Distinct Longitudinal Patterns of Absenteeism and Their Antecedents in Full-Time Australian Employees

Christopher A. Magee, Peter Caputi, and Jeong Kyu Lee
University of Wollongong

This paper investigated distinct longitudinal trajectories of absenteeism over time, and underlying demographic, work, and health antecedents. Data from the Household, Income, and Labor Dynamics in Australia Survey were used; this is a panel study of a representative sample of Australian households. This paper focused on 2,481 full-time employees across a 5-year period. Information on annual sick leave and relevant sociodemographic, work, and health-related factors was collected through interviews and self-completed surveys. Growth mixture modeling indicated 4 distinct longitudinal patterns of absenteeism over time. The moderate absenteeism trajectory (34.8%) of the sample had 4–5 days of sick leave per year and was used as the reference group. The low absenteeism trajectory (33.5%) had 1–2 days of absenteeism per year, while the no absenteeism trajectory (23.6%) had very low rates of absenteeism (<1 day per year). Finally, a smaller trajectory accounting for 8.1% of the sample had high levels of absenteeism (>11 days per year). Compared with the moderate absenteeism trajectory, the high absenteeism trajectory was characterized by poor health; the no absenteeism and low absenteeism trajectories had better health but may also reflect processes relating to presenteeism. These results provide important insights into the nature of absenteeism in Australian employees, and suggest that different patterns of absenteeism over time could reflect a range of demographic, work, and health related factors.

**Keywords:** absenteeism, growth mixture modeling, job security, work hours, health

Absenteeism, which refers to “the failure to report to work as scheduled” (Johns, 2008, p. 160), is a major contributor to reduced workplace productivity and has considerable financial costs through health insurance claims, overtime wages, and legal claims (Durr & Johns, 2008). Absenteeism can have longer term effects on productivity by contributing to conditions such as depression (Melchior et al., 2009) and leading to eventual withdrawal from the workplace (Westman & Etzion, 2001). In Australia, average rates of absenteeism range from 4 days per year (private sector employees) to 8 days per year (public sector employees) and vary by age, length of service, income, gender, organization size, and industry type (Audit Office of New South Wales, 2010). It is estimated that absenteeism costs the Australian economy at least $7 billion a year in lost productivity and health care costs (Medibank Private, 2005). Studies from North America and Europe also indicate that the economic costs of absenteeism are considerable (Confederation of British Industry, 2004; Cooper & Dewe, 2008; Goetzel et al., 2004).

Although a vast body of literature has investigated antecedents and consequences of absenteeism in numerous contexts (Johns, 2011), many aspects of absenteeism remain unclear. Few studies have investigated whether there are distinct longitudinal patterns of absenteeism in employees; this is an important consideration because patterns of absenteeism over time could vary considerably between individuals, reflecting the role of different antecedents. The current paper aimed to investigate the presence of distinct longitudinal trajectories of absenteeism, and their underlying antecedents to better understand the nature of absenteeism. The remainder of this introduction outlines some key theories of absenteeism, and briefly reviews existing longitudinal research examining antecedents of absenteeism. The need to examine distinct trajectories of absenteeism over time is then presented, followed by the aims and main research questions of the present study.

**Absenteeism Behavior**

Absenteeism is a complex phenomenon, with many interrelated factors having the potential to influence an employee’s decision and ability to attend work. Historically, a distinction has been drawn between involuntary absenteeism and voluntary absenteeism (Brooke, 1986; Johns, 2011; Nicholson, 1977; Steers & Rhodes, 1978). Involuntary absenteeism (also known as sickness absenteeism) refers to instances where employees do not attend work due to poor physical or mental health (Brooke, 1986; Steers & Rhodes, 1978). The term involuntary does not imply an employee...
lacks control over their decision to attend work; rather, it refers to the influence of external factors in constraining an employee’s ability to attend work (Beemsterboer, Stewart, Groothoff, & Nijhuis, 2009). In general, involuntary absenteeism behavior is characterized by duration rather than frequency of absenteeism spells (Brooke, 1986). Voluntary absenteeism differs in that it reflects a choice to withdraw or escape from a negative work environment (Steers & Rhodes, 1978). In other words, employees may choose to be absent from work as a way of escaping, avoiding, or compensating for adverse, demoralizing, or stressful work environments (Hardy, Woods, & Wall, 2003). Voluntary absenteeism is reflected by duration rather than frequency of missed days of work (Brooke, 1986).

Many conceptual models and frameworks have been proposed to explain voluntary and involuntary absenteeism. It is beyond the scope of this study to review all of these in detail; however some key theoretical perspectives are briefly presented. Nicholson’s (1977) attendance motivation model conceptualized absenteeism behavior on a continuum from primarily unavoidable (involuntary) to primarily avoidable (voluntary) absenteeism. Nicholson (1977) argued that contextual factors (e.g., personal characteristics, job characteristics, demographics) influence an employee’s level of attachment to work, which in turn affects how motivated they are to attend work. According to this model, attending work is the norm behavior until proximal events interfere with an employee’s ability to attend work or force them to make a decision about whether to attend work. Nicholson (1977) suggested that employees with higher levels of attendance motivation are less affected by these proximal events.

Steers and Rhodes (1978) proposed a widely cited conceptual model of attendance at work that provides an insight into voluntary and involuntary absenteeism. They proposed that demographic characteristics have an indirect influence on attendance behavior via two main variables: (a) an employee’s motivation to attend work and (b) an employee’s ability to attend work. Motivation to attend work reflects an employee’s affective response to their job (e.g., job satisfaction) and a range of internal and external pressures (e.g., economic, social, or personal pressures). According to this model, when an employee enjoys his or her work, they have a strong motivation to attend work, and thus take fewer absenteeism days (Steers & Rhodes, 1978). The model also proposes that factors such as illness and accidents, family responsibilities, and transportation problems may inhibit an individual’s ability to attend work regardless of motivation; these factors contribute to involuntary absenteeism (Steers & Rhodes, 1978). This model was extended by Brooke (1986) who outlined several exogenous (e.g., routinization, work involvement, role ambiguity, organizational permissiveness) variables and five endogenous variables (job satisfaction, job involvement, organizational commitment, health, and alcohol consumption), and hypothesized pathways by which these variables were related with each other and with absenteeism.

