# Master's Thesis: Health Economics

# Does commuting behaviour affect labour supply and employee well-being: a case of the UK from 2009 to 2017.

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**Abstract**

This study examines the effect of commuting on employee's general health, job satisfaction, and job hours, distinguishing between three dimensions of commuting: distance, time, and mode. The study uses the dynamic difference Generalised Methods of Moments (GMM) estimator to estimate causal impact of time on the three outcome variables using the longitudinal data for the British households form 2009-2017. Commuting time has a negative impact on an employee's Subjective Health as well Job Satisfaction. In particular, as travel time increases by 10 minutes, the Self-Assessed Health (SAH) score worsens by 0.4[1] and the Job Satisfaction score worsens by 0.7[2]. The causal relationship between commuting time and Job Hours could not be estimated. The study also found strong associations between commuting modes and the three outcomes. Active commuting was associated with better subjective health and driving to work with a distance of less than 35 miles worsens the SAH score. Distance and passive commuting were also associated with increased working hours. As travel time increased, active commuters worked 0.13 hours less when compared to passive commuters. Commuting actively (only cycling) decreased Job Satisfaction score as compared to passive commuting, however, within passive commuting, using a bus or a coach as a medium to commute increased Job Satisfaction

[1] On a 5-point scale; 1 being the best possible health.
[2] On a 7-point scale; 7 being the best possible Job Satisfaction.

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## 1 Introduction

Commuting to work is increasingly becoming a major concern for employee wellbeing. As commuting becomes a significant part of a workday, it may affect many aspects of an individual's life including mental and physical health, job performance, increased travel expenditure, and job satisfaction. The relationship between commuting and employee well-being is well documented in recent literatures: the evidence from these literatures support a negative association between commuting and employee wellbeing. However, most contributions in the area study the association of commuting and employee health utilizing only certain health factors as measurement outcome.

Additionally, to the best of my knowledge, the literatures published mostly focus on employee health or job factors but do not combine these outcomes to explain the implications of changes in commuting. Be that as it may, in the recent years, there has been an increased interest in the significance of commuting while explaining labour market outcomes. This is due to many reasons. The innovation in infrastructure and development of technology has been instrumental for labour mobility, however, having mentioned that, the average commute duration for most European countries has been increasing. (Hofmeister and Schneider, 2010). More than 20% of Europeans commute at least 90 minutes daily and most of the workers spend more than an hour a day traveling to and from work. (SDWORK 2018). A similar result was illustrated in the European Working Conditions Survey. The change in commuting time is especially interesting in the case of the UK where the average commute duration has been increasing at a faster rate than the commute distance, shown by the figure 1 from UK transport survey. As a matter of fact, according to Trades Union Congress (TUC), the average commuting time has increased over 5 mins from 2007 to 2017.

The clear indication of increasing significance of commuting time has generated academic interest into the analyses of commuting's effects on health and work-related activities. From a theoretical perspective, commuting time and distance may be expected to negatively affect health status; a longer commute may result in more stress, less physical activity, etc, leading to decline in subjective and objective health. However, empirical studies are multifaceted. Insights from these studies are detailed in the next section.

This analysis contributes to the literature in the area of commuting and labour market outcomes by providing a causal relationship between commuting, and employee health, job hours and job satisfaction. The study aims to provide an understanding of the potential change in employee behaviour with a change in commuting. This is achieved by analysing the causal impact (using a dynamic estimator) of commuting on three outcomes: employees' subjective health, job hours, and job satisfaction.

This study aims to provides answers to the following questions. Firstly: what is the causal impact of a change in commuting time on the three outcomes? Secondly: how does a change in commuting time, distance, and mode impact employee's perceived health, labour supply, and job satisfaction? Lastly: what is the association between active and passive commuting and the three outcomes?

The study utilizes data for the British population for 8 waves from 2009 to 2017 provided by Understanding Society. The UKHLS is a longitudinal dataset which comprises of about 40,000 households (at wave 1), the households are interviewed each year to collect the information. The dataset has detailed information about family, social life, health, education, income, and work of the interviewed households

To achieve the causal relationship between commuting time and the dependent variables, a dynamic estimator (Generalised Methods of Moments [GMM]) is utilized due to the lack of a good instrument variable and exogenous variation. However, due to the limited use of the dynamic estimations, a Fixed Effects (FE) model is used which removes individual time invariant heterogeneity and provides strong associations wherever GMM is not available, to answer the fore-mentioned questions.

The results from the GMM estimation support the evidence for a negative relationship between commuting time and employee wellbeing. Specifically, an increase in 10 minutes of travel time worsens Subjective-Assessed Health (SAH) score by 0.4 (decreases subjective health by 8%). Similarly, this increase also decreases Job Satisfaction score by 0.7 (a decrease in job satisfaction by 10%). The GMM estimation was not valid for Job hours. Additionally, from the FE models, commute distance has a negative but small association with subjective health. More interestingly, the individuals who drive to work located in less than a 35-mile radius are associated with negative subjective health. In particular, the health score (SAH) worsens by 0.07. Similarly, an increase of 10-minute travel time of active commuters is associated with a decrease in SAH by 0.02 indicating an improvement. Travel time and distance are both positively associated with Job hours, however, isolating the effect for active commuters suggests that with an increase in travel time, commuters work less when compared to passive commuters. The study did not find any significant effect of distance on Job Satisfaction. Moreover, for this analysis, active commuting (cycling) is negatively associated with Job Satisfaction, however, taking a bus/coach when compared to driving to work is associated with a positive increase in Job Satisfaction score.

The sections below provide a deep dive into these results. Specifically, section 2 provides an insight on the contributions and evidence from the literatures analysing the effect of commuting and employee wellbeing. Section 3 describes the dataset used in detail, providing definitions of the interest and dependent variables. Section 4 provides an explanation and a rationale for the empirical strategy employed in this analysis. Section 5 illustrates the results of the used empirical methodology. Section 6 discusses these results as well as the intuition and interpretation of these results and the last section provides a conclusion to the study.

# 2 Literature

## *2.1 Health and Commuting*

The relationship between health and commuting is quite complex as the literature provides many different viewpoints. A commute can consist of three different aspects that can affect employee health, working hours, and satisfaction. The first is commuting distance - longer commuting distance can have adverse effects on health, so much so that it can significantly increase the risk of mortality (Sandow et al., 2014). Sandow et al., 2014 analysed this effect for the Swedish population. Using a panel of individuals over 50 years of age from 1985 to 2008, they found a significant association between health and mortality for women. Analysing this effect, the authors suggested that women who have experienced long distance commutes face a significantly higher risk of mortality when compared to women who did not experience long distance commute. These results were statistically insignificant for men. As Sweden is a developed country with a developed transportation infrastructure, there is an implication that the role of travel mode over long distance commute may not be of significance. However, the insight that men and women may be subject to different mechanisms regarding the association between long distance commute and mortality is certainly reflected.

The second dimension of commuting is the time taken to commute. Like commuting distance, commuting time is negatively associated with health, especially mental health (Robert et al,. 2009). According to Roberts et al., 2009, commuting time had a detrimental effect on well-being of women, I.E, as commuting time increased, the psychological well-being of a woman employee decreased. Similar to Sandow et al., 2014, this association was also only significant for women. Roberts et al., 2009 also found that the effect is most negative for women who commute via car. The authors utilized a Fixed Effects model, unlike Sandow et al., 2014 to estimate this effect; controlling for income, housing qualities, and a set of conditioning variables. Moreover, the authors used a subset of the sample data to extract exogenous variation in the interest variable to estimate a casual effect. A similar result was presented by Milner et al., 2017. The authors found a negative relationship between commuting time and mental health (calculated using the 5-item mental inventory), however, this effect was quite small in magnitude and only significant for employees commuting over 6 hours a week. The authors found a much larger effect of commuting time for employees with low level of work freedom.

The third dimension of commuting is travel mode. Like time and distance, the medium used to travel influences an individual's health. However, unlike, the studies conducted for commuting time and distance that predominately reported negative associations; choice of commuting mode can have a positive association on health and wellbeing (Martin et al., 2017; Panter et al., 2018; Chatterjee et al., 2017). Regular to moderate physical activity is known to contribute to reductions in risk of over 20 chronic health conditions (Biddle and Mutrie, 2007; Humphreys et al., 2014; WHO, 2010). Martin et al.; 2017 illustrated this by investigating the association between wellbeing (measured as a 36-point Likert scale) and travel mode, time spent commuting via a travel mode, and switching to active commuting modes. Conducting a FE analysis for British Households over 14 years, the authors found a positive relationship between active commuting and wellbeing. The results also intensified the positive association between switching to an active mode of commuting and mental health.

The choice of commuting mode is also associated with mortality, Cardiovascular disease (CVD), and cancer mortality as presented by Panter et al., 2018. The authors found a significantly reduced risk of CVD for regular commuters using an active commuting mode. For non-regular commuters, choosing active commuting modes significantly reduced the risk of all-cause mortality. Chatterjee et al., 2017, utilizing Understanding Society's data, presented a stratified level of association between commuting mode and health factors. They found that walking to work reduced stress level in employees; cycling to work was associated with people with higher self-reported health; commuting by bus was associated with people with lower self-reported health and longer commutes by bus strongly reduces mental health. These results are further confirmed by the findings of Page et al., 2016. The authors conducted a study which encouraged employees of a UK based firm to change their primary mode of commuting to electric cycles. The results of the study illustrated a positive change in physical health of employees who opted to change the commuting mode.

The three dimensions of commuting have a complicated relationship with various health factors, and the fact that it can be broken down to further intricate levels magnifies the complexity. Having said that, the current literature primarily leads to the following hypothesis: An overall increase in commuting time or distance negatively affects different aspects of health; choosing active travel mode reduces the risk of adverse health effects when compared to passive modes.

### *2.2 Labour Supply, Job Satisfaction and Commuting*

Approximately 25% of the workers in the US in 2018 quit their jobs due to a bad commute (Robert Half, 2018). This can potentially be a result of the discussed dimensions of commuting. (Gutiérrez-i-Puigarnau et al., 2010; Chatterjee et al, 2017; Goerke et al., 2017). Gutiérrez-i-Puigarnau et al., 2017 defined labour supply as number of hours worked and investigated its association with commuting distance. Using employer-induced changes in distance, they found that commuting distance had a positive, however, small impact on daily and weekly working hours. This effect was slightly higher for women, however, still relatively small. In contrast, Goerke et al., 2017, did not find any significant relationship between commuting distance and labour supply. The authors used sickness absenteeism as there dependent variable which could partially justify these findings. However, in line with using absenteeism as a proxy for labour supply, Ommeren et al., 2009, found that if commuting distance were negligible, abseentism would decrease by 16%. Conflicting with the findings presented by Goerke et al., 2017.

Chatterjee et al., 2017, estimated an association between commuting and employee retention. They found a strong relationship between longer commutes and an increase in probability of changing jobs. However, interestingly, the authors also found an association between active commuting modes (especially cycling) and increased employee retention. According to Chatterjee et al., 2017, an extra 20 minutes of commute time decreases job satisfaction as much as taking a 19% pay cut. The study also portrayed a negative relationship between long distance commute and a reduction in job satisfaction. These results are further affirmed by Martin et al., 2014. The authors suggest that increasing commuting time decreases employee satisfaction and increases work stress.

As with health, the association between commuting, and labour supply and job satisfaction is convoluted. The literature presents a straightforward and negative relation between commuting and job satisfaction and a situational relationship with labour supply and working hours. Hence, making it difficult to create a hypothesis for the same.

## 3 Data

This study utilizes data of the British population from for 8 waves from 2009 to 2017 from Understanding Society. The UKHLS is a longitudinal dataset which comprises of about 40,000 households (at wave 1), the households are interviewed each year to collect the information. The dataset has detailed information about family, social life, health, education, income, and work of the interviewed households.

Three dependent variables are used for the analyses in the study. These variables are acquired from the household survey mentioned above. Hours worked per week is used for labour supply; employee wellbeing is segregated into employee's Self-Assessed Health and Job Satisfaction. These variables are described as follows. *Subjective Health:* A subjective health score is acquired for the mentioned 8 wave which answers the question "In general, would you say your health is…". This score ranges from 1-5. (1 – excellent; 2 - very good; 3 – good; 4 – fair; 5 – poor). This is an ordered categorical variable is used as the primary dependent variable for subjective/reported health.

