Exploring the relationship between commuting, health, well-being and job satisfaction: econometric insights

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Exploring the relationship between commuting, health, well-being and job satisfaction: Econometric insights

by

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DEDICATION

To my Mother,
whose enormous love,
sacrifice and encouragement
have granted me strength to go further.

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Abstract

Commuting is an unavoidable activity of daily working life, which helps us to get from home to work and vice versa. However, such activity can be stressful and reduce the time available for family and leisure. Indeed, negative effects of commuting on health and subjective well-being (SWB) have been found in the literature. However, not many studies have investigated the influence of commuting on a commuter's job satisfaction. With its link to performance at work, an examination of the effect of commuting on job satisfaction is likely to be useful in enhancing the general welfare of working-aged people. Moreover, apart from the individual connections with commuting, health, SWB and job satisfaction are potentially related to one another. Thus, exploring each of these three variables while controlling for the others would provide a clearer picture of the effects of commuting. Because of the endogeneity implied in these relationships, the literature has applied fixed effect (FE) models to control for time-invariant individual heterogeneity. However, the potential for reversed causality between the variables of interest calls for a more robust econometric technique to identify the causal relationships between commuting, health, SWB and job satisfaction. Without comprehensive control of multiple endogeneity sources, regression estimations can only provide association inference, rather than causal connections.

This thesis adopts a FE panel data analysis of the effects of commuting on SWB, health and job satisfaction. The first empirical study in Chapter 4 finds a negative association between commuting time and health. Private and public transport modes are both linked with deteriorating health, whereas cycling can improve it. The findings are consistent over subsamples in which regional and gendered differences are explored. Moreover, instrumental variables (IVs), together with the Generalised Method of Moments (GMM) estimator in linear FE models are employed in Chapter 5 to control for the endogeneity issues intrinsic to the study. This approach can strengthen causal insight, which is missing in the literature, and the thesis is one of the first studies to have employed IV in the investigation of potential commuting effects on health, SWB and job satisfaction. Chapter 5 identifies that longer time spent on active commuting can causally raise commuters' health. It is also likely that active commuting can indirectly improve satisfaction at work and with overall life.

Keywords: subjective well-being, SWB, Understanding Society, The UK Household Longitudinal Study, endogeneity, heterogeneity, reverse causality, simultaneity, fixed effects, life satisfaction, job satisfaction, health, commuting, commuting time, commuting modes, active commuting, instrumental variables, Generalized method of moments

LIST OF ABBREVIATIONS

BHPS	British Household Panel Survey
CBD	Central Business District
FE	Fixed effects
GMM	Generalized method of moments
IV	Instrumental variable
OECD	The Organisation for Economic Co-operation and Development
ONS	Office for National Statistics
POLS	Pooled Ordinary Least Squares
RE	Random effects
SWB	Subjective well-being
UK	The United Kingdom
UKHLS	The UK Household Longitudinal study (official acronym for Understanding Society)

Table of Content

LIST OF TABLES

LIST OF FIGURES

1 - INTRODUCTION

1.1. Background

Commuting is an essential activity of daily life which acts as a connection between home and work. It reflects the mobility of workforce and is a determinant of job choice (Rouwendal, 2004). On average, British commuters spend 30 minutes on a one-way trip from home to work and vice versa (Department for Transport, 2019), which is equivalent to an average of 139 hours in a year (Lyons and Chatterjee, 2008). Although companies have implemented work-from-home initiatives, commuting is still a large component of working life that is not likely to disappear in the near future. Time is a scarce resource (Becker, 1965) and with such a considerable portion of time spent on commuting, further causal analysis is needed to investigate the broader effects of commuting.

The urban economics literature has proposed that longer commuting duration is acceptable if the commuter is compensated by either better housing or higher salary (White, 1988). However, longer commuting time is often associated with stress and fatigue, and experiences during the commute trip can trigger subsequent negative mood upon arrival to work (Koslowsky, Kluger and Reich, 1995). Thus, it is plausible to anticipate that the longer the commuting duration, the more pessimistic commuters would feel in terms of their health and subjective well-being, which may consequently affect their job satisfaction. A study on commuting effects on health, subjective well-being (SWB) and job satisfaction is therefore pertinent for commuters' welfare and organisations' profitability.

Commuting is more than just the distance travelled and duration of time involved. Several transport modes are available for the purpose of commuting, although the variety may depend on local transport systems. The choice of commuting mode can have significant bearing on the commuter's health, SWB and job satisfaction. A car may offer privacy and convenience

(Gärling *et al.*, 2002), for example when the commuter needs to carry heavy objects (Shephard, 2008) or link the commute trip with household responsibilities, such as escorting children to school (Roberts, Hodgson and Dolan, 2011). Nevertheless, the use of a car can intensify air and noise pollution which can have implications on public health (European Commission, no date; Lyons and Chatterjee, 2008; Karanasiou *et al.*, 2014). It can also impose on commuters the sedentary cost of sitting idly for too long (Thorp *et al.*, 2011; Wilmot *et al.*, 2012). Additionally, car commuting may be subject to unpredictable events, for instance traffic congestion and may originate the perception of lack of control (Koslowsky, Kluger and Reich, 1995; Gottholmseder *et al.*, 2009). For public transport modes, there is likely to be some walking or cycling at either end of the journey or between changes so that the effect on health may be not as severe. However, public modes can make commuters experience unpredictability from delays, as well as inconvenience from crowded service or inflexible timetables (Cox, Houdmont and Griffiths, 2006). Alternatively, active commuting, which can be either walking or cycling, integrates physical activities into commuters' daily routine. Hence, it is likely to expect active commuting to be associated with better health (e.g. Hamer and Chida, 2008; Laverty *et al.*, 2013). Yet, walking and cycling as a means of commuting to work may be appreciated differently from recreational physical activities and be viewed more as a chore (Humphreys, Goodman and Ogilvie, 2013; Morris, 2015). Overall, different modes of transport may have notably different, if not contradictory, influences on the health, SWB and job satisfaction of commuters. These issues are discussed in depth in Section 2.4 below.

Moreover, there can be differences in the effects of commuting time and modes between genders because of the gender imbalance at workplace and within households. Finally, variations between local transport systems may create differentiated findings between regions.

1.2. Aims, research questions and objectives

The thesis aims to explore how commuting affects health, SWB and job satisfaction of individuals. This can contribute to understanding the consequences of commuting habits on commuters.

To achieve this aim, the thesis will focus on answering the following detailed research questions:

- Does commuting time affect health, SWB and job satisfaction?
- What are the effects of different commuting modes, and especially active travel modes, on health, SWB and job satisfaction?

Rather than just exploring associations, the thesis aims to produce causal inference between commuting and health, SWB and job satisfaction because this provides insight into cause and effect. Moreover, cities across European countries have transformed to become less compact and this phenomenon of urban sprawl necessitates the use of private transport modes which accompanies air and noise pollutions while reducing the chance for walking and cycling (European Environment Agency, 2006). In 2018, 64% of English citizens are either overweight or obese which are linked to serious health risks such as diabetes and the trend is increasing over the years (National Health Service, 2018). If active commuting is promoted successfully, the National Health Service (NHS) can release billions of pound from spending on diseases such as type II diabetes (Jarrett *et al.*, 2012). Findings on any possible causal effects of active commuting on commuters' health, SWB and job satisfaction can add to the justification of active transport's benefits. Thus, active commuting is the focal point in one of the empirical studies that focuses explicitly on causal relationships.

As the aim and detailed research questions are set, the thesis requires objectives, which forms a step-by-step action plan to help construct the thesis's structure. Firstly, the literature on commuting effect is reviewed, including theories and empirical studies, to identify any gaps within the topic. After that, a suitable data source that collects information for the variables of interest is chosen, together with potential econometric techniques that are applicable to the research questions. Empirical studies are then carried out. The first empirical chapter will examine any possible associations between commuting, including duration travelled and transport modes chosen, and the dependent variables of interest. Explorations of causal connections between active commuting and health, SWB and job satisfaction are then performed in the second empirical chapter. Finally, findings from the two empirical chapters are reflected on the aims and research questions detailed above to derive implications for the literature and future research.

1.3. Thesis structure

This thesis is organised as follows. Chapter 2 presents a review of the current literature on the potential effects of commuting on health, SWB and job satisfaction. Findings from the literature should help to pinpoint the areas that demand further research. These gaps underpin and justify the thesis's aims and more detailed research questions. Chapter 3 will examine any economic theories underlying commuting and its impacts which together with the literature review from Chapter 2 can provide guidance on the choice of variables for analysis. Conceptual issues existing within the models are discussed, which lead to the exploration of potential econometric techniques that can resolve these issues including linear Fixed effects (FE) models and the Generalized methods of moment (GMM) estimation approach with the use of instrumental variables (IVs). As the thesis focuses on empirical findings, the chapter introduces the main data source from the UK Household Longitudinal Survey (UKHLS) and variables employed throughout the thesis, including independent variables, dependent variables and a common set of control variables from the literature. Possible IVs are also described in this section. Drawn from all the details discussed prior in the chapter, the thesis's research design is then provided. The subsequent two chapters present the empirical studies that investigate the proposed research questions and contribute towards a solution for the thesis' aim. Chapter 4 offers empirical findings on linear FE models of any associations between commuting and health, SWB and job satisfaction in which commuting time and various transport modes are considered as well as heterogenous effects between genders and between regions. Chapter 5 then demonstrates the findings of the linear FE models in which the GMM estimation approach is applied with relevant and valid IVs discovered from the UKHLS data source. The GMM estimation approach is a powerful econometric technique that enables causal inference and offers novel findings for the literature on the causal influence of active commuting on health, SWB and job satisfaction. Finally, Chapter 6 presents how the empirical findings from the two previous chapters meet the thesis' aims, objectives and research questions. Also, implications for the literature and any limitations are presented and conclude the thesis.

From the empirical analysis in Chapter 4, it has been found that commuting generally is associated with lower health, especially if the commuter used either private or public transport modes. Public modes are also linked with reduced SWB and job satisfaction's scores of an average commuter. However, better health is connected with increased use of cycling. Focusing on the causal inference of active commuting with the support from IVs, Chapter 5 identifies that longer time spending on active modes can directly increase a commuter's health, and also indirectly improve SWB and job satisfaction of that person via the interconnection between health, SWB and job satisfaction. The literature requires more research on the implication of commuting on job satisfaction. Moreover, even though there are potential interconnections between health, SWB and job satisfaction determined throughout the literature, not many studies have included those variables in the models of one another when commuting effects are explored. Those interconnections can in turn restrict clear causal conclusions of the relationships between commuting, health, SWB and job satisfaction. Hence, the thesis seeks to close those gaps with the above findings of the negative associations between public commuting and job satisfaction. Other commuting modes, on the contrary, have little to no significant connections with job satisfaction. Furthermore, the variables health, SWB and job satisfaction are included in the models of one another and IVs are used to control for endogeneity issues stemming from their interrelations. To the best of the researcher's knowledge, no attempts have been made to apply IVs to derive causal inference in this topic area, and the positive causal results of active commuting yield strong evidences to support simple associations drawn from previous studies.

2 - LITERATURE REVIEW

2.1. Introduction

This chapter presents a general review of the current literature on commuting, especially how different commuting modes affect the general health, SWB and job satisfaction of workers. The benefits of active travel would be particularly examined in comparison with non-active travel modes. Section 2.2 introduces general definitions of the variables of interest, including commuting, health, SWB and job satisfaction. Section 2.3 describes the determinants of commuting mode choice and duration, whereas the effects of commuting on health, SWB and job satisfaction are evaluated in Section 2.4. Even though the commuting effects on health and SWB have been widely investigated in the literature, job satisfaction has not been considered when potential effects of commuting are studied. Moreover, health, SWB and job satisfaction are likely to link with each other and understanding the commuting effects on these three variables may be beneficial in improving workers' productivity and working experience. No research on commuting appears to have considered these interrelationships. The general literature has acknowledged the existence and studied each pair-wise relationship intensively. The thesis will review the literature on the pair-wise relationships in Section 2.5. Studies have included the variables of interest in each individual model, for instance, job satisfaction has been included as a control variable in models for health and SWB (Andersson, 2008; Park, Han and Kim, 2018), however no study has either focused explicitly on the three variables or controlled for their reversed causalities. Thus, Section 2.5 provides a brief examination of findings in the literature on the pairwise relationships between the three variables health, SWB and job satisfaction. With all the preceding sections reviewing the current literature on commuting, health, SWB and job satisfaction, the chapter then identifies in Section 2.6 several substantial gaps in the literature. The first gap is the lack of studies on how commuting can affect commuters' satisfaction in the workplace, which in turn would be useful to improve productivity of the workforce. Furthermore, due to the potential interlinks between health, SWB and job satisfaction, including them in each other's models would undoubtedly strengthen any findings on the impact of commuting. Finally, the chapter is concluded in Section 2.7.

2.2. Definitions

This section provides the common definitions for key variables in this thesis. Section 2.2.1 discusses active travel in the context of commuting. Subsequent subsections focus on health, SWB and job satisfaction which are the three dependent variables of interest in this thesis.

2.2.1. Commuting

Commuting is the act of travelling from home to work and vice versa. It is an essential part of daily time use and working life. The act of commuting varies in terms of duration, distance and complexity during a person's life (Wheatley and Bickerton, 2016). However, for most individuals, commuting is a regular journey for a short time period of the day (Green and Owen, 2006). Most people commute to the exact work location every day and do not need a lot of planning ahead. They can also combine commuting with various activities related to home, such as escorting children to school (Bhat, 1997).

Active commuting is the modes of travel to and from work that require physical activity. Thus, it can involve commuting exclusively by walking and/or cycling; or a combination of walking or cycling and motorised transport modes (Jones and Ogilvie, 2012). For example, taking public transport has been regarded by some studies (e.g. Fan, Wen and Kowaleski-Jones (2015)) as active travel because it may require walking or cycling at either end of the journey. Moreover, the World Health Organisation considers physical inactivity as one of the major sources of mortality and active travelling, including walking and cycling one of the physical activities recommended (World Health Organization, 2010). The main weekly physical activity recommendations for adults to develop health and fitness and limit non-communicable conditions are as follows:

> "Adults aged 18–64 years should do at least 150 minutes of moderate-intensity aerobic physical activity throughout the week, or do at least 75 minutes of vigorous-intensity aerobic physical activity throughout the week, or an equivalent combination of moderate- and vigorous-intensity activity."
>
> (World Health Organisation, 2010, p. 8)

The UK National Health Service recommends that adults of age 19 to 64 should have some physical activity daily. Similar to the World Health Organisation's, their latest recommendations include:

> "Adults should:
>
> ¶ aim to be physically active every day. Any activity is better than none, and more is better still
>
> ¶ do strengthening activities that work all the major muscles (legs, hips, back, abdomen, chest, shoulders and arms) on at least 2 days a week
>
> ¶ do at least 150 minutes of moderate intensity activity a week or 75 minutes of vigorous intensity activity a week
>
> ¶ reduce time spent sitting or lying down and break up long periods of not moving with some activity."
>
> (National Health Service, 2019)

Thus, active commuting integrates physical activity into a person's daily routine and in turn contributes to their physical activity requirement (Fan, Wen and Kowaleski-Jones, 2015). However, car use is the most popular mode both for travelling in general and specifically for the purpose of commuting in the UK (Sullivan, Kershaw and Cummings, 2016). Despite the fact that using cars involves less exercise, this trend in car using can be due to the perceived characteristics associated with cars other than travel duration and journey cost, such as flexibility, comfort and security (Eriksson, Friman and Gärling, 2013).

In theory, commuters are assumed to have control over the commuting journey's distance and duration via their job and housing location choices (Mills, 1967). However, in reality, there are limitations to their commuting choices which are connected to local job availabilities, requirements at work, housing markets and the commuting routines of other household members (Sandow, 2008). Challenges exist in dual-career households in linking two different commute paths. If no solutions of a convenient residential location are found, it would lead to compromise which is often borne by the female partner. They are more likely to choose jobs that are closer to home and forgo more diverse opportunities that may require higher mobility but offer career advancements (Sandow, 2008; Wheatley, 2014).

2.2.2. Subjective well-being

The research on SWB has only emerged since the second half of the 20th century (Diener, 1984), but it has received immense attention from both public policy and academia. In academic literature, there has been tremendous interest in SWB with approximately 170,000 pieces of research published recently (Diener, Lucas and Oishi, 2018) from multiple disciplines, such as social science, psychology and economics. In the context of Government policy, it is widely recognised that the monetary measure Gross Domestic Product (GDP) of each country is not a representative indicator of that country's welfare, or happiness (Stiglitz, Sen and Fitoussi, 2009). GDP is an aggregation of all the services and products produced within a country. Policies focusing on GDP would fail to acknowledge well-being in a more social context, such as health and poverty. In 2010, the then UK prime minister, David Cameron, delegated the newly launched Measuring National well-being programme to the Office for National Statistics (ONS) to put a focus on British citizens' well-being beside economic growth measures[1]. He argued that traditional measures of economic growth did not give an accurate reflection of national well-being and new measures in terms of quality of life are required. SWB is a conceptual approach that can measure the quality of life (Stiglitz, Sen and Fitoussi, 2009). Its best advantage is its reliance on individuals' own evaluations which can combine the individuals' diverse experiences and express their unique preferences.