Nicholson and Johns (1985) proposed that in addition to many person-level factors captured in the models outlined above, two social factors - absence cultures and the psychological contract—also have the potential to influence absenteeism. Absence cultures in a workplace can directly influence absenteeism for a given group of employees through shared norms. Employees may also observe the absence behaviors of other employees and the reactions to these behaviors (Nicholson & Johns, 1985). Furthermore, absence cultures may facilitate or constrain the effects of person level variables such as job satisfaction on absenteeism. Nicholson and Johns (1985) specifically postulated that two interrelated factors influence absence culture: (a) beliefs about absence and (b) assumptions about employment (the psychological contract). Nicholson and Johns (1985) argued that absence culture and psychological contract are able to account for differences in absenteeism behavior within and between organizations. For example, factors such as occupational status (e.g., white collar vs. blue collar workers) may lead to differing beliefs regarding the legitimacy of absences, which translates to different absenteeism behaviors.

These and several more recent conceptual frameworks and models (Halbesleben, Whitman, & Crawford, 2014; Johns, 2010; Schaufeli, Bakker, & Van Rhenen, 2009) provide insight into a range of factors that influence absenteeism behavior along the involuntary-voluntary continuum. They suggest that a range of demographic, work and job related, social, and health factors have the potential to influence absenteeism behaviors.

Existing Longitudinal Studies

A large number of studies have examined absenteeism behavior and underlying antecedents however, few studies have been theory based and most have been inconsistent in terms of the type and scope of antecedents examined. This section does not intend to provide an exhaustive review of the longitudinal evidence base, which is vast and encompasses a wide range of antecedents. Instead, the aim is to provide an indication of the main antecedents of absenteeism, consistent with established theoretical frameworks such as Steers and Rhodes (1978). For clarity, the findings are organized according to demographic characteristics, job satisfaction, psychosocial job characteristics, work characteristics, and health.

Demographic Characteristics

Factors such as age, sex, and socioeconomic status (e.g., education) have been found to predict levels of absenteeism. For example, age is inversely associated with absenteeism (Labriola, Lund, & Burr, 2006; Martocchio, 1989; Ng & Feldman, 2008), while in terms of sex females tend to have higher rates of absenteeism compared with males (Labriola et al., 2006; Mastekaasa & Olsen, 1998). Consistent with Steers and Rhodes (1978), these characteristics may have direct or indirect effects on absenteeism (e.g., indirect effects via health and motivation) or moderate the effects of the variables noted below on absenteeism.

Job Satisfaction

Job satisfaction is regarded as a key motivational factor underlying absenteeism behavior. In general, employees who have higher levels of job satisfaction have lower rates of absenteeism (Schaufeli et al., 2009; Ybema, Smulders, & Bongers, 2010). This is consistent with the proposition of many existing frameworks that employees who are more satisfied with aspects of their jobs will be more motivated to attend work and thus have lower rates of absenteeism (e.g., Brooke, 1986; Steers & Rhodes, 1978).
Psychosocial Job Characteristics

Many longitudinal studies utilizing theories such as the job-demands control model (Karasek, 1979), job demands resources model (Schaufeli et al., 2009), and the effort-reward imbalance model (Siegrist, 1996) have demonstrated that aspects of the psychosocial work environment are associated with absenteeism behavior. For example, low job control (Nielsen, Rugulies, Christensen, Smith-Hansen, & Kristensen, 2006; Smulders & Nijhuis, 1999; Väänänen et al., 2003; Virtanen et al., 2007), high job strain (Suominen et al., 2007), low social support (Melchior, Niedhammer, Berkman, & Goldberg, 2003), poor role clarity (Rugulies et al., 2007), workplace bullying (McTernan, Dollard, & Lamontagne, 2013), reduced organizational commitment (Bakker, Demerouti, de Boer, & Schaufeli, 2003), poor organizational climate, and poor leadership (Rugulies et al., 2007) have all been linked with higher absenteeism. Findings for factors such as job demands have been mixed (Smulders & Nijhuis, 1999; Virtanen et al., 2007), with some studies finding that higher job demands predict absenteeism in females but not males (Nielsen et al., 2006; Virtanen et al., 2007). Some studies have found that changes in psychosocial characteristics over time (e.g., reductions in job control and increases in job demands) predict greater absenteeism (Head et al., 2006; Vahtera, Kivimäki, Pentti, & Theorell, 2000). According to the theoretical perspectives outlined in the previous section, these psychosocial factors may lead to more absenteeism via lower job satisfaction and motivation to attend work, or by hindering the ability to attend work through elevated stress and poor health (Brooke, 1986; Nicholson, 1977; Steers & Rhodes, 1978).

Studies have increasingly examined the role of job security in absenteeism, and have revealed mixed results (Blekesaune, 2012). Some studies report that lower levels of job security lead to more absenteeism (Kivimäki et al., 1997); this can be interpreted in the context of stressor perspectives, as lower job security could lead to greater psychological distress and hence more sick leave (Blekesaune, 2012). In contrast, other studies have found that lower levels of job security lead to less absenteeism (Blekesaune, 2012); this finding can be explained by a disciplinary effect, as lower job security may be associated with fear of losing one’s job which leads to less absenteeism (Blekesaune, 2012). Blekesaune (2012) suggested that the disciplinary effect is most likely to account for short-term absenteeism, while the stressor effect accounts for longer-term absenteeism.

Work Characteristics

Characteristics of an individual’s work such as their job type, work schedule, and work hours have been linked with levels of absenteeism. For example, white-collar workers have been found to have lower absenteeism compared with blue-collar workers (Poussette & Hanse, 2002), which is consistent with Nicholson and Johns’ (1985) model. Studies have shown that working night shifts is associated with increased absenteeism; for many employees shift work is demanding and can be a source of stress, which could lead to poorer health and thus higher absenteeism (Fekedulegn et al., 2013). Findings for work hours are not clear, although some studies indicate that longer work hours are associated with lower absenteeism (Magee, Stefanic, Caputi, & Iverson, 2011). Other factors such as no access to sick leave benefits or self-employed status are also associated with lower rates of absenteeism (Benedix, Benach, Diez-Roux, & Roman, 2000).

Health and Illness

Health-related factors have consistently been shown to predict absenteeism behavior (Labriola et al., 2006; Schalk, 2011; ten Brummelhuis, Ter Hoeven, De Jong, & Peper, 2013). Short-term absences from work are often attributed to acute illnesses such as the common cold and influenza (Schaufeli et al., 2009), whereas long-term absences are attributed to chronic mental and physical health conditions including pain (e.g., neck pain), long-term disability, hypertension, depression, and migraines (Kääriä, Laaksonen, Leino-Arjas, Saastamoinen, & Labelma, 2012; Schaufeli et al., 2009). Poor psychological health (e.g., depression, anxiety, general psychological distress) and sleep disturbances (e.g., insomnia) also predict absenteeism (Knudsen, Harvey, Mykletun, & Overland, 2013; Roelen et al., 2014; Wada et al., 2013). Consistent with Steers and Rhodes (1978), poor health may contribute to involuntary absenteeism by constraining one’s ability to attend work.

