# Commuting time and Sickness Absence: Evidence from China

**Zicheng Wang**
jinan unviersity
**Jiachun Liu**
jinan university
**Murong Guo** ( 495233843@qq.com )
renmin university https://orcid.org/0000-0003-2318-9099

**Research article**

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# Abstract

Background: Most of employees in urban China have experienced a heavy commuting burden which has become an urgent issue that should be solved in the process of promoting the new urbanization strategy. However, not only has the exploration of relationship between commuting and sickness absence been still scant in China, but also there is no discussion made to analyze the mechanism linking the commuting time and sickness absence. To address these gaps, this study firstly investigates the commuting-absence effect as well as the potential transmission channel between them.

Methods: Using a unique dataset of 2013 Matched Employer-Employee Survey (CMEES) in China, we apply the zero-inflated negative binomial model to explore the nexus between the commuting and sickness absence. To discuss the potential mechanism linking commuting and sickness absence in the context of China, the estimations of the impact of the commuting on health-related outcomes and work efforts are performed to confirm transmission channels of commute-absence effect by the OLS and Logit regression model.

Results: The empirical results reveal that a longer commute has a positive effect on sickness absences, while it is still robust against several specifications. More importantly, the commuting-absence effect is mainly transmitted through health-related outcomes of employees, whereas we cannot find evidence that the effect is transmitted through shirking behavior s. Additionally, the heterogeneous effects of commuting-absence are differentiated across Hukou status, gender, pattern of commuter travel, scale of cities and types of enterprises .

Conclusion: The long commute induces to lower productivities through the sickness absence, that is, the longer journey from home to work is positively related with the increasing sickness absence, which keeps in consistency with previous studies. And the potential effect of commute-sickness absence is mainly transmitted through their health-related outcomes.


# Background

For millions of employees, the commuting is a routine but important component of daily life. With the rapid urbanization and increasing ownership of private vehicle, most of employees in urban China have experienced a heavy commuting burden [1], which is portrayed as “a plague that affects modern man” [2]. A large arrays of previous studies based on the optimal time allocation model firstly focused on the relationships between the commuting and the employees’ labor market performance [3, 4, 5]. With negative externalities of the sickness absence, the relationship between the commuting and sickness absence has been also attracted extensive attention in the discussions of occupational health policies [3, 6].

However, the debate whether the commuting has a positive effect on sickness absence or not has not been at a consensus theoretically yet. There are two kinds of different transmission channels applied to discuss it. For one hand, one transmission channel is that the absence for sickness might be affected positively by the commuting, that is, more time spent in commuting would induce employees to bargain for more additional days off [7]. Based on the theory of new welfare economics of well-being, a long journey from home-to-work is viewed as an activity of time-consumption, which is related with negative psychological and physical health outcomes [1, 8, 9]. Accordingly, the leisure time of employees for health-promoting plans, such as physical activities, relaxation and social participation may be crowded out by the longer commuting time [10]. As a result, longer commuting may increase the risk of health-related absence, which is regarded as the involuntary or unavoidable absenteeism. In addition, while leisure could be substituted for shirking by each other, there is more likely for shirking behaviors among those employees with a longer commute time [11], thereby increasing the probability of the voluntary or avoidable absenteeism. It implies that with the decreasing cost of absence, a longer commuting may lead to more benefit from their absence to ask for more leisure, which could be used for other purposes rather than for work [6]. Therefore, asking for “sickness” leave could be regarded as a result of rational decision.

For another, the second mechanism based on the theory of efficiency wage argues that the commuting time may be negatively related to the sickness absence, that is, individuals who choose to take a long commute must have been well compensated [6]. For instance, employers who are engaged in jobs involving a long commute always tend to pay their employees a higher salary to attract and retain them [9]. Hence, the willingness to take a long journey from home-to-work is associated with the higher work morale, which may weaken the motivation for the voluntary absenteeism [12]. Additionally, there is an unclear nexus between the commute and illness-related absence due to heterogeneous health effects of commutes across transportation modes [13, 14]. Active commuting tools, such as bicycles or walking, are related to increasing health-promoting activities significantly, which is beneficial for their physical health [13], and commutes could also act as an important buffer to keep in balance between work and private spheres, which has a negative effect on the sickness [15].

It is apparent that not only is the relationship between commuting and sickness absence theoretically ambiguous, but also it has still reached inconsistency in empirical studies. Using the cross-sectional data from London, Liepmann [16] found that there was no evidence supporting the commute-absence effect, while Kluger [17] revealed that there was a positive relationship between the commuting and absence in terms of the passive commuting. Hendriksen, Simons, Garre and Hildebrandt [18] further pointed out that the commuting had a negative effect on being absent among employees who cycled to work. An elaborate study conducted by Van and Gutiérrez-i-Puigarnau [3] suggested that a longer commuting might increase the likelihood of illness-related absence, but Künn-Nelen [13] did not draw the same conclusion by applying British Household Panel Survey (BHPS) data. Conversely, Goerke and Lorenz [6] found a positive causality between changes in commuting distance on sickness absence from work. However, previous studies have two limitations as follows. Firstly, it is important to be aware that absence due to sickness is a multi-factorial phenomenon [19, 20]. Most of studies were carried out in the European developed labor market to explore the commute-sickness absence effect for portraying the work-life balance for employees, whereas the discussion in the undeveloped Context like China is still scant. Another limitation is that the mechanism linking the commuting and sickness is still unclear, whereas the debate whether the commuting – absence effect is transmitted through health-related outcomes of employees or shirking behaviors is under discussion.

To fill these gaps, this paper builds on previous studies by examining the effect of commuting on sickness absence. Within the scenario of China, we try to address these questions: Whether a longer commute has a significantly positive effect on illness-related absence from work or not? If it does, what is the potential transmission channel between the commuting and sickness-absence?

This study contributes to the literature in several distinct ways. Firstly, following Goerke and Lorenz [6], we apply a unique dataset of the 2013 Matched Employer-Employee Survey in China and the zero-inflated negative binomial model to explore the nexus between the commuting and absence due to sickness.

Secondly, this study attempts to discuss the potential mechanism linking the commuting and sickness absence in the context of China, confirmed by the estimation of the impact of commuting on health-related outcomes and work efforts.

