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Does daily commuting behavior matter to employee productivity?

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ABSTRACT

This study is the first of its kind to explore the relationship between commuting behavior and employee productivity by drawing theories from multiple disciplines and providing empirical evidence from Australian cities. Relying on survey data collected from three major cities in Australia, this study finds that commuting distance is positively associated with absenteeism. This study also finds a positive association between active commuting (i.e., travel to work by walking or bicycling) and job performance in the middle-aged employees. The structural equation model further explored possible causal pathways from commuting to employee productivity, and the results reveal that commuting mode choices and commuting distance influence absenteeism and job performance through affecting commuting satisfaction and personal health, though commuting distance retains a direct impact on absenteeism after controlling for the indirect effects. In particular, the results suggest that the happy commuters are more productive, and the short-distance and active travel commuters are more likely to be the happy commuters. Overall, these findings support that commuting behaviors of employees influence their productivity at the workplace. Encourage active commuting not only improves the physical health of employees, but may also enhance their job performance, contributing to the economic benefits to employers and society.

1. Introduction

Commuting is an important component of daily work activities, significantly contributing to the wellbeing of working population, yet its impact on employee productivity has surprisingly been little studied. Employee productivity (also referred to as workforce productivity) is broadly defined as the efficiency of a worker, and it is important for organizations and societies (Diener, 2012). Previous studies on employee productivity have primarily focused on the roles of the socio-demographic and attitudinal characteristics of employees and the cultural and environmental features of organizations (Liao and Chuang, 2004). There are increasing debates in both academia and industry with respect to how commuting might influence employee productivity. There are claims, for example, that workers with a long commute are more likely to be burned out, stressed and fall ill (Evans et al., 2002; Novaco et al., 1990; Wener et al., 2003), and therefore more likely to be absent from work and perform poorly at work. There are also claims that workers who commute by walking and bicycling are more productive because of the health, cognitive and psychological benefits of active travel (Handy et al., 2014). Although these claims assume a causal relationship between commuting and productivity, studies that directly examine this relationship are quite sparse. Further, previous studies on travel behavior have primarily focused on the health and environmental impacts; however, research that directly addresses the economic impact of travel behavior is scarce. This significantly limits our ability to make effective transport policies that aim to improve economic outcomes.

This study is the first of its kind to explore the relationship between commuting and employee productivity by drawing theories from multiple disciplines and empirical evidence from three Australian cities. Addressing this research question is particularly important for urban transportation policies. How to strategically plan the transportation network, and prioritize the limited resources (including right-of-way and transportation funding) to support a more sustainable and productive urban system have been the critical issues for local and state governments. However, current policy debates over transportation and productivity are primarily around moving people or goods to destinations in a cost-effective and timely manner, largely ignoring the potential impact of transportation on the activities undertaken at the destination. This study tackles this critical issue by especially addressing the impact of daily commuting on job activities. In particular, this study aims to answer the two research questions: (1) whether commuting affects employee productivity? (2) how does daily commuting influence employee productivity?

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The evidence produced by this study contributes to the urban planning field and to practice and policy in several ways. First, this research makes a significant contribution to theories in travel behavior and urban planning and provides new empirical insights into how and to what extent commuting behavior contributes to employee productivity. Second, the research benefits government agencies in providing robust empirical evidence to inform transport policies on workforce productivity and justifications of transportation resources allocation. Third, this research also benefits employers in offering evidence-based strategies for managing employees' commuting behavior to improve overall organizational productivity.

2. How might commuting influence employee productivity?

Early work on the link between transportation and productivity has only been at the macro level, focusing on the impact of transportation infrastructure investment on economic productivity at state and national level. This type of work is usually framed into a traditional production function model, where transportation infrastructure is treated as a public capital, which like other inputs, such as private capital and labor that impact output. Transportation investment increases productivity by reducing travel costs and improving economies of agglomeration and economies of scale. Classical empirical studies include the work conducted by Aschauer (1989) and Munnell (1990), who are among those economists enthusiastic on finding the reasons of substantial decline of productivity in the United States compared with the "golden age" of the 1950s and 1960s. These studies are important and have significant influence on the U.S. policies of infrastructure spending in the 1990s. However, these studies have primarily focused on the firm side with an economic input-output analysis at the macro level.

Very few studies have investigated the link between transportation and productivity that focused on employees and used behavioral mechanisms at individual levels. In the early urban economic models, work productivity is assumed to be independent of commuting because it is argued that commuting cost could be fully compensated by wage premiums or lower land rents, so the commuting would not influence job satisfaction and performance. However, this early urban model rested on the premise that the labor market is perfect and fully competitive. Until recently, a more realistic labor market, which allows for worker's shirking behavior (e.g., less working effort or absenteeism), was integrated into early urban economic models. This new combined model, namely urban efficiency wage model (Zenou, 2009), argues that workers make trade-offs between leisure time at home and effort in work, and therefore workers with long commutes would put in less effort or shirk work because of reduced leisure time (Ross and Zenou, 2008). This model provides a theoretical foundation in economics to model the relationship between commuting and work productivity. However, only one empirical study (Van Ommeren and Gutiérrez-i-Puigarnau, 2011) was found to have formally tested this theoretical hypothesis using a direct measure of shirking behavior.

In addition to urban economics, other disciplines including public health, psychology, and brain science have also pointed out the possible paths that daily commuting could influence work productivity. Personal health, for example, has been argued to be a mediator in the relationship between commuting and work productivity. A number of studies (Evans et al., 2002; Novaco et al., 1990; Wener et al., 2003) have established the link between commuting and mental stress, while commuting stress can further spill over into domains such as work performance and family relationships (Novaco et al., 1990; Wener et al., 2005). Besides the mental health, it is well known that walking and bicycling for daily commuting could be important sources of physical activity, the lack of which is a major cause of obesity as well as other related chronic diseases (Bouchard et al., 2012). Obesity and chronic diseases significantly reduce workforce participation and increase absenteeism from work (Australian Institute of Health and Welfare, 2009). Therefore, commuting could affect work productivity through physical and mental health.

In addition to the path through personal health, commuting could also influence productivity through moods, emotions, and even psychological wellbeing. A growing number of studies have found active commuting by walking and bicycling is perceived as more "relaxing and exciting" than commuting by car and public transport, which are perceived as being more "stressful and boring" (Gatersleben and Uzzell, 2007). These positive or negative moods and emotions during the commuting influence moods and emotions during the work (Friman et al., 2017), thereby affecting work performance. Further, recent studies (Choi et al., 2013; Stutzer and Frey, 2008) also found that people with a longer commuting time report systematically lower subjective well-being than those with a shorter commute, and those who bike and walk to work are happier and more satisfied with life than public transport and car commuters (Martin et al., 2014). Given the strong evidence that happy people are more productive (Oswald et al., 2015), it is reasonable to hypothesize that active commuters and short-distance commuters would be more productive.

Finally, commuting mode choice might influence work productivity through cognitive ability. Physical activity is beneficial to brain function and cognition (Etnier et al., 1997; Hillman et al., 2008), which are closely related to the job performance of employees. It is, therefore, possible that active travel commuters might have better cognitive ability at work, at least in the first several hours of work after having an intense physical activity from bicycling and walking to work, and perform better than public transport and car commuters.

