity is reduced by 23% on occasions when they go to work sick. The average productivity loss when working while sick is relatively constant, and nearly all subgroups have productivity losses ranging between

**Table 1.** Summary Statistics for 2015 American Working Conditions Survey (AWCS) Sample, Overall and by Sick Leave.

| Respondent characteristics and absenteeism/presenteeism | (1) Total | (2) No sick leave | Days of available sick leave | | | |
|---|---|---|---|---|---|---|
| | | | (3) 1–5 | (4) 6–10 | (5) 11+ | (6) Not reported |
| Panel A: Respondent characteristics | | | | | | |
| Age | 45.2 | 46.2 | 43.7*** | 44.7* | 47.2 | 43.4*** |
| Female (%) | 46.0 | 48 | 39** | 44 | 54* | 46 |
| Blue collar (%) | 60.0 | 73 | 60*** | 55*** | 48*** | 50*** |
| Education > high school (%) | 68.0 | 62 | 65 | 67 | 77*** | 73*** |
| Work part time (%) | 24.0 | 40 | 12*** | 15*** | 13*** | 27*** |
| Household income >US$75,000 | 41.0 | 32 | 39** | 51*** | 51*** | 39** |
| Health problem ≧ 6 months (%) | 29.0 | 31 | 27 | 27 | 34 | 27 |
| Muscle/back problem (%) | 60.0 | 59 | 58 | 65* | 60 | 57 |
| Depression (%) | 37.0 | 41 | 35* | 27*** | 38 | 39 |
| Has sick leave (%) | 69.0 | 0 | 100 | 100 | 100 | 100 |
| Panel B: Absenteeism and presenteeism | | | | | | |
| Any absence from work (%) | 51.0 | 41 | 48* | 55*** | 71*** | 49** |
| Days absent | | | | | | |
| *Mean* (unconditional) | 3.0 | 2.4 | 2.1 | 3.5* | 4.5*** | 2.9 |
| Median (unconditional) | 1.0 | 0 | 0 | 1 | 2 | 0 |
| 90th percentile (unconditional) | 7.0 | 6 | 4 | 5 | 10 | 7 |
| *Mean* (conditional) | 5.9 | 5.8 | 4.3* | 6.4 | 6.3 | 6 |
| Median (conditional) | 3.0 | 3 | 2 | 3 | 3 | 3 |
| 90th percentile (conditional) | 12.0 | 14 | 10 | 8 | 12 | 14 |
| Ever worked while sick (%) | 69.0 | 68 | 70 | 73 | 69 | 68 |
| Percent productivity loss when working while sick | | | | | | |
| *Mean* | 23.0 | 25.5 | 21.8** | 21.4** | 22.2* | 22.2** |
| Median | 20.0 | 20 | 20 | 20 | 20 | 20 |
| 90th percentile | 50.0 | 50 | 50 | 40 | 50 | 50 |
| Observations | 1,839 | 575 | 260 | 321 | 335 | 348 |

*Note.* Statistics calculated using sample weights. Sample based on respondents who were working at baseline. Asterisks indicate test of equality of means between "no sick leave" column and each sick leave bin. "Days not reported" column includes workers who reported having access to sick leave but did not indicate the number of sick days for which they were eligible.
*$p < .1$; **$p < .05$; ***$p < .01$.

20% and 50% from the median to the 90th percentile. This range of estimated productivity losses is in line with Collins et al.'s (2005), who find that workers from the select firms in their study reported productivity losses between 17% and 36%, but slightly higher than the estimated 12% average productivity loss estimated in Burton et al. (2005) and in Goetzel et al. (2004).

There are some notable patterns in worker characteristics and absence trends depending on the amount of sick leave available to the worker. Despite having more physical jobs, blue-collar workers are significantly less likely to have access to sick leave, and have fewer days of sick leave available when they do have access: 73% of the sample without sick leave works in blue-collar occupations, compared with only 55% of the sample with 6 to 10 days of sick leave available. Similarly, the level of education and household income are both increasing in the number of available sick days. Notably, however, the incidence of health conditions is relatively stable across groups of workers with different amounts of (or any) available sick days. Both the share of workers who ever report missing work, and the number of days missed, are increasing in the number of available sick days. The incidence of presenteeism and the extent of productivity loss when working while sick are again fairly stable between groups.