Trajectories of Absenteeism Behavior

A large body of longitudinal research therefore indicates that a range of factors have the potential to influence absenteeism behavior. However, these studies provide only a partial insight into the nature of absenteeism and its antecedents. This is because most studies utilize analytic techniques that do not capture potential interindividual and intrindividual differences in absenteeism over time. These are important considerations as patterns of absenteeism behavior may vary considerably across time and between employees. These variations could be reflected in distinct longitudinal trajectories of absenteeism, which may have distinct antecedents. For example, some absenteeism trajectories could reflect the influence of motivational factors, some may reflect more constraint factors (e.g., health), while others reflect a combination of factors. Investigation of these intrindividual and interindividual variations in absenteeism, along with their antecedents, is needed to provide a more definitive insight into the nature of absenteeism.

To date, only a small number of studies have explored distinct longitudinal trajectories of absenteeism (Dello Russo, Miraglia, Borgogni, & Johns, 2013; Haukka et al., 2014; Haukka et al., 2013). In a representative sample of 3,420 Finnish employees followed for 7 years, Haukka and colleagues (2013) identified four distinct trajectories of absenteeism spells (defined as sickness absences periods spanning 10 or more consecutive working days). The largest trajectory (“low” sick leave) included 59% of employees who had no occurrences of long sickness absence spells. A small proportion of participants (9%) had a high occurrence of sickness absences each year. The remaining two trajectories were intermediary groups with ascending and descending patterns of absenteeism occurrences. Factors such as increased age, poor health (e.g., musculoskeletal, mental illness, obesity), physical workload, and low job control predicted the higher sick leave trajectories, suggesting that health and motivational factors could underlie these trajectories. In a subsequent study of female kitchen workers, Haukka et al. (2014) found three distinct absenteeism trajectories over a 2-year period: no absenteeism; intermediate
absenteeism, and high absenteeism. Bodily pain, smoking, and obesity predicted the intermediate trajectory, while depression, musculoskeletal disease, and bodily pain predicted the high absenteeism trajectory. These findings suggest that different health factors have unique influences on patterns of absenteeism.

Dello Russo at al. (2013) adopted a different approach and examined trajectories of absenteeism behavior in three groups of employees on the basis of how long they had been at the organization (i.e., their duration of tenure). The three groups examined were short-tenured (tenure <3 years), medium-tenured (tenured between 3 and 19 years), and high-tenured employees (tenure >19 years). At baseline, short tenured employees showed low rates of annual absenteeism (average 2 days a year) compared with the other two groups. However, this group showed an increase in absenteeism behavior over a 4-year period, such that levels of absenteeism increased to 4.5 days per year, which was similar with medium tenured employees. The results were interpreted within the context of organizational norms. That is, employees new to an organization initially showed lower rates of absenteeism, but a gradual increase in absenteeism to be consistent with those with longer job tenure. These results suggest that employees gradually conform to the dominant norm of the organization in relation to absenteeism behavior (Dello Russo, et al., 2013).

The Present Study

It has been well demonstrated that absenteeism is an important indicator of workplace productivity. Furthermore, several conceptual frameworks and models have identified a number of antecedents of absenteeism behavior, which have subsequently been supported by longitudinal research. However, a key limitation of existing studies is that intrindividual and interindividual variations in absenteeism over time have rarely been captured in previous studies. This is an important consideration because there may be distinct longitudinal trajectories of absenteeism, which have different underlying antecedents.

The aim of the present study was to investigate the presence and nature of absenteeism in a sample of full-time Australian employees over a 5-year period. The present study involved using a growth mixture modeling approach to identify and examine distinct longitudinal trajectories of absenteeism and their antecedents. This involved examining the following primary research question:

Research Question 1: Are there distinct longitudinal trajectories of absenteeism in full-time employees?

We also aimed to examine antecedents that predicted and distinguished between these trajectories. Based on the widely cited Steers and Rhodes (1978) model and existing empirical research, we focused on antecedents reflecting demographic characteristics (e.g., age, sex, education), job satisfaction, psychosocial work characteristics (e.g., job demands, job control, job security), work characteristics (e.g., work hours, work schedules, job type, sick leave entitlements), and health. This involved addressing three additional research questions.

Research Question 2: Do demographic characteristics (age, sex, education) predict absenteeism trajectories?

Research Question 3: Are characteristics of an individual’s job (e.g., work characteristics and psychosocial job characteristics) associated with absenteeism trajectories?

Research Question 4: Does health status distinguish between absenteeism trajectories?

Method

Participants

The Household, Income, and Labor Dynamics in Australia (HILDA) Survey is a representative longitudinal panel study of Australian households (Wooden, Freidin, & Watson, 2002). HILDA, which commenced in 2001, collects data from members of Australian households every 12 months through a series of interviews and self-completion surveys. In the first Wave of the study, members from 11,693 Australian households were invited to participate in the study. Of those households contacted, 7682 provided data from at least one household member leading to an initial sample size of 19,910. Of these individuals, 4,787 were aged younger than 15 years at the time of interview and were excluded, leaving a sample size of 13,158.

This paper utilized data from five recent waves of data (Waves 7 to 11). In this paper, we included participants aged 18 years and older who were employed full-time at each wave (n = 2,934); participants with missing absenteeism data were excluded (n = 453). This resulted in a final sample of 2,481 full-time employees.

Table 1 shows the characteristics of the final sample compared with those with missing absenteeism data. This table indicates some differences between the samples, particularly in terms of health and sick leave benefits. The HILDA Survey received ethics approval from the University of Melbourne Human Research Ethics Committee. Ethical approval to use these data in the present paper was obtained from our university’s Human Research Ethics Committee.

Measures

Absenteeism. Absenteeism was measured in relation to two interview questions that asked participants whether they had taken any sick leave in the previous 12 months, and if so, the number of sick leave days they had taken. The data were combined to create a count indicator of the amount of annual sick leave (in days) taken over the 5-year period.

Demographic factors. Information on age, gender, and highest level of education (coded as high school, completed high school, diploma/certificate, or university degree) was collected and included in the analysis.

Psychosocial work characteristics. The HILDA Survey consisted of five items examining different aspects of job satisfaction, including satisfaction with job security, hours of work, and work life balance. These items were assessed on an 11-point scale, with higher scores on all items indicative of higher levels of satisfaction.