Although these possible pathways indicate that commuting might influence work productivity, little research has been conducted to formally test these hypotheses. This study aims to fill this research gap by providing empirical evidence from three Australian capital cities. To inform theoretical and empirical explorations, a theoretical framework has been developed to link the built environment, commuting characteristics, physical and mental health, psychological states, cognitive ability and employee productivity. This framework is illustrated in Fig. 1.

3. Methods

3.1. Data and variables

Our primary method of data collection was a self-administered 10-page survey, which was distributed by a panel company through an online survey in May 2017. The study was limited to residents of three capital cities in Australia, Melbourne, Sydney, and Brisbane, who are aged over 18 and full-time employed, have a fixed place of employment and make regular commute trips every week. Sample quotas were set up based on the population of each city. Participants of the survey were recruited through a local panel company. Potential eligible participants were first randomly selected by the panel company from their database, and then were invited to participate in this study by emails. As the panel company provides a direct monetary incentive for the participants, for quality assurance purpose, two "trap" questions were added into the survey to identify the "speedster". Those who failed to correctly answer both questions were screened out. Further, a minimum time requirement for filling out the survey was embedded to identify the "speedster" who rushed through the questionnaire without reading questions and giving considered answers. In total, 2198 residents were contacted and responded to the survey, and among these responses, 237 were blocked because of ineligibility or "speedster", 840 were screened out because of quota limit, and the final number of valid responses is 1121. While the sample is not representative of the population, it covers a variety of employees in different industries and occupations (see Table 1).

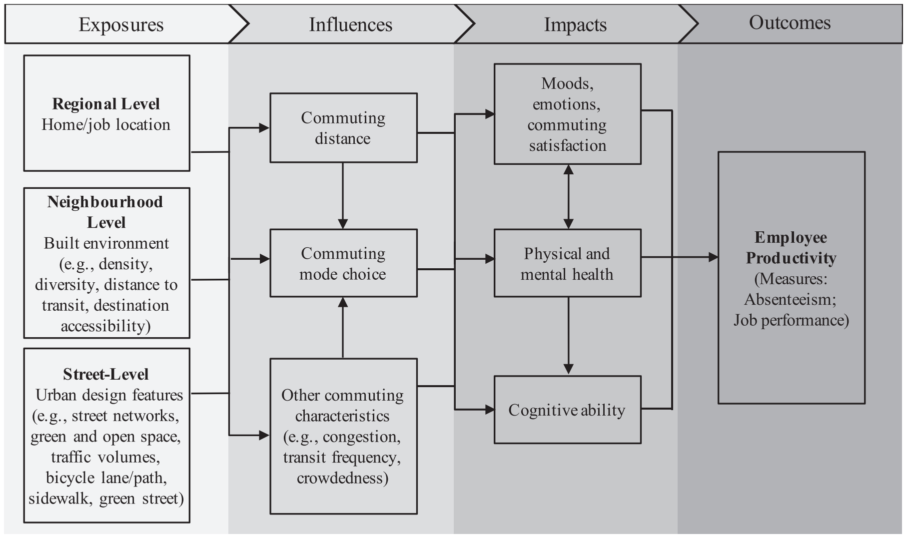

Fig. 1. Hypothesized pathways connecting the built environment, commuting, and employee productivity.

3.2. Independent variables

The key interest of this study is to look at the impact of the daily commute on employee productivity. Three commuting related variables were created, including commuting mode choice, commuting time and commuting distance. Commuting behavior was measured by asking respondents their *primary* mode (i.e., mode used for the longest portion of the trip) used for commuting in the past month. Original mode choices include seven categories, including car/vanpool with other household members, car/vanpool with other, car/driving alone, walking, bicycling, bus/tram, and train. For simplicity and to ensure each category has enough samples, the first three modes were aggregated into one category (car), and the last two were combined into one category (transit). Respondents were also asked to report their commuting distance and typical commuting time (one-way). In addition to the commuting variables, this study also measured other variables that are possibly associated with productivity, including the employee's socio-demographic characteristics, their health condition, their job industry, their occupation, and the city where they reside (Table 1). For health condition, both a single-item self-rated measure on the overall health condition, and measures on the levels of physical activity using the questions adapted from International Physical Activity Questionnaire (IPAQ) (Craig et al., 2003) were used in this study.

3.3. Dependent variables

Employee productivity was measured by absenteeism and job performance. Absenteeism is a commonly used and reasonable (inverse) measure of worker's productivity (Van Ommeren and Gutiérrez-i-Puigarnau, 2011). Both absenteeism and job performance measures were adapted from World Health Organization Health and Performance Questionnaire (HPQ), which has been validated and shows good concordance with archival (objective) performance measures from employers (Kessler et al., 2004; Kessler et al., 2003; Scuffham et al., 2014). For example, Kessler et al. (2003) conducted a calibration study of HPQ in four occupations (including both white-collar and blue-collar occupations) in the U.S., namely airline reservation agents, customer service representatives, automobile company executives, and railroad engineers, by comparing HPQ ratings with various objective data. They found that HPQ absenteeism reports were highly associated with the objective employer payroll records (r = 0.61–0.87), and HPQ performance ratings were significantly correlated with archival and ESM (Experience Sampling Method) performance data. These findings suggest that HPQ has excellent validity in measuring work performance and absenteeism. In another validation study, Kessler et al. (2004) further demonstrated that the HPQ work performance measures are reliable and sensitive to change by measuring performance at two time points using HPQ, supervisor ratings, and ESM.

For absenteeism, the respondents were asked to report the number of full days absent for both health and for other reasons in the past 4 weeks, respectively, in this study. For job performance, HPQ first asks seven decomposition questions about critical aspects of work performance (e.g., "How often was your performance higher than most workers on your job? How often was your performance lower than most workers on your job? How often did you do no work at times when you were supposed to be working? How often did you find yourself not working as carefully as you should? How often was the quality of your work lower than it should have been? How often did you not concentrate enough on your work? How often did health problems limit the kind or amount of work you could do?"), and then uses a global rating scale to assess overall work performance in a given period. Decomposition questions helped to facilitate active memory search preparing for answering complex survey questions, and this is one of the strategies in the design of HPQ to improve response accuracy (Kessler et al., 2003). Comparing with other scales (e.g., Work Productivity Scale, Stanford Presenteeism) that are more relevant to white-collar workers than to blue-collar workers, HPQ ensures the questions on job performance equally apply across different industries and occupations. In this study, the self-reported overall job performance in the past month was used as a dependent variable which was coded using an ordered scale from zero ("worst possible performance") to ten ("best possible performance"). The distributions of three dependent variables are in Fig. 2. Descriptive statistics of all variables are in Table 1.