## *Interactions Between Absenteeism and Presenteeism*

In Table 2, we explore characteristics associated with absenteeism and presenteeism in a logistic regression framework that controls for health, job characteristics, job demands, demographics, and availability of sick leave. Each column of Table 2 considers a different dependent variable: In column 1, the dependent variable is an indicator for whether an individual reports high rates of absenteeism (measured as five

**Table 2.** Cross-Sectional Prediction of Absenteeism and Presenteeism in 2015.

| Variable | (1) High absence rate | (2) Any presenteeism | (3) High productivity loss | (4) High productivity loss |
|---|---|---|---|---|
| Any presenteeism | 0.079*** | | | |
| | (0.022) | | | |
| High absence rate | | 0.110*** | 0.107*** | |
| | | (0.030) | (0.026) | |
| Health problem ≧ 6 months | 0.100*** | 0.086*** | 0.034 | 0.050** |
| | (0.018) | (0.024) | (0.026) | (0.025) |
| Muscle/back problem | 0.034 | 0.087*** | 0.007 | 0.011 |
| | (0.022) | (0.023) | (0.029) | (0.030) |
| Depression | 0.063*** | 0.151*** | 0.100*** | 0.111*** |
| | (0.019) | (0.025) | (0.027) | (0.027) |
| Job has high flexibility | −0.012 | 0.037 | 0.002 | 0.001 |
| | (0.019) | (0.023) | (0.026) | (0.027) |
| Job has high physical demands | 0.021 | 0.043* | 0.007 | 0.010 |
| | (0.024) | (0.025) | (0.032) | (0.032) |
| Job has high cognitive demands | 0.006 | 0.002 | 0.025 | 0.028 |
| | (0.019) | (0.023) | (0.026) | (0.026) |
| Age | −0.002** | −0.008*** | −0.003*** | −0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Female | 0.042** | −0.026 | 0.063** | 0.071*** |
| | (0.018) | (0.022) | (0.025) | (0.025) |
| Education > high school | −0.012 | 0.038 | 0.006 | 0.002 |
| | (0.027) | (0.032) | (0.038) | (0.038) |
| Household income > US$75,000 | −0.046** | 0.028 | −0.015 | −0.023 |
| | (0.020) | (0.024) | (0.028) | (0.028) |
| Blue collar | −0.016 | 0.006 | −0.031 | −0.033 |
| | (0.020) | (0.024) | (0.027) | (0.028) |
| Has sick leave | 0.080*** | −0.003 | −0.042 | −0.033 |
| | (0.021) | (0.023) | (0.027) | (0.027) |
| Observations | 1,794 | 1,794 | 1,207 | 1,207 |
| *Y* mean | 0.191 | 0.672 | 0.243 | 0.243 |

*Note.* Marginal effects from a logistic regression model. Sample includes all respondents who were working in the baseline survey. High absence rate is measured as five or more days absent from work in a year; high productivity loss is measured as a reported productivity loss of 30% or higher. All covariates and dependent variables measured in baseline survey in 2015. Robust standard errors in parentheses.
*$p < .1$; **$p < .05$; ***$p < .01$.

absences or more in a year); in column 2, the dependent variable is an indicator for whether the respondent reports ever working while sick; in column 3, the dependent variable is an indicator for high rates of productivity loss when working while sick (measured as a productivity loss of 30% or higher); finally, column 4 presents estimates of correlates of high productivity loss without controlling for absence rate.

Columns 1 and 2 reveal a strong correlation between high rates of absence and presenteeism: Individuals who report ever working while sick are nearly 8 percentage points more likely to have more than five absences in a year. Given that approximately 20% of the population reports more than five absences per year, this represents a substantial 40% increase in the probability of a worker having a high absence rate. Individuals with at least five absences in a year are 11 percentage points more likely to report ever working while sick. Although presenteeism is more common, this still represents a 16% increase in the probability of engaging in presenteeism relative to the mean of 67%. A high absence rate is also a significant predictor of having a high productivity loss when working while sick: Workers who have at least 5 days of absence in a year are 11 percentage points—nearly 50%—more likely to report that working while sick reduces their productivity by at least 30%. These patterns reflect the complex relationship between presenteeism and absenteeism. For example, workers with high absence rates may have exhausted any available leave, and thus may be forced to turn to presenteeism—even when they are quite ill and experience high productivity losses.

