# Absenteeism and Presenteeism among American Workers 

Nicole Maestas ${ }^{1}$, Kathleen J. Mullen ${ }^{2,3}$ and Stephanie Rennane ${ }^{2}$

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Labor force exit due to disability is often preceded by a gradual decline in health. Frequent or increased rates of absence from work or presenteeism (working while sick) could serve as a signal that a worker has begun transitioning out of the labor force. We analyze the relationship between absences, presenteeism and work outcomes using data from the American Working Conditions Survey and the American Life Panel. We establish baseline trends in absences and presenteeism for a nationally representative sample of U.S. workers and relate contemporaneous patterns in absences, presenteeism and interactions between the two behaviors to labor force outcomes three years later. Our findings indicate that on average absence rates and productivity losses when working while sick are quite low in the overall population. The median worker takes only one absence per year, and the average productivity loss while working sick is 20 percent. Secondly, absenteeism and presenteeism are highly positively correlated. Finally, we find no relationship between labor force outcomes and either absence rates or presenteeism except for individuals in the extreme right tail of the absence distribution. Workers with absence rates above the $95^{\text {th }}$ percentile and who engage in presenteeism have a significantly reduced probability of working or participating in the labor force three years later. These findings suggest it could be useful to target individuals with significant deviations from the normal patterns of absence for additional screening or intervention.

Keywords: absence rates, absenteeism, presenteeism, labor force transitions

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## 1. Introduction

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 also 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 for health reasons. 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 paper we use a novel data source to assess the extent of the relationship between absences, presenteeism, and changes in employment in order to better understand whether or how these indicators can serve as a useful signal of future labor force participation.

In theory, 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 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.

At the same time, absenteeism and presenteeism could have important interactions which also affect labor supply. 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. A worker with a lot of available sick leave may take an absence for a fairly minor illness, while a worker with an even more severe illness but with limited or no sick leave may choose to go to work. The choice between absenteeism and presenteeism likely varies by occupation or employer, and may also vary for the same worker over time. A worker may readily 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 available sick leave, or faces other penalties for missing work.

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 for this nationally representative sample, and examine the relationship between absenteeism and presenteeism. We then relate absenteeism, presenteeism and the interaction between absenteeism and presenteeism to labor force outcomes three 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.

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. Different surveys and databases capture this data over different time frames (e.g., over the past week, month or year), and often focus on select groups of employees or workers with specific health conditions. As a result, the existing literature is somewhat piecemeal, with studies focusing on a particular health condition or analyzing the effects in a particular workplace (e.g., Boles et al. 2004, Burton et al. 2005,

Callen et al. 2005, Kessler et al. 2001, Anesetti-Rothermel and Sambamoorthi 2001, Muchmore et al. 2003, Cohen et al. 2015, Pelletier et al. 2009, Howard and Potter 2014).

Some studies have measured the overall distribution of absenteeism or presenteeism in the United States (e.g., Davis et al. 2005, Susser and Ziebarth 2016, Ahn and Yelowitz 2016), and other studies relate absenteeism patterns to future disability benefit take up for manufacturing workers in the U.S. (Harrati et al. 2018) and for the overall workforce in Scandinavian countries (Andren 2007, Wallman et al. 2009, Gjesdal and Bratberg 2003). However, data limitations have prevented a comprehensive analysis of how absenteeism and presenteeism interact, 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 analysis leads to 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 $90^{\text {th }}$ percentile take 7 absences per year. While nearly two-thirds of the population reports working while sick at least once in the past year, productivity losses while working sick are also moderate, averaging around 20 percent. Second, absenteeism and presenteeism are highly correlated. Workers who report ever engaging in presenteeism are 36 percent more likely to have a high absence rate, and workers with a high absence rate are 13 percent more likely to report ever engaging in presenteeism. Furthermore, workers with a high absence rate are nearly 50 percent 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 relative to the overall distribution. We find that individuals with absence rates in the right tail of the distribution - individuals with absence rates above the $95^{\text {th }}$ percentile ( 10 days/year) - who also engage in presenteeism have a reduced probability of working or participating in the labor force three years later. These findings suggest it could be useful to target individuals with significant deviations from the normal patterns of absence for additional screening or intervention.

## 2. Background

## Defining Presenteeism and Absenteeism

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, on the other hand, 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. Both presenteeism and productivity loss are typically measured in self-reported survey data, while 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 compared to days of work missed due to illness specifically), data sources, and time frames (e.g., days missed over the last two weeks vs. over the last year). The lack of a standardized measure for absence rates and presenteeism in the literature presents a challenge for researchers attempting to synthesize findings across the literature.

Furthermore, absenteeism and presenteeism are often measured differently even when using the same definition. In principle, absences can be measured by simply counting the number of missed work days, but in survey settings respondents may experience recall bias when asked to report the number of absences over a given period of time. Collecting absence data directly from employer records minimizes this measurement error. However, administrative data are often limited to a select group of employers and may not be generalizable to the entire population of workers. Presenteeism is more difficult to measure objectively and is not captured in administrative records. Some survey-based measures of presenteeism ask workers to rate their productivity on a given day or week relative to their average productivity, and then follow up and ask the reason for the higher or lower productivity (e.g., due to illness or some other reason). Others simply ask if an individual went to work while sick, or felt like they were less productive on the job due to sickness. ${ }^{1}$ As a result, the incidence and extent of presenteeism are inherently subjective and could also be measured with error.