Thirdly, the heterogeneous commuting-absence effects with respect to Hukou status, gender, patterns of commuting, scale of cities and types of companies are taken into full consideration within the context of China.

The remainder of this study is organized as follows. Section 2 describes the data, including a discussion of descriptive statistics and presents the econometric method. All main empirical findings are given in Sect. 3. The discussion about the transmission channel between the commuting and sickness-absence as well as its heterogeneous effects is presented in Sect. 4. Finally, Sect. 5 will summarize all findings, policy implications and limitations of present study.

# Methods

### Data

We use the data from 2013 China’s Matched Employer-Employee Survey (CMEES), which is conducted by the School of Labor and Human Resources, Renmin University. Using the two-stage method of stratified sampling, the dataset was selected from an enterprise listing set up on the basis of the 2008 national economic census data. The sample was collected from managers who were responsible for employment relations or personnel matters in the private and public sector companies with 20 or more staffs. If a sampled enterprise refused to response, it would be replaced by another company with the same firm size in the same industry.

This study is a secondary analysis based on the data from the CMEES conducted by School of Labor and Human Resources, Renmin University all of which were subject to multiple stages of reviews by experts to address methodological, ethical and legal issues related to data collection. Final approvals of all CMEES surveys were required from the Research Ethics Committee of Renmin University to ensure that the data collection complied with ethical requirement according to the Statistics Act. Unfortunately, the commute time of the CMEES was only incorporated in 2013. There are 4,532 employees from 444 enterprises and 12 cities covered in China, including seven provincial capitals and five prefecture-level cities. The CMEES not only collects the rich information on the characteristics of company-level, demographic and employment traits for employees, but also provides the detailed information about both days absent for sickness and the commuting time, which is appropriate to discuss the effect of the commuting on sickness absence.

**Table 1 insert here**

A descriptive statistics for the whole sample is presented in Table 1. The proportions of rural-migrants[1] and urban employees are 21.74% and 78.26% respectively.

The dependent variable is the annual number of days absent from work due to sickness, which stems from the following question: “In the past year, how many days have you asked for a leave due to illness?”, which refers to all sickness absence both with and without a medical certification. For the whole samples, the average number of days absent for sickness was nearly 2.46, with a standard deviation of 7.42, which indicates that there are several cross-sectional variations. In addition, 60.26% of employees have not been absent for illness in 2012. Moreover, the duration of sickness absence among rural employees reached at 2.18, while it was slightly lower than urban employees (2.53) respectively. Figure 1 also presents the frequency distribution of days absent for sickness.

We treats the commuting time as the independent variable of interest, with a definition as minutes spent in one-way daily rather than the commuting distance. The mean of one-way commuting time was approximately 26 minutes, with a standard deviation of 20. As for rural migrants, the mean of one-way commuting time is approximately 6.20 minutes lower than urban employees, which implies that rural migrants tended to be shorter commuters. The reason is that a large proportion of rural migrant employees lived in employer-provided dormitories with short commute distance, which could decrease their cost of time [21]. The frequency distribution of commuting time is depicted in Figure 2.

According to previous studies, controlled variables are divided into three categories: individual-level variables (including personal characteristics and job-related traits), company-level variables (including company types and sectors) as well as city-level variables. With regards to individual-level variables, rural migrants were younger (a mean age of 29 years old) than urban employees (a mean age of 34 years old). Only 47% of rural migrants were married, whereas 72% of their urban counterparts were married. Although rural migrants have lower educational attainments than urban workers, most of them have completed the nine-year compulsory education. As for company-level variables, rural migrants were in a weaker position in the labor market, compared with urban employees. For instance, rural migrants were under more pressures, such as the difficulty of job-seeking, the frequent overtime, a higher risk of injuries with lower job security, more unstable employment relationships, and poorer wages. The second set of variables is applied to reflect the differences of sickness absence across company types and sectors, while an individual’s decision to skip work may be influenced by the personnel policies, organizational structure, or enterprise culture [22]. According to 2013 CMESS, nearly 80% of employees worked in the domestic private enterprises, while about 40% worked in the manufacturing sector, which may induce to a low rate to permit for sick leaves in these enterprises. With regards to city effect differentials, they could reflect the differentiated development of public transportation facilities among cities, which may have an influence on the commuting time varying across cities. About 97% of rural migrants mainly moved into first-tier and second-tier cities[2], as shown in Table 1.

**Empirical model**

The number of days absent for sickness is a count variable (0, 1, 2, 3, and so on). In present study, the over-dispersion might exist because the standard error of days absent for sickness was nearly two times than the mean (7.42 VS 2.46). Therefore, the ZINB model may be more appropriate for this study. To further check these count models, the countfit function in Stata software was used to compare all four count models. As depicted in Figure 3 and Figure 4, both the result of the residuals or a set of fit statistic from the tested models including AIC, BIC, and Vuong test of the ZINB model prove that the ZINB is better than others

The ZINB regression includes three steps. First, a Logit model is applied for the “certain zero” cases (described above) to predict whether an employee would be in this group or not. Then, an NB model is used for the prediction of the counts for those workers who are not certain zeros. Finally, all two models are pooled. For more information about the specific introduction of ZINB regression model, see Hilbe [23].

# Results

### Benchmark results

First, we employ three ZINB regressions to test the relationship between commuting time and the number of days absent for sickness. As shown in Table 2, Model (1) only includes the focal independent variable of commuting time without other controlled factors. Models (2), Models (3) and Model (4) adds individual characteristics, company traits and city-level variables step by step, and all regressions were used robust standard errors to adjust for the heterogeneity in the model.

### Table 2 insert here

The results are presented in Model (1). Without the control for individual demographic characteristics, the commute plays a significantly positive role in sickness absence. After adding the controls into Model 1, such as individual characteristics, job-related traits, company types, sectors and city scale, the commute-absence for sickness effect is still robust (as shown in Model (2) -Model (4)). In other words, employees might incline to ask for ill-related absence for nearly 1 day (exp (0.0038))[3], with an additional increase of 1 minute, which is consistent with the findings by Van and Gutiérrez-i-Puigarnau [3].