Not surprisingly, there is also a strong correlation between health conditions and absenteeism and presenteeism.

Workers with a health problem lasting 6 months or longer are 10 percentage points, or 50%, more likely to report high absence rates. Workers with a health problem lasting 6 months or longer are 9 percentage points more likely to report any presenteeism, a 13% increase in the probability of working while sick. Conditional on high absence rates, workers with a significant health problem are not significantly more likely to have a high productivity loss. However, as shown in column 4, workers with chronic health conditions are significantly more likely to have high productivity loss when we remove the indicator for high absences from the model. Workers with back or muscle problems are also significantly more likely to report having gone to work while sick. Finally, workers with depression are significantly more likely to engage in all these scenarios: Having depression increases the probability of having a high absence rate by 6 percentage points, increases the probability of reporting any presenteeism by 15 percentage points, and increases the probability of high productivity loss by 10 percentage points.

Older workers are less likely to have a high absence rate. Although potentially counterintuitive, this finding could reflect selection out of work for workers in poor health as they age or it could reflect cohort differences in philosophies toward work (e.g., Rhodes, 1983; Smola & Sutton, 2002). Individuals with more education are also significantly more likely to have a high absence rate, perhaps reflecting the greater availability of sick leave for this group. Conditional on other variables, having access to sick leave is not a significant predictor of a high absence rate or presenteeism. Some dimensions of job demands are predictive of high absence rates and presenteeism, with workers in flexible jobs less likely to report high absence rates or working while sick, and those in highly physical jobs more likely to report high absence rates and higher productivity losses when working while sick. We did not detect significant differences in absence rates or presenteeism for workers in jobs with high versus low cognitive demands. We considered alterative models that interacted job demands with health conditions, but did not have statistical power to assess whether job demands interact with certain health conditions to alter the likelihood of absenteeism or presenteeism.

### *The Relationship Between Absenteeism, Presenteeism, and Work*

Table 3 examines the association between worker absenteeism, presenteeism, and other characteristics during the baseline survey in 2015 and labor market outcomes 3 years later. Because work absence is only defined for people who are employed, the regressions are estimated conditional on working in 2015 and on responding to the quarterly demographic update module in 2018. The three outcomes of interest are defined by the variables described in section "Data and Method": working, being unemployed, and being disabled or retired 3 years later. We create indicators for the number of absences reported by the worker in four mutually exclusive groups: no absences, one to five absences, six to 10 absences, or 11 or more absences in the last year. For each outcome, we present results from two different logistic regression models. We first regress labor force outcomes on the absence indicators, an indicator for ever working while sick, job demands, worker demographics (age, gender, occupation, income, education, and access to sick leave), and health (having a health condition expected to last 6 months or more, having a muscle or back problem, or having depression) in columns 1 to 3. Then, we interact the absence indicators with the indicator for ever working while sick in columns 4 to 6. We also tried excluding the health controls from both models and find similar results.

In columns 1 to 3, we do not find any evidence that individuals with longer absence spells are more or less likely to be working 3 years later, compared with individuals without any absences during 2015. Although the sign of the coefficients on the absence categories suggests that workers are less likely to be working and more likely to be disabled or retired 3 years later, these coefficients are not statistically significant at standard levels and are all quite small, less than .05 in absolute value. The coefficients on health conditions suggest a similar pattern but are also not generally statistically significant.

Next, in columns 4 to 6, we interact presenteeism with the absence categories. Although the coefficients on the absence categories are not significant among workers with no reported presenteeism, we find that, among workers who engage in presenteeism, having 11 or more absences in 2015 is associated with a 6 percentage point increase in the likelihood of being disabled or retired in 2018 compared with those with no absences, representing an 80% increase in the probability of labor force exit relative to a base of 7%.

These findings suggest that substantial absenteeism *combined with* presenteeism could precede a shift out of the labor force 3 years later. Prior research from Scandinavia also finds that extremely high absence rates are most predictive of future transitions out of the labor force (e.g., Andren, 2007; Gjesdal & Bratberg, 2003; Wallman et al., 2009), but to our knowledge, this is the first evidence in a nationally representative sample of U.S. workers demonstrating that it is high absence *plus* presenteeism that predicts future labor force exit in the United States.