Another important consideration is the availability of employer-provided sick leave, which permits workers to take days off from work when ill without risk of job loss. Sick leave can be either paid or unpaid, and is often capped. There is no federal mandate to provide paid sick leave, although some states require employers to provide it. The Family and Medical Leave Act requires employers with 50 or more employees to provide at least unpaid sick leave for up to 12 weeks for personal or family illness.

According to the Bureau of Labor Statistics (BLS), in March 2015, 61 percent of private industry workers had some paid sick leave benefits. Of those, about 70 percent received a fixed number of paid sick days per year, and that fixed number varied by establishment size and length

[^1]of service. Private-sector workers in small firms (<50 workers) received an average of 6 paid sick days per year after one year of service, while those in large firms (100+ workers) received 8 days after one year of service; after 20 years of service, those in small firms received 7 paid sick days per year, compared to 10 days in large firms. The remaining 30 percent of private-sector workers with sick leave received it through a consolidated leave plan combining paid time off for any use. ${ }^{2}$ Although BLS does not provide information on sick leave use, it is likely that observed patterns of absence and presenteeism are shaped by the availability of sick leave. 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. Indeed, recent evidence from Europe finds that that increasing the generosity of short-term sick leave increases both the incidence and the duration of shortterm absences (e.g., Johansson and Palme 2002, Henrekson and Persson 2004, PettersonLindbom and Thoursie 2013, Hagglund 2013). ${ }^{3}$

## 3. Data and Methods

Our analysis primarily utilizes the American Working Conditions Survey (AWCS). The AWCS was administered in July 2015 to RAND American Life Panel (ALP) respondents who were ages 18-70. The ALP is a nationally representative panel of U.S. adults who take social science surveys regularly using the internet. The AWCS asked respondents about health conditions, workplace characteristics and preferences, labor market activity, occupation, income, work absences, and presenteeism. Some 3,131 ALP participants responded to the AWCS (response rate 64 percent), and just over 2,000 respondents were working for pay and therefore

[^2]were eligible to receive questions about absences and presenteeism. We use sample weights to make the data nationally representative (see Maestas et al., 2017, for more details).

To analyze labor market outcomes three years later, we match the 2015 AWCS to the most recent quarterly demographic update module, which was fielded to all ALP respondents in the spring of 2018-three years after the AWCS was fielded—and includes questions about respondents' current labor force participation. Approximately 70 percent of respondents in the 2015 AWCS also responded to the ALP demographic update in 2018.

## 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 to capture baseline worker characteristics 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 $0-100$ percent how much they think their productivity was affected while working sick. ${ }^{4}$ We use these variables to calculate statistics for the overall distribution of absenteeism and presenteeism and to create various measures of high absenteeism and presenteeism for values exceeding certain thresholds in the distribution, as discussed below.

[^3]We develop several other key variables for our analysis. First, we measure labor force participation three 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 percent 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. ${ }^{5}$

Additionally, we create several variables measuring various job demands that could have an impact on absence rates or presenteeism. We structure these variables after the categorizations used in other analyses using the AWCS (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 adapt their 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

[^4]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.

## Methods

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 to the other measures of absenteeism and presenteeism in the literature. After establishing the baseline distribution based on our measures, we construct distributions of absence rates and presenteeism for key subgroups in the population based on health and job characteristics. Next, we analyze crosssectional data from the 2015 AWCS in a multiple 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 this cross-sectional data form the 2015 AWCS to the 2018 ALP Demographic follow-up to assess the extent to which absenteeism and presenteeism predict various labor force outcomes three years later in a multivariate regression framework of the following form:

$$
y_{i t}=A_{i t-3} \beta+P_{i t-3} \delta+X_{i t-3} \theta+\varepsilon_{i t}
$$

We measure various labor force outcomes $y$ (working, being unemployed, disabled or retired) for worker $i$ in year $t=2018$, and relate these to data on worker absences and presenteeism behavior in $2015\left(A_{i t-3}\right.$ and $\left.P_{i t-3}\right)$ as well as other worker characteristics in $2015\left(X_{i t-3}\right)$ 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:

$$
y_{i t}=A_{i t-3} \beta+P_{i t-3} \delta+A_{i t-3} * P_{i t-3} \gamma+X_{i t-3} \theta+\varepsilon_{i t}
$$

In each of these models, the main coefficients of interest are $\beta, \delta$, and $\gamma$, which indicate the extent to which prior absence rates and/or presenteeism are significant predictors of future labor force activity.

## 4. Results

## Summary Statistics

We begin with summary statistics for the population of AWCS respondents who were working in 2015, overall and by access to sick leave. Table 1, 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) - (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 percent of the overall population works in a blue collar occupation ${ }^{6}$ and two-thirds have some level of education beyond a high school degree. Just under one-third 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 as well: 60 percent of respondents report having had muscle, joint or back pains at some point over the last 12 months. Just over one-third of the population reports having had depression at some point 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

[^5](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 fairly low absence rate is consistent with the earlier literature based on the NHIS and Commonwealth Health Insurance survey, which ask about absences in the past year (Ahn and Yelowitz 2016, Davis et al. 2005). Presenteeism is also quite common: 69 percent 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 percent on occasions when they go to work sick.