The OECD Guidelines on measuring SWB provide a broad definition of SWB as

> "good mental states, including all of the various evaluations, positive and negative, that people make of their lives, and the affective reactions of people to their experiences".
>
> (OECD, 2013, p. 29)

which is meant to cover all separable factors of SWB that have been recognised by different researchers.

SWB is the degree to which a person feels about the quality of their life and the term "subjective" signifies that this is a person's own evaluation of their well-being (Diener, Lucas and Oishi, 2018). It hopes to measure the experience of a person based on their own chosen criteria. It can depend on objective correlates such as income, health, education, however they are not its constituents (Diener, 1984). It is, therefore, different from a more

[1] https://www.gov.uk/government/speeches/pm-speech-on-wellbeing

comprehensive concept of well-being that may involve more objective features (Figure 2.1). However, Diener and his colleagues (2018) argue that such subjective characteristics makes SWB a better proxy measure for well-being. Individuals may consider the same objective life events differently due to differences in individuals' inherent characteristics and background. As a subjective measure, SWB is more likely to reflect these individually unique characteristics better than objective measures. Figure 2.1 below is constructed based on common well-being concepts studied in the literature.

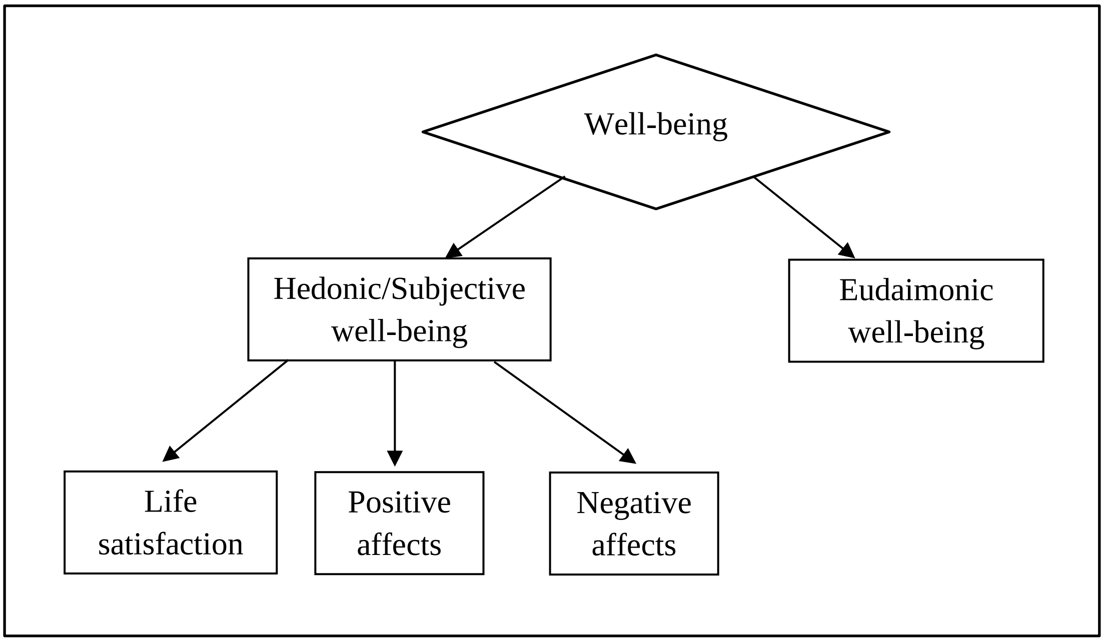

Figure 2.1: Components of well-being

SWB is derived from the hedonic view of well-being (Figure 2.1), in which the focus is on gaining pleasure and happiness and avoiding pain and discomfort (Kahneman, 1999). SWB reflects a person's evaluation of their quality of life. It can include cognitive evaluation of their overall life and its domains, and/or affective assessment involving their emotions and feelings (Diener *et al.*, 2017). The first component – cognitive life evaluation, or life satisfaction in Figure 2.1, is defined as self-evaluations of a person about their life as a whole or some specific domains of their life, such as their health, relationships, etc (Diener, 2006;

OECD, 2013). A standard is formed by the person based on what they think is appropriate for their life and then that standard is compared with their current situations in order for the person to deduct a self-evaluation of life satisfaction (Diener, 1984; Pavot *et al.*, 1991). Satisfaction with specific life domains may contribute to how a person assesses their overall quality of life, however different people are likely to attach different weights to each domain. It can be improved if the measures of different domains are aggregated into one measure. However, even then the choice of domains to be included in the measure depends on the researcher. Thus, a measure of overall life satisfaction is more appropriate than a sum of measures of different life domains (Diener *et al.*, 1985; Pavot *et al.*, 1991). The second component of SWB is affect. Affects are a person's feelings towards events in their life at a specific point in time (Diener *et al.*, 1999; OECD, 2013). Unlike life satisfaction being an overall self-evaluation measure, affect has two different aspects that need to be measured separately. Positive affects concern pleasant emotions such as joy, happiness, whereas negative affects comprise of unpleasant emotions such as sadness, anger, etc (Figure 2.1). Both types of affects can be temporary emotions such as excitement and sadness, as well as more long-term feelings of contentment or depression (Diener *et al.*, 2017). As suggested by Bradburn (1969), positive and negative affects are likely to be separate parts of SWB because the absence of one does not guarantee the existence of the other. Diener *et al.* (1985) provide an explanation of the (in)dependence of the two affects components. The two concepts involve the frequency and intensity dimensions of emotions. If the frequency dimension is being considered, they should be inversely related: if an individual is having positive affects more regularly, they are likely to experience negative emotions less often. Alternatively, the average levels of positive and negative affects over some time period, which take into account both dimensions of affects, tend to be independent from one another. This finding means that in terms of emotional intensity, positive and negative affects have to vary in the same direction so that the averages can be independent of each other.

Moreover, SWB is sometimes assumed to contain an additional component of eudaimonic well-being (Dolan, Layard and Metcalfe, 2011; OECD, 2013), which represents components of individuals' perceptions on their well-being which are not reported by their cognitive life satisfaction judgements and affects. It is referred as "psychological well-being" and more popular in the literature of psychology. Eudaimonic well-being attempts to reflect human's psychological requirement to feel that their life has meanings, they can have control over themselves and experience meaningful relationships with others (Ryff, 1989). Other characteristics in a human's life that this measure wishes to report include independence, personal growth, competence (Ryff, 1989; Tinkler and Hicks, 2011). Nevertheless, Diener, Lucas and Oishi (2018) suggest that eudaimonic well-being should be kept separated because it does not connect directly to their version of SWB, which is a global judgement of one's life quality from the point of view of themselves. The argument is that engagement with others may be important for well-being, however it should be treated as a covariate instead of a component of SWB. Moreover, even though the two concepts of SWB and eudaimonic well-being can sometimes overlap (Kashdan, Biswas-Diener and King, 2008), hedonic well-being and eudaimonic well-being have been two distinct perspective of well-being established in the literature (Ryan and Deci, 2001). Hence, it is treated as a separate factor of general well-being in Figure 2.1.

Researchers examine both SWB components - life satisfaction and human's affects, which have been found to be related to one another in the empirical literature. Life satisfaction is found to be related positively with positive affect and negatively with negative affect (Busseri and Sadava, 2011). It emphasises more on overall cognitive assessment of quality of life, whereas positive and negative affect focus on evaluation of emotions experienced. However, in the context of overall quality of life, human's affects, or affect evaluation, may not be the best measure. Affective evaluation involves emotions experienced by the respondent, which can be influenced by multiple factors and may not demonstrate their own judgement of the state of life (Diener, Lucas and Oishi, 2018). Diener (1984) argues that the measure of SWB should involve and focus on a global measure of a person's life as whole.

Moreover, some of the most popular SWB measures are single-item questions within survey studies which come with the advantage of being concise and compact (Diener, 1984). Although multiple-item measures can be more reliable, single-item measures have been found to possess adequate temporal reliability scores (Pavot and Diener, 1993). Single-item measures have also been found to have considerable criterion validity scores and behave similarly to the multiple-item Satisfaction with Life Scale (Diener, Emmons, *et al.*, 1985) when correlations between SWB measures and theoretically relevant variables are examined (Cheung and Lucas, 2014). Therefore, the validity and reliability of single-item measures support their adequacy in SWB research when a general global measure is needed.

2.2.3. Health

Health is defined by the World Health Organization (WHO) as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity (World Health Organization, 2006, p. 1). Mental health is an important aspect of health and according to the previous definition on health, the absence of mental conditions is not enough to define mental health. It is a cognitive state in which a person recognises their own potentials, is able to handle daily strain to perform effectively and contribute to the wider society (World Health Organization, 2018).

Health and well-being are overlapping factors whose distinctions are not always clear-cut in the literature. However, studies have employed distinct measures of health and SWB and found differentiated findings between their models (e.g. a study of physical acitivity by Rasciute and Downward, 2010; a study on commuting effects by Clark *et al.*, 2019). Hence, it is valid to regard the two concepts as related but distinguishable. Moreover, there are objective and subjective measures of general health, yet it is possible that the objective measures employed may not be an optimal measure (Diener, Lucas and Oishi, 2018). Diener and his colleagues (2018) provide an example that if a medical practitioner provides their assessment on a person's health as an objective measure, it may not take into account all the disorders that the person is experiencing and/or the potential influence of such conditions on their view.

2.2.4. Job satisfaction

As mentioned above, the global cognitive part of SWB can be made up of satisfaction of several life domains, including family, leisure time, work, etc. Job satisfaction is one of the domain-specific components of SWB. There are significant correlations connecting global cognitive, affective and domain-specific parts of SWB (Ettema *et al.*, 2010).

Job satisfaction is the level of satisfaction that a person feels in their job, including satisfaction with several job domains such as working conditions, development and training and work-life balance (Drobnič, Beham and Präg, 2010). Job satisfaction can be enhanced by improvements in domains of the job, and these changes can come from either the employee lowering their expectations or redistributing their weights on the job's domains with less weights placing on displeasing domains (Gazioğlu and Tansel, 2006). Nowadays, researchers focus more on the cognitive aspects of satisfaction at work, whereas studies in the past tended to follow Maslow's (1943) human motivation theory and emphasize on whether organizations could satisfy employees' personal needs, such as needs for achievement, for change (e.g. Kuhlen, 1963). Job satisfaction, according to Spector (1997, p.2), is either an overall feeling of a person for their job or a range of their attitudes towards that job's various facets. The global measure can be used when an overall satisfaction of one's job is of interest, whereas satisfaction with different job domains may be helpful for employers to identify areas for improvement (Lu, While and Louise Barriball, 2005). Common job aspects can be separated into four groups: company settings, nature of one's job, other people and rewards. The correlations between the satisfaction levels for different job aspects can be quite small, which demonstrate that an individual can have contrasting attitudes towards various aspects of their job, thus attitudes towards different domains may provide a clearer picture of how one feels about their job (Spector, 1985).

Overall, job satisfaction is important for organisations for the following reasons (Spector, 1997). Firstly, it is an employee's rights to receive fair and respectful treatment. Job satisfaction can reflect employees' happiness and satisfaction at work and signal the extent towards how a company's policy is treating their employees. Secondly, employees' job satisfaction is linked to absenteeism and turnover and can influence key company's health indicators, e.g. productivity or profits. Therefore, job satisfaction is important to a company's long-term viability and as a result, organizational and work psychology have been studying job satisfaction. It also has been studied in various other disciplines, such as economics (Gazioğlu and Tansel, 2006; Haile, 2009) and management (Aziri, 2011). These studies have investigated several determinants of job satisfaction. For individual characteristics, women are found to have higher job satisfaction than men (Clark, 1997; Gazioğlu and Tansel, 2006). Clark (1997) explains this phenomenon based on the differences in expectations between men and women with the latter having lower job expectations. And when job expectations are less likely to vary between genders, for example between younger workers, people with better educational qualifications or higher professional careers, and people working in a more male-dominated environment, the gender differences in job satisfaction tend to be eliminated.

Similar to the relationship between age and SWB (Blanchflower and Oswald, 2004), the literature has observed a U-shaped relationship between age and job satisfaction with British workers reaching the minimum satisfaction level for overall job satisfaction and its components around their 30s (Clark, 1996; Clark, Oswald and Warr, 1996; Gazioğlu and Tansel, 2006), while workers in the United States experiencing the minimum level closer to 40 years of age (Hochwarter *et al.*, 2001). It is possible that younger workers have little expectations in the early years of their career, thus are happier at the beginning. The more their experience and knowledge about the job market expands as they grow older, the less satisfied they are as their expectations are adjusted. After passing the minimum satisfaction level, the second phase of the U-shaped relationship between age and job satisfaction can be explained by a decrease in aspirations among older people. It may be either that they realise there are few options to switch from their established career, or that the older someone is, the less weight they attach to job aspirations (Clark, Oswald and Warr, 1996). However, there are evidences of a positive relationship between age and satisfaction (Shields and Price, 2002; Haile, 2009). Higher education levels can be connected with lower job satisfaction (Gazioğlu and Tansel, 2006) which can be due to higher aspiration for achievement among more educated people (Clark and Oswald, 1994, 1996). For other sociodemographic factors, the link between marital status and job satisfaction has mixed findings, for instance: Gazioglu and Tansel (2006) report that married workers tend to be less satisfied with their jobs compared to their non-married counterpart, which is contradictory to more satisfied married workers in Clark (1996). White employees have the highest job satisfaction levels and black employees report the lowest levels among white, Asian and black workers (Gazioğlu and

Tansel, 2006). For income, findings are dependent on the measures of income applied. A negative connection between job satisfaction and comparison income is identified in Clark and Oswald (1996) and Shields and Price (2002), in which comparison income can be past income, expected income or income from other family members. The larger the difference between a worker's income and someone else with similar jobs is, the more dissatisfied they would feel towards their jobs. When weekly income is used, positive relations with measures of job satisfaction are found (Shields and Price, 2002; Gazioğlu and Tansel, 2006). Workers may view their lower wage as an indicator of their employers not valuing their contributions highly.

2.3. Determinants of commuting duration and mode choice

In this section, important factors that can determine the time spent on commuting and the decisions on which transport mode to choose for the purpose of commuting are explored. It first discusses briefly the underlying theory of commuting behaviour that has been proposed in the literature to identify the theoretical determinants of commuting, and then empirical studies using both quantitative and qualitative methods are reviewed to explore other determining factors.

2.3.1. Underlying theory

Commuting behaviour can be based on economists' traditional utility theory (Quinet and Vickerman, 2004; Small and Verhoef, 2007). In essence, a rational consumer with income ῶ would choose the travel mode Ώ with travel cost ὴ that maximises their utility Ύ among other alternative travel modes. Based on this theory of utility maximisation, urban economics has developed the monocentric model to explore commuting behaviour (Mills, 1967). The monocentric model assumes that a city has one single centre of employment where all the firms concentrate, called the Central Business District (CBD). In the model, commuting is represented by the cost and time of travelling to work. As commuting time can be regarded as an opportunity cost for the commuter, their utility should be maximised if their travel time is minimised. This implies that similar effect should exist if distance travelled is minimised (Hamilton, 1982; White, 1988). To maintain the maximum equilibrium utility level, longer commutes must be compensated in terms of either cheaper housing or higher wages. Models for commuting behaviour will be discussed in more detail in Chapter 3. In the monocentric model of urban structure discussed above, it implies that important determinants of commuting include the cost of travelling, housing quality and income (Mills, 1967). In terms of housing quality, the further away the housing location is from the CBD, the cheaper the house becomes. However, it comes at a cost of higher commuting cost, both in terms of monetary value and also as an opportunity cost for commuters. The next Subsection 2.3.2 discusses in more detail how travel cost can influence the commuting decisions of individuals.

2.3.2. Travel cost

Travel cost consists of three components: the unit cost of travelling per traveller, the time and distance required for the journey (Headicar, 2009). Travel time and distance are determined by the transport systems, as well as the link between the transport systems and the demand pattern for land use distribution. The literature indicates that travel cost, time and distance are positively related: the longer the journey in terms of both duration and distance, the higher cost incurred. Travel duration and monetary cost are among the most important factors that commuters consider for choosing between commuting modes (Kingham, Dickinson and Copsey, 2001; Hensher, Stopher and Bullock, 2003; Shannon *et al.*, 2006; Eriksson, Friman and Gärling, 2008). The commute mode choice depends on the distance between work and home and the longer the distance, the more likely a person will choose train as their commuting method in the case of UK (Department for Transport, 2011). Alternatively, people tend to choose a more active mode if they need to cover a shorter distance (Guell *et al.*, 2012), and walking in larger cities is only practical for small distances that take up short portions of public transport's routes (Shephard, 2008).