3.4. Modelling methods

Given the nature of the dependent variables, negative binomial models were applied to predict absenteeism (called absenteeism model thereafter), while ordered logit models were employed to predict overall job performance (called performance model thereafter). Two separate models were estimated for the number of days absent for health reasons and the number of days absent for other reasons, respectively. Following Van Ommeren and Gutiérrez-i-Puigarnau (2011), we also used the natural logarithm of commuting distance and commuting time in the models as we found this specification improved model fit. While commuting distance and time were highly correlated,

Table 1
Descriptive statistics of variables ($n = 1121$).

Variables	Mean	Std. Dev.	Min	Max
Job performance				
# days absent for health problems last month	0.70	2.06	0	28
# days absent for any other reason last month	1.00	2.71	0	31
Overall job performance last month	7.51	1.58	0	10
Commuting characteristics				
Commuted distance (km)	19.69	18.36	0	150
Commute time (min)	36.41	23.58	1	180
Car	58%		0	1
Walk	6%		0	1
Bike	2%		0	1
Transit	34%		0	1
Soio-demographics				
Age[a]	4.16	1.14	2	7
Female	51%		0	1
Annual Household Income[b]	9.73	2.19	1	13
Education[c]	3.94	1.34	1	6
Health condition[d]	3.42	0.89	1	5
Physical activity (during the last 7 days, on how many days did you do the following activities for at least 10 min)				
# walk days	4.23	2.38	0	7
# jog days	1.03	1.75	0	7
# hosework days	3.62	2.23	0	7
# garden days	1.00	1.49	0	7
# bike days	0.63	1.51	0	7
# exercise days	0.72	1.58	0	7
# workout days	0.95	1.72	0	7
# gym days	0.93	1.74	0	7
# TV/Computer/Video Games days	4.94	2.44	0	7
Industry				
Agriculture, Forestry and Fishing	0.3%		0	1
Mining	0.5%		0	1
Manufacturing	6.0%		0	1
Electricity, Gas, Water and Waste Services	1.4%		0	1
Construction	4.0%		0	1
Wholesale trade	4.1%		0	1
Retail Trade	5.8%		0	1
Accommodation and Food Services	1.9%		0	1
Transport, Postal and Warehousing	4.9%		0	1
Information Media and Telecommunications	8.0%		0	1
Financial and Insurance Services	10.3%		0	1
Rental, Hiring and Real Estate Services	2.0%		0	1
Professional, Scientific and Technical Services	12.0%		0	1
Administrative and Support Services	5.7%		0	1
Public Administration and Safety	5.8%		0	1
Education and Training	8.8%		0	1
Health Care and Social Assistance	7.4%		0	1
Arts and Recreation Services	1.4%		0	1
Other Services	10.2%		0	1
Occupation			0	1
Executive, administrator, or senior manager (e.g. CEO, sales VP, plant manager)	11.1%		0	1
Professional (e.g., engineer, accountant, systems analyst)	42.3%		0	1
Technical support (e.g., lab technician, legal assistant, computer programmer)	6.8%		0	1
Sales (e.g., sales representative, stockbroker, retail sales)	7.7%		0	1
Operator or laborer (e.g., assembly line worker, truck driver, construction worker)	4.0%		0	1
Precision production and crafts worker (e.g., mechanic, carpenter, machinist)	1.9%		0	1
Clerical and administrative support (e.g., secretary, billing clerk, office supervisor)	23.0%		0	1
Service occupation (e.g., security officer, food service worker, janitor)	3.2%		0	1
City			0	1
Sydney	36.6%		0	1
Melbourne	40.6%		0	1
Brisbane	22.8%		0	1

[a] 1 = 18–24; 2 = 25–34; 3 = 35 = 44; 4 = 45–54; 5 = 55–64; 6 = 65–74; 7 = 65+.
[b] 1 = negative or zero; 2 = $1 - $9999; 3 = $10,000 - $19,999; 4 = $20,000 - $29,999; 5 = $30,000 - $39,999; 6 = $40,000 - $49,999; 7 = $50,000 - $59,999; 8 = $60,000 - $79,999; 9 = $80,000 - $99,999; 10 = $100,000 - $124,999; 11 = $125,000 - $149,999; 12 = $150,000 - $199,999; 13 = $200,000 or more.
[c] 1 = No qualifications; 2 = Secondary school; 3 = Tertiary (e.g., TAFE); 4 = Undergraduate; 5 = Graduate; 6 = Postgraduate.
[d] 1 = Poor; 2 = Fair; 3 = Good; 4 = Very good; 5 = Excellent.

they had different effects in absenteeism model and performance model. We have estimated all models using commuting distance and commuting time separately, and the results of models using commuting distance are reported in the main text while the results of those using commuting time are presented in Appendix. For commuting mode choice, transit was used as the reference group to compare with car, walking, and bicycling. For all regression models, socio-demographic characteristics, self-reported health condition and physical activity level of employees were controlled in the model, and dummies for industry, occupation and city were also included to account for unobserved heterogeneity between industries, occupations, and cities. As commuting might have different impact on cognitive functioning and therefore job performance for population at different age groups (Etnier et al., 1997), three separate models were estimated for younger adults (ages 18–34; $n = 338$), middle-aged adults (ages 35–54; $n = 603$) and older adults (ages 55–74; $n = 161$) respectively to capture the variance of the effects on job performance.

We also examined the endogeneity of commuting variables using the instrument variable (IV) technique, although the causal mechanisms of the reverse causation from absenteeism or job performance to commuting mode choice or commuting length are quite weak. Two instrument variables, population density at home location and population density at job location, were created using the geocoded home and job locations reported in the survey. These two instruments are strongly correlated with either the commuting distance (time) or commuting mode choice as evidenced by previous studies (Ewing and Cervero, 2010), but are unlikely to be determined by the absenteeism and job performance. While testing the endogeneity, all the dependent variables were treated as continuous and two-stage IV models were estimated.

In addition to the regression models, we further applied structural equation model (SEM) to examine the structural relationship between commuting characteristics, commuting satisfaction, personal health, absenteeism for health reasons, and job performance. This step aims to explore the key relevant pathways that commuting influences productivity, and better understand the causal mechanisms in the relationship between commuting and productivity. Based on the conceptual model in Section 2, an SEM model was specified as Fig. 3, which hypothesizes that commuting satisfaction, including the moods and emotions during commuting and overall satisfaction of commuting, and personal health mediate the effect of commuting characteristics on absenteeism and job performance. This is one of the hypotheses regarding how commuting behavior might influence job productivity described in Section 2. Commuting satisfaction was incorporated in SEM as a latent variable, which was measured using the adapted Satisfaction with Travel (STS) Scale developed by Ettema et al. (2011). This adapted measure includes both affective and cognitive components related to commuting, and consists of nine items scoring from −4 to 4