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 percent of the sample without sick leave works in blue collar occupations, compared to only 55 percent of the sample with 6-10 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.

## Characterizing the Distribution of Absenteeism and Presenteeism

Table 2 provides greater detail about the distribution of absences (Panel A), the prevalence of presenteeism (Panel B), and self-reported productivity loss when working while sick (Panel C), by health, age, and selected job characteristics. The first column repeats the means reported in Table 1 for the overall population, and additionally shows the median, $75^{\text {th }}$ and $90^{\text {th }}$ percentiles of the distributions of the continuous variables. Each of the subsequent columns divide the sample into two groups - for example, those with and without a health problem expected to last 6 months or more - and compares the distributions between these two binary categories. For each comparison, we report p-values from Kolmogorov-Smirnov (KS) tests of the equality of the distributions of the two groups.

A closer look at various points in the distribution provides further evidence of the relatively low rates of absence. For example, the $90^{\text {th }}$ percentile of number of absences over the past 12 months in the overall population is 7 days, and even among those with a health condition expected to last 6 months or longer, the $90^{\text {th }}$ percentile is 12 days of absence. Secondly, while there is some variation in the reported rates of presenteeism, it is highly prevalent across all subgroups in the population: even the lowest reported rate of presenteeism in any subgroup (respondents over age 50 ) is 58.2 percent. Similarly, the average productivity loss when working while sick is relatively constant, and nearly all subgroups have productivity losses ranging between 20 and 50 percent from the median to the $90^{\text {th }}$ percentile.

The most important differences in the distribution arise when comparing workers with and without health problems. Workers with health problems expected to last 6 months or longer, those with muscle or back problems and those with depression all report significantly higher rates of absence, presenteeism and productivity loss than those without the condition. The average number of absences in the last 12 months is 5.2 days for workers with a health problem
expected to last 6 months or longer, compared to 2.1 days for workers without a persistent health problem. For workers with muscle and back problems and depression, the average number of absence days per year are 3.4 and 4.3, respectively - both of which are significantly higher than the comparison groups' means of 2.3 and 2.2. Over three-fourths of workers with these health conditions report ever having engaged in presenteeism, and the share is particularly high for workers with depression: 82.5 percent of workers with depression report having worked while sick at least once during the last 12 months. Prior studies focusing exclusively on workers with particular mental health conditions have also found evidence of a positive relationship between mental health problems and absenteeism and presenteeism (e.g., Banerjee et al. 2017, Peng et al. 2016, Pelletier et al. 2009, Kessler et al. 2006). Not surprisingly, the KS test rejects the equality of the distributions of absenteeism and presenteeism between workers with and without these health conditions.

There are also some significant differences in absence and presenteeism patterns by age. Despite the fact that the KS test rejects the equality of the overall distribution of absences between workers above and below age 50, the mean, median and higher percentiles are similar. However, older workers are significantly less likely to engage in presenteeism than younger workers ( 58 percent compared to 76 percent), and report significantly lower average productivity losses even when they do engage in presenteeism. The distributions of absenteeism and presenteeism by job demands (physicality, flexibility and cognitive requirements) are similar as determined by the KS test. Workers in jobs with low cognitive demands and highly physical jobs also report higher mean rates of absence than those in the comparison groups, although the differences are only marginally statistically significant at the 10 percent level. Interactions between Absenteeism and Presenteeism

In Table 3, we explore characteristics that are associated with absenteeism and presenteeism in a multivariate regression framework that also controls for health, job characteristics, job demands, demographics, and availability of sick leave. Each column of Table 3 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 5 absences or more in a year); in column 2 the dependent variable is an indicator for whether the respondent reports ever working while sick; and 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 percent or higher).

Columns (1) and (2) reveal a strong correlation between high rates of absence and presenteeism: individuals who report ever working while sick are nearly 7 percentage points more likely to have more than 5 absences in a year. Given that approximately 20 percent of the population reports more than 5 absences per year, this represents a substantial 36 percent increase in the probability of a worker having a high absence rate. Individuals with at least 5 absences in a year are 9 percentage points more likely to report ever working while sick. While presenteeism is more common, this still represents a 13 percent increase in the probability of engaging in presenteeism relative to the mean of 67 percent. 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 12 percentage points - nearly 50 percent - more likely to report that working while sick reduces their productivity by at least 30 percent. 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 - perhaps even on occasions 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 11 percentage points, or 58 percent, more likely to report high absence rates. Workers with a health problem lasting 6 months or longer are also 8 percentage points more likely to report any presenteeism, a 12 percent increase in the probability of working while sick. Workers with back or muscle problems are also significantly more likely to report having gone to work while sick. And finally, workers with depression are significantly more likely to engage in all of these scenarios: having depression increases the probability of having a high absence rate by 7 percentage points, increases the probability of reporting any presenteeism by 14 percentage points, and increases the probability of high productivity loss by 10 percentage points.