Participants completed 12 items that examined aspects of their perceived work environment (e.g., “I have to work fast in my job”; “I have a lot of say in what I do at work”). Each item was assessed on a 7-point Likert scale (strongly disagree to strongly agree).
Exploratory and confirmatory factor analysis conducted in this paper indicated that there were two distinct factors. Factor 1 assessed issues surrounding flexibility and autonomy at work and was consequently labeled job control (Cronbach’s alpha = .89). Factor 2 assessed intensity of work and time pressures and was labeled job demands (Cronbach’s alpha = .77). Higher scores are indicative of high levels of job control and job demands respectively.

**Work characteristics.** The interviews and self-report questionnaires also collected information on the number of hours worked each week (coded as 35–39 hr, 40–49 hr, and ≥50 hr a week) and work schedule (coded as standard work hours [i.e., regular daytime shift] and nonstandard work hours [evening/night shifts, rotating shifts, irregular schedules]). Information was also collected on the type of job according to the Australian and New Zealand Standard Classification of Occupations (Australian Bureau of Statistics, 2006). This classification system distinguishes between eight major groupings of job types: (a) managers, (b) professionals, (c) technicians and trades workers, (d) community and personal service workers, (e) clerical and administrative workers, (f) sales workers, (g) machinery operators and drivers, and (h) laborers. Due to some small cell sizes, we merged Categories d, e, and f into a single category and g and h into a single category. This resulted in five job type categories.

**Health.** Self-reported mental and physical health were assessed via the Short-Form Health Survey (SF-36), a 36-item scale that assesses health across eight subscales (Ware, Kosinski, & Gandek, 1993, 2000). The Physical Functioning subscale (10 items) examines how well individuals are able to perform normal activities of daily living such as climbing stairs and kneeling. The Role Physical subscale (four items) assesses the extent to which physical health affects problems with work and other daily activities. The Bodily Pain subscale includes two items regarding the extent to which individuals experience pain and the effect on subsequent daily activities. Social Functioning (two items) asks participants to indicate the extent to which their physical and emotional problems affect their normal daily activities. Vitality (four items) assesses individual’s levels of vigor and energy. Role Emotional (three items) examines the effect of emotional problems on work or daily activities. Finally, the mental health subscale includes five items that assess levels of depression and anxiety. On all subscales, higher scores are indicative of better health.

### Statistical Analysis

Longitudinal trajectories of absenteeism were investigated using growth mixture modeling (GMM), which is a statistical approach that examines change in a given variable over time (Jung & Wickrama, 2008). Conventional growth modeling assumes that a single growth curve (or trajectory) is adequate for capturing change in an entire population, and that covariates affect growth factors in the same way for all individuals (Jung & Wickrama, 2008). However, there are often distinct subpopulations within a sample that have different patterns of change over time (Jung & Wickrama, 2008); these distinct patterns or trajectories are not accounted for using conventional analytic approaches. This is
particularly relevant in the context of absenteeism given some recent findings suggesting identified distinct longitudinal patterns of absenteeism (Dello Russo, et al., 2013; Haukka et al., 2014; Haukka et al., 2013). In addition, it is feasible that potential antecedents of absenteeism have a differential effect on these trajectories, which can also be examined using GMM. Therefore, GMM is an ideal approach for the present study because it can identify distinct trajectories of absenteeism as well as covariates that distinguish between the trajectories. Because absenteeism data were counts, with a highly skewed distribution and a high proportion of zero values, zero-inflated Poisson GMMs were tested in this paper (Muthén & Muthén, 1998 –2010).

Consistent with recent recommendations, the analyses involved three main steps (Jung & Wickrama, 2008; Muthén, 2006; Muthén, 2004). The first step, performed using Mplus Version 6.11 (Muthén & Muthén, 1998–2010), aimed to identify the number of distinct trajectories of absenteeism. This step involved testing a model with a single trajectory, following by a model with two trajectories, then three trajectories and so on until the optimal number of trajectories was identified. For this first step, covariates were not included in the models. Several sources of information were used to decide on the optimal number of trajectories. Three information criteria—Akaikes information criteria (AIC), Bayesian information criteria (BIC), and sample-size–adjusted BIC—were used to compare sequential models, with lower values for a model with k trajectories (e.g., three trajectories) suggesting an improved model fit compared with a model with k – 1 trajectories (e.g., two trajectories). Relying on these criteria alone can overestimate the number of trajectories, so bootstrap likelihood ratio tests (BLRT) were also used (Nylund, Asparouhov, & Muthén, 2007). The BLRT compares model fit between subsequent models (e.g., compares a three class model with a two class model); a significant BLRT suggests that the model with one more trajectory provides a significant improvement in model fit (Nylund et al., 2007). The optimal number of trajectories is informed by the specification of additional trajectories not leading to a significant BLRT. In deciding on the optimal number of latent classes, we additionally considered classification accuracy (informed by entropy > .80), trajectory size (to ensure trajectories were large enough to be examined meaningfully), and the distinctiveness of trajectories (to ensure identified trajectories were distinct from one another).

The aim of Step 2 was to identify covariates that were significantly associated with the trajectories identified in Step 1. This involved conducting multinomial logistic regression modeling using SPSS Version 19 to investigate covariates significantly associated with trajectory membership. Covariates that were significantly associated with the trajectories were retained for inclusion in Step 3.

The third step of the analysis involved testing a full GMM, whereby the significant covariates from Step 2 were added as time-invariant covariates to the GMM (specifying the number of distinct trajectories from Step 1). This step allowed the antecedents to influence the growth factors of the trajectories, and provided insight into how the trajectories varied by these antecedents (Muthén, 2004). This final model thus indicated the nature of the different trajectories and significant covariates that distinguished between these trajectories. The differences between the trajectories in regards to the antecedents are reported as odds ratios based on logistic regressions conducted within the GMM.

Results

Table 2 shows the model fit results for models tested in Step 1. These results indicate that specifying additional trajectories (e.g., two vs. one trajectory) led to improvements in model fit as indicated by significant BLRT results and lower relative values for the AIC, BIC, and sample-size–adjusted BIC. Despite these improvements, the size of each additional trajectory identified became smaller. In the four-class model, the smallest trajectory accounted for approximately 8% of the sample, while in models with five or more trajectories, the smallest trajectory accounted for <3% of the sample. These trajectories may be too small to examine meaningfully. As a consequence, the four-trajectory model was identified as the optimal solution, which is consistent with the number identified by Haukka et al. (2013, 2014).