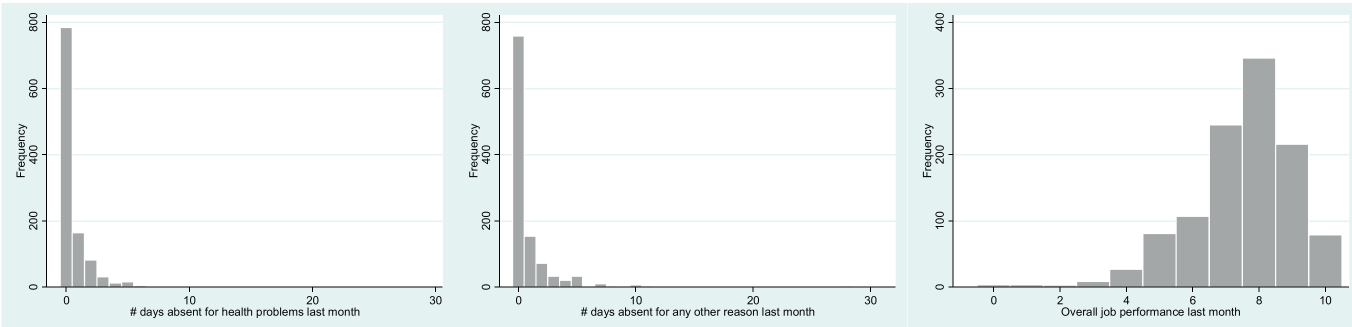

Fig. 2. Distribution of dependent variables.

to assess each aspect of commuting experiences. SEM model is commonly estimated using the maximum likelihood estimation, which assumes that the observed variables are multivariate normally-distributed. If the assumption does not hold true, standard errors will be underestimated, although parameter estimates may not be influenced (Kline, 2005). We, therefore, estimated the models using a bootstrapping approach, which is a process drawing repeated sample from the data (Hayes, 2009). In this study, we used Monte Carlo (or bootstrapped parameter estimates) bootstrapping set to generate 5000 samples, and the bias-corrected bootstrap confidence intervals were used to detect significant effects. The SEM model was estimated using AMOS 25.0.

4. Results and discussion

4.1. Impacts of commuting on absenteeism

Results of two negative binomial models for absenteeism are reported in Table 2. As expected and consistent with Van Ommeren and Gutiérrez-i-Puigarnau (2011), commuting distance is positively associated with the number of absent days for both health and other reasons. This suggests that commuting could influence absenteeism through both health and other mechanisms. First, workers with long commutes are more likely to get ill and therefore are more likely absent for health reasons. Second, workers with long commutes receive less net wage and less leisure time and therefore are more likely absent to avoid the commuting cost and time. To better illustrate the magnitude of the impact of commuting distance on absenteeism, the predicted number of days absent at different commuting distance scenarios were estimated and plotted in Fig. 4, while holding all other independent variables at their mean values. Using workers with a (one-way) commuting distance of 15 km (average commuting distance for Australian capital cities) as a reference group, workers with a commuting distance of 1 km would have 36% and 45% lower (expected) absent days for health and other reasons respectively, while workers with a commuting distance of 50 km would have 22% and 30% higher (expected) absent days for health and other reasons respectively. Comparing with the results from Van Ommeren and Gutiérrez-i-Puigarnau (2011), the magnitude of the

Table 2
Negative binomial models for absenteeism.

	# days absent for health problems		# days absent for any other reason	
	Coef.	z	Coef.	z
Car	−0.143	−0.860	−0.106	−0.610
Walk	0.065	0.170	0.065	0.180
Bike	−0.812	−1.370	0.166	0.310
Commute distance (in log)	0.162	2.100**	0.221	2.960***
Age	−0.018	−0.260	−0.095	−1.300
Female	0.143	0.940	0.266	1.600*
Income	0.045	1.200	0.072	2.080**
Education	−0.037	−0.590	0.065	1.010
Health condition	−0.410	−5.210***	−0.127	−1.410
Industry dummies	Included		Included	
City dummies	Included		Included	
Occupation dummies	Included		Included	
Physical activity	Included		Included	
Number of obs.	1102		1102	
Log-Lik. Intercept Only	−1179.7		−1348.0	
Log-Lik. Full Model	−1135.5		−1309.4	

* $p < .1$.
** $p < .05$.
*** $p < .01$.

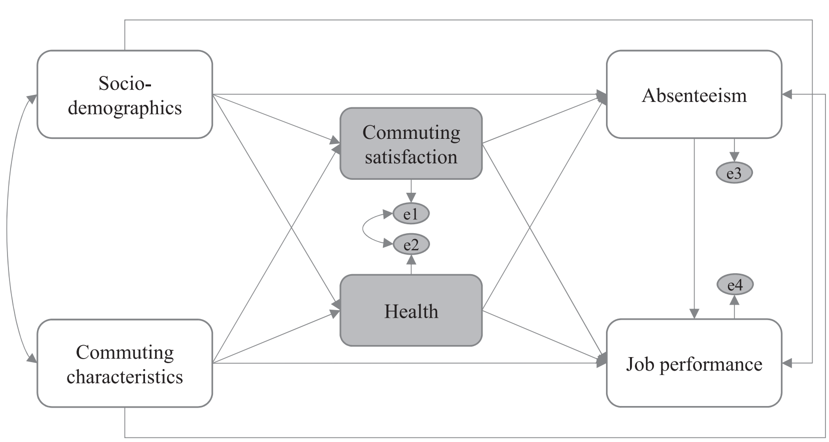

Fig. 3. SEM model specification.

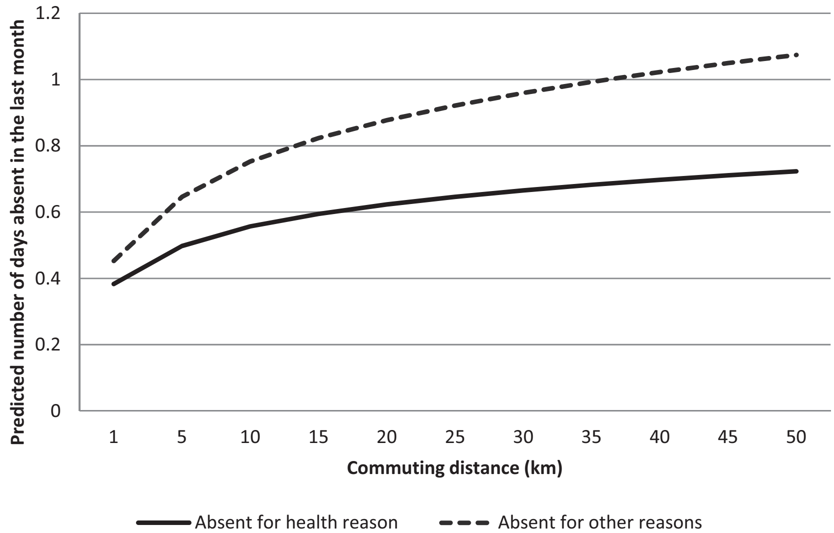

Fig. 4. Predicted number of days absent.

impact identified in this study is slightly higher (the elasticity: 0.162 vs. 0.095). This difference may reflect the varying strength of the relationship between commuting and absenteeism in different contexts, but may also suggest the unobserved confounders in this study lead to the overestimates of the effect. Finally, commuting modes were not associated with absenteeism in both models, although active travel commuters were hypothesized to have less absent days because of the health benefits from active travel.