Finally, older workers are less likely to have a high absence rate, presenteeism or high productivity loss when working while sick. While potentially counterintuitive, this finding could reflect selection out of work for workers in poor health as they age , perhaps after exhausting available leave, or it could reflect cohort differences in philosophies towards work (e.g., Rhodes 1983, Smola and Sutton 2002). Women are also significantly more likely to have a high absence rate, and significantly more likely to report high productivity losses when working while sick. Having access to sick leave is a significant predictor of a high absence rate, but is not significantly related to presenteeism or the extent of productivity loss when working while sick. Job demands are not predictive of high absence rates or presenteeism, with the exception of workers in highly physical jobs are more likely to report going to work while sick. 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 4 examines the association between worker absenteeism, presenteeism and other characteristics during the baseline survey in 2015 and labor market outcomes three years later. Because work absence is only defined for people who are employed, the regression is 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 3: working, being unemployed, and being disabled or retired three years later. We create indicators for the number of absences reported by the worker in four mutually exclusive groups: No absences, 1-5 absences, 6-10 absences, or 11 or more absences in the last year. For each outcome, we present results from two different 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) - (3). Then, we interact the absence indicators with the indicator for ever working while sick in columns (4)-(6). ${ }^{7}$

In columns (1) - (3), we do not find any evidence that individuals with longer absence spells are more or less likely to be working three years later, compared to individuals without any absences during 2015. While the sign of the coefficients on the absence categories suggest that workers are less likely to be working and more likely to be disabled or retired three years later, these coefficients are not statistically significant at standard levels and are all quite small,

[^6]less than 0.03 in absolute value. The coefficients on health conditions suggest a similar pattern but are also not statistically significant.

Next, in columns (4) - (6) we interact presenteeism with the absence categories. While the main coefficients on the absence categories are again not significant (indicating no association between absences and employment outcomes among workers with no reported presenteeism), we find that compared to workers without any absences, workers who engage in presenteeism and have 11 or more days of absence in 2015 are 7 percentage points less likely to be working in 2018, representing a decline in the probability of work of 8 percent relative to a base of 86 percent. Furthermore, individuals in this category (with 11 or more absences and presenteeism), are 7 percentage points more likely to be disabled or retired, representing an increase of 100 percent (relative to a base of 7 percent). Our results suggest that individuals with $11+$ absences who do not also report presenteeism are more likely to be working three years later; although this represents a small group ( 85 percent of respondents with 11 or more days of absence also report engaging in presenteeism), this group could be composed of people undergoing intensive treatment for recoverable conditions, such as cancer.

These findings suggest that substantial absenteeism combined with presenteeism could precede a shift out of the labor force three 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, Wallman et al. 2009, Gjesdal and Bratberg 2003), 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 U.S.

## 5. Conclusions

In this paper 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, 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 percent of workers do not report missing any days of work in the last year, and even the $90^{\text {th }}$ percentile is low at 7 absences per year. By contrast, presenteeism is very common: over 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 productivity losses when working while sick range around 20 percent.

We further find evidence of strong interactions between absenteeism and presenteeism. Workers who engage in presenteeism are 36 percent more likely to report more than 5 absences per year. Furthermore, individuals with high absence rates are 9 percentage points more likely to report ever working while sick, and nearly 50 percent more likely to report that working while sick reduces their productivity by at least 30 percent. 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,
on the other hand, are significantly less likely to report that they went to work while sick. We did not detect significant differences in absence rates or presenteeism for workers in jobs with high versus low flexibility, physicality, or cognitive demands. After testing these trends independently, we find that health characteristics and age are the strongest predictors in a multivariate regression framework: workers in poor health are significantly more likely to engage in absenteeism or presenteeism, while workers are significantly less likely to engage in absenteeism or presenteeism as they age.

Relating observed absenteeism and presenteeism to subsequent labor force outcomes (three 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 less likely to be working three years later, and more likely to be disabled or retired, 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 in order to maintain their employment.

These findings have important policy implications in the U.S. Specifically, workers with many absences could be a useful group to target for early interventions and accommodations. Since 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, implies that absence rates could be a useful signal for employers to identify individuals who are at risk for transitioning out of the labor force.

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Table 1: Summary Statistics for 2015 AWCS Sample, Overall and by Sick Leave

|  | (1) | (2) | (3) | (4) | (5) | (6) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Total | No sick leave | Days of available sick leave |  |  |  |
|  |  |  | 1-5 days | 6-10 days | 11+ days | Days not reported |
| Panel A: Respondent Characteristics |  |  |  |  |  |  |
| Age | 45.2 | 46.2 | 43.7*** | 44.7* | 47.2 | 43.4*** |
| Female (\%) | 46 | 48 | 39** | 44 | 54* | 46 |
| Blue collar (\%) | 60 | 73 | 60*** | 55*** | 48*** | 50*** |
| Education > high school (\%) | 68 | 62 | 65 | 67 | 77*** | 73*** |
| Work part time (\%) | 24 | 40 | 12*** | 15*** | 13*** | 27*** |
| Household income > \$75,000 | 41 | 32 | 39** | 51*** | 51*** | 39** |
| Health problem >= 6 mo (\%) | 29 | 31 | 27 | 27 | 34 | 27 |
| Muscle/back problem (\%) | 60 | 59 | 58 | 65* | 60 | 57 |
| Depression (\%) | 37 | 41 | 35* | 27*** | 38 | 39 |
| Has sick leave (\%) | 69 | 0 | 100 | 100 | 100 | 100 |
| Panel B: Absenteeism and Presenteeism |  |  |  |  |  |  |
| Any absence from work (\%) | 51 | 41 | 48* | 55*** | 71*** | 49** |
| Mean days absent (unconditonal) | 3.0 | 2.4 | 2.1 | 3.5* | 4.5*** | 2.9 |
| Median days absent (unconditional) | 1 | 0 | 0 | 1 | 2 | 0 |
| Mean days absent (conditional) | 5.9 | 5.8 | 4.3* | 6.4 | 6.3 | 6 |
| Median days absent (conditional) | 3 | 3 | 2 | 3 | 3 | 3 |
| Ever worked while sick (\%) | 69 | 68 | 70 | 73 | 69 | 68 |
| Mean pct productivity loss when working while sick | 23.0 | 25.5 | 21.8** | 21.4** | 22.2* | 22.2** |
| Median pct productivity loss when working while sick | 20 | 20 | 20 | 20 | 20 | 20 |
| Observations | 1,839 | 575 | 260 | 321 | 335 | 348 |