In the second stage of the analyses, the multinomial logistic regression models conducted with SPSS Version 19 indicated that age, sex, education, job type, work hours, work schedules, sick leave entitlements, job control, satisfaction with job security, satisfaction with hours worked, general health, and bodily pain were significantly associated with class membership as specified by the four-class model.

The full GMM was then tested in Mplus, with a four-trajectory model specified and the significant covariates from Step 2 included as time-invariant covariates in the model. The four absenteeism trajectories resulting from the full model are shown in Figure 1. The first trajectory (n = 879; 35.3%) included employees who took 4 to 5 days of sick leave annually. The amount of absenteeism increased over time at a decreasing rate as reflected by the significant linear (B = .18, p < .001) and quadratic functions (B = −.03, p = .038). This trajectory was labeled moderate absenteeism.

The second trajectory included 8.4% (n = 210) of the sample, and had high levels of absenteeism compared with the other trajectories. The linear (B = −.01, p = .891) and quadratic functions (B = .02, p = .73) were not significant for this trajectory, indicating no significant changes in absenteeism over time. This trajectory was labeled high absenteeism.

The third trajectory comprised 23.3% (n = 579) of the present sample, and included employees who essentially took no sick leave.

### Table 2

<table>
<thead>
<tr>
<th>Classes</th>
<th>AIC</th>
<th>BIC</th>
<th>Sample-size–adjusted BIC</th>
<th>BLRT p value</th>
<th>Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>91,038.90</td>
<td>91,056.29</td>
<td>91,046.76</td>
<td>—</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>69,405.93</td>
<td>69,446.49</td>
<td>69,424.25</td>
<td>&lt;.001</td>
<td>.94</td>
</tr>
<tr>
<td>3</td>
<td>63,474.33</td>
<td>63,538.06</td>
<td>63,503.11</td>
<td>&lt;.001</td>
<td>.94</td>
</tr>
<tr>
<td>4</td>
<td>61,534.55</td>
<td>61,621.41</td>
<td>61,573.75</td>
<td>&lt;.001</td>
<td>.91</td>
</tr>
<tr>
<td>5</td>
<td>59,947.14</td>
<td>60,057.22</td>
<td>59,996.86</td>
<td>&lt;.001</td>
<td>.91</td>
</tr>
<tr>
<td>6</td>
<td>58,740.55</td>
<td>58,873.82</td>
<td>58,800.74</td>
<td>&lt;.001</td>
<td>.92</td>
</tr>
<tr>
<td>7</td>
<td>57,845.84</td>
<td>58,002.28</td>
<td>57,916.49</td>
<td>&lt;.001</td>
<td>.93</td>
</tr>
<tr>
<td>8</td>
<td>57,022.71</td>
<td>57,202.33</td>
<td>57,103.83</td>
<td>&lt;.001</td>
<td>.92</td>
</tr>
</tbody>
</table>

Note. AIC = Akaikes information criteria; BIC = Bayesian information criteria; BLRT = bootstrap likelihood ratio test.

* The four-class model was considered optimal, given that models with five or more classes identified very small trajectories, despite improvements in model fit.
annual across the 5-year period. There was a significant trend for a decline in absenteeism over time as reflected by the linear function \((B = -.78, p = .003)\); the quadratic function indicated that this decline slowed with time \((B = .19, p = .013)\). This trajectory was labeled no absenteeism.

The final trajectory included 33.0% \((n = 822)\) of the present sample, and included employees who took 1 to 2 days of sick leave over the 5-year period; levels of absenteeism remained stable over time as reflected by nonsignificant linear \((B = -.05, p = .552)\) and quadratic growth functions \((B = .01, p = .709)\). This trajectory was labeled low absenteeism.

The characteristics of these trajectories are shown in Table 3 with the multivariate differences between the trajectories shown in Table 4. In order to interpret the multivariate differences in these characteristics between trajectories, it was necessary to select one trajectory as the referent. We decided on the moderate absenteeism trajectory as the referent for two main reasons. First, it was the largest trajectory, which can be used as a justification for selecting a suitable reference category. Second, the pattern of sick leave corresponds most closely with average levels of sick leave in Australia. Therefore, it may provide a useful indication of “typical” absenteeism patterns, and allow for meaningful comparisons with the other trajectories.

The GMM indicated that several covariates distinguished between the trajectories (see Table 4). Compared with the moderate absenteeism trajectory, the no absenteeism trajectory had a lower proportion of females \((OR = .50, p < .001)\), were younger \((OR = .96, p < .001)\), had better general health \((OR = 1.02, p < .001)\), and higher levels of job control \((OR = 1.03, p < .05)\). In addition, individuals in the no absenteeism trajectory were more likely to be managers \((OR = 2.01, p < .001)\), self-employed/business owner \((OR = 39.65, p < .001)\), and work long hours \((OR = 2.01, p < .001)\) compared with moderate absenteeism employees.

Compared with the moderate absenteeism trajectory, the low absenteeism trajectory had a lower proportion of females \((OR = .50, p < .001)\), were older \((OR = 1.01, p < .05)\), and had higher general health \((OR = 1.02, p < .001)\). These employees were also more likely to be a manager \((OR = 1.58, p < .05)\), self-employed/business owner \((OR = 3.72, p < .001)\), and work long hours \((OR = 1.73, p < .001)\) compared with moderate absenteeism employees.

Compared with the moderate absenteeism trajectory, the high absenteeism trajectory was characterized by older age \((OR = 1.03, p < .05)\), and poorer health as reflected by lower scores on the Bodily Pain \((OR = .99, p < .05)\), and General Health \((OR = .99, p < .05)\) subscales.

### Discussion

This study utilized a GMM approach to identify distinct trajectories of absenteeism and their antecedents in a sample of full-time Australian employees. The results identified four distinct longitudinal trajectories of absenteeism, which were labeled no absenteeism \((23.3\%)\), low absenteeism \((33.0\%)\), moderate absenteeism \((35.3\%)\), and high absenteeism \((8.4\%)\). A small proportion of individuals displayed annual fluctuations in absenteeism that deviated from these trajectories, perhaps reflecting factors such as injury, short-term illness, or organization changes that produce short-term changes in absenteeism (Hansson, Vingård, Arnér, & Anderzén, 2008). However, in general, the mean levels of absenteeism within each trajectory remained fairly stable over time. The present findings add to a small number of existing studies that have identified distinct trajectories of absenteeism behavior (Dello Russo, et al., 2013; Haukka et al., 2013, 2014).