## Conclusion

In this article, we use a novel data source to analyze patterns in worker absence and presenteeism, and explore the extent to which these patterns are associated with future labor force outcomes. We take advantage of the AWCS, a nationally representative sample of American workers with detailed information on worker and job characteristics,

**Table 3.** Impact of 2015 Absenteeism/Presenteeism on 2018 Labor Force Participation.

| | Logistic regression model 1 | | | Logistic regression model 2 | | |
|---|---|---|---|---|---|---|
| Variable | (1) Working | (2) Unemployed | (3) Disabled/retired | (4) Working | (5) Unemployed | (6) Disabled/retired |
| One to five absences | −0.007 | 0.003 | 0.007 | | | |
| | (0.021) | (0.011) | (0.015) | | | |
| Six to 10 absences | −0.007 | −0.014 | 0.017 | | | |
| | (0.041) | (0.025) | (0.028) | | | |
| 11+ absences | −0.022 | −0.013 | 0.041 | | | |
| | (0.039) | (0.026) | (0.025) | | | |
| Any presenteeism | −0.028 | 0.014 | 0.015 | | | |
| | (0.022) | (0.013) | (0.014) | | | |
| No presenteeism × 0 absences | | | | 0.017 | −0.008 | −0.008 |
| | | | | (0.028) | (0.016) | (0.018) |
| No presenteeism × 1–5 absences | | | | 0.026 | −0.017 | −0.012 |
| | | | | (0.040) | (0.026) | (0.029) |
| No presenteeism × 6–10 absences | | | | −0.042 | | 0.059 |
| | | | | (0.087) | | (0.045) |
| Presenteeism × 1–5 absences | | | | −0.013 | 0.006 | 0.013 |
| | | | | (0.025) | (0.013) | (0.019) |
| Presenteeism × 6–10 absences | | | | −0.002 | −0.009 | 0.003 |
| | | | | (0.045) | (0.026) | (0.034) |
| Presenteeism × 11+ absences | | | | −0.046 | −0.007 | 0.057** |
| | | | | (0.041) | (0.027) | (0.027) |
| Job highly flexible | 0.002 | 0.011 | −0.020 | 0.003 | 0.011 | −0.020 |
| | (0.021) | (0.011) | (0.016) | (0.021) | (0.011) | (0.016) |
| Job highly physical | 0.014 | 0.005 | −0.014 | 0.012 | 0.006 | −0.012 |
| | (0.022) | (0.015) | (0.014) | (0.022) | (0.015) | (0.014) |
| Job highly cognitive | 0.073*** | −0.024* | −0.031** | 0.074*** | −0.024* | −0.033** |
| | (0.022) | (0.014) | (0.016) | (0.022) | (0.014) | (0.016) |
| Health problem ≧ 6 months | −0.024 | −0.001 | 0.023 | −0.025 | −0.001 | 0.025* |
| | (0.020) | (0.011) | (0.014) | (0.020) | (0.012) | (0.014) |
| Muscle/back problems | −0.019 | 0.026* | −0.001 | −0.021 | 0.027* | 0.000 |
| | (0.022) | (0.014) | (0.016) | (0.022) | (0.014) | (0.016) |
| Depression | 0.001 | −0.007 | −0.005 | 0.003 | −0.008 | −0.005 |
| | (0.021) | (0.012) | (0.014) | (0.021) | (0.012) | (0.014) |
| Observations | 1,278 | 1,278 | 1,278 | 1,267 | 1,255 | 1,267 |
| *Y* mean | 0.866 | 0.0338 | 0.0707 | 0.866 | 0.0338 | 0.0707 |

*Note.* Data from 2015 AWCS and 2018 ALP Demographic update. Marginal effects from a logistic regression model. Independent variables are from the 2015 baseline survey, and dependent variables are from the 2018 ALP Demographic update. Labor force outcome variables are mutually exclusive. Unemployment includes individuals who are temporarily laid off. Regressions conditional on respondent working in 2015 and 2018. Marginal effect on "No presenteeism × 6–10 absences" excluded for unemployment (column 5) because there is no variation in the outcome for respondents in that category. Model controls for demographics, education, income, job characteristics, and sick leave. Robust standard errors in parentheses. AWCS = American Working Conditions Survey; ALP = American Life Panel.
*$p < .1$; **$p < .05$; ***$p < .01$.