*Job Hours:* The dataset also contains number of hours normally worked per week. This is a continuous variable answering the question "Thinking about your (main) job, how many hours, excluding overtime and meal breaks, are you expected to work in a normal week?" for the 8 waves.

*Job Satisfaction Score:* A subjective job satisfaction score is acquired form working individuals by answering the question "Please look at this card and tell me, all things considered, which number best describes how satisfied or dissatisfied you are with your present job overall? The score ranges from 1 – 7 (1 – Completely dissatisfied; 2 – Mostly dissatisfied; 3 – Somewhat dissatisfied; 4 – Neither satisfied nor dissatisfied; 5 – Somewhat satisfied; 6 – Mostly Satisfied; 7 – Completely satisfied)

The independent variables[3] used for the analysis are described as follows. *Commuting Distance:* This is a continuous variable which answers the question "About how far, in miles, do you live from your usual place of work?". This variable, however, is only available for 5 of the 8 waves.

[3] Commuting is segregated into three dimensions: Distance, Time, and Mode

*Commuting Time:* This is a continuous variable which answers the question "About how long does it usually take for you to get to work each day, door to door (in minutes)?" This is the primary interest variable of commuting used in this study.

*Commuting Mode:* This is a categorical variable that provides information regarding the mode of travel to work. The variable answers the question "How do you usually get to your workplace". The choices include of either a passive mode of commuting: drive myself by car or van; get a lift from someone from the household; get a lift from someone outside the household; motorcycle/scooter; taxi/minicab; bus/coach; train; underground or an active mode of commuting: cycle; walk

There are number of covariates also used for controlling for external effects. These are as follows. *Objective Health:* This is a categorical variable for objective health conditions. The variable answers the question "Do you have any long-standing physical or mental impairment, illness or disability? By 'long-standing' I mean anything that has troubled you over a period of at least 12 months or that is likely to trouble you over a period of at least 12 months." *Demographic Variables:* Variables including age, sex, education, marital status, race, country of birth, income. *Job related variables*: Variables including economic activity status and job status

### *3.1 Sample Selection and descriptive statistics*

The overall sample selected for this study is for individuals who are over the age of 16, have a positive commute distance. A sub selection is also introduced varying as per the model specification and the dependent variable. To avoid extreme results and data measurement issues, commuting distance is limited from 1 to 120 miles from home to work. Similarly, to avoid extreme results and measurement bias, commuting time is limited from 1 to 180 mins from home to work.

For the model analysing the relationship between commuting and subjective health, only individuals who have reported self-health score were included. For the job hours model, only individuals who have reported job hours over 2 hours were included. For the job satisfaction model, only individuals who have reported a satisfaction score were included.

Table 1 provides some insights from descriptive statistics of the data. As the table shows, the mean distance from work is 9.4 miles for the entire population. The data for distance is only available for 5 waves (waves 1, 2, 4, 6, and 8). About 13.5% (86.5% using passive modes of commuting) of the individuals in the surveys use active modes of commuting to the workplace and as expected, the distribution of these active commuters is concentrated in the first quartile of distance. Figure 2 illustrates the mean distance for all the waves. The mean distance in wave 1 is 9.14 which is increased to 9.73 in wave 8. Mean distance increases in every wave and the year on year growth rate ranges from 1% - 2.5% every year. This is in line with other studies conducted using similar datasets for commuting distances and commuting trends in England (Department of Transport UK). The dataset consists of 45% male individuals and 55% female individuals. As shown from the average distance (figure 3) for gender, women travel shorter distances to work from home, as compared to men. The decrease in the number of women traveling to work is prominent as the distance to work increases past 11 miles.

Figure 5-7 show descriptive statistics for the second dimension of commuting; travel time. The mean travel time for all the observations over 8 waves is 21.62 minutes as shown in table 1, with a minimum of 1 minute and a maximum of 180 minutes. The mean time in wave 1 is 25.93 minutes which increased to 26.43 in wave 8. However, the travel time to work, unlike distance, does not constantly grow year on year, as shown by the graph below. Similar to distance, as time increases there are a smaller number of women employees commuting than men. This is expected as for this particular dataset, men are more likely to travel longer distances and hence, usually, for a longer period of time. As shown by figure 6, the mean travel time for men is about 28 minutes, compared to 22 minutes for women.

Table 2-4 show statistics for the third dimension of commuting; travel mode. Approximately 85% individuals in the dataset use passive mode of commuting of which 61% is contributed by self-drivers. The remaining 15% are active commuters of which 11.5% is contributed by individuals who walk to work and 3.5% by individuals cycling to work. The split between female and male drivers is 55% to 45% respectively, which is the split of female to male individuals in the data. However, women getting a lift with someone from the household is significantly more than men (3.5 times more women than men). Similarly, almost twice the number of women walk to work as compared to men.

Lastly, the descriptive statistics for the dependent variables are illustrated in tables 3 and 4. As shown, the mean self-health score is 2.5 which is in between fair and good, the self-health score for all the waves has remained quite consistent, ranging from 2.5 - 2.6. As expected, the self-health score is higher (lower reported health) for elderly and lower (higher reported health) for relatively younger individuals. The mean Job Satisfaction score is 5.33 and the distribution is provided by table 6. The mean Job Satisfaction score for men and women is largely similar. Additionally, the mean working hours per week is 32.63 as shown in table 1. However, the mean working hours for men are significantly higher than women. On average, for this data, men work approximately 7 hours more (36.8 hours) than women (28.9 hours) per week.

## 4 Empirical Strategy

To get a causal relationship between commuting and the dependent variables, exogeneity of the interest variable is required. One of the strategies to make commuting exogenous is to use employer induced changes in commuting distance (Gutiérrez-i-Puigarnau et al., 2010) or exogenous changes in commuting time. However, due to the limited data availability, this strategy is non-implementable. Hence, the study looks for causality and a strong association between commuting and well-being and labour supply by controlling for the available covariates and employing statistical tools to provide an accurate estimate. To achieve the most accurate estimations, the study employs three different styles of statistical modelling. Firstly, a fixed effects model is considered (the null for the Hausman test of the presence of systematic error terms was rejected, hence, a fixed effects model was used) with different stages of specifications to estimate strong associations. Secondly, as two of the three dependent variables are ordered categorical variables, an elementary attempt on the Blow Up and Cluster (BUC) estimator is used as a robustness check and to reaffirm the direction of the relationship between the dependent variables and the regressors. Lastly, to tackle the problem of endogeneity a dynamic panel estimator is utilized (Generalised Moments Method). The rationale for the three models is discussed in the sections below.

### *4.1 Determinants of Employee Wellbeing and Job Hours*

In the broader definition of the term health, the determinants are given by the following standardized production function, where determinants are positively related to health:

**Health = h(Healthcare, Schooling, Nutrition, Prevention, Safety, ..)**

From the above production function, an understanding of the determinants can be achieved and according to the WHO, these determinants can be characterized in the following three categories: the social and economic environment; the physical environment; individual characteristics and behaviour

Similarly, the determinants of working hours can be extracted from Böheim J et al.,2005**.** The authors used Understanding Society data to analyse the differences in work time preference and suggested that following variables had an impact on working hours: job and employer related characteristic; individual demographic; local labour demand

Additionally, the determinants of job satisfaction can be referred from Javed et al., 2014. The authors used data from a self-administered survey to analyse the determinants that influence job satisfaction. These findings were similar to Viñas-Bardolet et al., 2013. The determinants of Job Satisfaction are as follows: work-place environment; employee empowerment; financial Job dimensions

Assuming that commuting is part of the following determinants: the social and economic environment, job and employer related characteristics, and work-place environment, this study isolates the suggested relationship to analyse the impact of commuting choice on the dependent variables.

### *4.2 Panel Models*

The first analysis uses panel models to estimate commuting's effect on the dependent variables. The panel model to be regressed is as follows:

**Panel Model:** $$\boldsymbol{Y_{it} = \beta_0 + \beta_1 X_{it} + \delta Z_{it} + \mu_{it} + \varepsilon_i} \quad \textbf{(1)}$$

In the equation above, $\boldsymbol{Y_{it}}$ is the dependent variable consisting of three different parameters; Self-Health scores (subjective health), Job Hours Worked (labour supply), and Job Satisfaction scores. The interest variables are represented by $\boldsymbol{X_{it}}$which includes commuting distances, commuting time, and travel mode. $\boldsymbol{\beta_1}$ is the coefficient of the interest variables. The matrix $\boldsymbol{Z_{it}}$ represents the time varying control variables, specifically**:** demographics, socio-economic situation, year dummies, weekly working hours, location, industry, education, income, and employment information. $\boldsymbol{\mu_{it}}$ is the unobserved time variant heterogeneity and individual idiosyncratic error terms and $\boldsymbol{\varepsilon_i}$ is the time invariant heterogeneity. Equation 1 is similarly specified to specifications described by Gutiérrez-i-Puigarnau et al., 2010. The authors use a First Difference model to analyse the effect of commuting distance on working hours controlling for household and work characteristics. Similarly, equation 1 controls for all the relevant and available household, work, as well as health characteristics.

With the given specifications in (1), both random effects and fixed effects model can by analysed. The Hausman test is used compare and suggest a preference between the two models. The null of the Hausman test is non significantly different coefficients (the error terms are systematic) suggesting $\boldsymbol{E(\varepsilon_i \mid X_{it} \,\&\, Z_{it}) = 0}$. The null hypothesis of the Hausman test for the above-mentioned model was rejected, suggesting FE approach to be appropriate.

**FE Model:** $$\boldsymbol{Y_{it} - \bar{Y}_i = \beta_0 + \beta_1(X_{it} - \bar{X}_i) + \delta(Z_{it} - \bar{Z}_i) + (\mu_{it} - \bar{u}_i)} \qquad \textbf{(2)}$$

The FE model subtracts the average of the original POLS model from itself, the unobserved time invariant heterogeneity is removed. Hence, if the determinants of commuting distance are constant over time, using the FE approach would eliminate the problem of endogeneity. The outcome of the model will be measured by the coefficient of the interest variables by reviewing the magnitude, sign, and significance. The coefficient will suggest the implications of a change in commuting on health, labour supply, and job satisfaction. For this model, there are three different variations of specifications regressed, to see the effect of adding additional parameters. this approach was also employed in Gutiérrez-i-Puigarnau et al., 2010. The first regression is the minimally adjusted model, which contains the interest variables with model restrictions. The second is the completely adjusted model, which contains all the interest variables in the correct specifications and the covariates. The final model contains a lagged term of commuting distance to see the significance of a historic effect of commuting distance.

As mentioned, the FE model controls for the time invariant heterogeneity, however, there is a cause for concern if the time variant factors influence both the dependent variables and commuting behaviour hence, creating not only the problem of endogeneity but also of reverse causality. Another concern arises with the presence of a bias caused due to an omitted variable. This is likely to be the case for the FE model. For instance, location of an individual's house will affect commuting as well as health due to the availability of healthcare facilities. As the residence location is unaccounted for in the analyses, estimations will not illustrate an accurate effect. Estimating a FE model with these specifications is likely to provide a strong association, however, not a causal relationship between commuting and the dependent variables.

The problem of endogeneity can be solved using a FE Instrumental Variable equation (IV), however, data limitations restrict the availability of good instruments. Additionally, instruments do not extract all the information available, for instance, the historic effect of variable are not accounted.

To present a causal relationship between commuting, and employee well-being and labour supply, this problem of endogeneity (unobserved heterogeneity, simultaneity, and dynamic endogeneity) must be tackled. However, the unbalanced, incomplete, and limited information in the available dataset does not permit the implications of causality for the relationship between the interest variables and the dependent variables using a static panel model. Given the nature and structure of the data, a dynamic estimator, as compared to POLS and FE, better controls for the sources of endogeneity (Ullah et al 2018). Hence, the Generalised Method of Moments (GMM) estimator is best suited for this analysis.