The car has been consistently the most common mode of transport in general (Department for Transport, 2019) and also for the specific purpose of commuting in England (Department for Transport, 2011). Headicar (2009) offers several explanations for this phenomenon. Even though public transport services have increased in real prices over time, fare inflation was still lower than the increase in disposable income. However, the cost of owning and using a car has not changed over a period of 25 years: in essence, it is cheaper to have a private car relatively to disposable income. In addition, when choosing a transport mode, the cost being considered tend to involve only 'out-of-pocket' expense, i.e. only fuel and parking fees for car use. Despite frequent fluctuations in global oil prices, the overall perceived travel cost of using the car is lower than that of public transport (Headicar, 2009). Cost being a determining factor for commuting is also confirmed in an intervention study which finds that the health benefits of active modes are not the primary determinant in mode choices but convenience, cost, speed and reliability are (Jones and Ogilvie, 2012). People with lower socio-economic status have no options other than walking, cycling or public transport in order to save money in the long run.

In terms of opportunity cost, the act of travelling can consume time that could be spent on other activities. This opportunity cost of lost time can generate a constraining effect, and it is likely that people take this opportunity cost into account when making decisions concerning travelling purposes (Shephard, 2008). Even if they can afford the monetary cost of travelling, the travelling duration that the journey may incur can make people decide against it, since the overall cost of travelling may outweigh the benefit of the main activity given up. However, one-off delayed incidents may influence commuters' daily mode choice rather than actual travel time savings and lead to bias.

2.3.3. Demographic and socioeconomic factors

Several demographic factors are identified as factors that can influence commuting and travel mode choice. For example, younger adults tend to choose public transport such as buses for travelling purposes, which can be an interaction with socio-economic variables, such as income (Sullivan, Kershaw and Cummings, 2016); meanwhile the age group 30-59 is found to have the highest number of business and commuting trips among all age groups (Department for Transport, 2011). Moreover, the need to control for gender, marital status and social class is also acknowledged within social science research on commuting choice (Guell *et al.*, 2012), suggesting that household, employment and social obligations have an influence on the decision-making of individuals.

Gender

In England, male commuters travel more in miles compared to their female counterpart (Owen and Green, 2000), which can be evidence of the distinctions in the job types that males and females hold (Department for Transport, 2011). Moreover, it is not uncommon that commuters can take advantage of one commute trip to carry out other purposes, such as the school run or grocery shopping; this phenomenon is regarded as "trip chaining" (Department for Transport, 2015, p. 1-2). Female commuters are more likely to link commuting with other purposes in the same trip (McGuckin and Murakami, 1999; Department for Transport, 2015).

The tendency for trip-chaining behaviour can stem from the gender imbalance in household responsibilities, in which women bear more of those duties (Roberts, Hodgson and Dolan, 2011). In addition, it is likely that commuters who perform trip chains would choose modes that can support their additional purposes. Trip chaining has been argued as being incompatible with either active transport (Shephard, 2008) or public transport (Wheatley and Bickerton, 2016). Female commuters choosing to use a car may not do so for the sake of convenience for themselves but because it may be best for trip-chaining purposes. This habit is particularly pronounced in women (McGuckin and Murakami, 1999), even though car dependency is also evident for male commuters with dependent children (Wheatley, 2014).

Considering both gender and ages together based on the 1991 Census data, Owen and Green (2000) find that the younger (16-29) and older (50-64) commuters do not have much differences between them, whereas the workers at the peak of their working age (30-49) can have longer commuting distance. For women, the authors point out the trend that as women get older, their commuting distance will shrink and the chance of them working near home increases. When marital status is considered for the gender differential in commuting habit, there is no significant difference on commuting time for women due to marriage, whereas married men spend more time commuting than non-married ones (McLafferty, 1997). It is possible that women’s unequal household responsibilities help facilitate their partners’ working and commuting schedules.

Ethnicity

The literature has found distinct commuting characteristics among different ethnicities. In terms of commuting modes, in the US, black people are the most likely to use public transport (Millar, Morrison and Vyas, 1986) and the least likely to have a car in their household among all ethnicities (Raphael *et al.*, 2001). Moreover, ethnic minorities are more likely to reside in high-density urban areas with available public transport network (for the UK: Owen and Green, 2000; for the US: Giuliano, 2003). Segregation could prevent black workers from suburban residential locations and limit them within the central area whether their workplace is in the CBD or in the suburban areas (Zax, 1990). As a result, they could be restricted from enjoying better housing in the suburban areas compared to their white colleagues. However, commuting time can be affected by the size and population density of a city. Cities with higher population density can lead to longer commuting duration for driving car and using public buses due to congestions, whereas a commute should take less time in polycentric, more dispersed areas (Gordon, Kumar and Richardson, 1989; Gordon, Richardson and Jun, 1991). Thus, ethnic minorities also tend to spend more time commuting than their white counterpart. Black women in the US are found to commute the longest on average when both genders and ethnicities are combined in a large sample of service workers (McLafferty and Preston, 1991). Black people mainly use public transport and spend more time commuting, while travelling fewer miles to work than their white counterpart. Using public transport in the US can take more time than driving a car while not covering all areas with substandard quality (Gautier and Zenou, 2010). Improving car access is likely to increase salaries and employment rates for ethnic minorities in the US (Gautier and Zenou, 2010) and in the UK (Patacchini and Zenou, 2005); however this is beyond the scope of the thesis. The racial differentials in commuting are not as heavily studied in the UK as in the US, nevertheless, there are similar trends observed. Workers from ethnic minorities backgrounds have longer commuting time (Battu and Sloane, 2004) and are more likely to commute by public transport which demonstrates their high population concentration in urban areas, whereas white workers have shorter commuting time and are more likely to use private transport (Owen and Green, 2000; Patacchini and Zenou, 2005). Owen and Green

(2000) find out that white men have longer commuting distances than men from most ethnic minorities, except for Chinese ethnicity, meanwhile white women cover shorter commuting miles than ethnic minority women. Nevertheless, the same data notes that Bangladeshi and Pakistani people are the most likely to have short commuting distances for both genders.

Social class

Those with occupations that demand higher skills can have more complicated commuting journeys and can be subject to higher mobility requirements. However, their family responsibilities can create constraints, especially in terms of residential location choice (Wheatley, 2014). Alternatively, lower-skilled people in the Britain have been reported to have lower than average commuting distance (Green and Owen, 2006). In terms of mode choice, different social classes may choose the same mode based on different basis, for example: while people with lower income may not have a choice other than walking or cycling (Jones and Ogilvie, 2012), those in higher class may choose walking because of health and environmental benefits or the sceneries (Green, 2009). Moreover, income and socio-economic class are strongly linked, thus the travelling trends for different income groups should be similar for the socio-economic classes. According to the Department for Transport, commuting distance and household income are related, more specifically household members in the highest income group commute a distance nearly 8 times longer than those in the lowest income quintile in 2011 (Department for Transport, 2011). However, it is possible that people from similar socio-economic groups may make different decisions because of the indirect influence from distinct perceptions, attitudes and preferences (Van Acker, Van Wee and Witlox, 2010).

2.3.4. Other factors

Habit

Status quo can be a major influence of how people pick travel modes. People may not evaluate every journey; their experience in previous trips and commitments may create a habit of using a particular travel mode (Mondschein, Blumenberg and Taylor, 2006). Examples of commitment can be low-scale commitment such as seasonal travel tickets, car ownership and high-scale commitments such as house ownership. In the case of commuting, people tend to form habit of their usual mode choice because of the repetitive nature of daily commute (Verplanken *et al.*, 1998). Having low self-control ability may make people delay re-evaluating their current mode to look for a healthier and more convenient alternatives (Mattauch, Ridgway and Creutzig, 2016).

Transport safety

The fear of traffic accidents is a vital consideration for walking and cycling (Shephard, 2008). Although there are potential benefits of cycling on health and mortality, they tend to be delayed onto later time in a person's life, which can make cycling less appealing (Edwards and Mason, 2014). People may be more inclined towards current road safety rather than cumulative health benefits, even after discounting for future value. Moreover, people tend to focus more on accident outcomes instead of estimating the likelihood of accidents (de Blaeij and van Vuuren, 2003). Thus, the probabilities of travel-related accidents may often be assumed higher than they are in reality.

Personal security

Similar to a home, a car can provide the psycho-social benefits of protection, autonomy and prestige, which will improve a person's ontological security, whereas public transport seems unable to do so (Hiscock *et al.*, 2002). Using cars can provide comfort, privacy and protect people from unpleasant social and weather conditions (Gärling *et al.*, 2002), meanwhile female travellers have reported feeling at risk when waiting at bus stops or train stations especially if those were dark and isolated (Hamilton *et al.*, 1991, cited in Hiscock *et al.*, 2002).

Social identity

The literature has identified social identity benefits that may influence the choice of different transport modes. People cannot have the autonomy of travelling whenever and wherever they prefer if using public transport, while using private transport can provide better social life and quicker access to leisure activities (Hiscock *et al.*, 2002). Indeed, car travelling can take a person from point of origin directly to the destination, while public transport often involves other modes of transport either at the beginning, or the end, or any changes during the journey (Gärling *et al.*, 2002). In the context of prestige, the influence of the current dominant culture of individualism and materialism make people desire a car more than before, even though the cost of owning one may be high. Material possessions are laden with symbolic meanings related to self-expression (Dittmar, 1992). Thus, the possession of a car fulfils a person's desire to express themselves and their status in society. Besides, cars and mass motorisation are often viewed as a crucial factor for a modern and individual lifestyle (Sheller and Urry, 2003). Alternatively, buses are perceived to be associated with low-income individuals and this view is strengthened by Root, Boardman and Fielding (1996) who find that bus transport is not the choice for higher-skilled individuals.

Moreover, there exists a relation between multiple identities and travel behaviour on regular journeys, and identities can anticipate travel mode used to go to workplace, to take children to schools and for other daily routine trips (Murtagh, Gatersleben and Uzzell, 2012). This finding is consistent with Gardner and Abraham (2007). For example, in the case of a parent choosing between walking children to school or taking them by car, if they are under pressure of getting to work on time, and being a worker is their central identity, then driving the children to school may be the preferred travel mode for the parent. But if a parent’s identity is stronger, then walking with children to school may be chosen. Such a relationship strengthens the need for management of multiple identities and suggests that travel behaviour in one domain can be influenced by identities that are the most important in other domains. Therefore, if a temporary conflict of identities emerges, car use may be able to avoid that and achieve successful management of multiple identities; for the example above, using a car may fulfil the needs of both worker and parent identities in certain circumstances (Murtagh, Gatersleben and Uzzell, 2012).

Weather

Weather can be an important factor that people may consider when choosing commute modes. For example, the choice of cycling to work may be restricted by weather: during hotter months, commuters may be reluctant to choose cycling as their work attire may be affected after the commute journey and in colder weather, they may get discouraged by strong wind, heavy rain and slippery streets (Shephard, 2008).

In this section, common factors that can influence the decisions of commuting duration and mode choices in the literature have been discussed. The next section will present how those decisions on commuting can in turn have an impact on health, SWB and job satisfaction of the commuter.

2.4. The impact of commuting

The most common commuting mode in England is car, either as a driver or passenger which makes up 62% of commuting trips and the average amount of time an English person spends on a one-way commuting trip is 30 minutes (Department for Transport, 2019). Thus, a person working full-time would spend roughly 300 hours per year on commuting. Such an amount of time experiencing traffic congestion during peak hours would have some effect on a person's health and SWB. Indeed, commuting can impose on commuters private expense, social costs from traffic congestion and environment pollution and also the mental cost of uncomfortable experience (Stutzer and Frey, 2008). A conceptual framework of how commuting can affect commuters objectively and subjectively during a commute, after a commute and for long term is provided by Chatterjee and his colleagues, and Figure 2.2 below adapts the conceptual model presented in the article (Chatterjee *et al.*, 2019, p. 3). In Figure 2.2, the objective impacts in rectangles are time, expense, physical effort spent on the commute, and in the longer term it can be physical health of commuters. The subjective influences, presented in circles, can be during the commute (affective emotions), after the commute (e.g. satisfaction with job) and for longer-term overall SWB.

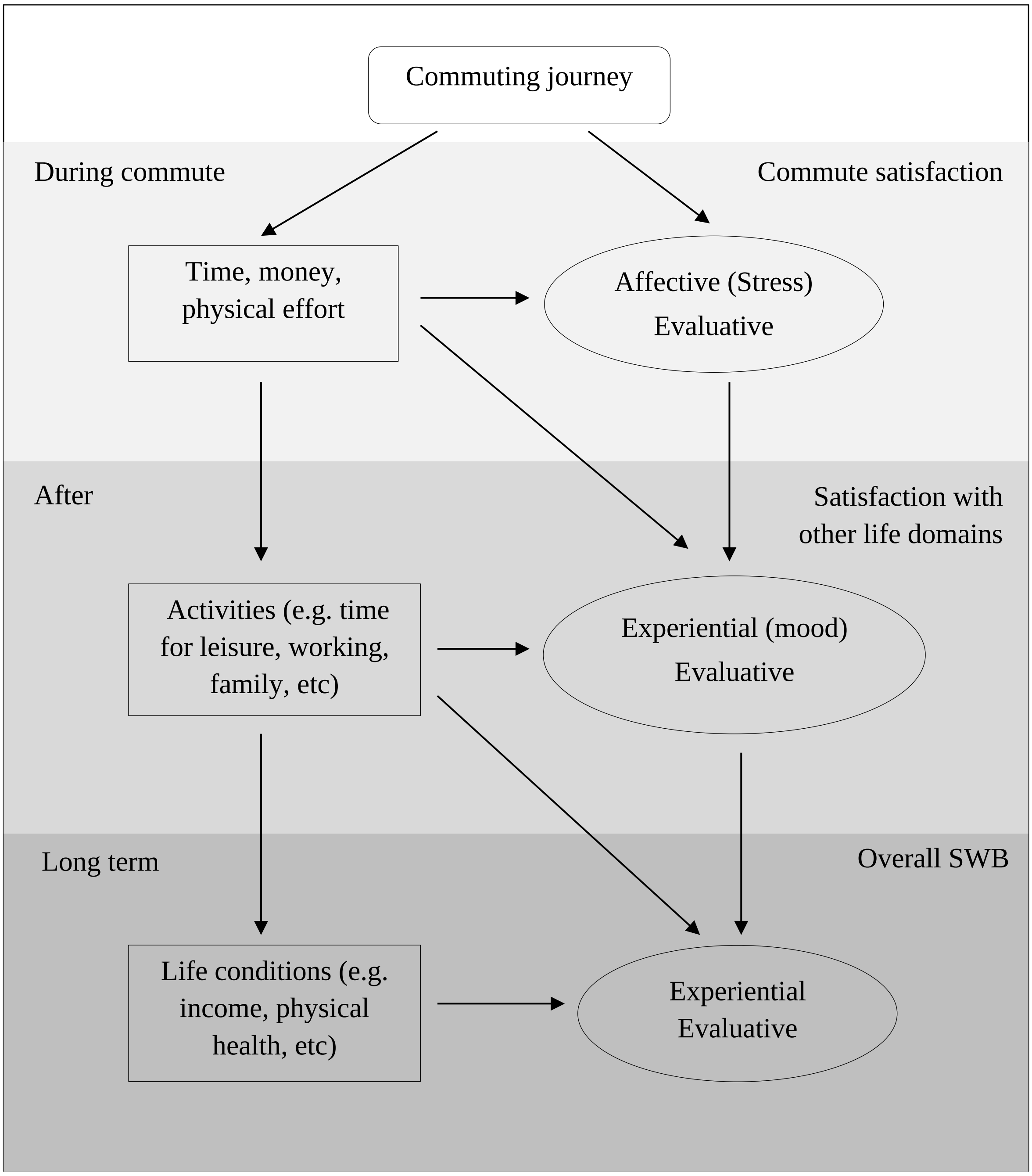

Figure 2.2: Conceptual model of the relationship between commuting and SWB

There is a well-established literature on how commuting can affect commuters' health (e.g. Lyons and Chatterjee, 2008; Hansson *et al.*, 2011; Laverty *et al.*, 2013; Künn-Nelen, 2015). Meanwhile, the effect of commuting on SWB has only been studied recently, and there is little research on how commuting can influence job satisfaction of commuters. Not only might commuting duration have some influence, but also transport modes with different characteristics might have heterogenous effects on health, SWB and job satisfaction. With the gender inequality in domestic responsibilities frequently cited in the literature, commuting effects can vary between female and male commuters in households with both working partners. Thus, this section will review the commuting impacts on the three variables of interest taking into account the heterogeneous effects from using different transport modes and between genders: Subsection 2.4.1 explores the commuting effect on SWB, whereas Subsection 2.4.2 examines the established literature of commuting effect on health, and benefits and drawbacks of various transport modes will be reviewed, especially for active commuting. The last Subsection 2.4.3 will investigate the small literature of how commuting may affect job satisfaction.