Notes: AWCS 2015. Statistics calculated using sample weights. Sample based on respondents who were working at baseline. Stars 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. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$.

Table 2: Distributions of Absences and Presenteeism by Worker Characteristics

|  | Total | Health problem $>=$ 6 months |  | Muscle/back problem |  | Depression |  | Age |  | Job Flexibility |  | $\begin{array}{\|r} \text { Cognitiv } \\ \text { of } \\ \hline \end{array}$ | $\begin{aligned} & \text { emands } \\ & \mathrm{b} \end{aligned}$ | Physica | $\begin{aligned} & \text { emands } \\ & \text { b } \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | No | Yes | No | Yes | No | Yes | $<50$ | $>=50$ | Low | High | Low | High | Low | High |
| Panel A: Number of absences in the last 12 months |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Mean | 3.0 | 2.1 | 5.2 | 2.3 | 3.4 | 2.2 | 4.3 | 3.0 | 2.9 | 3.4 | 2.6 | 3.2 | 2.6 | 2.1 | 3.1 |
| p50 | 1 | 0 | 2 | 0 | 1 |  | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |
| p75 | 3 | 3 | 5 |  | 4 |  | 5 | 3 | 3 | 3 | 3 | 3 | 3 | 2 | 3 |
| p90 | 7 | 5 | 12 |  | 8 |  | 10 | 7 | 6 | 8 | 6 | 7 | 6 | 5 | 7 |
| p-value | -- |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| N | 1839 | 601 | 1238 | 1133 | 705 | 690 | 1147 | 969 | 870 | 1142 | 697 | 789 | 1050 | 1437 | 402 |
| Panel B: Percent reporting any presenteeism in last 12 months |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Mean | 69.3 | 65.4 | 78.8 | 58.7 | 76.5 | 62.2 | 82.5 | 76.1 | 58.2 | 70.5 | 68.5 | 68.7 | 70.3 | 64.6 | 70.3 |
| p-value | -- |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| N | 1839 | 601 | 1238 | 1133 | 705 | 690 | 1147 | 969 | 870 | 1142 | 697 | 789 | 1050 | 1437 | 402 |
| Panel C: Percent productivity loss conitional on working while sick |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Mean | 23.0 | 22.1 | 24.7 | 20.2 | 24.4 | 19.4 | 27.6 | 24.6 | 19.5 | 22.8 | 23.2 | 22.7 | 23.5 | 23.4 | 22.9 |
| p50 | 20 | 20 | 20 | 20 | 20 | 20 | 30 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| p75 | 30 | 30 | 40 | 30 | 40 | 30 | 40 | 40 | 30 | 30 | 30 | 30 | 30 | 30 | 30 |
| p90 | 50 | 50 | 50 | 50 | 50 | 40 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 |
| p-value | -- |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| N | 1236 | 459 | 777 | 404 | 832 | 678 | 558 | 583 | 653 | 773 | 463 | 532 | 704 | 993 | 243 |

 of the distributions between each binary category (e.g., distribution of absences for respondents with depression vs. distribution of absences for respondents without depression). In Panel B, p-value is from a ttest.