worker health, and absence and presenteeism behavior. We document several important patterns about absences and presenteeism. First, workers report relatively few absences due to sickness: 50% of workers do not report missing any days of work in the last year, and even the 90th percentile is low at seven absences per year. By contrast, presenteeism is very common: More than two thirds of workers report going to work while sick at least once in the past year. Conditional on going to work while sick, however, workers are able to maintain some level of productivity: Average reported productivity losses when working while sick range around 20%.

We find evidence of both strong correlations between and interactions involving absenteeism and presenteeism. Workers who engage in presenteeism are 40% more likely to report more than five absences per year. Furthermore,

individuals with high absence rates are 11 percentage points more likely to report ever working while sick, and nearly 50% more likely to report that working while sick reduces their productivity by at least 30%. These patterns suggest a complex relationship between absenteeism and presenteeism. Workers may be more likely to substitute presenteeism for an absence from work once they have already accrued a long absence spell and face pressures to return to the job.

As expected, workers with significant health conditions (expected to last at least 6 months), workers with musculoskeletal problems, and workers with depression all report significantly higher absence rates, and are more likely to engage in presenteeism. Older workers, however, are significantly less likely to report high absence rates. Workers in jobs with greater flexibility and lower physical demands were less likely to report high absence rates and engaging in presenteeism. We did not detect significant differences in absence rates or presenteeism for workers in jobs with high versus low cognitive demands.

Relating observed absenteeism and presenteeism to subsequent labor force outcomes (3 years later), we find no relationship between labor force outcomes and either absence rates or presenteeism except for workers with an extremely high (relative to the typical distribution) number of absences in a year—workers with 11 or more absences and who report engaging in presenteeism. These individuals are significantly more likely to be disabled or retired 3 years later, even after controlling for health status. The co-occurrence of high absences and presenteeism could signal that these individuals have exhausted available leave options (if any), and work while sick to maintain their employment. Further research could explore reasons why absence rates and presenteeism independently do not have an effect on the labor market outcomes we study in this article. Possible explanations could include the influence of unobserved factors affecting the choice to miss work (e.g., worker motivation, or concerns about repercussions for absence from the employer or coworkers).

The decision to work while sick is complex. Each time a worker falls ill, he or she must decide whether to miss work or go to work while sick. This decision will depend on the severity of the worker's illness, the amount of sick leave available to the worker, and explicit and implicit expectations or pressure from the employer to report to work (Halbesleben et al., 2014). Workers with access to more sick leave may be more likely to miss work, even if their illness is less severe than someone without sick leave. A worker may choose to be absent rather than engage in presenteeism when the penalty for missing work is low, but the same worker may make a different choice once he or she has exhausted sick leave or faces other penalties for missing work (Bierla et al., 2013; Halbesleben et al., 2014). Recent evidence finds that increasing the generosity of short-term sick leave increases both the incidence and the duration of short-term absences (e.g., Hagglund, 2013; Henrekson & Persson, 2004; Johansson & Palme, 2002; Pettersson-Lidbom & Skogman Thoursie, 2013).

Recent proposals to reform the disability insurance system in the United States have suggested that employers should play a larger role in reducing inflows into disability insurance and maintaining employment among individuals with chronic health conditions (e.g., Autor & Duggan, 2010). Our findings suggest that workers with many absences and presenteeism could be a useful group to target for early interventions and accommodations. Measuring absence rates presents a fairly low-cost way to identify workers for such interventions because records on absences are already recorded by the employer. Because the overall distribution of absences is low, even across subgroups of workers with serious health problems, workers out sick more than 2 weeks in the past year deviate notably from the typical pattern and may need assistance, especially if they also engage in presenteeism. The strong correlation between high absenteeism and presenteeism and subsequent labor force exit, even controlling for health problems, suggests that absence rates could be a useful signal for employers to identify individuals who are at risk of transitioning out of the labor force.

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## Authors' Note

Additional results and copies of the computer programs used to generate the results are available from the corresponding author.

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