Besides, the analysis of individual characteristics, company traits and city-level variables are clearly shown in Models (2)–(4). The individual repressors have the expected effect. Compared with urban employees, rural migrants are less likely to be absent for sickness. This result was not surprising. In urban China, rural migrant employees would suffer more discrimination due to their Hukou status and the relatively weaker position in the labor market [24]. To take a day off may be at a cost of daily income at least and even may have greater likelihood to be dismissed. Second, higher wages were consistently associated with lower sickness absence. This finding is consistent with classic economic theory, which indicates that an increase in the opportunity cost of illness-related absence will lower the demand for sick leave. Moreover, as confirmed in previous studies, the results also prove that socio-economic characteristics, such as age, marriage, occupational and health status play an important role in sickness absence, whereas company-level characteristics have no significant impact on the absence for illness. A possible explanation is that with the implementation of China’s market liberalization reform in recent years, enterprises have introduced modern human resource management or organizational re-engineering to improve their competitiveness. The potential benefit gap, such as sickness pay has been shrinking gradually among enterprises, which might not affect the illness-related absence among employees [25].

### Robust checks

Several robust checks are performed to verify the sensitivity of the main findings, as shown in Table 3. In Model (5), it explores the effect of possible "outliers” on the dependent variable. The reasons why this process may be important are as follows. First, measurement error may be of relative significance for employees who had many absent days. Second, according to the regulation of sickness compensation in China,, employees who has been absent for more than six months could obtain less sick leave pay, the reduction of which is approximately 20% to 40% of daily wages[4]. Therefore, model (5) re-examined the same baseline model through exclusive observations for which absenteeism was less than 180 days during the past year. The results after the adjustment were virtually consistent with those presented for the baseline. Furthermore, to correct the measurement error, we also defined *sickness absence* as a dummy variable (it equals 1 if the individual took sick leave during the past year) to give an additional analysis of the commute-absenteeism relationship. The results are still robust (see model (6) in Table 3).

Similarly, we also treated it as a categorical variable instead of a continuous variable to deal with the measurement error in the independent variable of interest, *commuting time*. We defined those whose time spent in one-way daily travel is less than 10minutes (i.e., 0≤CT≤10minutes) as short-commuters. Those who traveled to work over 10minutes and less than 26minutes are middle-time commuters (i.e., 10<CT≤26minutes), while those who travel over 26minutes are long-time commuters (i.e., CT>26minutes). As shown in Model (7) in Table 3, only long-time commuters are inclined to be with the higher sickness absence, compared to short-commuters. Additionally, commuting time (CT) and its square (CT2) are included in the benchmark model, however, we find no evidence to support a U-shaped relation between the commuting time and sickness absence, which is in consistency with the findings from Künn-Nelen [13].

Model (8) is to re-estimate for those who have not been injured at work during the past year because the injury can play a vital role in the probability of becoming a commuter and of being absent from work. There is an image drawn that an employee with injury may be accompanied with many days absent for recuperation and the unwillingness to experience a longer commute, which may generate a few outliers. Hence, model (8) excludes observations for those who have been injured at work during the past year. For this restricted sample, the results are also of the robustness.

To obtain more robust results, Model (9) excludes observation of individuals whose medical expenditure in the past year was more than 10,000 yuan. The mean of the medical expenditure for whole sample is 1,083 yuan. An individual's medical expenditure that is nearly10 times than the average could have suffered from a serious illness and poor health, which may lead to outliers. After excluding these observations, the results are robust to reach a consensus.

Besides, there are some studies demonstrating that health effects of the commuting might be heterogeneous across transportation modes [13, 18], which may have an important impact on sickness absence. In Model (10), the variables of the modes of transportation were added to control its possible impact on the results. It was divided into the active mode and passive mode. The former refers to those who walked or cycled to work, while the latter includes those who drove cars or used public transportation. As shown in Table 3, the estimated coefficients of the interested variables do not statistically differ from one another, even when these variables were controlled.

**Table 3 insert here**

# Discussion

### Mechanism analysis

Why would a longer commuting induce to more sickness absence? There are two possible mechanisms transmitting in the commute-absence effect. One is that longer commutes might weaken employees' health outcomes, leading to additional health-related absence, which is recognized as an involuntary absenteeism. Thus, health-related outcomes, such as self-rated health status, degree of depression, BMI index, obesity, and annual medical expenses as dependent variables are taken into consideration in Model (11) –Model (15). The first two variables could be seen as proxies for subjective health, while others are proxies for objective health. Table 4 depicts the results and reveals that employees with the longer commuting time have lower subjective and objective health respectively, that is, a longer commuting was associated with poorer self-rated health status and a higher degree of psychological depression, and it also highly related with an increase of their BMI index, annual medical expenses as well as the risk of obesity. In this scenario, health-related outcomes do act as an important transmission channel through the nexus between the commuting and sickness absence. More time spent on commute might break the work-life balance among employees and tends to push more burdens on both objective and subjective health status, including a combination of the tension, tiredness, depression, irregular diet and so on, which might lead to the greater likelihood of the sickness-absence and lower their productivity.

**Table 4 insert here**

Another theory of urban efficiency wage claims that leisure and shirking are substitutable; the commuting may reduce the individual's net time endowment and increase the probability of shirking behaviors respectively, thereby inducing the voluntary absence. It is emphasized that the commute-absence effects could be probably transmitted by employees' work efforts to some extent. With the dataset unavailable, we apply weekly overtime and weekly work time as proxies for work effort to check this potential mechanism. Those with long hours of overtime and work time may be of higher motivation for their work instead of shirking. However, the results reveal that the commuting has no significant effect on the overtime, whereas it is turned up that a long commute has a significantly positive influence on the length of work time. Therefore, whether the effect of the commuting on the absenteeism for illness is transmitted by shirking behaviors or not has not been confirmed clearly (see model (16)-(17) in Table 4).

In conclusion, it is highlighted that there is a mechanism channel of health-related outcomes linking the commute-absence effect, whereas the transmission role of shirking behaviors representing the voluntary absence is not found.

### Heterogeneous effects

In this section, we attempt to estimate heterogeneous effects of commutes on absenteeism for sickness with respect to gender, transportation mode, the scale of cities, the type of enterprises and Hukou status, as shown in Table 5. This study is to disentangle different effects of commuting time on sickness absence in urban employees and rural migrants, we only analyzed the results of Hukou status, while other findings are shown in Table 5.