2.4.1. On SWB

Before 2008, the relationship between commuting and SWB did not receive a lot of attention and commuting was mainly investigated in relation with the compensation in the labour and housing market (Stutzer and Frey, 2008). A study by Stutzer and Frey (2008) was one of the first studies to explore the effect of commuting on SWB of people as a proxy for experienced utility. Experienced utility represents the hedonic approach to utility, which stems from Bentham (1789/1996) who proposes that human's choices are determined by two factors of gaining pleasure and avoiding pain. Alternatives have their own hedonic outcomes and a good decision between alternatives would be one where pleasure is maximised and pain minimised. Experienced utility is in essence the hedonic experience delivered by the chosen alternative. The hedonic experience can be reported with objective measures, such as brain reaction and subjective measures, such as SWB (Berridge and O'Doherty, 2014). Besides, another approach to utility is decision utility in which it is assumed that a person's own preferences can explain their choices. Decision utility represents a person's preferences which can be revealed by observing the choices they make (Kahneman, Wakker and Sarin, 1997; Kahneman and Sugden, 2005).

Since then, studies on the effect of commuting on human's SWB have expanded (Gatersleben and Uzzell, 2007; Roberts, Hodgson and Dolan, 2011; Martin, Goryakin and Suhrcke, 2014; Office for National Statistics, 2014; Wheatley, 2014; Lorenz, 2018; Chatterjee *et al.*, 2019). It is likely that the effect of commuting on a person's SWB can be different to that of travelling for other purposes, such as for leisure activities. Commuting is a necessary part of daily activities that enables a person to go from home to work and vice versa. It takes up time that could have been spent in other activities, such as leisure activities or time for family (Wheatley and Bickerton, 2016). Combined with negative effect of commuting stress, it is likely that commuting can have a negative influence on SWB. As suggested by Diener (1984), the cognitive life satisfaction part of SWB is more consistent and stable, compared to affective evaluation of temporary emotions, especially in the context of overall life satisfaction. Thus, the focus of this review will be commuting effect on life satisfaction.

Urban economic theory suggests that longer commuting distance is compensated by either cheaper housing or higher income at equilibrium (White, 1988). It would be expected that any adverse effect from a longer commute journey does not influence a commuter's SWB as it should be offset by the commuter either living in a cheaper house or earning higher salary. However, commuting has been found to have a negative effect on SWB in the literature. Studies have identified the negative effect for different countries, such as the UK (Office for National Statistics, 2014), Canada (Hilbrecht, Smale and Mock, 2014) and China (Nie and Sousa-Poza, 2018). For European citizens who work, having a long commute and heavy work intensity could reduce their life satisfaction especially if these two working conditions result in an unsatisfactory work-life balance (Drobnič, Beham and Präg, 2010).

Because of endogeneity, conclusions drawn from cross-section studies may not be causal. In terms of longitudinal studies, researchers have applied the FE panel-data estimator which takes account of the individual heterogeneity that can confound the relationship of interest. They find a negative relationship between commuting and SWB (e.g. Stutzer and Frey, 2008 for Germany; Morris, 2015 for the US). The same negative effect persists whether commuting time or distance is used, even for commuters having opportunities to redesign their commuting due to change in jobs and housing locations (Stutzer and Frey, 2008). This finding of a negative connection between commuting and SWB goes against the traditional economic theory developed for commuting. Stutzer and Frey (2008, p. 363) coin this phenomenon "The commuting paradox", in which a commuter travels longer than optimum for work while suffering lower life satisfaction.

There are three possible mechanisms accounting for the commuting paradox. These are health, bottom-up theory and lifestyle (Nie and Sousa-Poza, 2018). As discussed below, commuting can have a direct negative influence on commuters' physical and mental health (Koslowsky, Kluger and Reich, 1995). It can have an influence indirectly via reduction in sleeping time (Nie and Sousa-Poza, 2018). Commuting is also found to correlate with rising stress levels, especially among commuters with dependent children (Rüger *et al.*, 2017).The second mediator can be due to spill-over effects, in which stress from the commuting domain affects other domains of life satisfaction. Commuting has been found to have negative effect on satisfaction with job (Stutzer and Frey, 2008), with leisure time (Dickerson, Hole and Munford, 2014; Lorenz, 2018), with family life (Lorenz, 2018). The negative effect of commuting on SWB persists for both female and male commuters who are not satisfied with their leisure time (Roberts, Hodgson and Dolan, 2011). Finally, longer commuting time can be regarded as taking up time from other activities, such as for family (Rüger *et al.*, 2017) and leisure (Hilbrecht, Smale and Mock, 2014; Wheatley and Bickerton, 2016). For example, Hilbrecht, Smale and Mock (2014) find that reducing time for recreational physical activities is a pathway for the negative relationship between commuting distance of Canadian commuters and their life satisfaction. Moreover, the literature offers behavioural explanations for the commuting paradox against the traditional economics' assumption of rational consumers, for example: Stutzer and Frey (2008) suggest that commuters may not predict accurately the impact commuting can place on their SWB.

Conversely, this commuting paradox is not always present as there are studies that do not find any significant relationship between commuting and SWB (Dickerson, Hole and Munford, 2014; Clark *et al.*, 2019). Dickerson, Hole and Munford, (2014) suggest that the difference in findings could be because of cultural differences. However, employing the same German Socio-Economic Panel data as in Stutzer and Frey (2008), a recent study was not able to replicate the commuting paradox using commuting distance as the predictor (Lorenz, 2018). Moreover, the same study finds that commuters experience better housing and career conditions in return for a longer commute, thus the hypothesis arising from the urban economic theory seems to hold. Clark and his colleagues (2019) support this view with their data on British workers in which commuters who switch from shorter to longer commutes of more than 45 minutes are observed to have their income raised, in comparison to commuters whose commute duration remains short. The act of commuting may also be beneficial in helping commuters disconnect from work mentally (Wheatley and Bickerton, 2016)

With their findings of a commuting paradox, Stutzer and Frey (2008) offer a possible explanation for the commuting paradox. It could be due to the high transaction cost, which can either prohibit or make it difficult for workers to move their residence or change jobs. Yet, the authors find the paradoxical phenomenon persisting for commuters who have the opportunities to adjust their residence or jobs. In addition, another potential explanation is that while the SWB of a person is reduced with a longer commute, it can be compensated from potential benefits for their partner, which maintains the household's overall SWB. However, their data and other studies did not support the hypothesised explanation for the commuting paradox (Stutzer and Frey, 2008; Roberts, Hodgson and Dolan, 2011).

Gender inequality in both the labour market and household circumstances can predict potential gendered differences in commuting effect (Roberts, Hodgson and Dolan, 2011). In the labour market, women are more likely to work less hours and earn lower salaries than men (Madden, 1981), hence, commuting expense and the monetary value of time-use can be relatively larger for women. In the context of household circumstances, the female partner is likely to do more household duties and be less flexible with their schedule (Hersch and Stratton, 1994). Also, the housing location decision tends to depend more on the job location of the male partner, which can have implication on the job choices and commuting for the female commuter (Madden, 1981). Using psychological health as a SWB proxy, Roberts, Hodgson and Dolan (2011) reveal that only female commuters are impacted negatively by a longer commute while their male counterpart is unaffected even though male commuters have higher average commuting durations. The result still holds for male and female commuters working full time, those having skilled jobs or those that are primary earners, hence the possible reason of female's lower occupational status or shorter working schedule does not justify the gendered difference. The authors propose that it can be the result of female partners' greater domestic responsibilities, such as housework or childcare. Thus, women tend to be more sensitive to different time constraints such as a longer commute. Moreover, women exhibit a trip-chaining habit in which they carry out several household duties in one commuting trip, such as grocery shopping and school escort (McGuckin and Murakami, 1999). These stops will increase time constraints and in turn contribute to the stress of commuting for women. Similarly, both long and medium-duration commuting trips are found to be responsible to dissatisfaction across the SWB's life domains for women with dependent children, whereas only longer commuting has a worsening effect on men, despite women's shorter average commute time (Wheatley, 2014). The result advocates that the women's trip-chaining habit within their commute journey may be the reason for women's dissatisfaction with leisure time, instead of commuting itself. Both studies support the view that the inequality in household roles has an impact on the adverse effect of commuting on SWB for women (Roberts, Hodgson and Dolan, 2011; Wheatley, 2014). Consistent findings with Roberts, Hodgson and Dolan (2011) and Wheatley (2014) are found in other studies (Martin, Goryakin and Suhrcke, 2014; Wheatley and Bickerton, 2016), in which female participants suffer a negative influence from commuting.

Moreover, Roberts, Hodgson and Dolan (2011) identify that women who believe that they should become housewives while their husbands work suffer a large detrimental effect from commuting on their SWB. They propose that if a person's behaviour is not synchronised with their beliefs this may worsen SWB via the feeling of guilt. This is in line with Dolan, Peasgood and White (2008) who discuss the view that circumstances can be significant influences on life satisfaction.

Stutzer and Frey (2008) do not find any significant difference of the effect of commuting on SWB between public transport and car users. However, other studies find evidence of the heterogenous effect of different transport modes on SWB of commuters. Car use can have a negative impact on SWB (Hilbrecht, Smale and Mock, 2014; Martin, Goryakin and Suhrcke, 2014). Possible explanations include stress (Gatersleben and Uzzell, 2007), lack of social connection (Gottholmseder *et al.*, 2009) and potential effects on family because of its unpredictability (Wheatley and Bickerton, 2016). External mechanisms for the negative effect of car use can be the lack of control over the situations, such as traffic congestion, and behaviours of other road users (Gatersleben and Uzzell, 2007). However, the car with its ability to facilitate multiple purposes can offset some of the worsening effect of commuting, especially on women (Roberts, Hodgson and Dolan, 2011). Also, people tend to choose cars over other modes due to its reliability and autonomy (Hiscock *et al.*, 2002); however, traffic congestion can decrease the extent of car's reliability and the control commuters may have (Gatersleben and Uzzell, 2007). For public transport such as bus and train, the findings are mixed. In cross-sectional studies, using public transport is found to have either no association (Hansson *et al.*, 2011) or a negative association with SWB if commuting lasts for more than 30 minutes (Office for National Statistics, 2014). Public transport is viewed the most negatively among all commuting modes, which can be because of stress and boredom from long waiting time and unpredictable events such as delays (Gatersleben and Uzzell, 2007). Relying on public transport's timetable to schedule daily life can be inflexible and this lack of control over one's life can further generate stress (Hansson *et al.*, 2011). One way that public transport users can alleviate the negative effect is by doing something useful, such as socialising while commuting (Olsson *et al.*, 2013). Working while commuting by public transport is also an option that can have the additional benefit of shortening the working hours (Gatersleben and Uzzell, 2007), however participants in a qualitative study find it difficult to work productively that way (Wheatley and Bickerton, 2016), and overcrowding from other passengers may present inconvenience (Eriksson, Friman and Gärling, 2013).

In longitudinal studies, public transport is found to relate positively with SWB compared to using cars (Martin, Goryakin and Suhrcke, 2014). Both car and public transport can support women in their trip-chaining habit and reduce the negative impact of commuting on women (Roberts, Hodgson and Dolan, 2011). The possible pathway for the positive correlation between public transport and SWB can be that the use of public transport requires some walking or cycling at either end of the commute journey (Laverty *et al.*, 2013).

Active commuting modes are associated with higher SWB (Martin, Goryakin and Suhrcke, 2014; Chng *et al.*, 2016) and self-rated health (Hansson *et al.*, 2011), compared to car users.

The benefits of switching to active travel from car use can exceed possible advantages of reducing commuting time (Martin, Goryakin and Suhrcke, 2014). Cycling, regarded as a moderate intensity activity, is associated with the highest level of quality of life among all commute modes in a study on Sydney commuters (Crane *et al.*, 2016). Apart from the higher health benefit, cycling provides several opportunities that other modes lack such as higher level of control and perception of excitement during the commute trip (Gatersleben and Uzzell, 2007).

2.4.2. On health

Health is one of the determinants of SWB and an individual's SWB can have some influence on their health (Dolan, Peasgood and White, 2008; Diener, Lucas and Oishi, 2018). Thus, how commuting affects health can act as a possible mechanism of its influence on SWB. The nature of commuting can lead to stress because of unforeseeable incidents and commuters' perceived lack of control (Koslowsky, Kluger and Reich, 1995; Gottholmseder *et al.*, 2009). Stress can be generated from factors that slow the commute down, such as congestion, duration and speed (Stokols *et al.*, 1978). Stress is regarded as a causal pathway from social situations to mental health disorders, thus commuting stress could act as a systemic stressor linking commuting with mental health (Turner, Wheaton and Lloyd, 1995). In addition, stress is related to physical health indicators such as blood pressure (Koslowsky, Kluger and Reich, 1995; Lantz *et al.*, 2005). Between different commuting modes, active commuting can be perceived as interesting and relaxing, compared to the boring and stressful passive commuting modes (Gatersleben and Uzzell, 2007; Wheatley and Bickerton, 2016).

Apart from stress, longer commute journeys can have negative associations with subjective health and sleep quality (Hansson *et al.*, 2011; Künn-Nelen, 2015). There are other influences of commuting on health, involving higher risk of traffic accidents, cardiovascular abnormalities from air pollution, less time for sleep, leisure and health-related activities such as taking healthy diet, going to medical clinics, taking part in recreational physical activities (Lyons and Chatterjee, 2008; Hansson *et al.*, 2011; Christian, 2012; Wheatley and Bickerton, 2016). Thus, commuting is associated with not only health problems but also behavioural tendencies that can exaggerate those conditions. Based on US data, Christian (2012) calculates that an increase of 30 minutes from an average 60-minute commute journey would lead to a loss of 24.2 hours of exercise for a whole year . Those lost hours could be used to burn off calories even with moderate-intensity activities, thus a small increase in commuting time can have a significant implication on obesity.

Exposure to air pollution can lead to cardiovascular morbidity and mortality. However, commuters travelling by car are more likely to be exposed to higher proportion of particulate matter and black carbon than other modes (Lyons and Chatterjee, 2008; Karanasiou *et al.*, 2014). Shifting from motorised transport modes to active modes would provide health benefits in terms of pollution reduction, and more importantly increased daily physical activity level (Woodcock *et al.*, 2009).

Various commuting modes involve significantly different physical activity requirements, which may result in contrasting implications on health. Thus, research on the effect of commuting on health tends to distinguish between transport modes, such as between active and passive modes and explores their distinct influence on commuters' health. Active commuting modes include walking and cycling, i.e. those means of transport that require more physical activities. Some studies may include public transport as part of the active commuting category as it tends to include walking or cycling at either end of the public transport journey. Meanwhile, motorised transport modes require less physical movement and increase the sedentary time of commuters. Sedentary activities are those which require "1.0-

1.5 metabolic equivalent units (METs)", so not much more energy than that of the resting level (Pate, O'Neill and Lobelo, 2008, p. 174). Sedentary sitting imposes serious health consequences, including obesity, diabetes, cardiovascular diseases, cancer and higher mortality risk (Thorp *et al.*, 2011; Wilmot *et al.*, 2012). Moreover, there has been emerging evidence suggesting that sedentary behaviour is a separate risk towards health even for individuals engaging in sufficient levels of physical activities (Thorp *et al.*, 2011).

Using public transport, compared to using private modes such as a car to work can increase a commuter's average daily number of steps (Wener and Evans, 2007), lower the chance of being overweight (Laverty *et al.*, 2013), and reduce self-reported stress and low moods (Wener and Evans, 2011). Moreover, British commuters are more likely to report higher strain and difficulty in concentrating on their current tasks if they drive to work, which are two of the dimensions of the General Health Questionnaire (GHQ-12) by Goldberg and Williams (1988) (Martin, Goryakin and Suhrcke, 2014). Unpredictability can put a strain on car commuters and increase their stress level while train travel makes journeys more predictable and reduces the lack of control for commuters (Cox, Houdmont and Griffiths, 2006). In contrast, longer commute distances may require public transport users to take different buses within one journey, which may involve unexpected changes and delays (Hansson *et al.*, 2011). Also, relying on inflexible public transport's timetables to schedule one's life can affect the sense of control. Crowded carriages in public transport can increase stress and lead to reductions in the health and work performance of the commuter (Cox, Houdmont and Griffiths, 2006).

The dose-response connection between physical activity and health benefits (Haskell *et al.*, 2007; Oja *et al.*, 2011) means that the more physical activities you engage in, the better your health becomes. Both cycling and walking at a brisk pace are regarded as medium to vigorous-intensity physical activities that can contribute to a person's weekly physical activity recommendation (Haskell *et al.*, 2007). Moreover, studies have found a link between active commuting and an increase in commuters' recreational physical activities (Terzano and Morckel, 2011) and overall level of physical activity (Yang *et al.*, 2012) which may implicitly promote healthier habits and lifestyle. Besides, adapting physical activity into a daily activity such as commuting should be easier to maintain than keeping up with the habit of recreational physical exercises at paid venues. Apart from introducing physical activity into daily life, the nature of commute may make active commute journeys shorter than longer recreational physical exercises. It has been found that the aggregation of shorter sections of physical activity throughout the day tends to be better at reducing blood pressure compared to a continuous session of 40 minutes (Park, Rink and Wallace, 2006).