A key strength of the present study is that potential antecedents of these trajectories were examined. The antecedents explored in this study were consistent with well-established theories of absenteeism, most notably Steers and Rhodes’ (1978) model which proposes that absenteeism behavior reflects demographic characteristics, motivation to attend work, and ability to attend work. As will be discussed in more detail, our results indicate that the absenteeism trajectories differ on a range of these antecedents, suggesting differences in motivation and ability to attend work. In discussing these results, we utilize the moderate absenteeism trajectory as the reference trajectory. This is because this trajectory was the largest and had rates of absenteeism \((4–6\) days per year) that corresponded most closely with average absenteeism rates in Australia. Therefore, it provides a meaningful point of comparison for the other trajectories. The findings are discussed separately for each absenteeism trajectory.

### High Absenteeism Trajectory

The high absenteeism trajectory was the smallest of the four trajectories and was characterized by 11–13 days of absenteeism each year. There were several antecedents that distinguished the high absenteeism trajectory from the moderate absenteeism trajectory. In particular, employees in the high absenteeism trajectory had lower scores on the Bodily Pain and General Health subscales of the SF-36, which indicates poorer health. The General Health subscale assesses overall health, the likelihood of getting sick relative to others, and whether the individual expects their health...
to get worse over time (Ware et al., 1993, 2000). Although developed as a measure of physical health, research has consistently demonstrated that the General Health subscale also reflects aspects of mental health (Ware et al., 1993, 2000). The Bodily Pain subscale of the SF-36 assesses the levels of pain experienced in the past 4 weeks, and the extent to which pain interfered with work and housework. In combination, these two results indicate that employees in the high absenteeism trajectory experienced more pain and poorer physical and mental health compared with the moderate absenteeism trajectory. Consistent with Steers and Rhodes (1978), as well as many other theoretical perspectives (e.g., Brooke, 1986; Nicholson, 1977), it is feasible that poor health and pain observed in this trajectory lead to higher rates of absenteeism by constraining employee’s ability to attend work. These findings suggest that high rates of absenteeism may primarily reflect health constraint factors.

**Low Absenteeism Trajectory**

The low absenteeism trajectory accounted for one third of the sample, with average rates of absenteeism in this trajectory ranging from 2–3 days per year. Several characteristics distinguished employees in this trajectory from those in the moderate absenteeism trajectory. First, employees in the low absenteeism trajectory were older and more likely to be male. These findings are consistent with existing studies demonstrating that older age and male gender are associated with lower amounts of absenteeism (Darr & Johns, 2008; Feeney, North, Head, Canner, & Marmot, 1998; Martocchio, 1989; Mastekaasa & Olsen, 1998; Ng & Feldman, 2008; Steers & Rhodes, 1978). The reasons for different rates of absenteeism in males and females are not clear. Some existing studies have suggested that a range of factors including differences in job type and child care responsibilities could underlie these gender differences (Darr & Johns, 2008; Mastekaasa & Olsen, 1998), but this requires further investigation using measures that are able to examine these issues. In regards to age, existing research suggests that older employees have lower rates of absenteeism because they are better able to meet the requirements of their jobs (Martocchio, 1989) and/or have higher levels of job motivation (Ng & Feldman, 2008).

The results also indicated that employees in the low absenteeism trajectory had better health compared with the moderate absenteeism trajectory as reflected by higher scores on the General Health subscale of the SF-36. Consistent with Steers and Rhodes (1978), better mental and physical health could mean that an individual is more able to attend work, and have lower rates of absenteeism.

Individuals in the low absenteeism trajectory were also more likely to be managers, work long hours, and be self-employed/a business owner. Previous studies have indicated differences in absenteeism rates by occupational status and job level (Darr & Johns, 2008; Nicholson & Johns, 1985). For example, white collar

### Table 3

**Characteristics of the Four Sick Leave Trajectories Based on the Covariates Included in the Full Growth Mixture Model**