**Table 5 insert here**

Model (18a) and Model (18b) show the results for the benchmark model with Hukou status separately. Model (18b) only focuses on the commuting – absence effect among urban employees, and the results indicate that longer commuters are more likely to be absent for sickness. In comparison with urban employees, the positive relationship between the commuting and illness absence among rural migrants is not proved, as shown in Model (18a), and it is in contrast with of the finding by Chia [26], which suggested that migrants in Singapore had a higher possibility of sickness absence than their local counterparts, due to their disadvantage in the personal and work adjustments in destination cities.

The possible reason why rural migrants with longer commuting time do not induce a higher likelihood of absence for sickness is that rural migrants are exposed to the higher costs of sickness absence than urban employees, that is, rural migrants' access to homeownership in destination cities are legally restricted by the Hukou system5, which compels them to live in suburban areas6 that extremely lacks public facilities, such as formal hospitals and public transit system [24,27]. Once they get sick, they incline to choose a private clinic nearby in a "migrant villages" rather than a formal hospital far from their residence [28]. Therefore, these unregulated private clinics usually fail to provide official certificates, which are necessary to obtain permission of paid sick leave. Hence, these employees may suffer an extra economic loss of day-off work. In terms of the costs of illness-related absence without permission, rural migrants may be less likely to be absent even they are ill or discomfortable [14].

## Conclusion

With the rapid urbanization, to ensure the balance between work and life as well as promote the health for employees has been an urgent issue in occupational health security. Consequently, researches on the relationship between the commuting and absence due to sickness have been paid much attention in the context of European countries, whereas the exploration of commute-absence for illness effect and its potential transmission channels have been still scant in China context. To address these gaps, this paper applied a unique dataset of the 2013 CMEES and the zero-inflated negative binomial model to fill these gaps.

The findings demonstrate a significant relationship between commute and absenteeism for illness, which is consistent with the previous evidences [3, 6], whereas it is still robust against several specifications. More importantly, it further points out that health-related outcomes for employees mainly act as a transmission channel to the commuting-absence effect, that is, longer commutes might directly have an influence on both objective and subjective health to increase the likelihood of the sickness, which induces to more absence for illness. Additionally, the impacts of commutes on the absenteeism for sickness are differentiated across the Hukou status, gender, pattern of commuter, scale of cities and types of companies.

This study has several implications. Firstly, promoting the public transportation must be given priority in the process of new urbanization to relieve the heavy burden on employees with long commutes. Considering the negative externality of commuting on lower productivities, it is encouraged to provide dormitories by employers to reduce the duration of commutes. Finally, improving the social medical insurance is beneficial to ensure rural migrants to share the equal medical services as urban citizens and protect their legal rights to be paid for the sickness-leave, which will weaken the effect of commute on absenteeism for illness.

This study also has a certain limitation. The applied dataset of 2013 CMESS is a cross-sectional data. With the heterogeneous bias by the observed factors, the potential endogeneity might need to be addressed to explore the causality between commutes and the absenteeism for sickness in further studies.

# Notes

[1] A rural migrant was defined as a person who moved from rural to urban areas, but still kept their rural Hukou status. An urban citizen was treated as a person with a local non-agricultural Hukou.

[2] The classification of Chinese cities is mainly based on the following criteria: population and economic aggregate; per capita income and GDP; Human development index; the level of urban construction and the scale of the main urban area; regional radiating power and political status; science and education level and development potential; important industrial chains and supporting facilities. First-tier cities have the highest degree of development, second-tier cities are second, and third-tier cities are worst.

[3] Average marginal effects calculated by [Formula could not be displayed here. Please see the supplementary files section.]

[4] Sick Leave in China

https://ins-globalconsulting.com/sick-leave-managed-china/

[5] The eligibility criteria include local income tax payment certificates or social insurance in a certain length of time in the city. For example, Beijing stipulates that properties may not be bought by non-Beijing workers who cannot provide at least five years' worth of social security or local income tax payment certificates in the city and have no temporary registration in Beijing.

[6] The public rental housing promoted by the Ministry of Housing and Urban-Rural Development in 2010 is the only public housing scheme accessible to rural migrants, and its rent is generally lower than the market. Since 2014, the public rental housing has been merged with the cheap rental housing introduced in 1998 and targeted at accommodating lowest-income urban households at a nominal rent rate.

# Abbreviations

OLS: ordinary least squares; BHPS: British Household Panel Survey; CMEES: China's Matched Employer-Employee Survey; ZINB: Zero-inflated negative binomial regression; CT: commuting time.

# Declarations

**Ethics approval and consent to participate**

Not applicable

**Consent for Publication**

Not applicable.

**Availability of data and material**

The CMEES that support the findings of this study are available from School of Labor and Human Resources, Renmin University, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. CMEES are however available from the authors upon reasonable request and with permission of School of Labor and Human Resources, Renmin University. China’s Matched Employer-Employee Survey Data Access can be contacted for more information (yuhui_li@ruc.edu.cn; df594133@163.com).

### Competing interests

The authors declare that they have no competing interests.

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### Authors' contributions

Wang Zicheng took leadership and responsibility for the research activity planning and made substantial contributions to the conception and design of the Programme. Liu jiachun worked on the statistical analysis of the data. Guomu rong drafted the concept of the paper as well as participated in finalizing the manuscript. All authors read and approved the final manuscript.