### *4.2 GMM Estimator*

The estimator was developed for dynamic data modelling by Holtz-Eakin et al. (1988) and Arellano and Bond (1991). The idea behind the GMM estimator is picking estimates of the parameter by setting sample moments to be close to population counterparts (Newey 2007). The estimator uses moment conditions that are functions of the variables and data in the model, one such function is that the expectation of a variable at its true value is 0 (Roodman 2009). The GMM estimator not only provides a solution to the problem of endogeneity but is also applicable to the data and the situation (Roodman., 2009).

As with the FE models, both the difference and system GMM models can be estimated with these specifications. According to Bond (2001), the rule of thumb rule to choose between the difference and system GMM is to estimate the dynamic model by both pooled OLS and FE estimators. The pooled OLS estimates for the coefficient of the lagged dependent term are considered to be the upper bound, whereas, the FE estimates are considered to be the lower bound. This is followed by estimating the model via a difference GMM estimator. If the estimates of the coefficient for the lagged dependent term for the difference GMM estimator are close to the one achieved from the FE model, then the GMM estimates are downward biased due to the problems with instrumentation (increased gaps in an unbalanced dataset) and the system GMM estimator should be preferred. Running these regressions suggest that the two-step difference GMM estimator is preferred.

The difference GMM estimator develops first difference moments **(5)** and **(6)** which transform the original equation to tackle endogeneity.  For the analysis of this study, XTABOND2 command is used instead of the traditional XTABOND (Roodman., 2009). As the standard errors in a GMM estimation are severely downward biased, the XTABOND2 command makes the Windmeijer

(2005) finite-sample correction to the reported standard errors in two-step estimation (Roodman 2009).

GMM Estimation:

$$\boldsymbol{Y_{it} = \beta_1 Y_{it-1} + \beta_2 X_{it} + \delta Z_{it} + \mu_{it} + \varepsilon_i} \quad \textbf{(3)}$$

To eliminate individual fixed effects, a first difference of (3) is used

$$\boldsymbol{Y_{it} - Y_{it} = \beta_1(Y_{it-1} - Y_{it-2}) + (\beta_2 X_{it} - X_{it-1}) + \delta(Z_{it} - Z_{it-1}) + \mu_{it} - \mu_{it-1}} \quad \textbf{(4)}$$

The estimator then uses the following first difference moments:

$$\boldsymbol{E[Y_{it} - s(\mu_{it} - \mu_{it-1})] = 0 \text{ for } S>=2} \quad \textbf{(5)}$$

$$\boldsymbol{E[X_{it} - s(\mu_{it} - \mu_{it-1})] = 0 \text{ for } S >= 2} \quad \textbf{(6)}$$

The equation (3) represents the model used for the GMM estimation. (3) is similarly specified to equation (2) of the FE model but with a lag of the dependent variable present in the model, creating a dynamic setting. The difference GMM estimation require two types of instrument variables to overcome the problem of endogeneity. The first are the internal instruments which include endogenous variable or pre-determined variables. The second are the strictly exogenous variables. (Bond., 2001; Roodman., 2009)

The choice of strictly exogenous variables is dependent on two factors; availability of the data and economic rationale. Keeping these factors in mind, the strictly exogenous variables are as follows. *Year dummies***:** to control for the year effects, dummies for each wave are included as external instruments. *Country of Birth***:** Birthplace of an individual affects the decision making of an individual (McCrae et al 2005; Samuel P et al., 2017), hence, affecting the choice of workplace, commuting mode, and relativity required to provide a subjective self-health score. *Ethnicity:* For the similar reasons mentioned for country of birth, ethnicity is also included as a strictly exogenous variable. **Sex:** Gender has been linked to differentiation in preferences even after controlling for other factors that could manifest gender-based differentiation (Falk et al., 2017)

### *4.3 BUC Estimator*

As two out of the three dependent variables in this analysis are ordered categorical variable, a fixed effect ordered logit model is estimated as a robustness check. This, however, as mentioned earlier, is an elementary attempt to see the sign of the association between the two categorical independent variables (self-health score and job satisfaction score) and commuting behavior. According to Baetschmann et al 2011, the fixed effects logit model has two problems. Firstly, there is a problem of identification. The latent variable is indistinguishable from the unobserved time invariant heterogeneity. Secondly, the T (time) in the model must be treated as fixed and relatively small, hence, creating the incidental parameter problem (Lancaster 2000). Hence, Baetschmann et al 2011 proposed a CML estimator which estimates all possible dictomizations jointly. The BUC estimator is implemented by replacing every observation in the dataset by K-1 copies of itself (K is the number of categories of the depended variable) and dictomizing every K-1 copy of the observations, each at a different cut-off point. The estimator then uses CML logit to achieve estimates for the entire dataset, clustering standard error at individual level, hence the name Blow Up (blowing up the data) and Cluster (BUC). In the Monte Carlo simulations, the BUC estimator was never outperformed by other maximum likely hood estimators or the CML estimators. BUC is more immune to relatively small sample bias when compared to other consistent estimators. As mentioned earlier, this approach is used as somewhat of a robustness test for the FE and the difference GMM model and hence, a minimally adjusted model is analyzed to illustrate the sign and the significance of the association between commuting behavior, and self-assessed health and job satisfaction. The regressors included for the BUC estimator are objective health, commuting time, commuting distance, commuting mode, job hours, job satisfaction, and job status. Similarly, for job satisfaction as the dependent variable, same set of regressors are used, except for removing job satisfaction and including subjective health score.

## 5 RESULTS

### *5.1 Fixed effects analyses*

*5.1.1: Impact of distance on self-assessed health (SAH)*

The results for the FE models for commuting and SAH are illustrated in table 5. In the minimally adjusted model (model a), a 10% increase in distance is associated with a ¬0.0022 increase in SAH score (decrease in subjective health). This figure, however, only provides with an elementary association between distance and SAH. After adjusting for all covariates, the effect decreased to ¬0.002 with a 10% increase in distance. This decrease seems to be due to the absorption of some of the effect by the added covariates providing a more accurate relationship between distance and SAH. Many covariates had a significant effect on SAH including Job Satisfaction – compared to being completed dissatisfied, being somewhat, mostly, and completely satisfied is associated with a decrease in the SAH score (increasing the true value of SAH) by 0.11 and 0.15 respectively. SAH score is also higher when the participants of the survey were separated (an increase of 0.14 points) and lower if the participants were widowed (a decrease of 0.24 points) as compared to being single. The interaction term between distance and cycling has a negative coefficient suggesting, as distance increases, participants who use cycle as commuting mode report better SAH (the SAH score decreases). However, this effect is statistically insignificant for this dataset. In line with the hypothesis, the interaction term between driving and distance (below 35 miles) has a positive coefficient of 0.07, suggesting a driving a car to work located below a 35-mile radius, worsens SAH score by 0.07.

Due to the ordinal and categorical nature of the independent variable, an elementary analysis utilising the BUC estimator was also conducted. The results are stated in the appendix and points towards a similar association as the fixed effects analysis, however, the results are quite insignificant.

Lastly, the regression containing the first lag variable of distance suggested that distance from last wave may have a significant effect on health reporting in current wave as the coefficient of the lag variable is statistically significant and larger in magnitude than the current variable.

*5.1.2: Impact of time on SAH*

The minimally adjusted model yields a parabolic relationship between travel time to work and SAH score. The coefficient for travel time is negative, hence, as time increases, the participants report a decrease in SAH score (improvement in health). However, the positive coefficient of the squared variable implies that travel time initially deceases the SAH score but reaches a turning point and the relationship is inversed. Even after, adjusting for the covariates, a similar association was found. As travel time increases by 10 mins, SAH decreases by 0.02 (statistically significant at 10% significance), however, for every minute increase in travel time there is a decrease of 0.0001 in its effect on SAH score (significant at 10% significance level). However, as the figures suggest, these effects are quite small. Hence, to acquire a more accurate and robust association between time and SAH, a regression with time and grouped dummies is used. When compared with participants who travel less than 60 mins, participants who travel between 60 and 90 mins, participants who travel between 90 – 120 mins, and participants who travel more than 120 mins, report an increase in SAH score by 0.038, 0.0008, and 0.027, respectively. However, for this given sample and specification of the model, the three effects are highly statistically insignificant. Another interesting covariate is the is the interaction between active commuting and travel time. The coefficient of this interaction is negative and hence, an increase in travel time of 10 mins for active commuters decreases the SAH score by 0.02 (significant at 15% significance level)

*5.1.3: Impact of model of travel on SAH*

Mode of travel is directly included in the completely specified model. Compared to driving yourself to work, getting a lift from someone within the household increases reported SAH score by 0.1 and cycling to work decreases reported SAH by 0.08. These were the only two statistically significant modes of travelling.

*5.1.4: Impact of distance on Job Hours*

Shown in table 6, in the minimally adjusted model, the effect of distance on working hours is somewhat interesting. Similar to the hypothesis, there is a positive association illustrated between distance and working hours. Working hours increase by 0.07 as there is a 10% increase in distance (statistically significant at 5% significance level). However, due to the specification of the model, this is a weak association accounting for the effects of the unobserved covariates. After adjusting for all the covariates, the effect of decreased to 0.033 (contingent on model specification; significant at a 5% significance level). As expected, being unhealthy has a negative association with hours worked; reaffirmed by the coefficients of health (having a long standing illness decreases the working hours by 0.06) and SAH (as SAH score increases by 1, working hours decrease by 0.05), however, the effects are statistically insignificant for this data set. The coefficients of job satisfaction categories imply that the individuals who are relatively more satisfied with their job as compared to being completely dissatisfied work more hours. The magnitude of the effect can be seen from the table 6; however, are statistically insignificant. The specification with the interaction between active (cycling) commuting and distance also did not yield a significant result.

Finally, the specification containing the lag variable for distance yielded a similar result as prior specifications. The lag term has a positive association with hours worked (increase in 10% of last wave's distance increases job hours by 0.007; however, this effect is statistically insignificant) and its inclusion made the variable for distance form work statistically insignificant.

### *5.1.5: Impact of travel time on Job hours*

In minimally adjusted specification, travel time to work has a positive association with Job Hours. As shown by the coefficient of time, as travel time increases by 10 minutes, Job hours increase by 0.1, significant at 10% significance level. The inclusion of the squared term of travel time yielded a negative, quite small, and insignificant association. With the adjusted specification, an increase of 10 mins in travel time increase job hours by 0.08 hours (significant at a 5% significance level). The interaction term for active commuting and time suggests that as compared to individuals who commute passively, active commuters work 0.13 hours less with a 10 minutes increase in travel time (only significant at a 15% significance level).

The addition of group dummies suggests that comparing to individuals who travel less than 60 minutes, individuals who travel for more than 120 minutes work 2.5 hours more (significant at a 5% significance level). All the other groups are highly insignificant. Interestingly, an estimation of the interaction between driving to work and commuting less than 60 minutes computes a positive association with Job Hours. An individual adhering to these situations is associated to work approximately 0.8 hours more, significant at a 5% significance level.

The specification containing the lag term for distance inverses the relationship between travel time and hours worked. In this particular regression, as travel time increases by 10 minutes, working hours decrease by 1.2 hours (significant at 5% significance level) and this effect is reduced by 0.013 working hours every 10 minutes increase in travel time. This is potentially an indication of a strong association between the lagged term for distance and Job Hours.

### *5.1.6: Impact of travel mode on Job Hours*

As compared to driving yourself, individuals who get a lift from someone within the household and outside the household work 0.86 and 0.7 hours less respectively (significant at 5% and 10% significance level). Individuals who use bus as a commuting mode work 0.83 hours less as compared to self-driving employees. Individuals who walk to work as compared to driving, work 1.15 hours less. The other travel modes were statistically insignificant.