To further confirm the association between commuting distance and absenteeism, we further estimated several other models to check whether the association was still hold. As some of the respondents reported very high absenteeism rates (e.g. over 5 days in a month), we estimated models by excluding the responses with over 5 absent days (about 2% of the sample). The coefficient of commute distance (in log-transformation) was still statistically significant ($p < .05$) and the effect size was similar to the above estimates. We also created binary dependent variables (0 = zero absent days; 1 = one and above absent days) and estimated binary logit models, again, the commuting distance (in log-transformation) was positively and significantly ($p < .05$) associated with absenteeism. Further, models were estimated using commuting time instead of commuting distance, and the results are presented in Table A1 in Appendix. Clearly, the commuting time was also positively associated with absenteeism, but the association was only statistically significant in the model for absenteeism for other reasons.

As discussed in methods, two-stage instrument variable (IV) estimations were applied to examine the possible endogeneity of commuting variables. Separate IV models were estimated for absenteeism for health reasons and other reasons using commuting distance as the suspected endogenous variable. Results of the IV models and corresponding OLS models are presented in Table 3. The weak instrument tests in IV models indicated the two instruments were highly correlated with the endogenous variables and therefore were valid instruments, while the endogeneity tests (Wu-Hausman) in IV models suggested that the specified endogenous variables should actually be treated as exogenous. In other words, the two-stage IV models are just as consistent as the OLS models. In general, these tests suggest that endogeneity should not be a concern in this analysis. The effects of commuting distance on absenteeism were only significant in OLS models but not in IV models. This is not surprising because OLS models are more efficient than IV models. The relationships between commuting distance and absenteeism revealed in OLS models are similar to those in ordered logit models.

In addition to commuting variables, some socio-demographic variables were significantly associated with absenteeism. Female adults, for example, were more likely to be absent from work for other reasons but not for health problems, and this might be associated with the more family responsibilities of women and a more acceptable social culture for women absence (Patton and Johns, 2007). Further, this study found that higher income people were more likely to have more absent days, and this might because the higher income employees feel safer about their job security than the lower income employees. Finally, the health condition was negatively associated with the number of absent days for health problems.

4.2. Impacts of commuting on job performance

An ordered logit model with the whole sample was first estimated, and then another three separate models were estimated using a subsample based on age group. Results of the four models for job performance are presented in Table 4. For the model with the the whole sample, none of the commuting modes were statistically significant except the *car*, which was marginally significant in predicting job performance. Further, commuting distance was negatively associated with job performance, but the relationship was only marginally significant. Results of three models with subsamples suggest different associations between commuting behavior and job performance among different age groups. For the younger (aged 18–34) age group, car commuting was positively associated with job performance, while commuting distance was negatively associated with job performance. For the older (aged 55–74) age group, none of the commuting variables were statistically significant in predicting job performance. For employees aged 35–54, bicycling (b = 1.498, OR = 4.47, $p < .05$) and car commuters (b = 0.317, OR = 1.37, $p < .1$) had significantly better work performance than transit commuters, after controlling for socio-demographic characteristics of the employees and industries they work in. Walking commuters also performed better (b = 0.516, OR = 1.67, $p = .19$) than transit commuters, but this result was not statistically significant.

Similar checks of model results were also conducted for job performance models as we did for absenteeism models above, by repeatedly selecting different control variables and model specifications. These checks include comparing the model results with and without physical activity variables accounted for, by selecting different samples based on commuting distance, and using different model specifications (e.g. OLS). Results of ordered logit models using commuting time instead of commuting distance and the corresponding OLS models are presented in Table A2 and Table A3 in Appendix, respectively. Comparing with the models using commuting distance, the models using

Table 3
OLS and Two-stage IV models for absenteeism.

	# days absent for health problems				# days absent for any other reason			
	Two-stage IV		OLS		Two-stage IV		OLS	
	Coef.	z	Coef.	t	Coef.	z	Coef.	t
Car	-0.161	-0.950	-0.166	-1.000	-0.140	-0.590	-0.113	-0.470
Walk	0.137	0.400	-0.066	-0.370	-0.224	-0.410	0.020	0.060
Bike	-0.611	-1.810*	-0.685	-2.010**	-0.307	-0.330	-0.278	-0.290
Commute distance (in log)	0.191	1.380	0.101	1.810*	0.045	0.180	0.161	1.990**
Age	0.020	0.360	0.019	0.330	-0.027	-0.300	-0.027	-0.290
Female	0.111	0.740	0.089	0.600	0.297	1.570	0.304	1.600
Income	0.048	1.380	0.046	1.300	0.078	1.940*	0.077	1.880*
Education	0.041	0.840	0.033	0.660	0.087	1.060	0.087	1.050
Health condition	-0.361	-2.780***	-0.359	-2.700***	-0.121	-1.130	-0.113	-1.040
Industry dummies	included		included		included		included	
City dummies	included		included		included		included	
Occupation dummies	included		included		included		included	
Physical activity	included		included		included		included	
R-squared	0.059		0.060		0.050		0.052	
Number of obs.	1102		1102		1102		1102	
	IV diagnostics				IV diagnostics			
	Statistic	p-value			Statistic	p-value		
Weak instruments (F statistic)	125.06	0.00			125.06	0.00		
Wu-Hausman	0.22	0.64			0.23	0.63		

Robust standard errors were specified in all models presented in this table.
* p < .1.
** p < .05.
*** p < .01.

commuting time showed quite similar results except that the positive relationship between walking and job performance turned out to be marginally significant (b = 0.687, OR = 1.99, $p < .1$).

To further confirm the positive relationship between active commuting and job performance revealed in the middle age group and examine the possible endogeneity of commuting variables, a two-stage IV model was estimated using active travel (walking and bicycling was combined as one category) as the suspected endogenous variable and population density at home location and job location as the two instrument variables. Results of the IV models and corresponding OLS models are presented in Table 5. As shown in the table, the effects of active travel on job performance were positive, and this result was quite

Table 4
Ordered logit models for job performance.

	Whole sample		Age: 18–34		Age: 35–54		Age: 55–74	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Car	0.255	1.93*	0.505	2.00**	0.317	1.74*	−0.361	−0.82
Walk	0.113	0.41	0.130	0.28	0.516	1.32	−0.501	−0.48
Bike	0.565	1.23	−0.060	−0.06	1.498	2.46**	−0.828	−0.66
Commute distance (in log)	−0.092	−1.65*	−0.202	−2.09**	−0.053	−0.67	0.048	0.23
Age	0.281	5.33***	−0.371	−1.30	0.609	3.76***	0.716	1.14
Female	0.085	0.71	−0.167	−0.72	0.101	0.61	1.030	2.56**
Income	0.050	1.85*	0.072	1.47	0.037	1.00	0.062	0.64
Education	0.014	0.29	0.042	0.41	0.037	0.57	−0.108	−0.72
Health condition	0.425	6.36***	0.321	2.41**	0.547	5.83***	0.250	1.25
Industry dummies	Included		Included		Included		Included	
City dummies	Included		Included		Included		Included	
Occupation dummies	Included		Included		Included		Included	
Physical activity	Included		Included		Included		Included	
/cut1	−2.712		−5.024		0.637		0.457	
/cut2	−2.150		−3.605		1.044		0.869	
/cut3	−1.898		−1.936		1.333		1.164	
/cut4	−1.194		−0.714		2.156		1.396	
/cut5	−0.232		0.076		3.047		1.586	
/cut6	0.892		1.397		4.156		2.884	
/cut7	1.675		2.904		5.085		3.476	
/cut8	2.831		4.768		6.403		4.183	
/cut9	4.302				8.056		5.884	
/cut10	5.964				9.551		8.380	
Number of obs.	1102		338		603		161	
Log-Lik. Intercept Only	−1971.79		−607.97		−1057.96		−272.08	
Log-Lik. Full Model	−1895.20		−566.98		−991.92		−244.91	

* $p < .1$.
** $p < .05$.
*** $p < .01$.