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## References

1. Nie, P., & Sousa-Poza, A. (2016). Commute time and subjective well-being in urban China. China Economic Review.
2. Koslowsky, M., Kluger, A. N., & Reich, M. (2013). Commuting stress: Causes, effects, and methods of coping. Springer Science & Business Media.
3. Van Ommeren, J. N., & Gutiérrez-i-Puigarnau, E. (2011). Are workers with a long commute less productive? An empirical analysis of absenteeism. Regional Science and Urban Economics, 41(1), 1-8.
4. Gershenson, S. (2013). The causal effect of commute time on labor supply: evidence from a natural experiment involving substitute teachers. Transportation Research Part A, 54(2), 127-140.
5. Carta, F., & De Philippis, M. (2015). You've come a long way, baby. effects of commuting times on couples' labour supply. Social Science Electronic Publishing.
6. Goerke, L., & Lorenz, O. (2015). Commuting and sickness absence. Social Science Electronic Publishing.
7. Zenou, Y., (2002). How do firms redline workers? Journal of Urban Economics 52 (3), 391-408.
8. Roberts, J., Hodgson, R., & Dolan, P. (2011). "it's driving her mad": gender differences in the effects of commuting on psychological health.Journal of Health Economics, 30(5), 1064-1076
9. Stutzer, A., Frey, B.S., (2008). Stress that doesn’t pay: The commuting paradox. The Scandinavian Journal of Economics 110 (2), 339 – 366.
10. Hansson, E., Mattisson, K., Björk, J., Östergren, P. O., & Jakobsson, K. (2011). Relationship between commuting and health outcomes in a cross-sectional population survey in southern Sweden. BMC public health, 11(1), 834.
11. Ross, S.L. and Y. Zenou (2008), Are shirking and leisure substitutable? An empirical test of efficiency wages based on urban economics theory, Regional Science and Urban Economics, 38, 5, 498–517
12. Hassink, W. H. J., & Fernandez, R. M. (2017). Worker morale and effort: is the relationship causal?. Manchester School (4).
13. Künn-Nelen, A. (2016). Does commuting affect health?. Health economics, 25(8), 984-1004.
14. Hesketh, T. , Jun, Y. X. , Lu, L. , & Mei, W. H. . (2008). Health status and access to health care of migrant workers in china. Public Health Reports, 123(2), 189-197.

15. Olsson, L. E., Gärling, T., Ettema, D., Friman, M., & Fujii, S. (2013). Happiness and satisfaction with work commute. Social Indicators Research, 111(1), 255-263.
16. Liepmann, Kate, K. (1944). The Journey to Work: Its Significance for Industrial and Community Life .[J]. Economica (New Series), 12(45):57.
17. Kluger, A. N. . (1998). Commute variability and strain. Journal of Organizational Behavior, 19(2), 147-165.
18. Hendriksen, I. J., Simons, M., Garre, F. G., & Hildebrandt, V. H. (2010). The association between commuter cycling and sickness absence. Preventive medicine, 51(2), 132-135.
19. Alexanderson, K. (1998). Sickness absence: a review of performed studies with focused on levels of exposures and theories utilized. Scandinavian journal of social medicine, 26(4), 241-249.
20. Johns G, Nicholson N. (1982). The meanings of absence: new strategies for theory and research. Res Org Behav, 4, 127 - 72.
21. Li, B., & Duda, M. (2010). Employers as landlords for rural-to-urban migrants in Chinese cities. Environment and Urbanization, 22(1), 13-31.
22. Frankel, E. (1921). Labor absenteeism. Journal of Political Economy, 29(6), 487-499.
23. Hilbe, J. M. (2007). Negative Binomial Regression. Cambridge University Press
24. Zhao, P., & Howden-Chapman, P. (2010). Social inequalities in mobility: the impact of the hukou system on migrants' job accessibility and commuting costs in Beijing. International Development Planning Review, 32(3-4), 363-384.
25. Dale-Olsen, H. (2014). Sickness absence, sick leave pay, and pay schemes. Labour, 28(1), 40-63.
26. Chia, K. S. (1988). Sickness absence of migrants workers. Singapore Med J, 29, 387-92.
27. Wu, W., & Rosenbaum, E. (2008). Migration and housing: comparing China with the United States. Urban China in Transition, Blackwell Publishing, 250-267.
28. Peng, Y., Chang, W., Zhou, H., Hu, H., & Liang, W. (2010). Factors associated with health-seeking behavior among migrant workers in Beijing, China. BMC health services research, 10(1), 69.

# Tables

### Table 1 Descriptive statistics

| Variable | All samples (N= 4,324) | | Rural Workers (N=940) | | Urban Workers (N=3384) | |
|---|---|---|---|---|---|---|
| | mean | Std. | mean | Std. | mean | Std. |
| **Dependent variable** | | | | | | |
| Sickness absence | 2.4556 | 7.4155 | 2.1827 | 5.4877 | 2.5318 | 7.8692 |
| **Independent variables** | | | | | | |
| Commuting time(CT) | 26.1978 | 20.133 | 21.3538 | 18.3642 | 27.5338 | 20.3952 |
| **Control variables** | | | | | | |
| **1.Individual Level** | | | | | | |
| **(1)Personal variables** | | | | | | |
| Age | 33.2241 | 9.8471 | 29.0202 | 8.9004 | 34.3918 | 9.7799 |
| Male | 0.4545 | 0.498 | 0.5064 | 0.5002 | 0.4401 | 0.4965 |
| Married | 0.6652 | 0.472 | 0.4739 | 0.4996 | 0.7183 | 0.4499 |
| Education year | 13.2367 | 2.8078 | 12.4096 | 2.9063 | 13.4668 | 2.7361 |
| **(2)Job related traits** | | | | | | |
| **Occupation categories** | | | | | | |
| Manager | 0.1771 | 0.3818 | 0.1466 | 0.3539 | 0.1855 | 0.3888 |
| Skilled worker | 0.2050 | 0.4037 | 0.2280 | 0.4198 | 0.1986 | 0.3990 |
| Ordinary worker | 0.6179 | 0.486 | 0.6254 | 0.4843 | 0.6159 | 0.4865 |
| **Job condition** | | | | | | |
| Job strain | 2.9101 | 1.1178 | 3.0021 | 1.0766 | 2.8846 | 1.1279 |
| Overtime(hours/per week) | 3.3669 | 5.3424 | 3.8826 | 5.9184 | 3.2242 | 5.1635 |
| Training time(days/per year) | 6.8506 | 15.0699 | 6.2089 | 13.3385 | 7.0288 | 15.5136 |
| Job tenure(years) | 5.3188 | 6.4301 | 2.8269 | 3.0517 | 6.0102 | 6.9309 |
| Job security | 3.618 | 0.7765 | 3.5606 | 0.7622 | 3.6339 | 0.7798 |
| Injure | 0.0234 | 0.1512 | 0.0351 | 0.1842 | 0.0201 | 0.1404 |
| wage (year | 35634 | 25390 | 34698 | 21772 | 35883 | 26265 |
| **2.Company Level** | | | | | | |
| **(1)Company types** | | | | | | |
| Stated owned enterprise(SOE) | 0.1470 | 0.3541 | 0.0628 | 0.2428 | 0.1704 | 0.3760 |
| Foreign owned enterprise(FOE) | 0.0584 | 0.2346 | 0.0554 | 0.2288 | 0.0593 | 0.2361 |
| Domestic private enterprise(DFE) | 0.7946 | 0.404 | 0.8818 | 0.3230 | 0.7704 | 0.4207 |
| **(2)Sector** | | | | | | |
| Manufacture | 0.3913 | 0.4881 | 0.3479 | 0.4765 | 0.3050 | 0.4605 |
| **3.City Level** | | | | | | |
| First-tier city | 0.1970 | 0.3978 | 0.2753 | 0.4469 | 0.1752 | 0.3802 |
| Second-tier city | 0.6174 | 0.4861 | 0.7012 | 0.4580 | 0.5941 | 0.4911 |
| Third-tier city | 0.1856 | 0.3888 | 0.0235 | 0.1515 | 0.2307 | 0.4213 |