Active commuting has been found in the literature to be associated with lower Body Mass Index (BMI), lower chance of being obese, overweight, (Laverty *et al.*, 2013), lower chance of diabetes and cardiovascular morbidity, such as high blood pressure, stroke, heart conditions and mortality (Hamer and Chida, 2008), and many other health outcomes, including depression, dementia, breast cancer and colorectal cancer (Woodcock *et al.*, 2009). The longer the duration spent on active commute (i.e. at least 2 miles), the greater the health benefits are found; thus, it exhibits a dose-response pattern similar to that observed for physical activity and health (Laverty *et al.*, 2013). With all the consistent findings of benefits for mental and physical health associated with active commuting, it can potentially contribute to the national budget by saving on healthcare costs. Based on findings by Woodcock *et al.* (2009), it has been found that increasing active travel would save approximately £17 billion for the NHS budget from not having to spend on the above conditions after 20 years, especially for type-2 diabetes (Jarrett *et al.*, 2012). Besides, many benefits would accumulate after the 20-year period because of the long lag before improvement in several health outcomes such as cancers and dementia.

With its higher energy requirement, cycling should have more pronounced effect on health than walking (Crane *et al.*, 2016). Shephard (2008) analyses the health impacts of active commuting theoretically based on energy expenditure. The author suggests that while a weekly energy spending of 4MJ is associated with improved mortalities indicators, the normal walking speed of a person should be approximately 5km/h and can meet the requirement with a one-way 22-minute walking journey over a distance of 1.9km over the weekly 5 working days. Cyclists, meanwhile, should meet the energy requirement within an 11-minute commute journey every day. Similarly, cycling requires more energy per hour of activity than walking. The 2011 Compendium of Physical activities assigns 4.0 Metabolic Equivalent (MET) units for walking to work, and 6.8 MET for cycling to work (Ainsworth *et al.*, 2011). Therefore, cycling as a means to commute should contribute more towards the weekly exercise recommendation of WHO (World Health Organization, 2010) and bring more improvements for health than walking. A meta-analysis review focusing exclusively on the health impact of cycling reports that there are consistent findings from clinical trials, through intervention to observational studies that cycling is connected with better fitness and reduced risk of cardiovascular diseases, cancer, obesity and mortality (Oja *et al.*, 2011). Furthermore, even though traffic accident risk exists, the long-term positive effects on health and mortality rates of cycling would be greater than the fatality rate of accidents (Edwards and Mason, 2014). Nevertheless, the health benefits of cycling can be delayed until later ages, thus may not attract younger adults whose mortality rate is linked more to traffic accidents. Besides, cycling has certain health disadvantages compared to the other active mode, walking. Apart from the risk of traffic accidents, people who walk and cycle inhale polluted emission from motorised modes, but cyclists are more exposed because they require more ventilation and are positioned closer to motorised transport (Shephard, 2008).

2.4.3. On job satisfaction

The costs and rewards of a job are the determinants of a person's satisfaction of that job (Rusbult and Farrell, 1983). Hence, commuting should reduce a person's utility from working as a cost to that person. In addition, it is possible that commuting has an aftermath effect such that the experience during the commute will influence how an individual feels at work (Chatterjee *et al.*, 2019). Apart from the health effect of commuting stress mentioned in previous sections, commuting stress is connected to negative emotions commuters experience when getting to work. This can manifest itself in being late or regularly absent from work and reduce cognitive skills (Koslowsky, Kluger and Reich, 1995). However, there have only been a few studies considering the association between commuting and job satisfaction. As an attempt to explain their commuting paradox, Stutzer and Frey (2008), noted earlier, anticipate a positive relationship between commuting time and job satisfaction in hope that commuters with longer commuting time would be compensated with a better career, i.e. a compensation in a specific life domain. However, negative associations between the two factors are found for both employees and self-employed individuals. A study by Crawley (2014) has explicitly explored the connection between commuting time and satisfaction in the workplace, even though the study employs cross-sectional data on one specific city in the UK. This study discovers a negative association between commuting time and job satisfaction: people who commute with a lengthier duration will be less satisfied with their jobs than those with shorter journeys. However, income can potentially reduce the negative effect of commuting on job satisfaction as workers earning above average salary do not experience the negative relation while below-average earners do (Crawley, 2014). A recent study by Clark *et al.* (2019) identifies that a longer commute is linked with higher mental strain, reduced mental health and lower job satisfaction, although the study does not distinguish between different transport modes.

This section has reviewed the impact of overall commuting time and the heterogenous effects of different transport modes on SWB, health and job satisfaction that have been studied in the current literature. Potential differences between genders are also presented. The literature on the commuting effect on health and SWB is much more than what have been researched for the effect on job satisfaction. Commuting stress can impact both health and SWB and yield a spill-over effect on job satisfaction after a commuter arrives at work. Understanding how these dependent variables may be related to one another can be beneficial for the subsequent empirical studies, and the next section will review findings on those connections in the literature.

2.5. Pairwise relationships

Commuting can affect health and SWB via stress and other common factors. Job satisfaction, even though not heavily researched in the commuting literature, is a domain-specific measure of SWB (Diener, 2006). It is likely that a person with good health will be able to perform better at work, which can lead to higher job satisfaction. Hence, health, SWB and job satisfaction are potentially related with one another and this section will deliver a brief review of those connections between the dependent variables of interest.

2.5.1. SWB – Health

There are several factors that can have an impact on SWB, and health has been identified as one of them. A considerable number of studies find that subjective health and SWB are significantly related (e.g. Diener, 1984; Gerdtham and Johannesson, 2001), although the subjective nature of both health and SWB can raise doubts about the larger relationship between them being confounded (Diener, Lucas and Oishi, 2018). However, similar findings are found when objective health indicators are applied as predictors of SWB to advocate for the use of subjective measures (Zautra and Hempel, 1984; Oswald and Powdthavee, 2007; Blanchflower and Oswald, 2008). Between mental and physical health, SWB has a stronger correlation with the mental component, which is as expected based on their similar conceptual notions (Dolan, Peasgood and White, 2008).

Furthermore, it is possible for a bidirectional relationship to exist between health and SWB (Diener, 1984). This suggests that SWB can have an influence on health and longevity. Indeed, there are a substantial number of studies examining this particular relationship and evidence advocating for the influence of SWB on a person's health is extensive based on longitudinal and experimental studies (Diener and Chan, 2011; Diener *et al.*, 2017). In their review of the SWB literature, Diener, Lucas and Oishi (2018) indicate that association studies find a positive relationship between SWB and health and suggest a causal relationship from SWB to health in which individuals with higher SWB scores will be more likely to choose healthier actions, such as better diet choice, recreational physical activities, frequent health checks and not smoking (Grant, Wardle and Steptoe, 2009; Boehm, Vie and Kubzansky, 2012; Kim, Kubzansky and Smith, 2015). The meta-analysis by Chida and Steptoe (2008) reveals that better ratings of SWB measures, including positive affect and life satisfaction are connected with falls in mortality rates, especially for healthy populations. Similar conclusions are drawn based on experimental studies based on human and animal subjects (Diener and Chan, 2011). The impact is significant statistically as well as has a large effect size: happier individuals are likely to have longer longevity by a maximum of 10 years, compared to those with lower SWB (Veenhoven, 2008; Diener and Chan, 2011). If these additional years are accompanied with happiness and good health, it would be worth the attention from the Government and institutions to take into account SWB for public health improvement. However, most studies on this topic do not separate various concepts of SWB, thus there is no clear evidence on which SWB components have the most significant impact on health and longevity (Diener and Chan, 2011).

Further reasons for which SWB will be associated with health could reflect the biological mechanism where SWB improves the immune system, pain endurance and limits the effect of stress (Howell, Kern and Lyubomirsky, 2007). Meanwhile, psychological stress is connected with factors of age deterioration (Epel *et al.*, 2004). Howell and his colleagues (2007) further suggest that shorter-term indicators of health, such as improved immune system, are associated with temporary affects, whereas focusing on global cognitive SWB can be linked with better longer-term health measures, for example cardiovascular conditions.

2.5.2. SWB – Job satisfaction

As discussed in Section 2.2.4, job satisfaction is regarded as a specific domain on work-related matters of life satisfaction. There are two theories that can explain the relationships between SWB and job satisfaction (Diener, Lucas and Oishi, 2018). Firstly, the bottom-up theory suggests that an individual assesses objective aspects of their life with the guidance of their own values and preferences. Those assessments are then summed up to derive the global judgment of their life's quality. Thus, according to this theory, the causality direction flows from job satisfaction to life satisfaction. For instance, it is revealed that there is a significant relation between working conditions and quality of life, which means worse working conditions can be associated with reduced life satisfaction (Drobnič, Beham and Präg, 2010).

By contrast, the top-down theory argues that an individual may have some general inclinations towards a more positive or negative perspective of their life overall. These inclinations may have impact on how the individual evaluates certain life domains, such as job satisfaction. Studies have revealed that it is possible that both theories can be present in the relationship between life satisfaction and its domains. This suggests that similar to the relation between SWB and health, it is possible for a reciprocal relationship between SWB and job satisfaction.

2.5.3. Health – Job satisfaction

A positive relationship between job satisfaction and health has been found in the literature over time (e.g. Ramirez *et al.*, 1996; Fischer and Sousa-Poza, 2009; Dirlam and Zheng, 2017). A meta-analysis of the current literature found a correlation of 0.312 between self-reported job satisfaction and health measures (Faragher, Cass and Cooper, 2005). However, the studies used in Faragher, Cass and Cooper (2005) are mainly cross-section data with small sample sizes, whose inherent econometric issues such as endogeneity, can potentially render the coefficients found in these studies biased. In particular, significant associations between dissatisfied workers and mental health conditions such as burnout (Ramirez *et al.*, 1996), lower self-esteem, higher levels of anxiety and depression dominate the literature (Faragher, Cass and Cooper, 2005). Furthermore, job satisfaction can affect health via its influence on the stress level at work. The stress level a person feels in their job is found to link with several negative mental health outcomes, however treatments could improve both mental and physical health (Schneiderman, Ironson and Siegel, 2005). The effect from satisfaction in one's job on health could stem from a number of employment conditions including physical conditions such as air quality, workplace safety and automation degree and also psycho-social conditions, for example: work stress, job security, hierarchical position (Stansfeld *et al.*, 1997; Stansfeld, Head and Marmot, 2000). More recent studies found biological evidence that job satisfaction is associated with immune functioning (Nakata *et al.*, 2010). A positive relationship between job satisfaction and health could imply fewer resources would be spent on health for both the individuals and the employers. Fischer and

Sousa-Poza (2009) support this with significantly negative relations between job satisfaction and hospital visits, work accidents and sick leave.

This section has presented a review of the pairwise relationships between the dependent variables of interest health, SWB and job satisfaction. The causality direction within the relationships are not clear-cut and there are possibilities for reciprocal relationships between the variables.

2.6. Gaps in the literature

The previous sections have presented a review of the current literature on the relationships between commuting and SWB, health and job satisfaction. Longer commuting time is associated with lower subjective and objective health, whereas there are contradictory findings identified in the commuting paradox in which commuters are not compensated in terms of overall SWB as their commute duration lengthens. Besides, commuting modes with different characteristics can impose various effects on commuters. However, it is clear from Section 2.4.3 that there is limited research on the commuting effect on job satisfaction. Job satisfaction is linked with workplace performance and in turn can influence an organisation's functioning. Experience during commuting can have a spill-over effects on the moods when arriving at work. Thus, looking at commuting effect on job satisfaction is of importance for organisations to improve their employees' welfare and consequently the organisations' performance.

Moreover, Section 2.5 has explored the literature on the pairwise relationships between the dependent variables of interest in this research and identified the possibilities of bidirectional connections between them. Apart from the gap in the literature exploring the commuting effect on job satisfaction, the possible connections between health, SWB and job satisfaction make examining all three features simultaneously important and more complex. This has not been done elsewhere in the literature. In terms of econometric analysis, including health, SWB and job satisfaction as covariates in the models of each other would allow better control of mediating factors and generate a clearer view of the impacts of commuting, thus reduce the omitted variable bias.

To the best of the researcher's knowledge, only a few studies in the literature have included both job satisfaction and self-reported health status in regression models of commuting on SWB as reviewed above (Roberts, Hodgson and Dolan, 2011; Martin, Goryakin and Suhrcke, 2014). However, these studies and the literature in general employ FE models, which can only control for individual unobserved heterogeneity. The literature has recognised the possibility of reverse causality between the dependent variables and the predictors, e.g. happier and healthier people may choose more active commuting modes which can further increase their health and SWB. For example, in the model of SWB, active commuting and health can influence SWB, but the direction of causality can also flow from SWB to these two covariates. Nevertheless, this cause of endogeneity has not been controlled for in the literature. With the literature lacking cause-outcome inference between the variables of interest, this study aims to investigate the causal relationships between commuting and health, SWB and job satisfaction. Because of the heterogenous effects between different commuting modes, this study will distinguish between transport modes and explore each separately. The literature has been clear on the detrimental effects of private non-active modes, such as using cars, on health and SWB of commuters. Walking and cycling can act as a solution for the current health and environmental problems challenging the UK. This study intends to explore and hopes to inform policy makers on the impact of active commuting on British commuters.

The above reflections underpin the research questions addressed in this thesis:

- Does commuting time affect health, SWB and job satisfaction?
- What are the effects of different commuting modes, and especially active travel modes, on health, SWB and job satisfaction?

In Chapter 4, FE panel-data estimators are employed to explore the effects of commuting time and different modes on health, SWB and job satisfaction on the full sample as well as regional and gender specific samples. Chapter 5 will examine the causal effects of active commuting modes and their durations on health, SWB and job satisfaction. The use of IVs in this chapter will aid causal inference between the variables of interest.

2.7. Conclusions

This chapter has introduced a review of the current literature on the commuting effects on health, SWB and job satisfaction. Definitions of the variables of interest have been provided, together with possible determinants of commuting mode choices and duration. Findings on the influence of commuting duration and heterogeneous effects of different commuting modes on health, SWB and job satisfaction have been reviewed. In general, longer commuting time is associated with worsened health conditions and reduces time available to health-related activities. Meanwhile, there are mixed findings for the overall effect of longer commuting time on SWB. Some studies have found evidence for the commuting paradox whereas others identified that commuters are compensated for longer commute duration. In terms of different commuting modes, the use of car and public transport for commuting purposes are often found to be associated with deteriorating subjective and objective health indicators and lower SWB ratings. These effects come from the nature of car and public transport being subject to unpredictability and lack of control, for example traffic congestion and delayed services. Car and public transport are regarded as being stressful and generating boredom, whereas active commuting provides sense of control and excitement. Car commuting also exacerbates environmental issues and impose the sedentary behaviour. On the contrary, active commuting has been linked with higher quality of life. By introducing regular physical activities into daily life, it is not surprising that active commuting modes are connected to better health outcomes and can contribute to health service's budget saving. Cycling tends to have a more pronounced effect on health due to higher energy consumption in cycling. Furthermore, the gender inequality in domestic responsibilities may dictate the differences in commuting effects between female and male commuters.

Based on the literature review, several gaps in the literature have been identified. Even though job satisfaction reflects employees' welfare and can influence their performance at work, there is a lack of studies on the effect of commuting on job satisfaction. The spill-over effect can be at play, in which commuting experience is likely to affect the moods of commuters when they arrive at work later. Moreover, as it is likely that health, SWB and job satisfaction are linked together, including them as covariates in the models as well as analysing their simultaneity should provide a clearer perspective on how commuting influences each of these variables.

3 - METHODOLOGY

3.1. Introduction

The previous chapter has reviewed the current literature on what has been learned about how commuting affects health, SWB and job satisfaction, and specific gaps have been identified. In order to make a contribution to the literature and cover the identified gaps, an overall framework on research methodology and economic theory is required. This chapter presents the methodological approach applied throughout this thesis, as well as the data and empirical models used to investigate the research questions. Section 3.2 covers what methodological framework is employed and why it is an appropriate choice for this thesis. Current theories that have been applied in the literature are discussed in Section 3.3, along with the specific theory underlying this analysis.