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Table 5
OLS and Two-stage IV models for job performance (for employees aged 35–54 only).

	OLS		Two-state IV	
	Coef.	t	Coef.	z
Active travel	0.432	4.24***	0.481	2.55**
Commute distance (in log)	−0.036	−0.61	−0.019	−0.34
Age	0.419	4.13***	0.378	3.27***
Female	0.070	0.47	0.004	0.03
Income	0.025	1.59	0.023	1.45
Education	0.015	0.65	0.027	1.28
Health condition	0.405	6.92***	0.425	7.05***
Industry dummies	Included		Included	
City dummies	Included		Included	
Occupation dummies	Included		Included	
Physical activity	Included		Included	
R-squared	0.17		0.17	
Number of obs.	603		603	
			IV diagnostics	
			Statistic	*p*-value
Weak instruments (F statistic)			480.27	.00
Wu-Hausman			0.02	.89

Robust standard errors were specified in all models presented in this table.
** $p < .05$.
*** $p < .01$.

consistent between the OLS and IV models. The diagnostics of the IV model indicated the two instruments were highly correlated with the endogenous variables and therefore were valid instruments, and the endogeneity test (Wu-Hausman) suggested that the specified endogenous variable should actually be treated as exogenous. In general, these tests suggest that endogeneity should not be a concern in this analysis.

Taken together, these findings generally support a positive relationship between active commuting and job performance in the middle age group (aged 35–54), and this may reflect the health and cognitive benefits of active travel modes. It is well known that walking and bicycling for daily transportation, such as to work, could be two of the easiest way to reach the recommended daily amount of physical activity. While little research effort has centered on the potential effects of active travel on cognitive function and job performance in adults, many previous studies have investigated the association between physical activity and academic performance in school-aged children and most of them found a significant positive relationship (Chomitz et al., 2009; Coe et al., 2006; Dwyer et al., 2001; Sibley and Etnier, 2003; Taras, 2005). The results of this study support a positive relationship between active travel and job performance in middle aged adults.

Some early research investigated the relationship between physical activity and cognitive performance in older adults (Baylor and Spirduso, 1988; Hassmén and Koivula, 1997; Pierson and Montoye, 1958), and these studies concluded that regular physical activity is beneficial to the cognitive ability in older adults. The results of this study, however, could not find a positive association between active commuting by walking and bicycling and job performance among older adults. This is probably because we have too few walking (only 7) and bicycling (only 4) commuters in our older group sample to identify any effects.

Further, in two of the four models, age was positively associated with job performance, while previous research has reported mixed results. These two studies (Ng and Feldman, 2008; Waldman and Avolio, 1986) based a meta-analysis concluded that older employees had higher job performance, while another study, also based a meta-analysis, revealed that age and job performance were unrelated (McEvoy and Cascio, 1989). Finally, it is not surprising that health condition is positively associated with the job performance.

4.3. Structural relationships between commuting characteristics, commuting satisfaction, absenteeism, and job performance

An SEM model specified as Fig. 3 was estimated to explore the possible mechanism of the relationship between commuting behavior and job productivity, and the model results are presented in Fig. 5. For simplicity, only statistically significant ($p < .05$) relationships were presented. The SRMR fit index suggests a good fit and CFI fit index suggests an acceptable fit (CFI = 0.92, SRMR = 0.03) based on Hu and Bentler (1999), who suggest a cutoff value close to 0.95 for CFI and a cutoff value close to 0.08 for SRMR are needed to conclude there is a relatively good fit between the hypothesized model and the observed

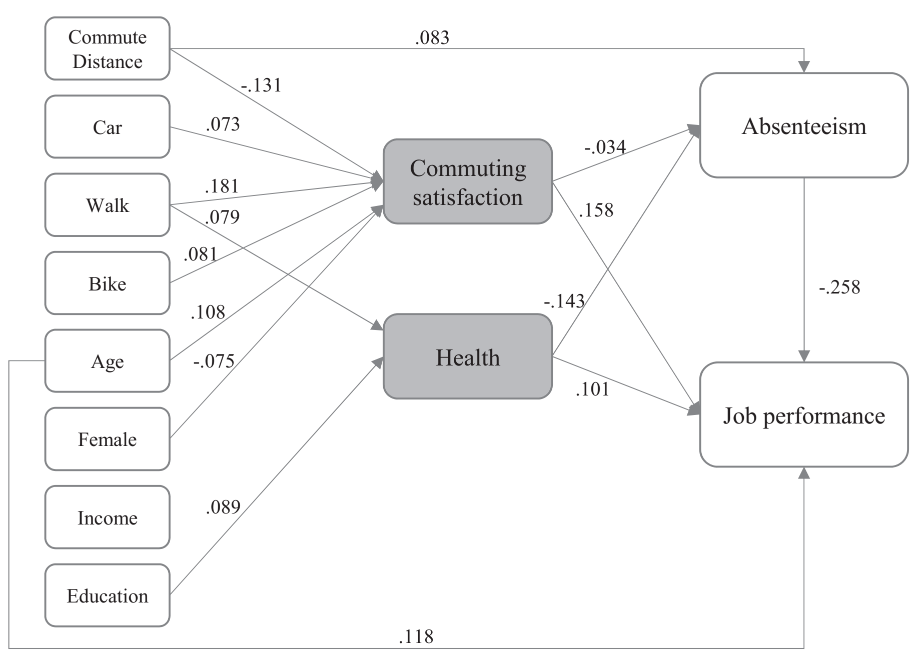

Fig. 5. SEM model results.
Note: only statistically significant ($p < .05$) coefficients were labeled.

Table 6
Factor loadings on commuting satisfaction.

Now, thinking a little more about your commuting trips over the past 4 weeks. Please indicate on each of the scales below how you felt overall during your trips to work.

Fed up	⟷	Engaged	0.820
Stressed	⟷	Calm	0.695
Trip was low standard	⟷	Trip was high standard	0.822
Trip was the worst I can think of	⟷	Trip was the best I can think of	0.770
Time pressed	⟷	Relaxed	0.750
Tired	⟷	Alert	0.840
Trip worked poorly	⟷	Trip worked well	0.752
Worried I would not be in time	⟷	Confident I would be in time	0.823
Bored	⟷	Enthusiastic	0.795

Table 7
Indirect effects.