Table 3: Cross-sectional Prediction of Absenteeism and Presenteeism in 2015

|  | (1) | (2) | (3) |
| :---: | :---: | :---: | :---: |
|  | High Absence Rate | Any Presenteeism | High Productivity Loss |
| Any presenteeism | $\begin{gathered} \hline 0.0679 * * * \\ (0.0179) \end{gathered}$ |  |  |
| High absence rate |  | $\begin{gathered} 0.0949 * * * \\ (0.0250) \end{gathered}$ | $\begin{gathered} 0.124 * * * \\ (0.0325) \end{gathered}$ |
| Health problem $>=6$ months | $\begin{gathered} 0.111^{* * *} \\ (0.0216) \end{gathered}$ | $\begin{gathered} 0.0836 * * * \\ (0.0231) \end{gathered}$ | $\begin{gathered} 0.0357 \\ (0.0268) \end{gathered}$ |
| Muscle/back problem | $\begin{gathered} 0.0311 \\ (0.0194) \end{gathered}$ | $\begin{gathered} 0.0932 * * * \\ (0.0252) \end{gathered}$ | $\begin{aligned} & 0.00680 \\ & (0.0273) \end{aligned}$ |
| Depression | $\begin{gathered} 0.0711^{* * *} \\ (0.0217) \end{gathered}$ | $\begin{gathered} 0.144 * * * \\ (0.0242) \end{gathered}$ | $\begin{gathered} 0.102 * * * \\ (0.0276) \end{gathered}$ |
| Job has high flexibility | $\begin{aligned} & -0.0120 \\ & (0.0205) \end{aligned}$ | $\begin{gathered} 0.0377 \\ (0.0234) \end{gathered}$ | $\begin{aligned} & 0.00164 \\ & (0.0272) \end{aligned}$ |
| Job has high physical demands | $\begin{gathered} 0.0143 \\ (0.0214) \end{gathered}$ | $\begin{aligned} & 0.0454 * \\ & (0.0273) \end{aligned}$ | $\begin{aligned} & 0.00779 \\ & (0.0309) \end{aligned}$ |
| Job has high cognitive demands | $\begin{aligned} & 0.00479 \\ & (0.0197) \end{aligned}$ | $\begin{aligned} & 0.00322 \\ & (0.0230) \end{aligned}$ | $\begin{gathered} 0.0263 \\ (0.0266) \end{gathered}$ |
| Age | $\begin{aligned} & -0.00165 * * \\ & (0.000786) \end{aligned}$ | $\begin{gathered} -0.00755 * * * \\ (0.000935) \end{gathered}$ | $\begin{gathered} -0.00290^{* * *} \\ (0.00106) \end{gathered}$ |
| Female | $\begin{gathered} 0.0431 * * \\ (0.0180) \end{gathered}$ | $\begin{aligned} & -0.0256 \\ & (0.0218) \end{aligned}$ | $\begin{gathered} 0.0625 * * \\ (0.0245) \end{gathered}$ |
| Education > high school | $\begin{aligned} & -0.0119 \\ & (0.0287) \end{aligned}$ | $\begin{gathered} 0.0377 \\ (0.0329) \end{gathered}$ | $\begin{aligned} & 0.00475 \\ & (0.0387) \end{aligned}$ |
| Household income > \$75,000 | $\begin{gathered} -0.0454 * * \\ (0.0197) \end{gathered}$ | $\begin{gathered} 0.0298 \\ (0.0243) \end{gathered}$ | $\begin{gathered} -0.0161 \\ (0.0278) \end{gathered}$ |
| Blue collar | $\begin{aligned} & -0.0164 \\ & (0.0201) \end{aligned}$ | $\begin{aligned} & 0.00610 \\ & (0.0243) \end{aligned}$ | $\begin{gathered} -0.0316 \\ (0.0274) \end{gathered}$ |
| Has sick leave | $\begin{gathered} 0.0741^{* * *} \\ (0.0188) \end{gathered}$ | $\begin{gathered} -0.000260 \\ (0.0237) \end{gathered}$ | $\begin{aligned} & -0.0431 \\ & (0.0276) \end{aligned}$ |
| Constant | $\begin{gathered} 0.0961 \\ (0.0587) \end{gathered}$ | $\begin{gathered} 0.791 * * * \\ (0.0698) \end{gathered}$ | $\begin{aligned} & 0.280 * * * \\ & (0.0775) \end{aligned}$ |
| Observations | 1,794 | 1,794 | 1,207 |
| R-squared | 0.074 | 0.105 | 0.059 |
| Ymean | 0.191 | 0.672 | 0.243 |

[^7]Table 4: The Impact of 2015 Absenteeism/Presenteeism on 2018 Labor Force Participation