Moreover, as the research question prompts investigation into causal effects between commuting, health, SWB and job satisfaction, Section 3.4 will consider what methods the current literature has harnessed to derive causal inference. Causal effects can only be deduced if conceptual issues associated with the study are controlled for. Those conceptual issues are discussed in Section 3.5, including measurement for the dependent variables and endogeneity. Given the methodological and theoretical framework, as well as the conceptual issues, possible econometric model options are explained in Section 3.6. Section 3.7 will introduce the data source that the thesis is based on – the UK Household Longitudinal Survey (UKHLS), known as Understanding Society - which has gathered information on the British population since 2009. Approximately 40,000 households were interviewed in Wave 1 – 2009. The main variables for this thesis are related to individual response data of adults from the UKHLS' mainstage survey and will also be presented in Section 3.7. Commuting choice and duration will be the independent variables whose effects on health, SWB and job satisfaction are of interest. As the determinants of commuting have been specified in the previous literature review chapter, the variables representing those determinants along with other variables that could potentially influence the relationships investigated are included as confounding variables. Some examples of such variables are age, gender and marital status. The most suitable models for the empirical studies in this thesis are proposed, along with their assumptions in Section 3.8 along with other research design of the thesis. Section 3.9 concludes the chapter.

3.2. Methodological framework

This section outlines the philosophical and methodological framework for the thesis. Justifications of the approach adopted along with its implications for the thesis's research strategy are provided.

Economists have studied the subject of commuting behaviour based on the traditional economic theory of utility maximisation: other things being equal, commuters would choose from available commuting modes the one that offers the greatest utility. Even though utility is an abstract concept that is difficult to quantify, SWB, and happiness are closely related concepts (Blanchflower and Oswald, 2004; Fujiwara and Campbell, 2011) that can be used as proxy-measures. They have been recorded by self-reported measures in both psychology and economics research. A great deal of studies in these two fields then examine relationships between their variables of interest by applying empirical models on the variables. These are examples of quantitative research which focuses on the quantification of the data gathering and analysis process, whereas words meaning is the emphasis in qualitative approach (Bryman and Bell, 2007). Moreover, Bryman (2012, p. 36) suggests that the quantitative approach regards social reality as 'an external, objective reality' and possesses a deductive stance in terms of the connection between theory and research. Thus, the main objective of quantitative research is investigating and testing hypotheses stemming from existing theories in the literature. With the purpose of investigating the causal effect of commuting on various human outcomes, the objective view of quantitative approach is more suitable for the construction and analysis of data to derive causal conclusions in this thesis.

The ontological and epistemological assumptions implied in the approach should be considered since they are the fundamental assumptions creating the foundation of the thesis' research strategy. For social research, Blaikie (1993) defines ontology as assumptions about the nature of social reality and epistemology as assumptions imposed by the approaches to achieve knowledge of the chosen reality. The thesis' priority is to contribute to the commuting literature which lacks evidence on causal effects of commuting on health, SWB and job satisfaction. Based on Blaikie (1993), Realism is the ontological assumption adopted for this thesis, which can provide a rationale for focusing heavily on identifying causal or generative mechanisms that produce phenomena. The appropriate epistemology to address causality involves Empiricism and Rationalism. The idea is to create models of generative mechanisms and these models form hypothetical descriptions of the mechanisms, which can be examined in comparison to empirical evidence.

With the chosen quantitative approach and assumptions on ontology and epistemology, a deductive research strategy will be the guideline of this thesis. Deductive strategy is based on deductive reasoning and involves using observations and findings to refute false hypotheses or conjectures, whereas inductive strategy is about deriving general theories from observations (Blaikie, 1993). In this thesis, the aim is to study the causal effects of commuting on human subjective states, and it is based on utility theory. A deductive research strategy would allow the empirical studies within the thesis to test econometric models of the effects of commuting with the support of available survey observations.

To put this research approach into practice, the theoretical foundation of the thesis is first presented, followed by a review of empirical tests undertaken in the literature which can provide guidance in choosing suitable empirical methods.

3.3. Theoretical framework

The current section first provides a review of the theories employed in the current literature, then the theory chosen as the foundation of the thesis will be presented.

As noted above a person's travel demand can be understood based on the theory of utility maximisation (Quinet and Vickerman, 2004; Small and Verhoef, 2007). In this theory, a person is a consumer trying to maximise their utility:

$$U = u(x, \mathbf{z}) \tag{3.1}$$

This utility function shows the consumer's preferences for quantities of good x and of other goods included in vector $\mathbf{z}$. Wanting to maximise their utility given in (3.1), the consumer is subject to a budget constraint:

$$p_x x + \mathbf{p}_z \mathbf{z} = y \tag{3.2}$$

where p_x is the price of good x, vector $\mathbf{p}_z$ includes the prices of all other goods, and y is the income of the consumer.

The consumer's utility maximisation problem can then be stated as follows:

$\max_{x,\mathbf{z}} u(x, \mathbf{z})$ subject to $p_x x + \mathbf{p}_z \mathbf{z} = y$. The optimal solutions for this constrained maximisation problem (i.e. the optimal quantities of goods) are denoted as follows:

$$\begin{aligned} x^* &= x^*(p_x, \mathbf{p}_z, y) \\ \mathbf{z}^* &= \mathbf{z}^*(p_x, \mathbf{p}_z, y) \end{aligned} \tag{3.3}$$

The solution set (3.3) can be substituted into the utility function (3.1) and one can derive the utility for different combinations of prices of goods and a consumer's income. The derived utility function is called the indirect utility function v which gives the maximum attainable utility given prices p and budget y

$$v(p, y) = u(x^{*}(p, y), z^{*}(p, y)) \tag{3.4}$$

When facing a choice among travel modes i with associated costs p_i, a utility-maximising consumer chooses the mode which maximises utility $v_i = v(p_i, p, y)$ among all transport modes i.

Commuting behaviour based on utility maximisation is a topic of interest in urban economics to derive conclusions on urban structure (Rouwendal, 2004). Commuting is represented by the monetary and opportunity (time) cost of travelling to work. The monocentric model of urban structure developed by Mills (1967), as discussed in the previous chapter, is a widely cited model that seeks to explain the sizes and structures of metropolitan areas. Commuting cost is a significant component of this model as urban structure is highly related to transportation cost. In the simplest case where jobs are all located at the central business district (CBD), the further away the housing is from the CBD, the cheaper the housing and the higher the commuting cost will be. The author also considers that the opportunity cost of travel time is a significant cost for travellers. Thus, utility theory should predict that commuters would maximise their utility if their travel time is minimised (Hamilton, 1982; White, 1988). In equilibrium, cheaper housing in further locations can be regarded as a compensation for longer commuting time to preserve commuters’ utility (White, 1988; Rouwendal, 2004). The model can be extended for the case of employment decentralisation, i.e. when jobs are available away from the CBD. White (1988) provides a simple explanation of this extension: In this case, commuting is still minimised if their job location is closer to the CBD than their house to the CBD, which is regarded as inward commuting. However, not all commuters can travel inwardly. To attract workers and compensate for their suboptimal commuting, the wages paid for these commuters must be higher than for the inward travellers because workers strive for maximising net salary after deducting the commuting cost. Consequently, as longer commute reduces a person's utility, there must be compensation for longer commute in terms of either cheaper housing or higher wages in order to shift the utility back to the equilibrium level. Based on the utility maximisation theory, any alternative combinations from the labour and housing markets on the same indifference curve should yield the same utility for a commuter (McFadden, 2001). Those combinations from the two markets would determine the corresponding commute durations. Therefore, a longer commute is expected to produce the same level of utility as a shorter time span because the commuter would be compensated from either market. The literature, as reviewed by Stutzer and Frey (2008), shows empirical evidence of compensation for commuting distance in terms of land and housing prices and heterogenous wages.

While urban transport models include commuting and its compensation in labour and housing markets, DeSalvo and Huq (1996) seek to improve the models by introducing mode choices and the assumption that income has an influence on mode choices and the monetary commuting cost. Now, a rational commuter would choose a mode choice with a combination of speed and time that minimise the monetary and opportunity cost of commuting. It is derived from their model that when a commuter's wage rate increases, they would switch to a quicker mode and save on commuting time. The authors notice the change in pattern of housing location relative to income in the US with more affluent households living further away from the CBD. A possible explanation is technology change leading to the introduction of quicker but more costly modes, such as cars, which only the rich found economical. In addition, the differences between countries in the pattern of housing-income are likely due to countries not having the same monetary cost for various transport modes, and different real wages between countries can be a contributing factor.

The most prominent type of utility in travel choice modelling is decision utility. As mentioned in Chapter 2, decision utility represents an individual's preferences and can be reflected in the weights assigned to objective attributes of alternative options when one makes choices (Ettema *et al.*, 2010; De Vos *et al.*, 2016). The combination of weights can be unique to individuals who incorporate their own preference into their decision utility. Alternatively, experienced utility is the hedonic experience derived from the choice made by an individual, and thus regarded as being closer to the original concept of utility proposed by Bentham (1789/1996), which comprises of avoiding pain and gaining pleasure", than decision utility (Ettema *et al.*, 2010). Ettema and his colleagues (2010) argue that experienced utility is not the same as the prediction of experienced utility - anticipated utility, which is the cognitive process of anticipating what the outcome derived from a particular choice should be. Humans tend to overestimate their reactions to future events, and this phenomenon is known as impact bias (Wilson and Gilbert, 2005). The impact bias, according to Wilson and Gilbert (2005), firstly includes a combination of an overestimation of how large the impact someone would expect to derive from a particular event (e.g. result of a football match from their favourite team) and an underestimation of how other events from their daily life can affect and make them move on from that particular event. Secondly, the bias also comprises the inability to predict how quickly it will take them to fully make sense and adapt emotionally to an unexpected event (e.g. unexpectedly receiving a high grade). Moreover, decision utility is also conceptually different from anticipated utility. Theoretically, there is no difference between anticipated utility and experienced utility due to the assumption within utility theory that consumers have perfect information, thus are well-informed about outcomes of alternatives. However, due to cognitive bias and lack of information, experienced utility is different from either decision utility or anticipated utility (Ettema *et al.*, 2010). Because this thesis focuses on how alternative transport modes, particularly active mode choices, can impact individuals' subjective characteristics, experienced utility may be a more suitable theoretical concept. A proxy of experienced utility has received growing attention in the economic field. This is SWB, and it has been advocated by Kahneman (1999) as a measure of human's welfare. It is argued that SWB can complement decision utility which is currently used in cost-benefit analysis for policies (Ettema *et al.*, 2010; Fujiwara and Campbell, 2011; Martin, Goryakin and Suhrcke, 2014). The decision utility approach in the cost-benefit analysis for policies represents an examination of alternative choices based on weighted attributes, whereas SWB reflects the impact of choices on overall life satisfaction and specific affects, as discussed in Chapter 2. Before 2008, the literature has mainly investigated the compensation of longer commute in the context of higher wages or cheaper housing. Stutzer and Frey (2008) is one of the first studies examining the direct effect of commuting on utility with the application of SWB as an indicator for experienced utility. Since then, studies that apply SWB measures in this topic have expanded.

This thesis is interested in how different commuting mode choices, especially active transport modes, can impact workers' welfare. Thus, the utility maximisation theory applied for the case of commuting choice is an appropriate underlying basis. As discussed above, experienced utility will be assumed as a more suitable concept for workers' welfare in this thesis. Instead of following the indirect utility approach, the thesis will incorporate the method implemented in studies by Stutzer and Frey (2008) and Roberts, Hodgson and Dolan (2011), in which measures of SWB are used as a proxy for experienced utility to investigate the utility equation directly. For instance, Stutzer and Frey (2008) use a linear empirical model to investigate commuters' SWB with the parameter ᛏ being the change in utility when there is a change of D minutes in commuting time:

ό | ᛏ Ὀ - (3.5)

3.4. Methodological review of literature

Before assessing the best method to examine the causal relationships between commuting, health, SWB and job satisfaction, it is instructive to review what methodological approaches are available in the literature. Karl Pearson was believed to have said that “Correlation does not imply causation” (Heckman, 2000, p.1). Heckman (2000) argues that in general, there is a lack of attention paid to a clear definition of causal parameters and also a structural framework to approach causal inference, hence causal models are used in the economics literature as a tool for interpreting data and analysing current policies. A counterfactual statement is of the form “If X had been the case, then Y would have occurred” which is made when it can be acknowledged that X is definitely not the case (Dawid, 2000, p. 408). According to Morgan and Winship (2015), a large proportion of research in the social sciences is interested in cause-and-effect questions, even though finding clear-cut answers for these questions is not always feasible because of the limitations that researchers have to deal with when gathering and analysing data. The authors have advocated the application of the counterfactual model approach in causal inference against simple regression modelling. The following material on the counterfactual approach to causal inference follows from Morgan and Winship (2015).

The counterfactual model for causality provides a unified framework of estimation approaches to give answers for causal effect questions. It can also be referred as the potential outcome model, which was originated in the 1900s (Rubin, 2005). The model can be simplified as follows. Firstly, assume that each person in a population can be exposed to two different states of a cause. Each state possesses its own unique conditions and could in turn influence the outcome. The alternative causal states are regarded as treatments; and if there are only two treatments of interest, they are called ‘treatment’ and ‘control’. Although each person in the population of interest can only experience one treatment state at any point in time, the model's main assumption is that each person experiences a potential outcome for each treatment state. These outcomes are considered as counterfactual since they can only happen in theory but cannot be observed in real life.

In a two-state case, a person's potential outcomes are the true values of outcome in the causal question when they experience the two treatment states. Denote the potential outcomes for a person i as y_i^1 for the treatment state and y_i^0 for the control state. In theory, an individual-level causal effect can be calculated by taking the difference y_i^1 - y_i^0. Logicaly, both y_i^1 and y_i^0 cannot happen simultaneously, thus individual-level causal effects cannot be estimated. Instead, researchers investigate an observed dependent variable Y which adopt the values of outcome y_i that equals to y_i^1 for people that experience the treatment state and y_i^0 if they are exposed to the control state. Attention is placed on average causal effects calculated by investigating the value y_i for groups of participants with common attributes. In order to carry out this analysis, researchers attempt to model the process in which participants from different groups experience the cause in the question. Several defendable assumptions are included to facilitate the computation of the 'average unobservable counterfactual value' for each group (Morgan and Winship, 2015, p.5). If there is a relevant method to calculate the average difference from the data available and the assumptions can be supported, the derived average difference for y_i can be used for cause-and-effect inference.

The incorporation of causal questions is advocated in this model, with counterfactual differences clearly presented, such as "if variable D originally taking value of d had instead taken value of d', then how much would the value for outcome variable Y have varied?". The assumptions of the potential outcome models include supposing that the data are created from an extensive random-sample survey applied to a population that is well-defined. Also, the percentage and characteristics of individuals exposed to treatments in the population of interest are assumed to be fixed during the process of the causal exposure.

Moreover, causal relationships can be presented graphically which can facilitate in explaining estimating strategies for causal inference.

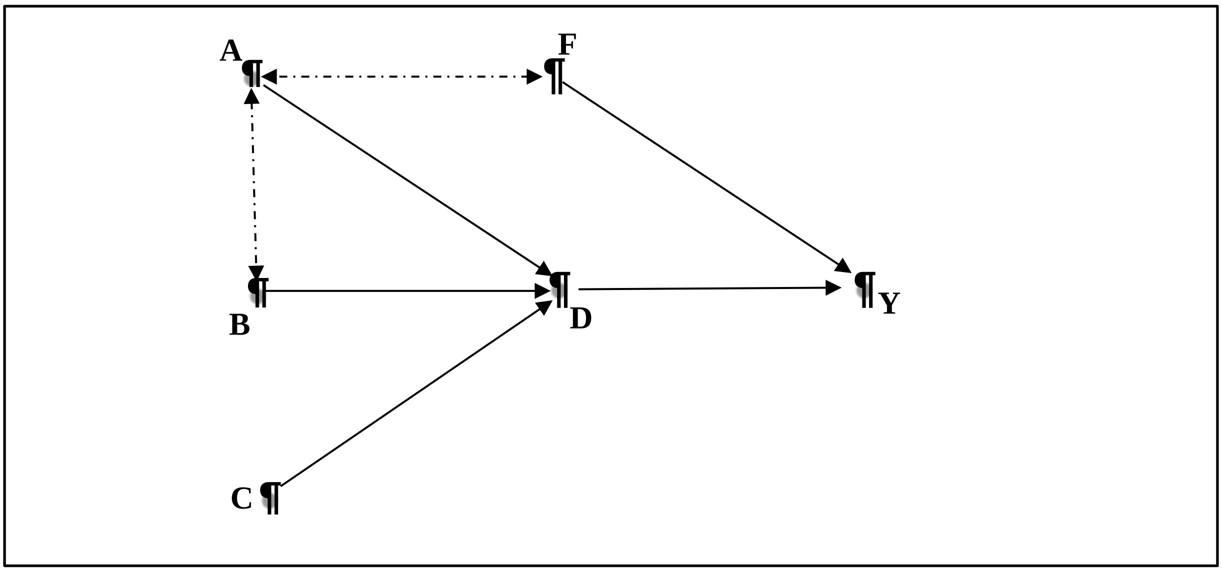

Figure 3.1: A map of causal relationships

Figure 3.1 demonstrates an example of a causal graph (Morgan and Winship, 2015, p.30). Each node, including A, B, C, D, F and Y is an observable random variable and each single-headed arrow represents a causal effect caused by the variable at the origin to the one at the end of the arrow. Each dashed double-headed arrow illustrates the presence of an unobserved variable that can cause both variables at either end of the arrow. This type of arrow signifies a common cause only, rather than any relations with unknown sources or direct causal effects between the variables at the two ends. The causal variable is assumed to be D, the outcome variable Y and the causal effect of D on Y is of interest here.