**Table 2 Estimation results on commuting time and sickness absence outcomes (full sample)**

| | Model(1) | Model(2) | Model(3) | Model(4) |
|---|---|---|---|---|
| **Independent variables** | | | | |
| CT | 0.0037$^{*}$ | 0.0045$^{**}$ | 0.0045$^{**}$ | 0.0038$^{**}$ |
| | (0.0022) | (0.0021) | (0.0021) | (0.0019) |
| **1.Individual Level** | | | | |
| (1) **Personal variables** | | | | |
| Age | | -0.0776$^{**}$ | -0.0744$^{**}$ | -0.0674$^{**}$ |
| | | (0.0338) | (0.0340) | (0.0321) |
| Age2 | | 0.0008$^{*}$ | 0.0008$^{*}$ | 0.0007$^{*}$ |
| | | (0.0004) | (0.0004) | (0.0004) |
| Male | | -0.0307 | -0.0548 | -0.0572 |
| | | (0.0821) | (0.0814) | (0.0813) |
| Married | | 0.2259$^{*}$ | 0.2068 | 0.2215$^{*}$ |
| | | (0.1271) | (0.1268) | (0.1196) |
| Education year | | 0.0391 | 0.0316 | 0.0530 |
| | | (0.1270) | (0.1238) | (0.1284) |
| Education year2 | | -0.0036 | -0.0034 | -0.0041 |
| | | (0.0052) | (0.0051) | (0.0052) |
| Migrant | | -0.2830$^{**}$ | -0.2695$^{**}$ | -0.2767$^{**}$ |
| | | (0.1347) | (0.1317) | (0.1335) |
| **(2)Job-related traits** | | | | |
| **Occupation categories: Ordinary worker(ref.)** | | | | |
| Manager | | 0.0837 | 0.0954 | 0.1128 |
| | | (0.0979) | (0.0986) | (0.1015) |
| Skilled worker | | 0.2996$^{**}$ | 0.3049$^{**}$ | 0.2987$^{**}$ |
| | | (0.1412) | (0.1412) | (0.1324) |
| **Job conditions** | | | | |
| Job strain | | 0.0055 | 0.0084 | 0.0132 |
| | | (0.0397) | (0.0396) | (0.0406) |
| Overtime | | -0.0037 | -0.0030 | -0.0033 |
| | | (0.0092) | (0.0090) | (0.0085) |
| Training | | 0.0065$^{**}$ | 0.0068$^{**}$ | 0.0069$^{**}$ |
| | | (0.0031) | (0.0032) | (0.0031) |
| Job tenure | | 0.0084 | 0.0040 | 0.0044 |
| | | (0.0068) | (0.0072) | (0.0072) |
| Job security | | -0.0190 | -0.0118 | -0.0116 |
| | | (0.0449) | (0.0452) | (0.0462) |
| Injure | | 0.6757$^{**}$ | 0.6637$^{**}$ | 0.6272$^{**}$ |
| | | (0.2885) | (0.2966) | (0.3014) |
| Log wage | | -0.2417$^{**}$ | -0.2323$^{**}$ | -0.3055$^{***}$ |
| | | (0.0952) | (0.0958) | (0.1104) |
| **2.Company Level** | | | | |
| (1)**Company type:** DPS(ref.) | | | | |
| SOE | | | 0.2035$^{*}$ | 0.1850 |
| | | | (0.1181) | (0.1210) |
| FOE | | | -0.0865 | -0.0898 |
| | | | (0.1311) | (0.1336) |
| **(2)Sector** | | | | |
| Manufacture | | | -0.0833 | -0.0831 |
| | | | (0.0865) | (0.0856) |
| **3.City Level** | | | | |
| First-tier city | | | | 0.2359 |
| | | | | (0.2028) |
| Second-tier city | | | | 0.0290 |
| | | | | (0.1101) |
| **Constant** | 0.8003$^{***}$ | 5.4678$^{***}$ | 5.3629$^{***}$ | 5.7611$^{***}$ |
| | (0.0644) | (1.3393) | (1.3195) | (1.3048) |
| LP | -7517.0401 | -6736.583 | -6707.531 | -6679.993 |
| $N$ | 4268 | 3855 | 3849 | 3840 |

Model: Negative binomial regression (Model(1)), zero-inflated negative binomial regression(Model(2)-(4))

Note: Robust standard errors in parentheses $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$ The inflate judgment equation in the model is estimated by the logit model. The selection of variables is almost consistent with the negative binomial regression model. To save space, the coefficient estimation results of the inflate judgment equation are not listed.

**Table 3 Robust Checks**

| | Model(5) Excluding Sickness leave>180 | Model(6) Sickness leave as dummy variable | Model (7) Commuting as categorical variable | Model (8) Excluding Injure=1 | Model (9) Excluding medical cost>10000 | Model (10) Add transport modes variables |
|---|---|---|---|---|---|---|
| **Independent variables** | | | | | | |
| CT | 0.0033* | 0.0040** | | 0.0040** | 0.0040** | 0.0039** |
| | (0.0019) | (0.0018) | | (0.0019) | (0.0019) | (0.0020) |
| Mid-commuter | | | 0.0987 | | | |
| | | | (0.1008) | | | |
| Long-commuters | | | 0.2475** | | | |
| | | | (0.1136) | | | |
| Constant | 5.8772*** | -2.9063** | 5.9937*** | 6.0289*** | 5.0493*** | 5.6020*** |
| | (1.3172) | (1.1485) | (1.3136) | (1.3064) | (1.1647) | (1.2894) |
| LP | -6637.977 | -2527.1623 | -6678.317 | -6492.852 | -6384.452 | -6676.545 |
| *N* | 3839 | 3840 | 3850 | 3747 | 3742 | 3840 |

Model: Zero-inflated negative binomial regressions are used in all models except for Model (6) (Logit)

Note: Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Only the coefficients for the commuting time (CT) variables and constant are reported in NB model. Like in the main tables, the following control variables are included: individual level, company level and city level.