|  | (1) <br> Working | (2) <br> Unemployed | (3) <br> Disabled/ <br> Retired | (4) <br> Working | (5) <br> Unemployed | (6) <br> Disabled/ <br> Retired |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1-5 Absences | $\begin{gathered} -0.00473 \\ (0.0212) \end{gathered}$ | $\begin{aligned} & 0.00336 \\ & (0.0118) \end{aligned}$ | $\begin{aligned} & -0.00134 \\ & (0.0147) \end{aligned}$ | $\begin{aligned} & 0.00814 \\ & (0.0375) \end{aligned}$ | $\begin{aligned} & -0.00585 \\ & (0.0169) \end{aligned}$ | $\begin{aligned} & -0.0109 \\ & (0.0289) \end{aligned}$ |
| 6-10 Absences | $\begin{aligned} & -0.00735 \\ & (0.0423) \end{aligned}$ | $\begin{gathered} -0.0130 \\ (0.0201) \end{gathered}$ | $\begin{gathered} 0.0137 \\ (0.0313) \end{gathered}$ | $\begin{aligned} & -0.0567 \\ & (0.106) \end{aligned}$ | $\begin{gathered} -0.0178 \\ (0.0138) \end{gathered}$ | $\begin{aligned} & 0.0947 \\ & (0.103) \end{aligned}$ |
| 11+ Absences | $\begin{aligned} & -0.0259 \\ & (0.0467) \end{aligned}$ | $\begin{gathered} -0.0144 \\ (0.0225) \end{gathered}$ | $\begin{gathered} 0.0446 \\ (0.0381) \end{gathered}$ | $\begin{gathered} 0.129^{* * *} \\ (0.0292) \end{gathered}$ | $\begin{gathered} -0.0325^{*} * \\ (0.0145) \end{gathered}$ | $\begin{gathered} -0.0779 * * * \\ (0.0280) \end{gathered}$ |
| Any presenteeism | $\begin{aligned} & -0.0256 \\ & (0.0212) \end{aligned}$ | $\begin{gathered} 0.0118 \\ (0.0103) \end{gathered}$ | $\begin{gathered} 0.0113 \\ (0.0159) \end{gathered}$ | $\begin{gathered} -0.0148 \\ (0.0275) \end{gathered}$ | $\begin{aligned} & 0.00652 \\ & (0.0143) \end{aligned}$ | $\begin{aligned} & 0.00526 \\ & (0.0204) \end{aligned}$ |
| Health problem $>=6$ months | $\begin{aligned} & -0.0254 \\ & (0.0222) \end{aligned}$ | $\begin{gathered} -0.000755 \\ (0.0117) \end{gathered}$ | $\begin{gathered} 0.0202 \\ (0.0168) \end{gathered}$ | $\begin{aligned} & -0.0252 \\ & (0.0221) \end{aligned}$ | $\begin{gathered} -0.000858 \\ (0.0117) \end{gathered}$ | $\begin{gathered} 0.0206 \\ (0.0167) \end{gathered}$ |
| Muscle/back problems | $\begin{aligned} & -0.0184 \\ & (0.0212) \end{aligned}$ | $\begin{gathered} 0.0234 * * \\ (0.0118) \end{gathered}$ | $\begin{aligned} & -0.00315 \\ & (0.0153) \end{aligned}$ | $\begin{aligned} & -0.0194 \\ & (0.0212) \end{aligned}$ | $\begin{gathered} 0.0235^{* *} \\ (0.0119) \end{gathered}$ | $\begin{aligned} & -0.00285 \\ & (0.0152) \end{aligned}$ |
| Depression | $\begin{aligned} & 0.00225 \\ & (0.0224) \end{aligned}$ | $\begin{aligned} & -0.00741 \\ & (0.0127) \end{aligned}$ | $\begin{aligned} & -0.00170 \\ & (0.0156) \end{aligned}$ | $\begin{aligned} & 0.00355 \\ & (0.0224) \end{aligned}$ | $\begin{aligned} & -0.00755 \\ & (0.0128) \end{aligned}$ | $\begin{aligned} & -0.00258 \\ & (0.0156) \end{aligned}$ |
| Presenteeism * 1-5 Absences |  |  |  | $\begin{aligned} & -0.0191 \\ & (0.0445) \end{aligned}$ | $\begin{gathered} 0.0131 \\ (0.0220) \end{gathered}$ | $\begin{gathered} 0.0137 \\ (0.0334) \end{gathered}$ |
| Presenteeism * 6-10 Absences |  |  |  | $\begin{aligned} & 0.0550 \\ & (0.114) \end{aligned}$ | $\begin{aligned} & 0.00735 \\ & (0.0266) \end{aligned}$ | $\begin{aligned} & -0.0939 \\ & (0.107) \end{aligned}$ |
| Presenteeism * 11+ Absences |  |  |  | $\begin{gathered} -0.188 * * * \\ (0.0596) \\ \hline \end{gathered}$ | $\begin{gathered} 0.0232 \\ (0.0304) \\ \hline \end{gathered}$ | $\begin{aligned} & 0.147 * * * \\ & (0.0504) \\ & \hline \end{aligned}$ |
| Total effect - Presenteeism * 11+ Absences |  |  |  | $\begin{gathered} \hline-0.0730 \\ (0.0570) \end{gathered}$ | $\begin{gathered} \hline-0.0030 \\ (0.0280) \end{gathered}$ | $\begin{gathered} \hline 0.0740 \\ (0.0460) \end{gathered}$ |
| Observations | 1,278 | 1,278 | 1,278 | 1,278 | 1,278 | 1,278 |
| R-squared | 0.036 | 0.022 | 0.101 | 0.039 | 0.022 | 0.105 |
| Ymean | 0.866 | 0.0338 | 0.0707 | 0.866 | 0.0338 | 0.0707 |

[^8]Table A1: Baseline Absence and Presenteeism Rates in the Extant Literature

| Study | Data Sources | Sample | Statistics | Measured frequency |
| :---: | :---: | :---: | :---: | :---: |
| Ahn and Yelowitz 2016 | NHIS 2005-2013 | US Adults ( $\mathrm{n}=9,632$ ) | - 3.7 (3.0) absences per year on average for workers with (without) paid sick leave <br> - 13-17 percent report more than 5 absences per year | Absences per year |
| Howard and Potter 2014 | NHIS, 2000 and 2010 | US Adults 18+ employed within last 12 months with obesity-related chronic conditions ( $\mathrm{n}=18,860-2000$, 16,626-2010) | - 47/41 percent reported at least one absence in the last year in 2000/2010 <br> - Majority of workers with any absence report 2-6 days <br> - Obesity associated with $94 \%(34 \%)$ higher absence rate in 2000 (2010) | Days missed per year |
| Davis et. al. 2005 | Commonwealth Fund Biennial Health Insurance Survey, 2005 | US adults, 19-64 ( $\mathrm{n}=4,350$ ) | - 64 percent took at least one sick day in a year <br> - 20 percent took 6 or more sick days in a year <br> - 50 percent reported at least one occasion of presenteeism per yr <br> - 20 percent reported 6 or more occasions of presenteeism per yr | Absenteeism/ presenteeism rates per year |
| Garcia-Serrano and Malo $2014$ | European Community <br> Household Panel, 1995-2001 | European households $(\mathrm{n}=$ 83.754) | $\cdot$-1-2.9 absence days per month for individuals with disabilities <br> - 0.5-0.8 absence days per month for individuals without disabilities | Absence days per month |
| Kessler et. al. 2001 | Midlife Development in the United States, 1995-1996 | US Adults, 25-54, ( $\mathrm{n}=2,074$ ) | - 17.5 percent reported one missed work day in the past month <br> - Unconditional (conditional) mean missed work days: 1.1 <br> (6.3) <br> - 20.2 percent reported a cut-back work day in the past month <br> - Unconditional (conditional) cut-back days: 1.1 (5.4) | Absenteeism/reduced productivity in the last 30 days |