Among approaches for causal estimation suggested by Morgan and Winship (2015), the instrumental variable strategy, that is proposed for this research as indicated in the subsequent

Section 3.6 and 3.8, is illustrated based on Figure 3.1 as follows. An exogenous variable can be used as an instrumental variable to eliminate covariation between the causal variable and the outcome variable and estimate indirectly the causal effect between the two variables. In Figure 3.1, variable C is a suitable instrumental variable, as it affects variable D but has no relation with the outcome variable Y, except indirectly via its influence on variable D. The causal effect of D on Y can be calculated by the proportion of the relation between Y and C and between D and C. It is not essential to observe variables A, B and F in this strategy. For this strategy, it requires an assumption of linearity, in which the relations between C and D and between D and Y are linear.

Moving on from approaches to causal inference, the type of data one uses in a study can also constrain the method of analysis and also whether causal inference is possible. Cross-section data which observe a sample of population at a specific point in time cannot provide insights into intertemporal relationships between variables of interest. On the contrary, panel data, or longitudinal data, record observations of the same subjects repeatedly over regular time periods, could deal with certain inherent problems of cross-section data. There are a few advantages of panel data. Firstly, there exists a gain in estimation precision due to the increase in observations observed over several time periods for a respondent. Moreover, panel data observes the same individuals over time, thus can capture time-fixed unobserved individual characteristics, i.e. heterogeneity while cross section data cannot. This allows for more consistent parameter estimation with the use of fixed effect (FE) and random effect (RE) models. Although omitted variable bias from heterogeneity in cross-section model may be avoided by using instrumental variables, finding relevant and valid IVs may not be straightforward.

There are many econometric methods available for panel data, however examining issues unique to each research study can guide the decision on which is the most appropriate choice of econometric method for causal inference. The main conceptual issues that are intrinsic to the dependent variables SWB, health and job satisfaction are identified in Section 3.5, and potential econometric methods that can explore the research questions and provide remedies for those conceptual issues will be discussed in Section 3.6.

3.5. Conceptual issues

This section considers the conceptual issues that may limit the ability to draw causal inferences to answer the research questions in this thesis. The problem of endogeneity in survey data, along with its various types will be discussed in Subsection 3.5.1. In addition, as the thesis utilises secondary data which records the variables of interest using survey questions with a range of categorical options, such as Likert scales, the ordinal nature of the variables might require discrete choice modelling. However, a study by Ferrer-i-Carbonell and Frijters (2004) exploring whether it is possible to assume cardinality for a categorical SWB variable may allow for a wider choice of models from the linear modelling approach. Subsection 3.5.2 will review the assumptions for the dependent variables of interest.

3.5.1. Endogeneity

In a regression model, the independent variables are assumed to be exogenous and unrelated to the unobserved factors in the error term, whether it is a linear (Cameron and Trivedi, 2005) or discrete choice model (Train, 2009). When this assumption is violated and there is some relation between a predictor and the error term, the predictor is regarded as being endogenous and the model encounters the problem of endogeneity. The word ‘endogenous’ means “caused by factors inside the systems” (Cameron & Trivedi, 2005, p. 78). Estimating regression coefficients without proper control for the relation between predictors and unobserved variables would lead to inconsistency in coefficient estimation. To illustrate this point, a linear cross-section model can be used as an example. Firstly, stating the definition and Gauss-Markov assumptions of a multiple regression model would be beneficial for the discussion. The subsequent material follows from Wooldridge (2016, p. 92):

Assumption A1: Linear in parameters

The population model is given as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + u, \tag{3.6}$$

with $\beta_0, \beta_1, \dots, \beta_k$ being the unknown parameter coefficients of interest and u being the random error term. The error term u consists of all the unobserved factors that influence y. This assumption gives a definition to the multiple regression model.

In the ordinary least square approach (OLS), the coefficient estimators $\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_k$ are estimations of the true model's unknown parameters $\beta_0, \beta_1, \dots, \beta_k$ that minimise the sum of square residuals.

Assumption A2: Random sampling

A random sample of n observations $\{(x_{i1}, x_{i2}, \dots, x_{ik}, y_i): i = 1, 2, \dots, n\}$ is available.

The thesis will assume that the data sample used from the UKHLS is random.

Assumption A3: No perfect collinearity

In the sample and population, the independent variables $x_1, x_2, \dots, x_k$ are not constant and there is no exact linear relation between them.

This assumption requires that none of the predictors is a linear combination of the others. Otherwise, the situation is regarded as perfect collinearity and the model cannot be estimated with OLS. Predictors are allowed to correlate with each other, but not perfectly correlated.

Assumption A4: Zero conditional mean

$$E(u \mid x_1, x_2, \ldots, x_k) = 0 \qquad (3.7)$$

This assumption requires that given any values for the predictors $x_1, x_2, \ldots, x_k$, the error term u has expected value equal to 0. The assumption is necessary for unbiasedness of OLS coefficient estimation. An OLS estimate is regarded as an unbiased estimation of the true parameter in the population if:

$$E(\hat{\beta}_j) = \beta_j \text{ for all } j = 0, 1, \ldots, k \qquad (3.8)$$

When any predictor $x_1, x_2, \ldots, x_k$ is related to the error term u, there exists the problem of endogeneity.

Assumption A5: Homoskedasticity

The variance σ^2 of the error term u is the same for any values of the independent variables

$$Var(u \mid x_1, x_2, \ldots, x_k) = \sigma^2 \qquad (3.9)$$

If this assumption does not hold, the model is said to experience heteroskedasticity.

With all assumptions clearly specified, endogeneity can be explained graphically as follows. Assume that an underlying population model is given as:

$$y = \beta x + u \qquad (3.10)$$

where u is an error term. The OLS regression model assumes that the predictor x and the error term u are not correlated. Hence, the $\hat{\beta}_{OLS}$ estimate is consistent and represents the direct effect on y from an exogenous change in x. As shown in the Figure 3.2 below, there are two separate independent influences on y from x and u.

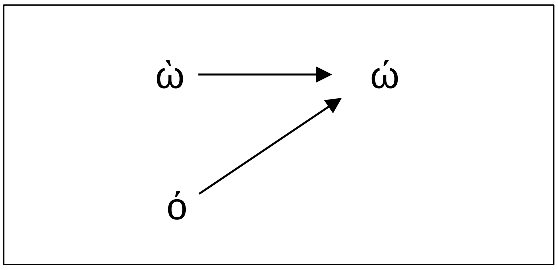

Figure 3.2: Independent influences on the dependent variable y

However, there are situations where potential correlations between predictors and the error term could exist. For example, when the commuting duration by cycling (ὼ) is used as a predictor for health status (ώ), being active is a clear factor that can influence both the duration spent on commuting by cycling of a person ὼ and their health status ώ. If being active is left out from the regression model, it will be included as a part of the error term ό, which comprises of all unobserved factors that influence health status ώ Thus, there is a correlation between ὼ and error term ό As ὼ changes, there are now two effects on ώ One is the direct effect of ↾ ὼ and the other is the indirect effect from ό influencing ώ via ὼ

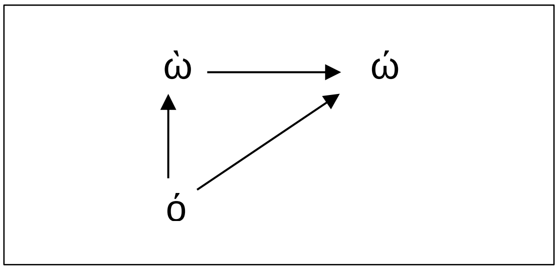

Figure 3.3: Endogeneity problem

The aim of regression analysis is to estimate the effect on y from an exogenous change in x, which is represented by a consistent ↾ . The correlation between x and u violates the OLS assumption and leads to a $\hat{\beta}_{OLS}$ estimation that includes both the direct and indirect effects. If the OLS regression model is expressed in calculus as follows:

$$y = \beta x + u \qquad (3.11)$$

then $\hat{\beta}_{OLS} = \frac{dy}{dx} = \beta + \frac{du}{dx} \neq \beta$. So the OLS estimation of β is inconsistent and biased.

A formal definition of consistency in regression estimation with multiple regressors is as follows. According to Cameron & Trivedi (2005, p. 72), a linear regression model in matrix notation is given as follows:

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u} \qquad (3.12)$$

where $\mathbf{y}$ is an $N \times 1$ vector of dependent variables, $\mathbf{X}$ is an $N \times K$ regression matrix and $\mathbf{u}$ is an $N \times 1$ error vector. The OLS estimator is the estimator that minimises the sum of squared errors and given as:

$$\hat{\beta}_{OLS} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$$

and it can be written as

$$\hat{\beta}_{OLS} = \beta + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u} = \beta + (N^{-1}\mathbf{X}'\mathbf{X})^{-1}N^{-1}\mathbf{X}'\mathbf{u}$$

Thus, we have

$$\text{plim}\,\hat{\beta}_{OLS} = \beta + (\text{plim}\,N^{-1}\mathbf{X}'\mathbf{X})^{-1}\,\text{plim}\,N^{-1}\mathbf{X}'\mathbf{u}.$$

where plim refers to the probability limit. The OLS estimator is consistent if and only if $\text{plim}\,\hat{\beta}_{OLS} = \beta$, which requires

$$\text{plim}\,N^{-1}\mathbf{X}'\mathbf{u} = 0$$

This condition can be met if $E[\mathbf{x}_i u_i] = 0$ or in other words, **x** and error term **u** are not correlated, as required in Assumption A4. The independence of the predictors and error term is an OLS regression assumption to ensure consistency of parameter estimation. However, in the presence of endogeneity, the predictors and error term are correlated and parameter estimations inconsistent if OLS models are applied. Inconsistent estimates caused by endogeneity can only be interpreted as associations, rather than causal relations and directions between variables of interest. Also, endogeneity can create biased estimation, and lead to incorrect magnitude of associations estimated (Cameron and Trivedi, 2005). Therefore, the presence of endogeneity weakens causal inference analysis, and conclusions about associations between the variables of interest do not adequately fulfil the goal of studying causal relationships in this thesis.

There are three causes of endogeneity that can lead to the correlation between a predictor and the error term, including omitted variables, simultaneity and measurement error (Roberts and Whited, 2011). The following discussion about different endogeneity causes relies on Wooldridge (2016).

Omitted variable bias occurs when a crucial variable belongs to the population but is not included in the empirical model, which can be due to ignorance or data limitation. Given a population regression model with two predictors x_1 and x_2 that satisfies assumptions A1 to A4 above:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + u \qquad (3.13)$$

The relationship between y and x_1 is of interest, thus a sample model is estimated. An unbiased estimation of β_1 would require a sample model comprising of both x_1 and x_2.

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 \qquad (3.14)$$

However, x_2 is left out due to either data limitation or poor model specification:

$$\tilde{y} = \tilde{\beta}_0 + \tilde{\beta}_1 x_1 \qquad (3.15)$$

If x_2 is correlated with x_1, the estimator $\tilde{\beta}_1$ is not the same as the unbiased OLS estimator $\hat{\beta}_1$. In fact,

$$\tilde{\beta}_1 = \hat{\beta}_1 + \hat{\beta}_2 \tilde{\delta}_1 \tag{3.16}$$

where $\tilde{\delta}_1$ is the slope parameter when x_2 is regressed on x_1. Thus, $\tilde{\beta}_1$ is a biased estimate for β_1.

$$E(\tilde{\beta}_1) = E(\hat{\beta}_1 + \hat{\beta}_2 \tilde{\delta}_1) = E(\hat{\beta}_1) + E(\hat{\beta}_2)\tilde{\delta}_1 = \beta_1 + \beta_2 \tilde{\delta}_1$$

When observations are combined into matrix form, it can be calculated that $\text{plim}\, \hat{\beta} = \beta + \delta\lambda$, where $\delta = \text{plim}\left[\left(N^{-1}X'X\right)^{-1} N^{-1}X'z\right]$ is the probability limit of the OLS estimation of the omitted variable z on the included predictors x, and λ is the coefficient of z in the population model. This misspecification is regarded as omitted variable bias and occurs as long as the omitted regressor is correlated with the included ones, i.e. $\delta \neq 0$ (Cameron and Trivedi, 2005, p. 93). Therefore, endogeneity due omitted variables can cause the coefficient estimation to be biased and inconsistent.

Cross sectional data reports observations of a sample of subjects at a point in time, meanwhile data in time-series studies records the observations over many time periods of one particular subject, e.g. a company or a country. The data in this thesis is a panel data set which combines features of both cross sectional and time series data. Whereas a pooled cross-sectional data set observes random samples of a population over different time periods, a panel data set, or a longitudinal data set, collects information the same subjects over time. This means that the observations from panel data can no longer be assumed to be independently distributed over time (Wooldridge, 2016). One of the analysis options is to separate omitted variables that capture this lack of independence into those that are constant and those that vary over time. Given a linear panel model with a single predictor x_{it}, this can be illustrated as follows

$$y_{it} = a_i + \beta_1 x_{it} + u_{it} \tag{3.17}$$

where u_{it} is the idiosyncratic error term, i represents cross section and t represents time periods.

Those unobserved variables that are fixed over time and have an impact on the dependent variable y_{it} are captured by the variable a_i. The variable a_i only has a subscript i to signify that it only varies across individuals, not across time periods. It is called unobserved heterogeneity and can be characteristics that are unique to each individual, for example, personalities. Apart from that, the idiosyncratic error term u_{it} consolidates all the unobserved factors that are time-varying and influence y_{it}.

As the relationship between x_{it} and y_{it} is of interest, Pooled Ordinary Least Squares (POLS) can be applied to Equation (3.17) to estimate β_1 by pooling all the time periods and ignoring the time series aspect. However, to achieve a consistent estimate for β_1, it is required that the predictor x_{it} is uncorrelated with the composite error term of $(a_i + u_{it})$. If the Gauss-Markov assumption applies, x_{it} is uncorrelated with the idiosyncratic error u_{it}. However, it is still possible for a correlation between the predictor x_{it} and the unobserved heterogeneity effect a_i, which will make the POLS estimation for β_1 biased and inconsistent. This is regarded as heterogeneity bias and a part of omitted variable bias. An example of a heterogeneity bias in the context of this study is that intrinsically happy and healthy people are more likely to rate their health, SWB and job satisfaction highly and at the same time use more active modes for their daily commute. It is likely that heterogeneity exists in the data and a technique that can control and remove this bias is the FE method and detail of the technique is discussed in Subsection 3.6.1.

The second cause of endogeneity is measurement error. This occurs when a variable in a regression model is measured by an inaccurate measure. Measurement error is different from using a proxy measure for a variable. A proxy measure is related with the variable of interest, whereas in the case of measurement error, the variable of interest is well-defined and quantitatively meaningful, however, the way it is measured in a study may involve some error. Measurement error in regression models can stem from measurement error in the dependent variable or in the independent variables.

In the case when the dependent variable is subject to measurement error, assume that y^* is the dependent variable of interest in the population model which is given as follows

$$y^* = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k + u \tag{3.18}$$

The population model is assumed to satisfy all the Gauss-Markov assumptions discussed above. A variable y is measured as an observable version of y^*, for example: if household annual savings is the variable of interest, then estimated annual savings is likely to be measured. Then the difference between the true variable and the recorded variable $e_0 = y - y^*$ is the measurement error in the population. To estimate the true model (3.18), the observed variable $y^* = y - e_0$ is substituted into the model

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k + u + e_0 \tag{3.19}$$

The error term is the combination of $u + e_0$. If the OLS approach is applied to estimate this model, because the true model is assumed to meet all the OLS assumptions, the error term u has zero mean $E(u) = 0$ and no correlation with all predictors x_j. The measurement error e_0 can be assumed to have zero mean; even if that is not the case, it would only lead to a biased intercept estimation of β_0. What is more important to consider is a potential correlation between the measurement error e_0 and the predictors x_j. It is normally assumed that there is no correlation between them, thus the OLS coefficient estimations for x_j would be unbiased and consistent. The thesis follows the literature and assumes that the measurement error is only a random error while measuring and reporting data and it is uncorrelated with the predictors (Wooldridge, 2016).