### *5.1.7: Impact of Distance on Job Satisfaction*

As shown in table 7, in the minimally adjusted specification, distance from work and job satisfaction have a positive association; as distance increases by 10%, job satisfaction increases by 0.01 units (statistically significant at a 15% significance level). After completing the model with all the additional covariates, the effect of distance on job satisfaction decreases significantly and is statistically insignificant (coefficient – 0.0098). As in the earlier analyses, the interaction term of driving a car and distance was included. The results suggest that if an individual drives more than 35 miles to work, the Job Satisfaction score decreases by 0.23 (significant at 5% significance level). However, if an individual drives less than 35 miles to work, the Job Satisfaction score increases by 0.13 (significant at 15% significance)

Coefficient of the variable for self-health score implied a negative association between the score and job satisfaction; as the score increases by 1 (deterioration in health), job satisfaction decreases by 0.09 (significant at a 5% significance level). Similarly, a year's increase in age decreases job satisfaction score by 0.045 (significant at a 5% significance level).

Similar to SAH, job satisfaction is an ordered categorical variable. Hence, another elementary investigation into the fixed effects ordered logit model was attempted, however, the approach yielded insignificant results.

*5.1.8: Impact of travel time on Job Satisfaction*

In respect to the minimally adjusted model, an increase in travel time by 10 minutes decreases job satisfaction score by 0.02 (significant at a 5% significance level). The addition of the squared term in this specification does not change the significance and magnitude of travel time, however, suggests a concave association between time travelled and job satisfaction. As travel time increases by 10 minutes, job satisfaction score decreases by 0.02, however, this effect is decreasing by 1.22E-05 every minute increase in travel time. This parabolic association is confirmed in the completely specified model; as travel time increase by 10 mins the individual's job satisfaction score decreases by 0.05 (significant at a 10% significance level) and this effect is decreases by 0. 0000432 as travel time increases by 10 minutes. In this model, the effect of both travel time and the square of travel time is almost decreased by 50% suggesting the absorption of the effect by other covariates. To check for the robustness of this effect, time dummies were employed as with other two independent variables; as compared to traveling less than 60 minutes to work, traveling 60 to 90 mins and traveling 90 to 120 minutes decreases the job satisfaction score by 0.8 and 0.6 respectively (however, these effects are not statistically significant for this data set), however, as suggested by the parabolic association, traveling for more than 120 minutes as compared to less than 60 minutes increases the job satisfaction score by 0.6 (statistically significant at a 5% significance level).

As for the interaction term with distance, the interaction term between travel time and active mode of commuting was included, however, this was statistically insignificant.

*5.1.9: Impact of travel mode on Job Satisfaction*

Travel modes were directly included in the completely specified model. As compared to driving yourself to work, using an active model of transport, I.E. cycle, reduces job satisfaction score (cycling to work is statistically significant at a 5% significance level; walking to work is statistically insignificant) by 0.161. However, as compared to driving to work, taking either the bus or coach increases job satisfaction score by 0.14 (statistically significant at a 5% significant level). Other modes of travel were statistically insignificant for this data set.

## 5.2 GMM Analyses

*5.2.1 SAH*

Table 8 represents the difference GMM estimation for SAH score. As distance, was only available for 5 waves (1, 2, 4, 6, and 8), including the variable would create serial correlation in the model rendering the results inaccurate. Hence, this estimation does not include commuting distance. Unlike the FE model, the impact of commute time on SAH in the GMM estimation is quite significant and substantial. A 10 minutes increase in travel time increases the SAH score by 0.4. Like the FE model, there is a concave relationship between travel time and SAH: with every 10 minutes increase in travel time, its effect on SAH decreases by 0.006. However, this effect is relatively small. In the GMM estimation, Job Satisfaction has a positive impact on subjective health (a point increase in job satisfaction decreases SAH score by 0.02). This is unlike the FE model, however, as GMM is a more accurate estimator, the results from this estimation is preferred. The effect of long-standing impairment is replicated in the GMM model. Having a long-standing impairment has a positive effect on subjective health score (deterioration in health).

Due to the nature of the estimator, introduction of the interaction terms made the model weaker and hence, were excluded from the estimations.

There are two diagnostics test available for the GMM estimator to check the model's validity and strength. The first is the test for overidentification of instruments (Hansen-Sargan test; too many or weak instruments). If the null of the tests is rejected, the instruments are not valid. The GMM estimation for SAH does not reject the null hypothesis of Hansen-Sargan test (at 10% significance level), making the instruments valid. The second diagnostic test for the estimation accounts for the serial correlation in the model. The null for the Arellano-Bond test for AR is no serial correlation. For the SAH estimation, the null is not rejected, making the model valid.

#### *5.2.2 Job Hours*

The GMM estimation for Job hours illustrates similar results to the FE model. An increase in commute time increase job hours significantly. The magnitude of this impact is quite high relatively (increase in 10 minutes of commute time increases job hours by 2.7). The extreme magnitude of the coefficient is due to the invalidity of the model. The model fails both the diagnostic test for serial correlation and instrument validity (at 10% significance level), making the results invalid.

#### *5.2.3 Job Satisfaction*

Like the GMM estimations for Job Hours, the estimation for Job Satisfaction yielded similar results to its FE counterpart. An increase in travel time by 10 minutes decreases Job satisfaction score by

0.7 (significant at a 10% significance level). This effect is more substantial than the effect portrayed in the FE model (0.05 decrease in satisfaction).

The concave relationship between time and job satisfaction is also present in the GMM estimation, illustrated by the positive and significant coefficient of the squared term for travel time. The effect of time on job satisfaction decreases by 0.007 as travel time increases by 10 minutes.

The model for Job satisfaction rejects the null hypothesis for both Hansen-Sargan test for instrument validity and the Arellano Bond test for auto correlation; making the model and instruments valid.

## 6 Discussion

Overall commute has been found to have a negative association with employee health and wellbeing. Consistent with other literatures, this study also represents evidence which supports the negative relationship between commuting and health. This study focused on perceived employee health (SAH), and the results illustrate a negative impact of commuting and employee's subjective health. The results from the GMM estimation provide a causal negative relationship between commuting time and SAH. Ceteris Paribus, an increase in travel time by 10 minutes, worsens SAH score by 0.4 on a scale of 1-5 (¬ 8% deterioration). An individual's perception of own general health decreases as time to commute increases. However, for active commuters when compared to passive commuters, an increase in travel time betters their subjective health. This is, perhaps, due to an increase in physical activity. As approximately 85% of the individuals in the sample are passive commuters, an overall increase in travel time is harmful to the subjective health of employees.

Due to the negative connotations associated with travel time, an increase in commuting time could potentially disincentivise employees, increase absenteeism, and decrease job satisfaction. In fact, the GMM estimation found that an increase in travel time by 10 minutes decreases job satisfaction score by 0.7 on a 7-point scale (¬ 10% decrease). As mentioned earlier, satisfaction achieved from a job is dependent on social and financial factors related to the job. A significant decrease in satisfaction due to an increase in travel time ascertains commuting time as a major determinant of Job Satisfaction. Interestingly, on the contrary to Chatterjee et al., 2017, active commuting was associated with a decrease in Job Satisfaction when compared to passive commuting, and, using bus/coach as a medium to commute was associated with an increase in Job Satisfaction when compared to driving yourself to work. However, these effects portray only an association and not an impact. For instance, individuals who use active commuting mode (cycling) may have a job description which is unsatisfactory. As the stratification of job description was not accounted for in the model, a presence of reverse causality between commuting mode and job satisfaction may not be denied.

The results for General Health and Job Satisfaction provides evidence for the potential dislike towards commuting by employees. As both the outcomes discussed above are in form of subjective scoring, the negative impact of commuting time is essentially changing subjective views for the worse.

The model for the Job hours with GMM estimation was invalid and with the given limitations of the dataset, GMM estimation could not be conducted for Job hours. However, the FE model portrayed positive association between Job hours, and commuting time and distance, which is in line with the previous literature. The analysis for job hours has some restrictions. It is not always certain for an employee to have freedom to choose their working hours, however, the data for degrees of freedom in the job was not available and hence, was not included in the model. The positive association between commuting and Job Hours suggests that when facing longer commutes, employees may choose a job with longer working hours or, if they have high degrees of freedom, might decide to work longer.

## 7 Conclusion

The growing significance of commuting has generated a great interest in health and labour economics. This has led many studies to analyse the effect of commuting on employee wellbeing and behaviour. The studies investigating this effect find a negative association between commuting and employee wellbeing, however, to the best of my knowledge, most of these studies only present an association. The studies that have tried to estimate causal impact of commuting have done so by isolating the exogenous variation in commuting distance. This approach, however, loses a substantial amount of information and observations. These studies illustrate evidence of a decrease in mental and physical health, life satisfaction, and job satisfaction associated with commuting.

This study uses the longitudinal data collected by Understanding Society. This data is collected in the form of surveys and include around 40,000 households. The study utilizes a dynamic estimator (GMM) to estimate a casual impact of commuting time on Subjective Health and Job Satisfaction. However, this estimator could not be used to estimate accurate effects of categorical covariates and hence, the FE models were used to estimate strong associations. Thus, the estimates from the GMM estimator are interpreted as causal results and estimates from the FE models are interpreted as associations.

The results from this study reaffirms a negative relationship between commuting and employee wellbeing and illustrates a positive association between commuting and labour supply. The analyses somewhat answer the questions raised in the earlier sections of the study. Firstly, commuting time has a causal impact on an employee's perceived health and job satisfaction. This causal impact could only be estimated for the subjective outcomes. Specifically, increasing travel time for 10 minutes, one way to work, worsens subjective health score by 0.4[4] and job satisfaction score by 0.7[5]. These results can be explained by the dislike an individual feel towards longer commutes. These results imply that a more flexible work environment in terms of commuting (allowing work from home) could increase Job Satisfaction and General Employee Health which could further result in higher productivity and motivated employees.

Additionally, the study illustrated an association between the other dimensions of commuting and the three outcome measures. In general, subjective health betters with a decrease in commute

[4] On a scale of 1-5; 1 being the best health possible
[5] On a scale of 1-7; 7 being the best job satisfaction possible

distance, however, the effect is relatively small. The effect does become prominent when coupled with commuting mode. The subjective health of a car commuter is worse of when driving short distances (35-mile radius) when compared to other modes of travelling (especially cycling). In particular, the SAH worsens by 0.07[6] for these commuters. In general, active commuting is associated with better subjective health. These associations could be further implied to encourage active mode of traveling for a betterment in general employee health.

The study did not find a significant association between Job Satisfaction and commute distance. Active commuters were worse off for Job Satisfaction when compared to passive commuters, however, within passive commuting, traveling by bus or coach increased Job Satisfaction score by 0.14.

Commute distance, however, has a positive association with Job hours. Workers who experience 10% longer commutes are likely to work 0.035 hours more. Moreover, as travel time increases, active commuters work 0.13 hour less when compared to passive commuters. The association may suggest an increase of passive commuting to increase work hours, however, due to the nature of the job as well as the degrees of freedom an employee gets to choose their working hours, this implication may not always result in increased labour supply. In fact, an increase in travel time and active commuting may decrease job satisfaction and subjective health, potentially worsening productivity and negating the effect of increased job hours.

Having recommended the implications of the study, there are some limitations to the analyses presented. Firstly, the data can be a subject to interviewer bias. Due to the structure of the questions used in the survey, the respondent might have a partiality towards a preconceived response. This could potentially distort the raw data available and create inaccurate estimates. Furthermore, there is a probability of the presence of a recall bias. As majority of the questions in the survey are based on incidents happening over a period of time, a misremembrance could misrepresent the data and the estimates. Additionally, there is a possibility of a selection bias. Individuals who are unhealthy might either work from home or not work at all. Conducting the analyses for individuals with a positive commute distance pre-selects the data, potentially creating a selection bias. Moreover,

[6] On the 5-point scale

even after conducting the GMM analysis, the information lost due to an omitted variable bias could provide inaccurate results. One such variable could be amount of physical exercise achieved.

Following the results illustrated in this analysis for the British households, future line of research could investigate the causal impact of travel mode for commuters to understand the accurate effect of choosing the particular travel medium. In particular, these studies can form a controlled study to analyse the effect of changing the travel mode to further the understanding of commuting’s effect on employee wellbeing and organisational behaviour.