<table>
<thead>
<tr>
<th>Sick leave, mean (SD)</th>
<th>No absenteeism</th>
<th>Low absenteeism</th>
<th>Moderate absenteeism</th>
<th>High absenteeism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year 1</td>
<td>.16 (.52)</td>
<td>1.92 (2.36)</td>
<td>4.25 (3.46)</td>
<td>11.08 (11.22)</td>
</tr>
<tr>
<td>Year 2</td>
<td>.09 (.37)</td>
<td>1.95 (1.98)</td>
<td>5.01 (3.87)</td>
<td>11.09 (10.12)</td>
</tr>
<tr>
<td>Year 3</td>
<td>.07 (.33)</td>
<td>1.85 (1.90)</td>
<td>5.34 (3.80)</td>
<td>11.06 (10.92)</td>
</tr>
<tr>
<td>Year 4</td>
<td>.05 (.24)</td>
<td>1.69 (1.67)</td>
<td>5.63 (4.58)</td>
<td>12.30 (12.40)</td>
</tr>
<tr>
<td>Year 5</td>
<td>.13 (.50)</td>
<td>1.91 (2.10)</td>
<td>5.31 (4.04)</td>
<td>13.00 (11.62)</td>
</tr>
<tr>
<td>Age mean (SD)</td>
<td>42.94 (10.56)</td>
<td>39.29 (11.09)</td>
<td>37.64 (10.95)</td>
<td>41.58 (10.63)</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>487 (27.9)</td>
<td>626 (35.9)</td>
<td>526 (30.1)</td>
<td>107 (6.1)</td>
</tr>
<tr>
<td>Female</td>
<td>93 (12.7)</td>
<td>195 (26.5)</td>
<td>347 (47.2)</td>
<td>100 (13.6)</td>
</tr>
<tr>
<td>Bodily Pain subscale, mean (SD)</td>
<td>80.39 (18.28)</td>
<td>82.56 (18.17)</td>
<td>79.09 (19.51)</td>
<td>70.17 (22.98)</td>
</tr>
<tr>
<td>General Health subscale, mean (SD)</td>
<td>75.44 (16.92)</td>
<td>75.92 (16.58)</td>
<td>72.01 (17.42)</td>
<td>65.60 (20.21)</td>
</tr>
<tr>
<td>Job security, mean (SD)</td>
<td>8.13 (1.92)</td>
<td>8.31 (1.72)</td>
<td>8.30 (1.83)</td>
<td>8.49 (1.68)</td>
</tr>
<tr>
<td>Job control, mean (SD)</td>
<td>6.80 (2.05)</td>
<td>7.15 (1.89)</td>
<td>7.37 (1.81)</td>
<td>6.92 (1.92)</td>
</tr>
<tr>
<td>Job control, mean (SD)</td>
<td>30.37 (8.04)</td>
<td>25.92 (8.21)</td>
<td>24.76 (8.47)</td>
<td>23.37 (8.52)</td>
</tr>
<tr>
<td>Work schedule, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard</td>
<td>455 (21.9)</td>
<td>707 (34.1)</td>
<td>732 (35.3)</td>
<td>179 (8.6)</td>
</tr>
<tr>
<td>Nonstandard</td>
<td>125 (30.6)</td>
<td>114 (27.9)</td>
<td>141 (34.6)</td>
<td>28 (6.9)</td>
</tr>
<tr>
<td>Job type, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Professional</td>
<td>165 (38.6)</td>
<td>151 (35.3)</td>
<td>92 (21.5)</td>
<td>20 (4.7)</td>
</tr>
<tr>
<td>Manager</td>
<td>115 (17.2)</td>
<td>220 (33.0)</td>
<td>259 (38.8)</td>
<td>73 (10.9)</td>
</tr>
<tr>
<td>Trade/Technician</td>
<td>122 (28.2)</td>
<td>143 (33.1)</td>
<td>144 (33.3)</td>
<td>23 (5.3)</td>
</tr>
<tr>
<td>Laborer</td>
<td>101 (16.1)</td>
<td>196 (31.2)</td>
<td>264 (42.0)</td>
<td>68 (10.8)</td>
</tr>
<tr>
<td>Clerical, etc.</td>
<td>77 (23.7)</td>
<td>111 (34.2)</td>
<td>114 (35.1)</td>
<td>23 (7.1)</td>
</tr>
<tr>
<td>Sick leave benefits, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No benefits</td>
<td>71 (51.1)</td>
<td>42 (30.2)</td>
<td>24 (17.3)</td>
<td>2 (1.4)</td>
</tr>
<tr>
<td>Self-employed</td>
<td>263 (78.7)</td>
<td>55 (16.5)</td>
<td>12 (3.6)</td>
<td>4 (1.2)</td>
</tr>
<tr>
<td>Access to benefits</td>
<td>246 (12.3)</td>
<td>724 (36.1)</td>
<td>837 (41.7)</td>
<td>201 (10.0)</td>
</tr>
<tr>
<td>Work hours, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>35–39 hr</td>
<td>61 (11.2)</td>
<td>152 (27.8)</td>
<td>262 (47.9)</td>
<td>72 (13.2)</td>
</tr>
<tr>
<td>40–49 hr</td>
<td>215 (18.5)</td>
<td>401 (34.2)</td>
<td>458 (39.0)</td>
<td>99 (8.4)</td>
</tr>
<tr>
<td>50 hr or more</td>
<td>304 (39.9)</td>
<td>268 (35.2)</td>
<td>153 (20.1)</td>
<td>36 (4.7)</td>
</tr>
</tbody>
</table>
workers such as managers and professionals have been shown to have lower rates of absenteeism compared with blue collar workers (Darr & Johns, 2008; Nicholson & Johns, 1985). Although we are unable to determine the reasons for these differences from the present data, Nicholson and Johns’ (1985) work on absence culture and psychological contract suggests that certain job types (including managers) have lower rates of absenteeism because of guilt over absences and a perception of absences as illegitimate (Nicholson & Johns, 1985). Thus, some employees in managerial roles may avoid taking time off work when needed because of these factors.

Employees in this trajectory were also more likely to be self-employed or a business owner. Although all Australian employees, with the exception of those employed casually, are eligible for paid sick leave (Fair Work Ombudsman, 2010), individuals who are self-employed may be reluctant to take time off due to factors such as illness because of potential for lost income (Benavides et al., 2000). Individuals in this trajectory were also more likely to work longer hours, which is consistent with some findings demonstrating that longer work hours are linked with less absenteeism (Magee et al., 2011).

The results discussed above suggest a range of different processes underlying the low levels of absenteeism in this trajectory. On the one hand, it is feasible that because of their better general health relative to the moderate absenteeism trajectory these employees do not need to take as many days off work each year. That is, for these employees better general health means they are less constrained to attend work. Thus, this could be a healthy group of employees who do not need to take much time off work.

However, this low absenteeism trajectory may represent a group of employees who are less inclined to take time off work when they are unwell. This is consistent with the concept of presenteeism, which can be defined as employees attending work when they are unwell and should be absent from work (Aronsson & Gustafsson, 2005; Dew, Keefe, & Small, 2005; Johns, 2010). Presenteeism is associated with productivity losses that are estimated to outweigh losses associated with absenteeism (Cooper & Dewe, 2008; Hemp, 2004). A range of factors have the potential to contribute to presenteeism, including organizational policies relating to sick leave and downsizing, ease of replacement, perceived pressure for supervisors or coworkers to attend work while unwell, and low levels of job security (Aronsson & Gustafsson, 2005; Johns, 2011). The present study did not include a measure of presenteeism, so it is not possible to determine whether some employees in this trajectory had higher levels of presenteeism. However, the findings for job type, long work hours, and self-employed/business owner status are consistent with existing theories and findings relating to presenteeism. Therefore, it is feasible that certain characteristics of jobs (e.g., job type, self-employed status) increase the likelihood of low absenteeism and high presenteeism. These possibilities warrant investigation in future research.

### No Absenteeism Trajectory

Employees in the no absenteeism trajectory reported very low rates of absenteeism annually over the 5-year period, suggesting
they essentially took no sick leave days each year. This is an interesting finding because it suggests that although rates of absenteeism in Australia range from 4–8 days per year, a substantial proportion of full-time employees (approximately 25% in this sample) take very few (if any) sick days each year.

Similar to the low absenteeism trajectory, these individuals were more likely to be male, and have higher levels of general health relative to the moderate absenteeism trajectory. As noted above, these factors may contribute to lower rates of absenteeism. However, these individuals were younger, which is an interesting finding given that studies generally find that older (not younger) age is linked with lower absenteeism (Martocchio, 1989; Ng & Feldman, 2008). The reasons for this divergent finding are not clear and require further investigation.

Employees in the no absenteeism trajectory had higher levels of job control, suggesting more autonomy and flexibility; previous research suggests that more job control could benefit health and well-being by allowing individuals to better balance their work and nonwork commitments, and recover from work stress (Alamursula et al., 2006). It is therefore feasible that higher levels of job control could contribute to lower rates of absenteeism over time (Nielsen et al., 2006; Smulders & Nijhuis, 1999; Väänänen et al., 2003; Virtanen et al., 2007).