**Table 4 Mechanism analysis: Dependent variables: health outcomes and work effort**

| | Health outcomes | | | | | Work effort | |
|---|---|---|---|---|---|---|---|
| | Model (11) Self-rated health | Model (12) Depression | Model (13) BMI | Model (14) Obesity (0-1) | Model (15) Medical cost | Model (16) Weekly overtime | Model(17) Weekly work time |
| **Independent variable** | | | | | | | |
| CT | -0.0012** | 0.0017** | 0.0096*** | 0.0057*** | 0.0026* | -0.0005 | -0.0238*** |
| | (0.0006) | (0.0007) | (0.0025) | (0.0019) | (0.0015) | (0.0048) | (0.0072) |
| Constant | 4.1849*** | 3.1390*** | 17.2314*** | -3.7487*** | 3.5637*** | 4.2111 | 78.4016 |
| | (0.3363) | (0.4514) | (1.5696) | (1.2353) | (0.9160) | (3.0986) | (5.3124) |
| $R^2$ | 0.0887 | 0.0776 | 0.2033 | | 0.1052 | 0.0484 | 0.1274 |
| *N* | 3849 | 3846 | 3849 | 3849 | 2419 | 3849 | 3859 |

Note: Robust standard errors in parentheses $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$ Only the coefficients for the commuting time (CT) variables and constant are reported. Like in the main tables, the following control variables are included: individual-level, company-level and city-level.

**Table5 Heterogeneous effects with respect to hukou status, gender, transportation mode, cities and companies**

| | Model(18a)Migrant=1 | Model (18b) Migrant=0 | Model (19a) Male=1 | Model (19b) Male=0 | Model (20a) Active mode=1 | Model (20b) Active mode=0 |
|---|---|---|---|---|---|---|
| CT | 0.0004 | 0.0046** | -0.0010 | 0.0054** | 0.0056 | 0.0026 |
| | (0.0036) | (0.0021) | (0.0024) | (0.0022) | (0.0044) | (0.0021) |
| _cons | 8.4989*** | 6.3050*** | 4.1225** | 6.3274*** | 5.9521*** | 5.7538*** |
| | (2.6496) | (1.3987) | (1.9518) | (1.6407) | (2.2543) | (1.5139) |
| LP | -1307.955 | -5330.877 | -2817.721 | -3819.681 | -2064.543 | -4572.777 |
| *N* | 797 | 3043 | 1748 | 2092 | 1273 | 2567 |
| | Model (21a) First-tier city | Model (21b) Second-tier city | Model (21c) Third-tier city | Model (22a) State-owned Enterprise(SOE) | Model (22b) Foreign-owned enterprise(FOE) | Model (22c) Domestic private enterprises(DPE) |
| CT | 0.0051* | 0.0020 | -0.0059 | -0.0034 | -0.0120*** | 0.0054** |
| | (0.0028) | (0.0025) | (0.0076) | (0.0048) | (0.0044) | (0.0021) |
| _cons | 3.9536 | 5.7898*** | 6.4641*** | 7.7893** | -1.2967 | 6.0404*** |
| | (4.1956) | (1.5617) | (2.4705) | (3.8768) | (4.5309) | (1.4638) |
| LP | -1181.867 | -4026.74 | -1351.594 | -894.8259 | -324.5178 | -5407.72 |
| *N* | 713 | 2364 | 763 | 588 | 213 | 3039 |

Model: Zero-inflated negative binomial regressions are used in all models.

Note: Robust standard errors in parentheses $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$ Only the coefficients for the commuting time (CT) variables and constant are reported in NB model. Like in the main tables, the following control variables are included: individual level, company level and city level.