## Tables and Figures

**Figure 1: Trends in commuting (UK Transport Survey)**

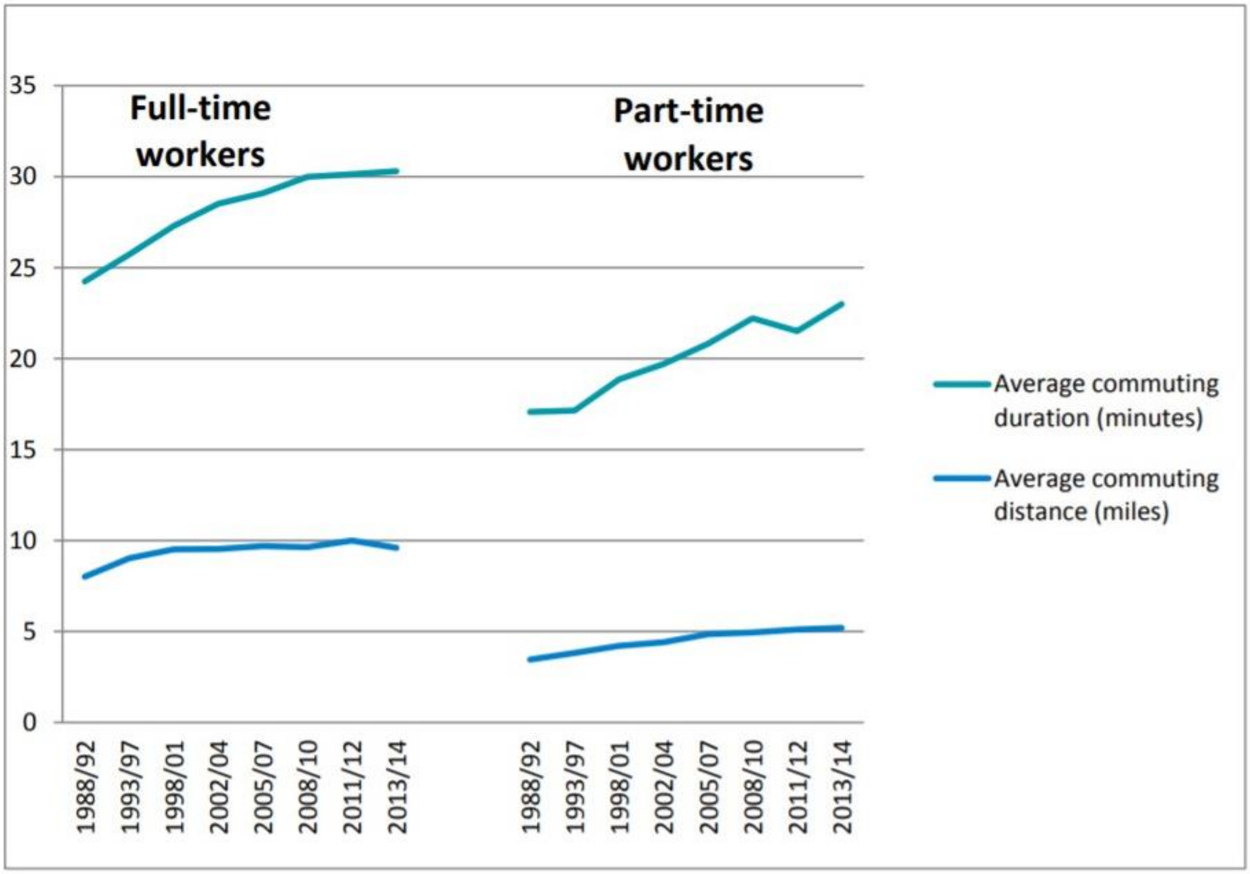

**Table 1: Summary Statistics of Dependent and Interest Variables**

| ***Variable*** | ***Obs*** | ***Mean*** | ***Std.Dev.*** | ***Min*** | ***Max*** |
|---|---|---|---|---|---|
| Distance | 91,027 | 9.40963 | 12.5568 | 0 | 120 |
| Travel Time | 162,373 | 25.7735 | 21.6297 | 0 | 180 |
| Travel Mode | 163,868 | 3.99057 | 8.41013 | 1 | 97 |
| SAH | 254,742 | 2.59393 | 1.13739 | 1 | 5 |
| Job Hours | 180,627 | 32.6362 | 11.4286 | 0.1 | 97.9 |
| Job Satisfaction | 193,359 | 5.33106 | 1.41063 | 1 | 7 |