However, other findings suggest that this trajectory could be characterized, at least to some extent, by presenteeism in a similar manner to the low absenteeism trajectory. For example, employees in this trajectory had higher odds of being self-employed or a business owner. As noted above, they may be less inclined to take time off work due to financial concerns or loss of business (Benvides et al., 2000). Employees in this trajectory were also more likely to be managers. Consistent with the low absenteeism trajectory and Nicholson and Johns’ (1985) theory, some managers may avoid taking time off work when unwell due to perceptions of sick leave as not being legitimate.

These findings in combination with those for low absenteeism trajectory, suggest caution when interpreting levels of absenteeism. It is possible that some employees are healthier or have better control over the working arrangements and thus do not need to take as much time off work. This could translate into low rates of absenteeism over time. However, low absenteeism is not necessarily an indicator of healthy and productive employees. This is because some employees may feel pressure to avoid taking time off work when they are unwell because of workplace cultural factors (e.g., perceptions of absence as less legitimate) or financial reasons (e.g., loss of income for self-employees). This may indicate higher rates of presenteeism which also has the potential to contribute to lost productivity, perhaps at levels higher than absenteeism (Hemp, 2004).

**Strengths and Limitations**

The present study provides an important extension on existing absenteeism literature. First, the sophisticated modeling approach to examine longitudinal data across five time points provided insights into intrapersonal and interindividual differences in patterns of absenteeism over time. This supports a small number of studies that have recently identified distinct longitudinal trajectories of absenteeism (Dello Russo, et al., 2013; Haukka, et al., 2014; Haukka et al., 2013). The sample size was also relatively large, providing sufficient statistical power to identify and distinguish between the four absenteeism trajectories. In addition, we were able to examine whether demographic, work and job characteristics, and health status differentiated between these groups. This is important because well-established theories of absenteeism, such as Steers and Rhodes’ (1978) model, suggest that these factors are important predictors of absenteeism behaviors. Thus, our results provide insight into some of the factors that may predict certain patterns of absenteeism over time.

There are some limitations of the present study that warrant discussion. First, absenteeism data were derived from self-reported retrospective recall of absenteeism over a 12-month period. Self-report measures are widely used but can lead to underestimates of absenteeism; this may explain why the rates of absenteeism reported in this paper were lower than studies using records-based data (Johns & Miraglia, 2015). However, Johns and Miraglia (2015) indicated that absenteeism data from self-report measures have reasonable rank order convergence with data obtained through more objective measures (e.g., organizational records). Therefore, although the identified trajectories may not provide a precise indication of absenteeism amount, they are likely to accurately capture patterns of absenteeism over time.

Another consideration is that research has demonstrated that the frequency and duration of absenteeism spells is important in distinguishing between voluntary and involuntary forms of absenteeism (Bakker, Demerouti, de Boer, & Schaufeli, 2003). For example, more frequent spells of absenteeism could reflect motivational factors (such as low job satisfaction), whereas longer spells are due to health impairment (Bakker et al., 2003). Future research capturing frequency and duration, as well as the underlying reasons for absences will be important in further delineating the nature of longitudinal trajectories.

The present study also focused on absenteeism only. In order to make clearer conclusions about the implications of each trajectory for employee productivity, future research will need to explore other components of productivity such as presenteeism. This is particularly important for the low absenteeism trajectories, where lower rates of absenteeism could potentially be offset by higher rates of presenteeism.

There are some other issues that require consideration. A small proportion of participants (15.4% of the initial, eligible sample) were excluded due to missing absenteeism data. The characteristics of these participants differed significantly from those who were included in the final sample. Most notably, excluded participants had poorer self-reported health, lower job security, and were more likely to be self-employed compared with included participants. As discussed above, these factors have important implications for patterns of sick leave over time and thus it is feasible that excluded individuals could represent a unique subgroup of employees who have differing patterns of sick leave over time. Thus a potential limitation of this paper is that the exclusion of individuals due to missing data could have implications for the nature and size of the identified trajectories.

The present paper also focused on full-time employees, and it is possible that employees who work part-time hours have very different patterns of absenteeism reflecting differing antecedents. Part-time employees are an important population, with existing research demonstrating differences between part-time and full-time employees in relation to a number of domains such as job...
involvement; these associations vary depending on specific work arrangements (e.g., permanent/temporary, voluntary/involuntary; Thorsteinsson, 2003). These and other factors may lead to differing patterns of absenteeism reflecting differing antecedents compared with full-time employees. We propose that the unique characteristics and considerable heterogeneity of part-time employees warrant separate investigations to fully understand trajectories of absenteeism and the associated antecedents. Therefore, it is suggested that in addition to clarifying the nature of distinct absenteeism trajectories in full-time employees, future studies are also conducted to explore absenteeism trajectories and their antecedents in part-time employees.

Furthermore, some of the potential antecedents assessed in this study were assessed using short-scales or single items scales (e.g., job satisfaction). This is a potential limitation because these measures may not provide a comprehensive insight into these factors. Despite this, single-item scales generally provide appropriate and valid measures of these constructs and correspond well with multiple item scales (Wanous, Reichers, & Hudy, 1997). Factors not examined in this paper such as insomnia, work-life balance, and organization factors such as specific policies and cultural factors regarding sick leave and leadership could also be important predictors of these trajectories and require investigation in future research.

Conclusions

This paper provides a novel insight into different patterns of absenteeism over time in a large, heterogeneous sample of Australian employees. The results demonstrate that several sociodemographic, health, and work-related factors underlie these trajectories, which is consistent with existing theories of absenteeism. The pattern of results for the high absenteeism trajectory suggests that poor health may constrain an employee’s ability to attend work. The findings for low absenteeism and no absenteeism suggest a range of potential underlying factors, which may reflect a greater ability and motivation to attend work or higher levels of presenteeism. These findings require further investigation, with measures of presenteeism needed to better understand these trajectories. Nevertheless, these results have important implications for employers and organizations, as they could inform strategies to minimize the effects of absenteeism on lost workplace productivity. These may include providing employees with more flexible work conditions (e.g., options to work from home, or have variable start and finish times), greater autonomy, and improved coping skills. Although there is a need to limit avoidable absenteeism (e.g., through prevention strategies), it is also important that organizations foster workplace cultures that encourage employees to take sick leave when they are unwell to prevent presenteeism which could ultimately lead to greater productivity losses.

References


Received April 27, 2014
Revision received February 3, 2015
Accepted February 16, 2015

---

E-Mail Notification of Your Latest Issue Online!

Would you like to know when the next issue of your favorite APA journal will be available online? This service is now available to you. Sign up at http://notify.apa.org/ and you will be notified by e-mail when issues of interest to you become available!