## Figures

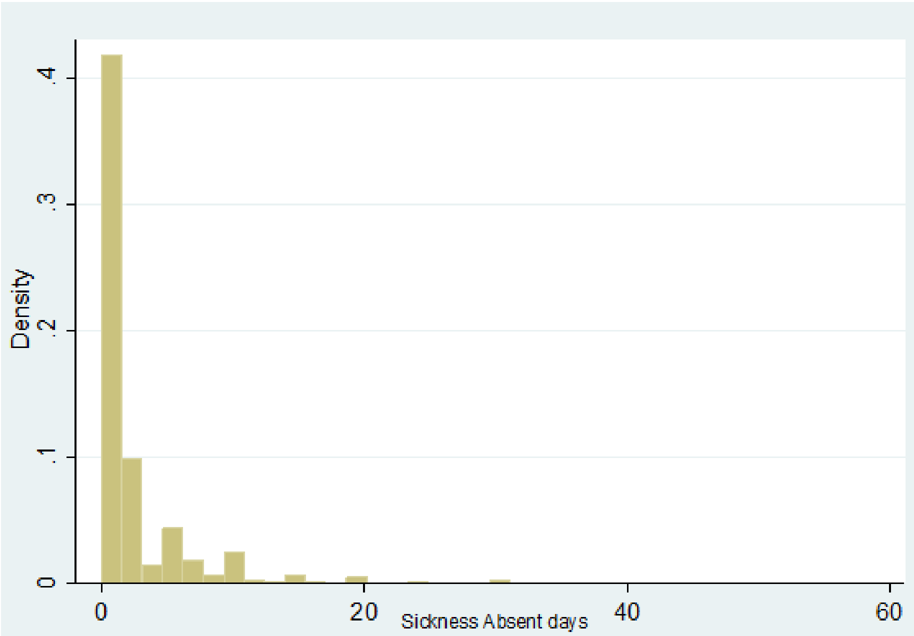


**Figure 1**

Frequency Distribution of Number of Days Absent

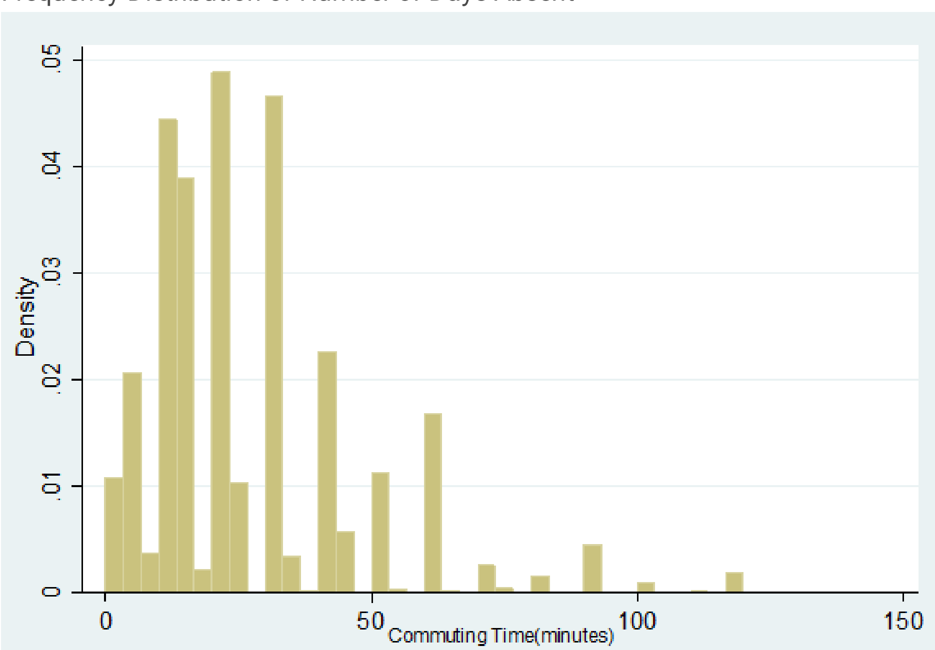


**Figure 2**

Frequency Distribution of the Commuting Time

| | | | | | | |
|---|---|---|---|---|---|---|
| PRM | | BIC= 826.744 | AIC= 8.436 | Prefer | Over | Evidence |
| vs | NBRM | BIC= -17948.376 | dif= 18775.120 | NBRM | PRM | Very strong |
| | | AIC= 3.557 | dif= 4.880 | NBRM | PRM | |
| | | LRX2= 18783.376 | prob= 0.000 | NBRM | PRM | p= 0.000 |
| vs | ZIP | BIC= -11326.390 | dif= 12153.133 | ZIP | PRM | Very strong |
| | | AIC= 5.242 | dif= 3.194 | ZIP | PRM | |
| | | Vuong= 20.008 | prob= 0.000 | ZIP | PRM | p= 0.000 |
| vs | ZINB | BIC= -17984.950 | dif= 18811.694 | ZINB | PRM | Very strong |
| | | AIC= 3.509 | dif= 4.928 | ZINB | PRM | |
| NBRM | | BIC= -17948.376 | AIC= 3.557 | Prefer | Over | Evidence |
| vs | ZIP | BIC= -11326.390 | dif= -6621.987 | NBRM | ZIP | Very strong |
| | | AIC= 5.242 | dif= -1.685 | NBRM | ZIP | |
| vs | ZINB | BIC= -17984.950 | dif= 36.574 | ZINB | NBRM | Very strong |
| | | AIC= 3.509 | dif= 0.048 | ZINB | NBRM | |
| | | Vuong= 8.831 | prob= 0.000 | ZINB | NBRM | p= 0.000 |
| ZIP | | BIC= -11326.390 | AIC= 5.242 | Prefer | Over | Evidence |
| vs | ZINB | BIC= -17984.950 | dif= 6658.561 | ZINB | ZIP | Very strong |
| | | AIC= 3.509 | dif= 1.733 | ZINB | ZIP | |
| | | LRX2= 6666.815 | prob= 0.000 | ZINB | ZIP | p= 0.000 |

**Figure 3**

Tests and Fit Statistics

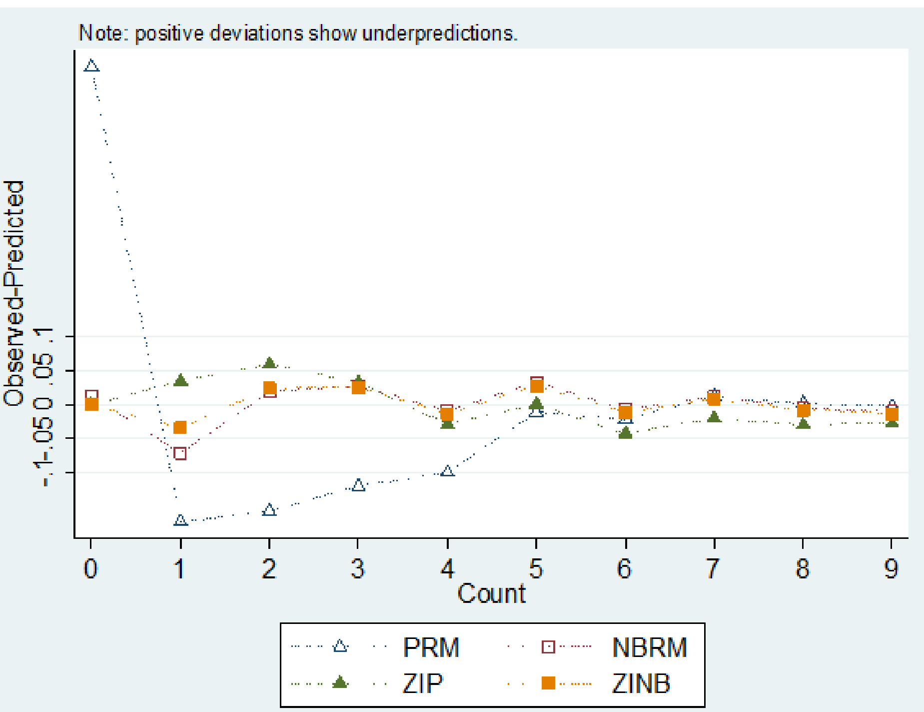


**Figure 4**

Observed-Predicted Deviations for Count-Data Models

## Supplementary Files

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- Notesformula.docx