**Figure 2: Mean Distance Per Wave**

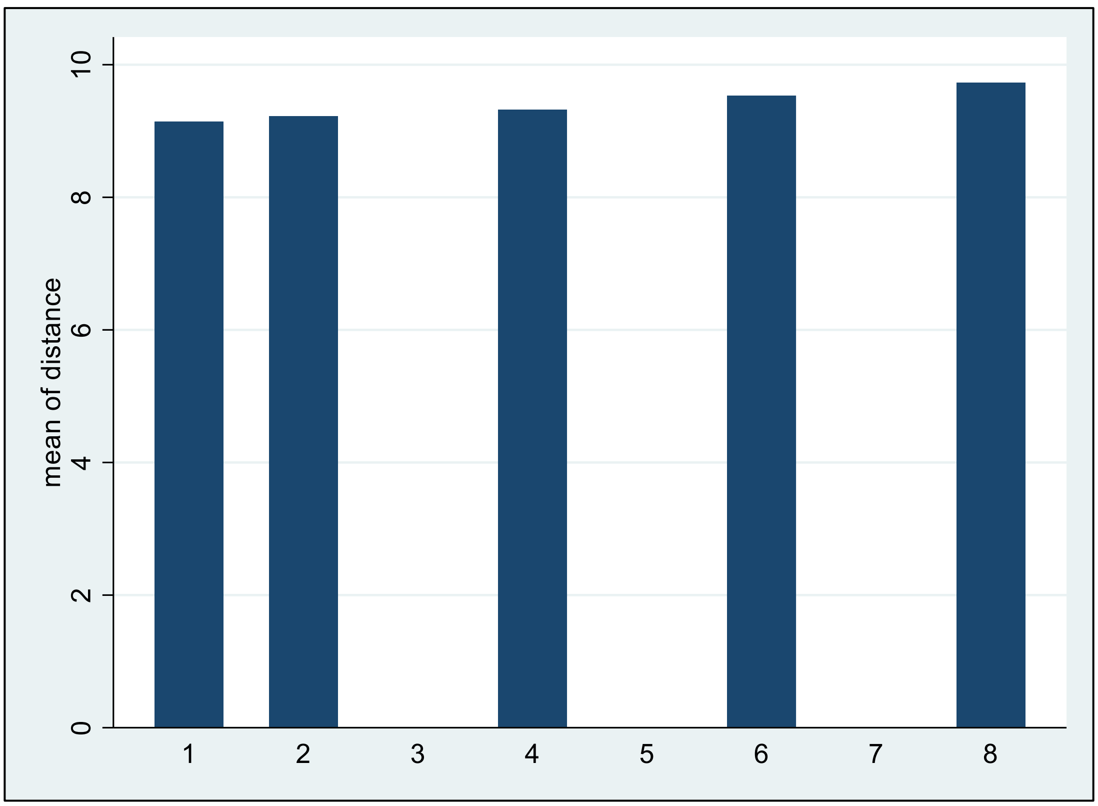

**Figure 3: Mean Distance by Gender**

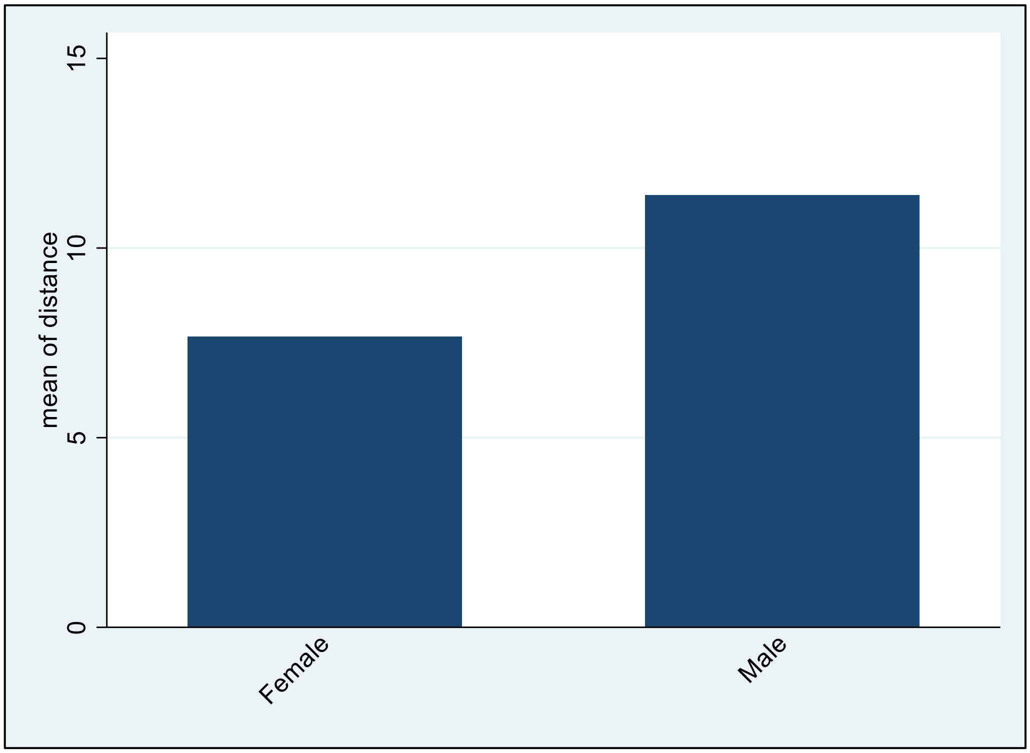


**Figure 4: Mean distance by Mode**

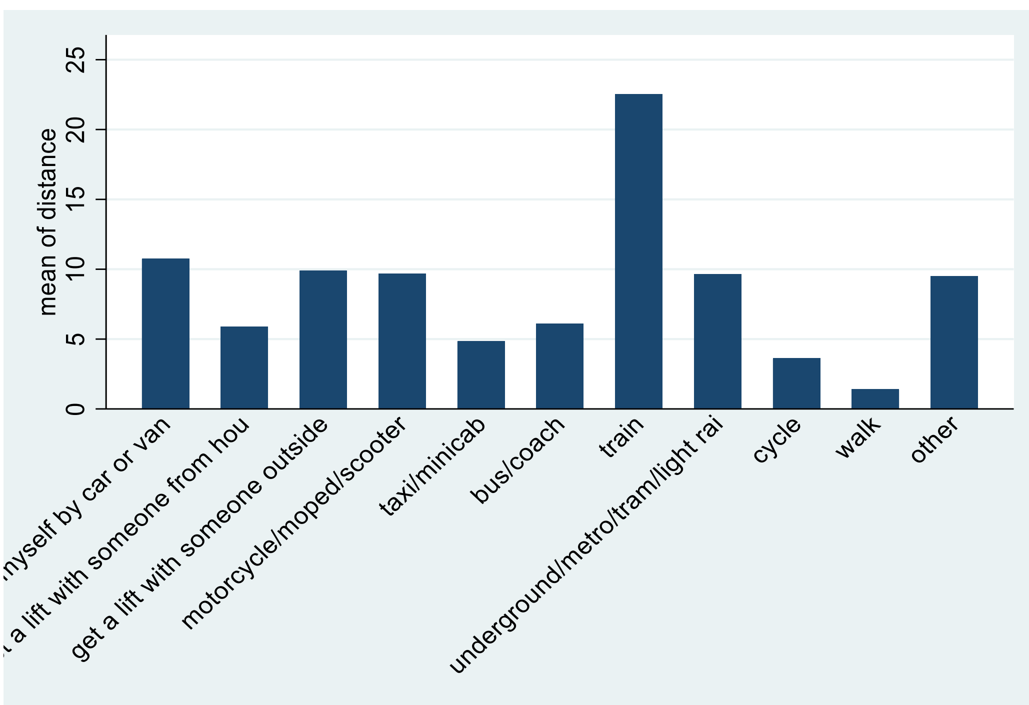

**Figure 5: Mean of Travel Time by Waves**

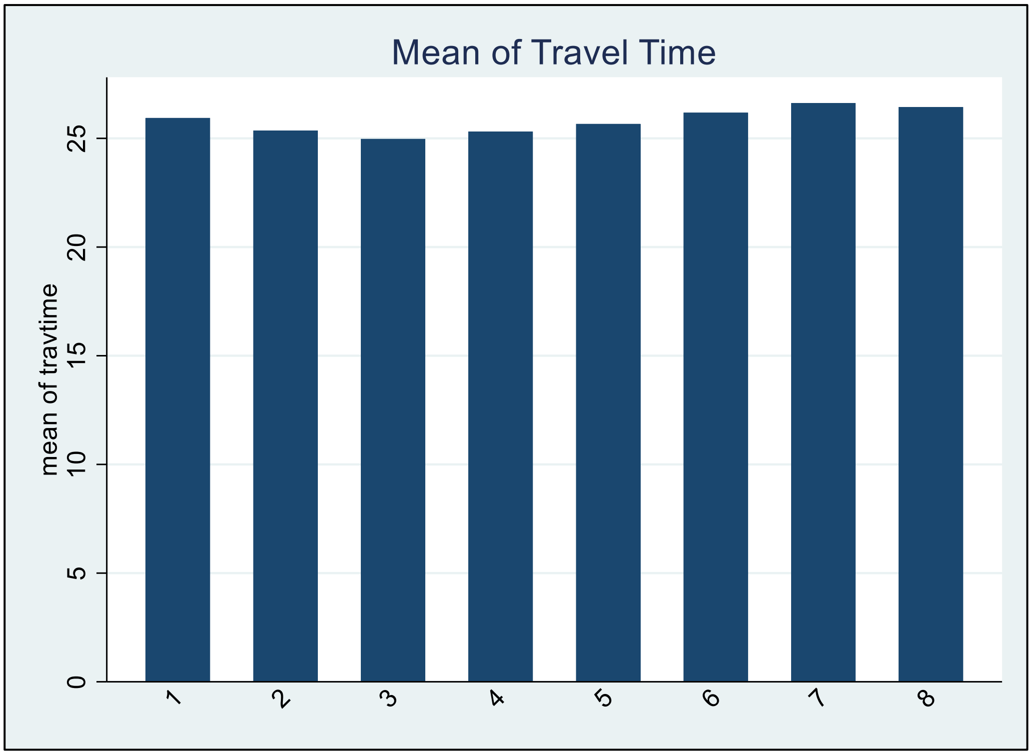


**Figure 6: Mean Travel Time by Gender**

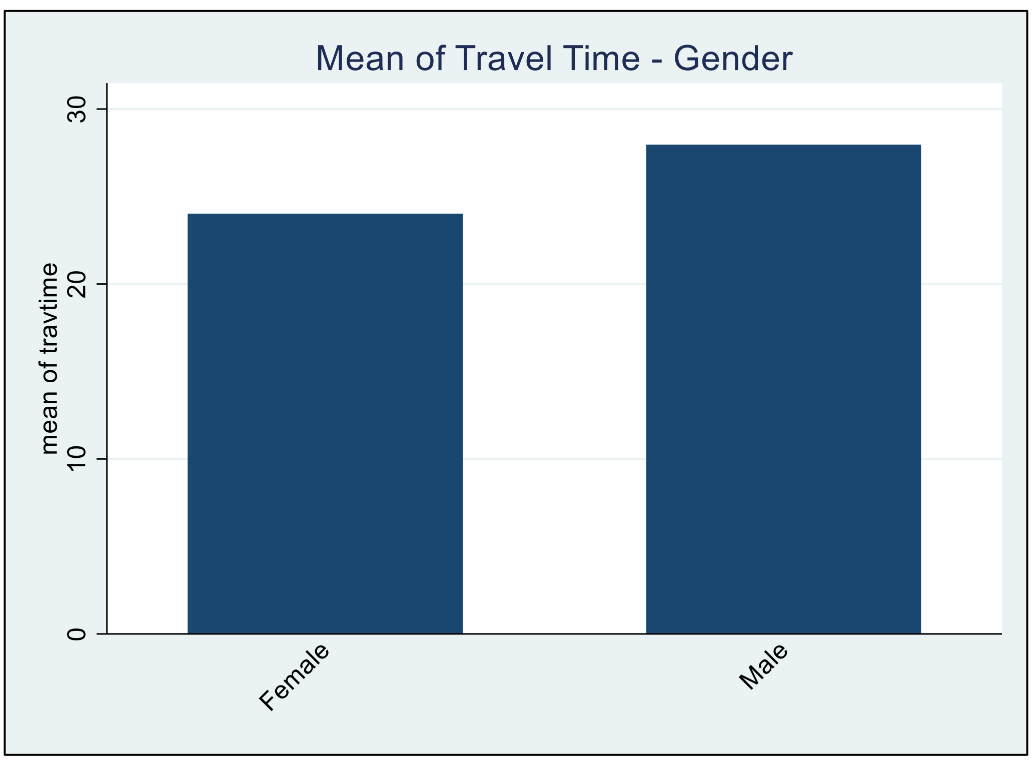

**Figure 7: Mean of Travel Time by Mode**

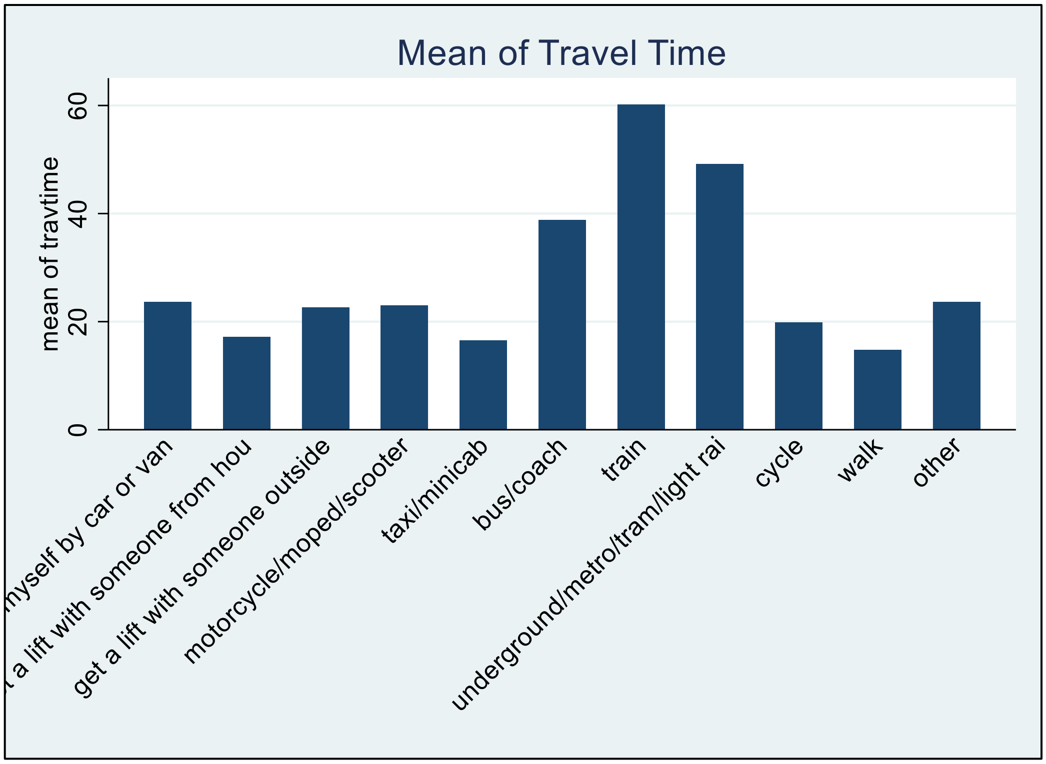

**Table 2: Travel Mode Statistics**

| *Mode of transport for journey to work* | *Freq.* | *Percent* | *Cum.* |
|---|---|---|---|
| Drive Myself by Car Or Van | 100,748 | 61.48 | 61.48 |
| Get A Lift with Someone From Household | 6,525 | 3.98 | 65.46 |
| Get A Lift with Someone Outside The Hou | 3,489 | 2.13 | 67.59 |
| Motorcycle/Moped/Scooter | 1,116 | 0.68 | 68.27 |
| Taxi/Minicab | 615 | 0.38 | 68.65 |
| Bus/Coach | 12,370 | 7.55 | 76.2 |
| Train | 8,041 | 4.91 | 81.1 |
| Underground/Metro/Tram/Light Railway | 4,660 | 2.84 | 83.95 |
| Cycle | 5,361 | 3.27 | 87.22 |
| Walk | 19,832 | 12.1 | 99.32 |

**Table 3: Statistics for Subjective Health Score**

| ***General Health*** | ***Freq.*** | ***Percent*** | ***Cum.*** |
|---|---|---|---|
| Excellent | 45,180 | 17.74 | 17.74 |
| Very Good | 84,637 | 33.22 | 50.96 |
| Good | 70,692 | 27.75 | 78.71 |
| Fair | 36,912 | 14.49 | 93.2 |
| Poor | 17,321 | 6.8 | 100 |
| Total | 254,742 | 100 | |

**Table 4: Statistics for Job Satisfaction**

| **Job Satisfaction** | **Freq.** | **Percent** | **Cum.** |
|---|---|---|---|
| Completely dissatisfied | 4,056 | 2.1 | 2.1 |
| Mostly dissatisfied | 6,229 | 3.22 | 5.32 |
| Somewhat dissatisfied | 14,024 | 7.25 | 12.57 |
| Neither satisfied or dissatisfied | 16,440 | 8.5 | 21.07 |
| Somewhat satisfied | 43,719 | 22.61 | 43.68 |
| Mostly satisfied | 74,369 | 38.46 | 82.15 |
| Completely satisfied | 34,522 | 17.85 | 100 |

**Table 5: Fixed Effects Regression for SAH** [7]

| ***SAH*** | ***Model A*** | ***Model B*** | ***Model C*** |
|---|---|---|---|
| Log of Distance | 0.0225* | 0.0215* | -0.065 |
| | -0.028 | -0.049 | -0.119 |
| Job Status | -0.002 | -0.002 | -0.001 |
| | -0.328 | -0.331 | -0.954 |
| Job Hours | -0.001 | -0.001 | -0.006 |
| | -0.280 | -0.359 | -0.094 |
| Travel time | -0.00187* | -0.002 | 0.000 |
| | -0.045 | -0.051 | -0.949 |
| Traveltime2 | 0.0001 | 0.0001 | 0.0001 |
| | -0.094 | -0.076 | -0.980 |
| Health | 0.260*** | 0.255*** | 0.171** |
| | 0.000 | 0.000 | -0.001 |
| ldistance_l1 | | | 0.027 |
| | | | -0.110 |
| Get a lift from household | | 0.0918** | 0.232 |
| | | -0.009 | -0.065 |
| Bus | | 0.032 | -0.247 |
| | | -0.338 | -0.061 |
| Train | | -0.034 | -0.188 |
| | | -0.417 | -0.216 |
| Underground | | -0.046 | -0.241 |
| | | -0.392 | -0.228 |
| Cycle | | -0.0890* | -0.522** |
| | | -0.035 | -0.003 |
| Walk | | 0.017 | -0.059 |
| | | -0.569 | -0.629 |
| Age | | 0.0107** | 0.003 |
| | | -0.002 | -0.884 |

[7] P values under the coefficients. Not all variables have been shown in the table. Please refer to Appendix.