Table A1 con't: Baseline Absence and Presenteeism Rates in the Extant Literature

| Study | Data Sources | Sample | Statistics | Measured frequency |
| :---: | :---: | :---: | :---: | :---: |
| Boles et. al. 2004 | Survey data from an online health assessment, including WPAI questionnaire, 2001 | Employees at large US employer ( $\mathrm{n}=2,264$ ) | - 1.8 percent reported absenteeism in the last week <br> - 6.6 percent reported presenteeism in the last week | Average absenteeism / presenteeism rates in the last week |
| Susser and Ziebarth 2016 | American Time Use Survey <br> Leave Supplement, 2011 | US adults, ( $\mathrm{n}=6,354$ ) | - 4.8 percent take sick leave in any given week <br> - 2 percent go to work sick in any given week | Average absenteeism / presenteeism rates per week |
| Burton et. al. 2006 | Health risk assessment survey, with questions about work limitations and productivity, 2002 and 2004 | US employees of a financial services company, 18-64 ( $\mathrm{n}=$ 7,000) | - 12 percent productivity loss due to presenteeism on average <br> - Each risky behavior associated with 1.9 percent increase in productivity loss | Reported productivity loss in last two weeks |
| Callen et. al. 2005 | Survey data - health risk assessment, 2010 | Employees at company based in Tennessee $(\mathrm{n}=1,728)$ | $\cdot \sim 30$ percent reported at least one day of presenteeism in last 4 weeks <br> - Unconditional mean: 0.5 days of presenteeism <br> - 6 percent reported more than 2 days of presenteeism | Reduced productivity rates in the last 4 weeks |


[^0]:    ${ }^{1}$ Harvard Medical School and NBER; ${ }^{2}$ RAND; ${ }^{3}$ IZA. This research was supported by the U.S. Social Security Administration through grant \#5 DRC12000002-06 to the National Bureau of Economic Research as part of the SSA Disability Research Consortium. The opinions and conclusions expressed are solely those of the authors and do not represent the opinions or policy of SSA or any agency of the Federal Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, expressed or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of the contents of this report. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply endorsement, recommendation or favoring by the United States Government or any agency thereof. We thank David Zingher for excellent research assistance and Amal Harrati and participants of the 2018 DRC Annual Conference for helpful comments.

[^1]:    ${ }^{1}$ See Goetzel et al. 2004 for a review of survey instruments for measuring productivity losses, including the Worker Productivity and Activity Impairment questionnaire.

[^2]:    ${ }^{2}$ See https://www.bls.gov/opub/ted/2016/number-of-paid-sick-leave-days-in-2015-varies-by-length-of-service-and-establishment-size.htm for more details.
    ${ }^{3}$ For a comprehensive discussion of the prior literature on absenteeism and presenteeism, see Mullen and Rennane 2017.

[^3]:    ${ }^{4}$ This question is similar to the presenteeism question in the Work Productivity and Activity Impairment Questionnaire, which asks workers to rate the extent of their productivity loss on a scale from 1-10.

[^4]:    ${ }^{5}$ We include workers who report being temporarily laid off in the unemployment category. Self-employment is another possible category, however less than 1 percent of respondents select self-employment as an option, and all of them also report that they are working and so are included in the working category.

[^5]:    ${ }^{6}$ Blue-collar occupations, defined as occupations with Standard Occupation Classification codes of 31 or higher, denote occupations that usually do not require a college degree.

[^6]:    ${ }^{7}$ We also tried excluding the health controls from both models and find similar results.

[^7]:    Notes: AWCS 2015. Sample includes all respondents who were working in the baseline survey. High absence rate is measured as 5 or more days absent from work in a year; high productivity loss is measured as a reported producitivity loss of 30 percent or higher. All covariates and dependent variable measured in baseline survey in 2015. Robust standard errors in parentheses. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$

[^8]:    Notes: Uses 2015 AWCS and 2018 ALP Demographic update. Independent variables are all measured at the time of the baseline survey in 2015, and dependent labor force outcomes are measured three years later in the 2018 ALP Demographic follow-up. Labor force outcome variables are mutually exclusive.
    Unemployment variable includes individuals who report being temporarily laid off. All regressions conditional on respondent working during the baseline survey in 2015 and ALP follow up in 2018. Regression includes additional controls for age, gender, education, income, occupaton, job demands and access to sick leave. Robust standard errors in parenthesis. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05$, ${ }^{*} \mathrm{p}<0.1$.