	Commute Distance	Walk	Bike	Car
Indirect effects through commuting satisfaction				
Absenteeism	0.009**	−0.012**	−0.005**	−0.005**
Job performance	−0.048***	0.039***	0.016	0.019*
Indirect effects through health				
Absenteeism	0.004	−0.012***	−0.002	0.001
Job performance	−0.027***	0.017*	0.003	0.004

* $p < .1$.
** $p < .05$.
*** $p < .01$.

data. Further, the standardized loadings of the nine observed indicators assessing commuting satisfaction are of sufficient magnitude, ranging from 0.695 to 0.840 (Table 6).

First, as hypothesized, the commuting characteristics could influence absenteeism and job performance through commuting satisfaction. After controlling for socio-demographics, all commuting characteristics were significantly associated with commuting satisfaction. In particular, walking, bicycling, and car commuters were more satisfied with their commuting comparing with transit commuters. Commuting distance was negatively associated with commuting satisfaction. These findings align well with recent studies on travel satisfaction (De Vos et al., 2015; Smith, 2017; St-Louis et al., 2014; Ye and Titheridge, 2017).

Second, the relationship between commuting and personal health was relatively weak. Only walking to work was positively associated with personal health, while bicycling to work was not. This is unexpected as bicycling is perceived to have more health benefits than walking because of the higher intensity of the bicycling activities. Indeed, the finding of a recent empirical study with a large sample in the UK suggests that bicycling to work has a stronger association with a range of cardiovascular diseases than walking to work (Celis-Morales et al., 2017). The different result of this study might attribute to the measure of health outcome, which is a generic health measure rather than the physical activity focused health measure as commonly used in previous studies, as well as the small sample of bicycling commuters.

Third, commuting satisfaction was negatively associated with absenteeism, suggesting that people who were satisfied with their commuting were less likely to be absent from work. Further, commuting satisfaction was positively associated with job performance, implying that people who were satisfied with their commuting were more likely to perform well in their job. These findings support that the psychological states during the commuting could have spillover effects on job productivity. Two possible causal mechanisms could explain this finding. The first mechanism is that the emotional responses evoked by commuting could have transitory (e.g. the first hour after commuting) effects on moods at work (Friman et al., 2017), thereby influencing job performance. The second mechanism is that commuting satisfaction could have accumulative and long-term impacts on absenteeism and job performance.

Fourth, consistent with the hypothesis, personal health is negatively associated with absenteeism, while positively associated with job performance. Previous studies also reported that health, particularly mental health, significantly influences work absence and performance (Wynne-Jones et al., 2009). For example, this study (Lerner and Henke, 2008) found that employees with depression have more absences and at-work performance deficits.

Fifth, as shown in the model results, except a direct effect from commuting distance on absenteeism, the commuting characteristics primarily influence absenteeism and job performance through commuting satisfaction and personal health. We have further tested the mediating effects of commuting satisfaction and personal health respectively using the bootstrapping method. The estimation results (Table 7) revealed that the relationships between commuting characteristics and job productivity (as measured by absenteeism and performance) were mediated by commuting satisfaction, as indicated by most of the significant indirect effects. Comparing with the mediating effects of commuting satisfaction, there were relatively less significant indirect effects through affecting personal health. Overall, however, these findings support the mediation hypothesis. Finally, the model results also revealed that absenteeism was negatively associated with job performance, and this finding aligns well with previous studies (Bycio, 1992).

5. Conclusions

This study examined the relationship between commuting behavior and job productivity as measured by absenteeism and workplace performance. Possible causal mechanisms were first proposed by drawing theories from multiple disciplines and empirical work was followed based on a survey data collected from three major cities in Australia. The results of regression models reveal that commuting distance is positively associated with absenteeism, and commuting mode choice is associated with job performance while this relationship is only statistically significant in employees aged 35–54, after accounting for socio-demographics, work industries, occupations, and physical activities of employees. Overall, these findings support the hypothesis that commuting behavior could influence job productivity. The SEM model further explored possible causal pathways from commuting to job productivity, and the results confirm that commuting mode choices and commuting distance influence absenteeism and job performance through affecting commuting satisfaction and personal health, though commuting distance retains a direct impact on absenteeism after controlling for the indirect effects.

This study has several limitations that future research can help to address. First, although we have developed strategies which include restricting sample selection and including a range of controlling variables to reduce the risk of confounding factors, other unobserved factors that are associated with job productivity may lead to estimation bias (i.e., omitted variable bias). Future research may consider employing natural experiment design to collect longitudinal data, for example, using the experience sampling method (ESM) to collect time-stamped sequence data will allow for a visual examination of covariate patterns of psychological states and job performance and making rigorous causal inferences. Second, both absenteeism and job performance, the two measures used to measure productivity in this study, are subjective measures, which are subject to recall bias, though previous studies have shown a high consistency between the subjective measures used in this study and the archival (objective) measure from the employers (Kessler et al., 2003). Future research could consider using multiple sources of data when available to reduce the measurement errors. For example, ESM generates moment-in-time data that can reduce recall bias of survey instruments and archival performance data even for a subsample could help to validate the estimation results. Third, cognitive ability is also one possible mediator that links commuting and job productivity, but it was not measured in this study. Future study may explore this causal pathway. Fourth, it is worth noting that travel modes mentioned in this study are the *primary* travel mode (i.e., mode used for the longest portion of the trip) for commuting, which could be a combination of different travel modes, when possible, future research should collect data on all travel modes used in a commuting trip and it would be enlightening to see the impacts of multimodal commuting on job productivity. Fifth, bicycling commuters were not well represented in our sample (2% of the sample), and this may lead to the underestimation of the impact of bicycling on health and psychological states, and therefore, the job productivity. Lastly, the relationship between commuting distance/time and productivity (performance and absenteeism) may be nonlinear, and there might be certain thresholds in commuting distance/time that the impact of commuting on job performance and absenteeism become significant. Further, these thresholds might be different for different people using different travel modes. Testing this hypothesis could be an interesting follow-up study of this research.

This study found commuting by walking and bicycling has both psychological and health benefits, which in turn promote job productivity. This suggests that encouraging active commuting not only improves the physical and mental health of employees, but may also enhance their job performance, contributing to economic benefits to employers and society. Commuting related strategies should be considered in employers' overall strategy for improving job performance. These strategies should aim to promote active commuting and shorten commuting time. Providing safe bike parking and showers at work site, for example, could significantly raise bicycling to work (Hunt and Abraham, 2007; Noland and Kunreuther, 1995; Wardman et al., 2007). For governments, more transport infrastructure funding should be allocated to active travel, given to the economic benefits of walking and bicycling to work. In most states of Australia, only a tiny portion (< 2%) of transport funding was devoted to bicycling infrastructure, whereas in the Netherlands most municipalities have specific bicycling budget allocations to ensure continuity in implementing bicycling policies (Ministry of Transport, 2009).