**Table 6: Fixed Effects regression for Job Hours**[8]

| ***Job Hours*** | ***Model A*** | ***Model B*** | ***Model C*** |
|---|---|---|---|
| Log of Distance | 0.778*** | 0.330*** | 0.463 |
| | 0 | 0 | -0.123 |
| Job Status | -0.178*** | -0.0447** | -0.022 |
| | 0 | -0.006 | -0.742 |
| Travel Time | 0.0117* | 0.008* | -0.120*** |
| | -0.027 | 0.037 | 0 |
| Travel Time2 | -6.1E-05 | - | 0.00130*** |
| | -0.169 | - | 0 |
| Health | -0.141 | -0.0658 | 0.456 |
| | -0.112 | -0.609 | -0.237 |
| SAH | - | -0.0631 | -0.301 |
| | - | -0.318 | -0.106 |
| Getting a lift within Household | - | -0.867** | -1.541 |
| | - | -0.004 | -0.09 |
| Getting a lift outside Household | - | -0.698 | 0.0438 |
| | - | -0.054 | -0.968 |
| Bus | - | -0.831** | -0.733 |
| | - | -0.003 | -0.441 |
| Train | - | -0.455 | -1.105 |
| | - | -0.19 | -0.314 |
| Underground | - | -0.153 | -0.447 |
| | - | -0.738 | -0.756 |
| Cycle | - | -0.110 | 0.685 |
| | - | -0.756 | -0.589 |
| Walk | - | -1.150*** | 0.159 |
| | - | 0 | -0.858 |
| ldistance_l1 | - | - | 0.0725 |
| | - | - | -0.552 |
| N | 79910 | 47148 | 9027 |

[8] P values below coefficient. Not all variables have been shown in the table. Please refer to Appendix

**Table 7: Fixed Effects Regression for Job Satisfaction**[9]

| ***Job Satisfaction*** | ***Model A*** | ***Model B*** | ***Model C*** |
|---|---|---|---|
| Log of Distance | 0.0182 | 0.00987 | -0.132 |
| | -0.102 | -0.623 | -0.086 |
| Job Status | -0.00727** | -0.00085 | -0.00656 |
| | -0.001 | -0.805 | -0.702 |
| Travel Time | -0.00214* | -0.00514** | -0.00754 |
| | -0.038 | -0.003 | -0.284 |
| Travel Time2 | 1.22E-05 | 0.0000432** | 0.000166** |
| | -0.154 | -0.002 | -0.008 |
| Health | -0.0875*** | -0.0552* | -0.158 |
| | 0 | -0.048 | -0.11 |
| SAH | - | -0.0898*** | -0.122* |
| | - | 0 | -0.011 |
| Bus | - | 0.143* | -0.187 |
| | - | -0.02 | -0.446 |
| Cycle | - | -0.161* | -0.261 |
| | - | -0.038 | -0.424 |
| Age | - | -0.0445*** | -0.077 |
| | - | 0 | -0.079 |
| ldistance_l1 | - | - | -0.0364 |
| | - | - | -0.247 |
| N | - | 80111 | 47256 |

[9] P-value below the coefficients. Not all variables have been shown in the table. Please refer to Appendix

**Table 8: GMM estimation for SAH**

| *SAH* | *Coef.* | *Std. Err.* | *t* | *P>t* | *[95% Conf.* | *Interval]* |
|---|---|---|---|---|---|---|
| SAH Lag1 | 0.040855 | 0.026355 | 1.55 | 0.121 | -0.0108 | 0.092514 |
| Travel Time | 0.045064 | 0.029547 | 1.53 | 0.127 | -0.01285 | 0.102978 |
| Travel Time2 | -0.00043 | 0.000289 | -1.5 | 0.133 | -0.001 | 0.000132 |
| Job Hours | -0.00475 | 0.004601 | -1.03 | 0.302 | -0.01377 | 0.004266 |
| Travel Mode | -0.00146 | 0.001251 | -1.17 | 0.242 | -0.00392 | 0.000987 |
| Martial Stat | 1.1722 | 0.469293 | 2.5 | 0.013 | 0.252347 | 2.092053 |
| Job Stat | -0.03452 | 0.017542 | -1.97 | 0.049 | -0.06891 | -0.00014 |
| CountryBirth | -0.26096 | 0.148267 | -1.76 | 0.078 | -0.55157 | 0.029661 |
| Sex | 5.868491 | 27.56154 | 0.21 | 0.831 | -48.1544 | 59.89141 |
| Education | 0.02784 | 0.016559 | 1.68 | 0.093 | -0.00462 | 0.060297 |
| Health | 0.250489 | 0.029112 | 8.6 | 0 | 0.193427 | 0.307551 |
| Race | 0.088658 | 0.103522 | 0.86 | 0.392 | -0.11425 | 0.291569 |
| Dwave3 | -0.04251 | 0.016403 | -2.59 | 0.01 | -0.07466 | -0.01036 |
| Dwave4 | -0.04608 | 0.026876 | -1.71 | 0.086 | -0.09876 | 0.006602 |
| Dwave5 | -0.07537 | 0.035947 | -2.1 | 0.036 | -0.14583 | -0.00491 |

**Table 9: GMM estimation for Job Hours**

| ***Job Hours*** | ***Coef.*** | ***Std. Err.*** | ***t*** | ***P>t*** | ***[95% Conf.*** | ***Interval]*** |
|---|---|---|---|---|---|---|
| Job Hours Lag1 | 0.36309 | 0.021237 | 17.1 | 0 | 0.321464 | 0.404716 |
| Self Health | 0.033685 | 0.088016 | 0.38 | 0.702 | -0.13883 | 0.206205 |
| Travel Time | 0.272876 | 0.172017 | 1.59 | 0.113 | -0.06429 | 0.610044 |
| Travel Time 2 | -0.00253 | 0.001698 | -1.49 | 0.137 | -0.00586 | 0.000803 |
| Travel Mode | 0.001879 | 0.01022 | 0.18 | 0.854 | -0.01815 | 0.021912 |
| Martial Stat | -0.47355 | 2.835256 | -0.17 | 0.867 | -6.03091 | 5.083819 |
| Job Stat | 0.01636 | 0.052493 | 0.31 | 0.755 | -0.08653 | 0.119251 |
| CountryBirth | -0.02319 | 0.016081 | -1.44 | 0.149 | -0.05471 | 0.008332 |
| Sex | -2.53545 | 1.406842 | -1.8 | 0.072 | -5.29299 | 0.222091 |
| Education | 0.000928 | 0.009122 | 0.1 | 0.919 | -0.01695 | 0.018808 |
| Health | 0.305397 | 0.16276 | 1.88 | 0.061 | -0.01363 | 0.624422 |
| Race | 0.017552 | 0.027502 | 0.64 | 0.523 | -0.03635 | 0.07146 |
| Pay | 4.17E-05 | 1.51E-05 | 2.76 | 0.006 | 0.000012 | 7.13E-05 |
| Dwave2 | -0.19401 | 0.225792 | -0.86 | 0.39 | -0.63658 | 0.248563 |
| Dwave3 | -0.1526 | 0.165127 | -0.92 | 0.355 | -0.47626 | 0.171066 |
| Dwave4 | -0.13414 | 0.086049 | -1.56 | 0.119 | -0.30281 | 0.034523 |

**Table 10: GMM estimation for Job Satisfaction**

| ***Job Satisfaction*** | ***Coef.*** | ***Std. Err.*** | ***t*** | ***P>t*** | ***[95% Conf.*** | ***Interval]*** |
|---|---|---|---|---|---|---|
| Job Satisfaction Lag1 | 0.110879 | 0.021775 | 5.09 | 0 | 0.068197 | 0.15356 |
| Job Hours | 0.012536 | 0.005134 | 2.44 | 0.015 | 0.002472 | 0.022599 |
| Self Health | -0.01047 | 0.053093 | -0.2 | 0.844 | -0.11453 | 0.093601 |
| Travel Time | -0.07704 | 0.040417 | -1.91 | 0.057 | -0.15626 | 0.002181 |
| Travel Time2 | 0.000715 | 0.000394 | 1.82 | 0.07 | -5.7E-05 | 0.001486 |
| Travel Mode | -0.00024 | 0.00186 | -0.13 | 0.896 | -0.00389 | 0.003403 |
| CountryBirth | 0 | (omitted) | | | | |
| Sex | -71.1761 | 50.32109 | -1.41 | 0.157 | -169.81 | 27.45801 |
| Education | 19.94949 | 16.3594 | 1.22 | 0.223 | -12.1165 | 52.01545 |
| Health | 0.079455 | 0.062366 | 1.27 | 0.203 | -0.04279 | 0.201699 |
| Race | -42.8017 | 35.11659 | -1.22 | 0.223 | -111.634 | 26.03011 |
| Pay | 2.03E-06 | 3.33E-06 | 0.61 | 0.542 | -4.50E-06 | 8.57E-06 |
| Dwave3 | -0.13303 | 0.031943 | -4.16 | 0 | -0.19564 | -0.07042 |
| Dwave4 | -0.07683 | 0.033095 | -2.32 | 0.02 | -0.1417 | -0.01196 |
| Dwave5 | -0.11467 | 0.033869 | -3.39 | 0.001 | -0.18106 | -0.04828 |

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Appendices:

A.1 Self-Assessed Health FE Model

| *Self_Health* | *Coef.* | *Std. Err.* | *t* | *P>t* | *[95% Conf.* |
|---|---|---|---|---|---|
| Log of Distance | 0.021528 | 0.01092 | 1.97 | 0.049 | 0.000124 |
| Job Status | -0.00187 | 0.001925 | -0.97 | 0.331 | -0.00564 |
| Job Hours | -0.00081 | 0.000879 | -0.92 | 0.359 | -0.00253 |
| Traveltime | -0.00187 | 0.000958 | -1.95 | 0.051 | -0.00374 |
| Traveltime2 | 1.36E-05 | 7.66E-06 | 1.77 | 0.076 | -1.42E-06 |
| Health | 0.254963 | 0.015077 | 16.91 | 0.000 | 0.22541 |
| | | | | | |
| *Job Satisfaction* | | | | | |
| mostly dissatisfied | -0.01921 | 0.040615 | -0.47 | 0.636 | -0.09882 |
| somewhat dissatisfied | -0.02865 | 0.037256 | -0.77 | 0.442 | -0.10168 |
| neither satisfied or dissatisfied | -0.05064 | 0.037544 | -1.35 | 0.177 | -0.12423 |
| somewhat satisfied | -0.0557 | 0.035463 | -1.57 | 0.116 | -0.12521 |
| mostly satisfied | -0.10803 | 0.034979 | -3.09 | 0.002 | -0.17659 |
| completedly satisfied | -0.15109 | 0.036847 | -4.10 | 0.000 | -0.22331 |
| | | | | | |
| *Marital Status* | | | | | |
| married | 0.043906 | 0.036052 | 1.22 | 0.223 | -0.02676 |
| in a registered same-sex civil partnership | -0.07359 | 0.188506 | -0.39 | 0.696 | -0.44308 |
| separated but legally married | 0.123368 | 0.057167 | 2.16 | 0.031 | 0.011316 |
| divorced | 0.082404 | 0.055221 | 1.49 | 0.136 | -0.02583 |
| widowed | -0.25143 | 0.122784 | -2.05 | 0.041 | -0.4921 |
| separated from civil partner | -0.30552 | 0.36701 | -0.83 | 0.405 | -1.0249 |
| an ex-civil partner,civil p'ship legally dissolved | -1.01831 | 0.870631 | -1.17 | 0.242 | -2.72483 |
| surviving civil partner (partner died) | 0 | (omitted) | | | |
| countbirth | -9.3E-05 | 0.000571 | -0.16 | 0.871 | -0.00121 |
| qfhigh | 0.000987 | 0.000347 | 2.85 | 0.004 | 0.000307 |
| racel | -0.00217 | 0.000983 | -2.21 | 0.027 | -0.0041 |
| jbterm1 | -0.02319 | 0.025125 | -0.92 | 0.356 | -0.07243 |
| | | | | | |
| *Travel Mode* | | | | | |
| get a lift with someone from household | 0.091821 | 0.034951 | 2.63 | 0.009 | 0.023314 |
| get a lift with someone outside the household | 0.04994 | 0.042709 | 1.17 | 0.242 | -0.03378 |
| motorcycle/moped/scooter | 0.003645 | 0.087762 | 0.04 | 0.967 | -0.16838 |
| taxi/minicab | 0.012445 | 0.114248 | 0.11 | 0.913 | -0.21149 |
| bus/coach | 0.03208 | 0.033511 | 0.96 | 0.338 | -0.03361 |
| train | -0.0338 | 0.041668 | -0.81 | 0.417 | -0.11547 |

| | | | | | |
|---|---|---|---|---|---|
| underground/metro/tram/light railway | -0.04628 | 0.054059 | -0.86 | 0.392 | -0.15224 |
| cycle | -0.08903 | 0.042132 | -2.11 | 0.035 | -0.17162 |
| walk | 0.017119 | 0.030078 | 0.57 | 0.569 | -0.04184 |
| other | -0.01791 | 0.06942 | -0.26 | 0.796 | -0.15398 |
| Sex | -0.29176 | 0.36522 | -0.80 | 0.424 | -1.00763 |
| Pay | -1.75E-06 | 1.15E-06 | -1.52 | 0.129 | -4.00E-06 |
| Age | 0.010735 | 0.003476 | 3.09 | 0.002 | 0.003922 |
| _cons | 2.060147 | 0.220858 | 9.33 | 0.000 | 1.627244 |

### A.2 Job Hours Fixed Effects Model

| *Job Hours* | *Coef.* | *Std. Err.* | *t* | *P>t* | *[95% Conf.* | *Interval]* |
|---|---|---|---|---|---|---|
| Log of Distance | 0.330492 | 0.089896 | 3.68 | 0 | 0.154287 | 0.506697 |
| Job Status | -0.04477 | 0.016316 | -2.74 | 0.006 | -0.07675 | -0.01279 |
| Traveltime | 0.00823 | 0.003956 | 2.08 | 0.037 | 0.000476 | 0.015983 |
| Health | -0.06566 | 0.128814 | -0.51 | 0.61 | -0.31814 | 0.186831 |
| | | | | | | |
| Job Satisfaction | | | | | | |
| mostly dissatisfied | -0.25095 | 0.344314 | -0.73 | 0.466 | -0.92583 | 0.423942 |
| somewhat dissatisfied | 0.347039 | 0.31584 | 1.1 | 0.272 | -0.27204 | 0.966116 |
| neither satisfied or dissatisfied | 0.003128 | 0.318275 | 0.01 | 0.992 | -0.62072 | 0.626977 |
| somewhat satisfied | 0.315737 | 0.300627 | 1.05 | 0.294 | -0.27352 | 0.904994 |
| mostly satisfied | 0.379446 | 0.296581 | 1.28 | 0.201 | -0.20188 | 0.960773 |
| completedly satisfied | 0.042222 | 0.312469 | 0.14 | 0.893 | -0.57025 | 0.654692 |
| | | | | | | |
| Martial Status | | | | | | |
| married | -0.00302 | 0.305674 | -0.01 | 0.992 | -0.60216 | 0.596135 |
| in a registered same-sex civil partnership | -0.40631 | 1.598093 | -0.25 | 0.799 | -3.53873 | 2.726107 |
| separated but legally married | 0.324873 | 0.484701 | 0.67 | 0.503 | -0.62519 | 1.274932 |
| divorced | 0.232861 | 0.468189 | 0.5 | 0.619 | -0.68483 | 1.150556 |
| widowed | -1.27681 | 1.041101 | -1.23 | 0.22 | -3.31747 | 0.763851 |
| separated from civil partner | -0.78737 | 3.111435 | -0.25 | 0.8 | -6.88608 | 5.311339 |
| ex-civil partner,civil p'ship legally dissolved | 2.88107 | 7.381078 | 0.39 | 0.696 | -11.5866 | 17.34869 |
| surviving civil partner (partner died) | 0 | (omitted) | | | | |
| | | | | | | |
| Country Birth | 0.002415 | 0.004844 | 0.5 | 0.618 | -0.00708 | 0.011909 |
| Education | 0.002381 | 0.00294 | 0.81 | 0.418 | -0.00338 | 0.008143 |
| Race | 0.010665 | 0.008331 | 1.28 | 0.201 | -0.00566 | 0.026994 |
| job Term | -2.63931 | 0.212125 | -12.44 | 0 | -3.05509 | -2.22352 |
| Seex | -5.56543 | 3.095951 | -1.8 | 0.072 | -11.6338 | 0.502932 |
| Self Health | -0.06249 | 0.063197 | -0.99 | 0.323 | -0.18636 | 0.06138 |
| | | | | | | |
| Travel Mode | | | | | | |
| get a lift with someone from household | -0.86288 | 0.296264 | -2.91 | 0.004 | -1.44358 | -0.28217 |
| get a lift with someone outside the household | -0.6988 | 0.362089 | -1.93 | 0.054 | -1.40853 | 0.010925 |
| motorcycle/moped/scooter | 0.512964 | 0.74402 | 0.69 | 0.491 | -0.94539 | 1.971313 |
| taxi/minicab | -0.04524 | 0.968542 | -0.05 | 0.963 | -1.94367 | 1.853198 |
| bus/coach | -0.83166 | 0.282603 | -2.94 | 0.003 | -1.38559 | -0.27773 |
| train | -0.45512 | 0.353098 | -1.29 | 0.197 | -1.14723 | 0.236981 |

| | | | | | | |
|---|---|---|---|---|---|---|
| underground/metro/tram/light railway | -0.15315 | 0.45757 | -0.33 | 0.738 | -1.05003 | 0.743732 |
| cycle | -0.11073 | 0.357054 | -0.31 | 0.756 | -0.81059 | 0.589128 |
| walk | -1.15893 | 0.25369 | -4.57 | 0 | -1.65618 | -0.66167 |
| other | 0.252171 | 0.588515 | 0.43 | 0.668 | -0.90137 | 1.405717 |
| | | | | | | |
| Pay | 0.029572 | 0.004987 | 5.93 | 0 | 0.019798 | 0.039346 |
| Usualpay | 2.66E-05 | 2.73E-05 | 0.98 | 0.329 | -2.7E-05 | 0.00008 |
| Age | 0.041835 | 0.029473 | 1.42 | 0.156 | -0.01594 | 0.099605 |
| _cons | 35.4366 | 1.856235 | 19.09 | 0 | 31.7982 | 39.075 |

### A.3 Job Satisfaction Fixed Effects Model

| *Job Satisfaction* | *Coef.* | *Std. Err.* | *t* | *P>t* | *[95% Conf.* | *Interval]* |
|---|---|---|---|---|---|---|
| Log of Distance | 0.009868 | 0.020058 | 0.49 | 0.623 | -0.02945 | 0.049183 |
| Job Status | -0.00085 | 0.003447 | -0.25 | 0.805 | -0.00761 | 0.005906 |
| Travel Time | -0.00514 | 0.001753 | -2.93 | 0.003 | -0.00858 | -0.00171 |
| Travel Time2 | 4.32E-05 | 0.000014 | 3.09 | 0.002 | 1.58E-05 | 7.06E-05 |
| Health | -0.05519 | 0.027922 | -1.98 | 0.048 | -0.10992 | -0.00046 |
| | | | | | | |
| Marital Status | | | | | | |
| married | -0.00769 | 0.066432 | -0.12 | 0.908 | -0.13791 | 0.122521 |
| in a registered same-sex civil partnership | 0.167916 | 0.347361 | 0.48 | 0.629 | -0.51294 | 0.848776 |
| separated but legally married | 0.107169 | 0.105283 | 1.02 | 0.309 | -0.0992 | 0.313535 |
| divorced | 0.004056 | 0.101622 | 0.04 | 0.968 | -0.19513 | 0.203244 |
| widowed | -0.22965 | 0.226257 | -1.02 | 0.31 | -0.67314 | 0.213835 |
| separated from civil partner | -0.31963 | 0.676201 | -0.47 | 0.636 | -1.64505 | 1.005787 |
| ex-civil partner,civil p'ship legally dissolved | -2.94275 | 1.604041 | -1.83 | 0.067 | -6.08682 | 0.201324 |
| surviving civil partner (partner died) | 0 | (omitted) | | | | |
| | | | | | | |
| countbirth | -0.00302 | 0.001052 | -2.87 | 0.004 | -0.00508 | -0.00096 |
| qfhigh | -0.00081 | 0.000637 | -1.26 | 0.206 | -0.00205 | 0.000443 |
| racel | 0.001464 | 0.001809 | 0.81 | 0.419 | -0.00208 | 0.00501 |
| jbterm1 | -0.05736 | 0.045799 | -1.25 | 0.21 | -0.14713 | 0.032411 |
| self_health | -0.08984 | 0.013692 | -6.56 | 0 | -0.11668 | -0.063 |
| | | | | | | |
| Travel Mode | | | | | | |
| get a lift with someone from household | 0.018334 | 0.064214 | 0.29 | 0.775 | -0.10753 | 0.144199 |
| get a lift with someone outside the household | 0.0934 | 0.078488 | 1.19 | 0.234 | -0.06044 | 0.247245 |
| motorcycle/moped/scooter | -0.10055 | 0.160889 | -0.62 | 0.532 | -0.41591 | 0.214804 |
| taxi/minicab | 0.155697 | 0.21051 | 0.74 | 0.46 | -0.25692 | 0.568317 |
| bus/coach | 0.143087 | 0.061615 | 2.32 | 0.02 | 0.022315 | 0.263858 |
| train | 0.033565 | 0.076681 | 0.44 | 0.662 | -0.11674 | 0.183867 |
| underground/metro/tram/light railway | 0.187704 | 0.099529 | 1.89 | 0.059 | -0.00738 | 0.382791 |
| cycle | -0.16098 | 0.077585 | -2.07 | 0.038 | -0.31305 | -0.00891 |
| walk | 0.000251 | 0.055287 | 0 | 0.996 | -0.10812 | 0.108619 |
| other | 0.034232 | 0.127898 | 0.27 | 0.789 | -0.21646 | 0.284924 |
| | | | | | | |
| Sex | 0.185902 | 0.672909 | 0.28 | 0.782 | -1.13306 | 1.504868 |
| Pay | 6.07E-07 | 2.12E-06 | 0.29 | 0.775 | -3.56E-06 | 4.77E-06 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Usual Pay | -3.23E-06 | 5.93E-06 | -0.54 | 0.586 | -1.5E-05 | 8.40E-06 |
| Age | -0.04448 | 0.006354 | -7 | 0 | -0.05693 | -0.03202 |
| _cons | 7.329482 | 0.397203 | 18.45 | 0 | 6.550927 | 8.108037 |

## A.4 Self Assessed Health BUC Estimator

| ***Self Health*** | ***Coef.*** | ***Std. Err.*** | ***z*** | ***P>z*** | ***[95% Conf.*** | ***Interval]*** |
|---|---|---|---|---|---|---|
| Distance | 0.089633 | 0.213886 | 0.42 | 0.675 | -0.32958 | 0.508842 |
| Travel Time | -0.00197 | 0.178068 | -0.01 | 0.991 | -0.35098 | 0.347034 |
| Health | 0 | (omitted) | | | | |
| Jobhours | -0.12766 | 0.286882 | -0.45 | 0.656 | -0.68994 | 0.434615 |
| Sex | 0 | (omitted) | | | | |
| Age | 1.106569 | 0.562287 | 1.97 | 0.049 | 0.004507 | 2.208632 |
| Race | 0 | (omitted) | | | | |
| Job Term | -27.4321 | 22.43304 | -1.22 | 0.221 | -71.4 | 16.53588 |
| Job Status | 0.53658 | 7.252557 | 0.07 | 0.941 | -13.6782 | 14.75133 |
| Education | 0 | (omitted) | | | | |

## A.5 Job Satisfaction BUC Estimator

| ***Job Satisfaction*** | ***Coef.*** | ***Std. Err.*** | ***z*** | ***P>z*** | ***[95% Conf. Interval]*** | |
|---|---|---|---|---|---|---|
| Distance | -0.40421 | 0.738528 | -0.55 | 0.584 | -1.851694 | 1.043282 |
| Traveltime | -0.27233 | 0.348314 | 0.78 | 0.434 | -.4103522 | .9550122 |
| Health | 0 | (omitted) | | | | |
| Job Hours | -0.87158 | 0.849774 | -1.03 | 0.305 | -2.537109 | .7939421 |
| Sex | 0 | (omitted) | | | | |
| Race | 0 | (omitted) | | | | |
| Job Status | -3.14149 | 2.498316 | -1.26 | 0.209 | -8.038097 | 1.755123 |
| Education | 0 | (omitted) | | | | |
| Travel Mode | 2.583359 | 1.746814 | 1.48 | 0.139 | -.8403334 | 6.007052 |