The findings of this research also provide evidence from the perspective of economic impact to support the urban planning policies, such as jobs-housing balance, that aim to reduce commuting distance and time. In Australia, over 8 million people commute to work every weekday, and on average, the full-time workers spend 5.75 h a week (around 15% of their working time based on a national 38-hour working week) travelling to and from work, based on the 2013 HILDA data. The commuting time in all Australian capital cities has increased over the last two decades due to increased road congestion and urban expansion (BITRE, 2016). As suggested by this study, the long commute will not only place physical and mental burden on workers but also directly influence their work participation and engagement, leading to a direct loss of productivity in the workplace. Further, urban sprawl is pervasive in Australia, and due to the long commuting distance, most people relies on private cars (about 75%) or transit (about 10%) for daily commuting, while only about 4% walk to work and 1% bicycle to work, according to the Census data of 2016. This study and several previous studies have consistently found that transit commuters have the lowest level of travel satisfaction comparing with other modes users, and this negative impact on satisfaction will further influence their productivity in the workplace. Polices that aim to improve transit accessibility, reliability and frequency could help to improve the subjective experience of transit commuters, and therefore mitigating the negative impacts of transit commuting on job productivity. Driving is better than transit in commuting satisfaction, however it has been found to be a stressful way to commute (Legrain et al., 2015) and is associated with series of health problems (Novaco and Gonzalez, 2009) and lower social capital (Mattisson et al., 2015), which all play a role in one's job performance and productivity. Planning policy such as polycentric cities proposed in Sydney and Melbourne that aims to achieve a jobs-housing balance within a smaller geographic area will help to reduce the car dependent commuting and encourage active commuting, potentially improving employee's commuting satisfaction, health and productivity. Finally, given the health and economic benefits of active commuting, both the ‘hard’ policies focusing changing the built environment and providing infrastructure and ‘soft’ policies targeting influencing individual attitudes and perceptions are needed to encourage walking and bicycling to work. Based on the Victorian Integrated Survey of Travel and Activity 2012–2014, about 50% of commuting trips in Victoria are within 10 km, however, only 3% of these trips were travelled by bicycling and 17% by walking. This suggests that commuting distance is not the only barrier for active commuting, better pedestrian and bicycling infrastructure, social marketing and education programs helping to change the attitudes, norms and perceptions, and strategies to create a safe environment for walking and bicycling are also necessary to promote active commuting, which is beneficial to employee productivity.

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Appendix A

Table A1
Negative binomial models for absenteeism.*

	# Days absent for health problems		# Days absent for any other reason	
	Coef.	z	Coef.	z
Car	−0.113	−0.660	−0.021	−0.110
Walk	−0.168	−0.460	−0.118	−0.340
Bike	−0.796	−1.350	0.206	0.390
Commute time (in log)	0.117	1.070	0.266	2.310**
Age	−0.022	−0.330	−0.094	−1.290
Female	0.125	0.830	0.261	1.570
Income	0.046	1.230	0.074	2.160**
Education	−0.038	−0.610	0.064	0.980
Health condition	−0.414	−5.230***	−0.109	−1.210
Industry dummies	Included		Included	
City dummies	Included		Included	

(*continued on next page*)

Table A1 (*continued*)

	# Days absent for health problems		# Days absent for any other reason	
	Coef.	z	Coef.	z
Occupation dummies	Included		Included	
Physical activity	Included		Included	
Number of obs.	1102		1102	
Log-Lik. Intercept Only	−1179.7		−1348.0	
Log-Lik. Full Model	−1137.1		−1311.0	

* $p < .1$.
** $p < .05$.
*** $p < .01$.

Table A2
Ordered logit models for job performance.

	Whole sample		Age: 18–34		Age: 35–54		Age: 55–74	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Car	0.241	1.72*	0.401	1.49	0.369	1.92*	−0.429	−0.93
Walk	0.242	0.92	0.181	0.39	0.687	1.83*	−0.770	−0.86
Bike	0.565	1.22	−0.096	−0.09	1.544	2.53**	−0.933	−0.76
Commute time (in log)	−0.063	−0.73	−0.295	−1.74*	0.086	0.72	−0.091	−0.37
Age	0.283	5.36***	−0.402	−1.41	0.600	3.70***	0.717	1.14
Female	0.097	0.80	−0.112	−0.49	0.117	0.71	1.019	2.54**
Income	0.049	1.82*	0.076	1.54	0.036	0.97	0.057	0.60
Education	0.018	0.37	0.048	0.47	0.040	0.61	−0.099	−0.66
Health condition	0.425	6.34***	0.319	2.40**	0.551	5.86***	0.245	1.23
Industry dummies	Included		Included		Included		Included	
City dummies	Included		Included		Included		Included	
Occupation dummies	Included		Included		Included		Included	
Physical activity	Included		Included		Included		Included	
/cut1	−2.685		−5.479		1.150		−0.088	
/cut2	−2.124		−4.065		1.557		0.325	
/cut3	−1.871		−2.411		1.846		0.621	
/cut4	−1.168		−1.201		2.669		0.853	
/cut5	−0.207		−0.415		3.560		1.043	
/cut6	0.915		0.899		4.667		2.342	
/cut7	1.696		2.405		5.592		2.935	
/cut8	2.850		4.274		6.905		3.642	
/cut9	4.319				8.560		5.341	
/cut10	5.982				10.060		7.839	
Number of obs.	1102		338		603		161	
Log-Lik. Intercept Only	−1971.79		−607.97		−1057.96		−272.08	
Log-Lik. Full Model	−1896.29		−567.65		−991.88		−244.87	

* $p < .1$.
** $p < .05$.
*** $p < .01$.

Table A3
OLS models for job performance.

	Whole sample		Age: 18–34		Age: 35–54		Age: 55–74	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Car	0.175	1.47	0.241	1.08	0.240	1.60	−0.275	−0.62
Walk	0.190	0.83	0.144	0.36	0.533	1.79*	−0.480	−0.54
Bike	0.540	1.42	0.442	0.54	1.002	2.15**	−1.000	−0.77
Commute time (in log)	−0.049	−0.67	−0.200	−1.44	0.066	0.70	−0.231	−0.96
Age	0.183	4.13***	−0.281	−1.21	0.413	3.28***	0.523	0.82
Female	0.062	0.60	−0.171	−0.88	0.079	0.61	0.606	1.62
Income	0.033	1.44	0.026	0.64	0.020	0.70	0.023	0.24
Education	0.014	0.34	0.059	0.68	0.021	0.41	−0.096	−0.67
Health condition	0.344	6.21***	0.221	2.04**	0.410	5.84***	0.124	0.66
Industry dummies	Included		Included		Included		Included	
City dummies	Included		Included		Included		Included	
Occupation dummies	Included		Included		Included		Included	
Physical activity	Included		Included		Included		Included	
Number of obs.	1102		338		603		161	

(*continued on next page*)

Table A3 (*continued*)

	Whole sample		Age: 18–34		Age: 35–54		Age: 55–74	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Log-Lik. Intercept Only	−2068.2		−626.5		−1106.5		−323.2	
Log-Lik. Full Model	−2009.0		−592.3		−1046.8		−298.5	

* $p < .1$.
** $p < .05$.
*** $p < .01$.

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