In the case that the predictors experience measurement error, assume that the population model given as follows satisfied the OLS assumptions.

$$y = \beta_0 + \beta_1 x_1^* + u \tag{3.20}$$

The OLS approach applied to (3.20) should give an unbiased and consistent estimate for β_1. However, if x_1^* is not observed and x_1 is chosen instead, then the measurement error is the difference between the two variables $e_1 = x_1 - x_1^*$. As in the case when the dependent variable experiences measurement error, e_1 is assumed to have zero mean in population $E(e_1) = 0$. As the population model (3.20) satisfied the Gauss-Markov assumptions, it is intuitive to assume that u has no relation with x_1 and x_1^*.

Assumptions about the measurement error e_1 would influence whether the OLS estimation would be unbiased and consistent. If e_1 is not related to the measured variable x_1, the population model (3.20) would be estimated as

$$y = \beta_0 + \beta_1 x_1 + u - \beta_1 e_1 \tag{3.21}$$

The new error term is $u - \beta_1 e_1$ and each element of it is assumed to have zero mean and no correlation with the predictor x_1. Therefore, the OLS estimates for both parameters β_0 and β_1 are unbiased and consistent.

However, if e_1 is assumed to be uncorrelated with the unobserved true variable x_1^*, e_1 must be correlated with the predictor x_1 because $e_1 = x_1 - x_1^*$. Then the OLS estimation in (3.21) is biased and inconsistent. This thesis assumes that any potential measurement error in the predictors is unrelated to the measured predictor variables.

The third possible source for endogeneity is simultaneity, which occurs when one or more predictors are simultaneously determined with the dependent variable, typically via an equilibrium process. For instance, in the context of this thesis, more active commuting can increase the health status of a commuter, but at the same time, a commuter with better health may be more likely to choose active commuting modes. Simultaneity is often associated with a simultaneous equation model, which is a system of structural equations. In each equation of the system, one or more predictors are jointly determined with the dependent variable. For example, we have a 2-equation model as follows:

$$y_1 = \alpha_1 y_2 + \beta_1 z_1 + u_1 \tag{3.22}$$
$$y_2 = \alpha_2 y_1 + \beta_2 z_2 + u_2 \tag{3.23}$$

where z_1, z_2 are exogenous, hence not correlated with u_1, u_2.

Assume that Equation (3.22) is of interest and subject to estimation, it is required that y_2 has no correlation with u_1. Substituting y_1 in (3.22) into Equation (3.23) will result in

$$y_2 = \alpha_2(\alpha_1 y_2 + \beta_1 z_1 + u_1) + \beta_2 z_2 + u_2$$

Rearranging should give

$$(1 - \alpha_2\alpha_1) y_2 = \alpha_2\beta_1 z_1 + \beta_2 z_2 + \alpha_2 u_1 + u_2 \tag{3.24}$$

This equation is only solvable for y_2 if we assume $\alpha_2\alpha_1 \neq 1$. Then Equation (3.24) will be transformed into

$$y_2 = \pi_1 z_1 + \pi_2 z_2 + v_2 \tag{3.25}$$

with $\pi_1 = \frac{\alpha_2\beta_1}{1-\alpha_2\alpha_1}$, $\pi_2 = \frac{\beta_2}{1-\alpha_2\alpha_1}$ and $v_2 = \frac{\alpha_2 u_1 + u_2}{1-\alpha_2\alpha_1}$.

In Equation (3.22), z_1 is not correlated with u_1 by assumptions. OLS estimation requires that y_2 and u_1 to be uncorrelated also. However, Equation (3.25) illustrates that y_2 and u_1 are related if there is a correlation between v_2 and u_1. As v_2 can be expressed as a function of u_1 and u_2, it should be the case that they are correlated with each other. Thus, the OLS estimation experiences simultaneity bias from the correlation between y_2 and u_1.

In a general case with more than two predictors as in Equation (3.26) below, endogeneity due to correlation between one predictor and the error term can cause parameter estimations of all predictors $x_1, x_2, \ldots, x_k$ to be biased.

ώ ᶦ ي ᶦ ₒώₒ ȢȢȢ ᶦ ₒώₒ ó (3.26)

All these three sources of endogeneity can make an OLS estimate biased and inconsistent. Applying simple OLS models for the data in this thesis without controlling for endogeneity is not adequate to deduce causal effects from each of the predictors. However, as noted above, instrumental variable (IV) analysis can be used to control for all three endogeneity types and provide consistent parameter estimates. In the case of simultaneity, an equation within a simultaneous equation system is regarded as identified if the number of excluded exogenous variables is at least as many as that of endogenous variables in the equation. The IV estimation approach can be applied using any exogenous variable within the system that is not included in the same equation. It is possible to estimate each equation in the system separately with the two-stage least squares (2SLS) approach; however, system estimations tend to be more efficient. A system estimation approach for simultaneous equation models is the three-stage least squares (3SLS) approach.

In general, as briefly discussed in Subsection 3.4, the IV approach produces only exogenous variation from the endogenous predictor ώas illustrated in the following Figure 3.4. To carry out an IV approach with observational data, an instrumental variable ά is required. The variable ά needs to satisfy the requirements that it is correlated with the endogenous variable ώ but not with the error ό. Thus, it is possible that ά is correlated with ώ but only with an indirect effect via ώ as illustrated below.

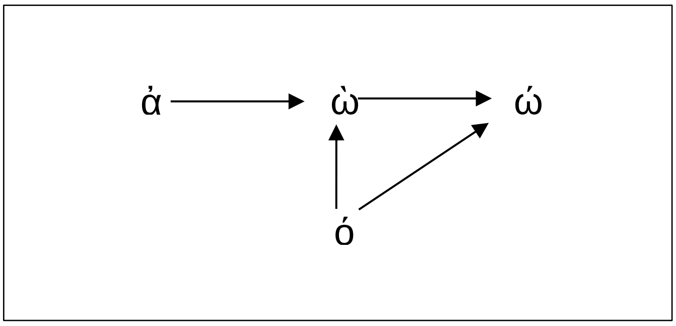

Figure 3.4: Controlling endogeneity with instrumental variable

3.5.2. Measurement of dependent variables

In this subsection, alternative treatments from the literature for the dependent variables of interest, i.e. health, job satisfaction and SWB will be investigated, together with the implications for subsequent estimation analysis.

The variables of interest, i.e. health, job satisfaction and SWB, are often measured in surveys by questions that require self-reported subjective responses. The responses comprise of categories representing different values and these categories have a clear order between themselves. In statistics, these are considered ordinal variables and the appropriate method for ordinal dependent variables is an ordered choice model. However, there are possible variations in how one may choose to view these variables. Ferrer-i-Carbonell and Frijters (2004) review psychology and economic literature on how the two fields treated SWB as a variable. A survey question on life satisfaction is frequently used in the literature to represent and investigate the SWB of a person (Stutzer and Frey, 2008; Roberts, Hodgson and Dolan, 2011). Typically, respondents can choose their answer based on a Likert scale. An example for such a question is as follows, taken from the UKHLS survey as this study's SWB measure:

"On a scale of 1 to 7 where 1 = 'Completely Dissatisfied' and 7 = 'Completely Satisfied', please tell me the number which you feel best describes how dissatisfied or satisfied you are with the following aspects of your current situation… Your life overall".

(Institute for Social and Economic Research (ISER) University of Essex, 2015, p.573-575)

The potential values are different categories, represented by a range from 1 to 7. The psychology literature tends to treat the life satisfaction question which represents SWB variable as cardinal. It means that the difference in life satisfaction level between values 1 and 2 of a person is the same with that of values 4 and 5 across different individuals.

Conversely, some economic literature assumes that SWB is an ordered variable. The differences between each pair of consecutive values may be treated as uneven, though they are monotonically related. Thus, some economists have used ordered logit models (Blanchflower and Oswald, 2004; Benz, 2005; Andersson, 2008; David G Blanchflower and Oswald, 2008) or converted SWB into a binary variable to apply FE conditional logit models (Stutzer and Frey, 2006; Andersson, 2008). It is also possible to present results assuming both cardinality and ordinality for robustness checks (Stutzer and Frey, 2006). Nevertheless, ordinal models do not easily facilitate controlling for fixed individual heterogeneity and FE estimations in ordered probit models can potentially give biased or inconsistent coefficient estimates (Ferrer-i-Carbonell and Frijters, 2004). The authors then find qualitatively similar results between linear FE model and ordered models of SWB and conclude that whether SWB is assumed to be cardinal or ordinal is not important to estimation results, whereas controlling for time-invariant heterogeneity with FE estimations may be of more importance in SWB modelling. Hence, as long as the fixed individual heterogeneity is controlled for, the difference in the choice of modelling SWB is not significant and one can assume that SWB is adequately measured as continuous. Following the results from Ferrer-i-Carbonell and Frijters (2004), studies in the literature have treated their categorical SWB (Stutzer and Frey, 2008; Roberts et al., 2011; Martin et al., 2014; Morris, 2015) and health measures (Künn-Nelen, 2015) as continuous. Dickerson and his colleagues (2014) re-examine the debate and report similar results with findings in Ferrer-i-Carbonell and Frijters (2004) that a linear FE model is an alternative for an ordered FE model to investigate SWB. Therefore, it is possible to regard the ordinal variable SWB as a continuous variable legitimately. The ease of interpretation in using linear FE models is also an advantage because their coefficient estimations can be translated into marginal effects (ONS, 2014; Morris, 2015). In contrast, the coefficients in ordered models are linked with an underlying latent variable and do not directly provide a marginal effect (Dickerson et al., 2014). Unlike in OLS models, conditional mean functions do not exist in the case of both binary and ordered probit models, thus the magnitude of parameter estimates does not have explanatory power, only the statistical significance is useful for interpretation (Hensher, Rose and Greene, 2005).

Meanwhile, another variable of interest in the thesis is job satisfaction. It is a domain of SWB and measured by a similar question and a 7-point Likert scale in the UKHLS survey

“On a scale of 1 to 7 where 1 means 'Completely dissatisfied' and 7 means 'Completely satisfied', how dissatisfied or satisfied are you with your present job overall?”

(Institute for Social and Economic Research (ISER) University of Essex, 2015, p. 420)

Also, the health variable used in this thesis is a subjective health status variable, asking how a respondent rates their own health status subjectively on a 5-point Likert scale

“In general, would you say your health is...1-Excellent, 2-Very good, 3-Good, 4-Fair, 5-Poor”

(University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2015, p. 560)

The same subjective health variable has been treated as cardinal in the literature. For example, Künn-Nelen (2015) investigates how commuting affects objective and subjective health measures and finds consistent findings between linear models and ordered models of subjective health status. Therefore, based on the advantages of cardinality assumption, the dependent variables health, SWB and job satisfaction in this thesis will be considered as continuous variables. Assuming cardinality will allow exploiting well-established econometric techniques in the literature to control for more important endogeneity issues that are inherent in this thesis.

This section has investigated the problems of endogeneity that exist in this study. Alternative assumptions on the dependent variables have also been reviewed, the choice of which can influence how the endogeneity issues can be controlled for. Based on the cardinality assumption for the dependent variables in this thesis, the next section will explore the econometric techniques that can control for the conceptual issues discussed in this section.

3.6. Applicable econometric techniques

As discussed in Section 3.5.2, the thesis follows the approach proposed by Ferrer-i-Carbonell and Frijters (2004) in which categorical measures are considered cardinal, hence linear models for continuous variables are applicable. The availability of panel data such as the one used in this thesis would allow FE models to control for heterogeneity. Studies following Ferrer-i-Carbonell and Frijters (2004) have incorporated linear FE models in exploring the relationships between commuting and health and SWB (e.g. Stutzer and Frey, 2008; Roberts, Hodgson and Dolan, 2011; Künn-Nelen, 2015). However, some studies have admitted that the lack of valid IVs prevents them from challenging their assumption of exogeneity for commuting (Roberts, Hodgson and Dolan, 2011). The thesis will exploit the advance in linear econometric methods to control for endogeneity with the help of IVs. This section will explain the general econometric techniques that will be applied throughout the thesis, namely FE model and GMM estimation method using IVs. The material discussed in this section follows from Cameron and Trivedi (2005).

3.6.1. Panel Data Methods: FE, RE and POLS

The data from the UKHLS that will be incorporated in this study is a longitudinal data set, or a panel data set. As discussed in Section 3.5, panel data possesses several advantages over cross-sectional data, one of which is that it allows researchers to control for the unobserved heterogeneity. Panel data are incorporated in studies mainly because researchers can assume a correlation between the unobserved effect and the predictors (Wooldridge, 2016) which needs to be controlled for.

Panel data observe the same individuals over time. A general linear model applied to a panel dataset can allow the two coefficients α and β to vary across periods t and respondents i.

$$y_{it} = \alpha_{it} + \mathbf{x}_{it}'\beta_{it} + u_{it}, \tag{3.27}$$

(Cameron and Trivedi, 2005, p. 698)

in which $i = 1, \ldots, N$ represents survey respondents and $t = 1, \ldots, T$ represents time waves of interview in this thesis. The dependent variable y_{it} and the error term u_{it} are scalar variables, whereas $\mathbf{x}_{it}$ is a $K \times 1$ vector of predictors.

As the number of unknown parameters to be estimated is greater than the observations available, this model is far too general and inestimable. In order to compute meaningful parameter estimations, restrictions are required on how the parameters α and β vary across i and t and on the characteristics of error term u_{it}.

The POLS model has the most restrictions applied. The intercept and slope coefficients α and β are limited to be constant across all respondents and time waves.

$$y_{it} = \alpha + \mathbf{x}_{it}'\beta + u_{it} \tag{3.28}$$

(Cameron and Trivedi, 2005, p. 720)

If the predictors $\mathbf{x}_{it}$ are not correlated with the error term u_{it}, then α and β can be consistently estimated using the POLS estimator. However, the error term u_{it} may be correlated for the same respondent over the observed time periods. Thus, a standard error that is robust to serial correlation should be used in place of the usual standard error from cross section models, which in this case can be biased downward and affect hypothesis testing's results.

Because the study focusses on the choices of potentially heterogenous individuals and their effects on the individuals' subjective welfare, the most appropriate choice across all linear panel models would be one that includes individual effects. Such a model is the individual-specific effects model, including the FE and RE models. As the name suggested, the intercept parameter α_i in this model is assumed to vary across individuals only and represents the characteristics that are unique to each individual

$$\acute{\omega}_{it} = \tilde{\omega} + \alpha_i + \mathbf{x}_{it}'\beta + \varepsilon_{it} \tag{3.29}$$

(Cameron and Trivedi, 2005, p. 726)

in which $\tilde{\omega}$ is a constant scalar intercept, $\acute{\omega}_{it}$ and ε_{it} are scalar variables and $\mathbf{x}_{it}$ a $K \times 1$ vector of predictors. Each β is assumed to be constant across time and individuals, whereas α_i is time-fixed individual heterogeneity effect which is regarded to be unobserved in the data set. As α_i is unobserved, thus the error term will be transformed into $u_{it} = \alpha_i + \varepsilon_{it}$. The error term ε_{it} is identically and independently distributed (iid) over i and t.

The use of control variables can control for the unique individual characteristics, however not all can be taken into account and some will be unobservable. Those unobservable characteristics can be unique qualities of a person that, for instance, make them healthier and also at the same time more likely to choose active commute modes over passive ones. Personality is a frequently-cited source of heterogeneity in SWB literature (Ferrer-i-Carbonell and Frijters, 2004; Boyce, 2010) although there is no definite answer on what constitutes unobserved heterogeneity (Boyce, 2010). In order to examine the independent effect of active commuting modes on the dependent variables of interest, these unobserved heterogeneity effects must be controlled for. The FE and RE models are suitable for this study as they incorporate the assumption that the individual effect α_i is an unobserved random variable. Also, because α_i is unobserved, it cannot be estimated consistently. The FE models assume that the unobservable individual effect α_i is correlated with the predictors in x_{it}, whereas they are considered to be independent from one another in the RE models.

The FE estimator, or the within estimator can provide consistent and efficient estimation by taking the differences between an individual's characteristics and their across-time means in equation (3.29) as follows:

$$y_{it} - \bar{y}_i = (\alpha_i - \bar{\alpha}_i) + (x_{it} - \bar{x}_i)'\beta + (\varepsilon_{it} - \bar{\varepsilon}_i) \tag{3.30}$$

(Cameron and Trivedi, 2005)

As α_i is assumed to be fixed over time, its means over time is itself, i.e. $\bar{\alpha}_i = \alpha_i$, hence it is removed in (3.30), along with the constant intercept μ and any time-invariant predictors. Then, the FE estimator is an OLS estimator for β between $y_{it} - \bar{y}_i$ and $x_{it} - \bar{x}_i$. The FE estimator produces efficient parameter estimations if the individual heterogeneity α_i is correlated with the predictors and the error ε_{it} term is iid. However, the FE estimation only focuses on the within-people variation and excludes the between-people variation. In the case where within-people information is low, this estimation method can be inefficient and may produce unreliable estimates.

If a RE model is applied in (3.29), the unobserved heterogeneity α_i is regarded as being independent from the predictors. In addition, the heterogeneity α_i and the original error term ε_{it} are further assumed to be iid, i.e. $\alpha_i \sim [\alpha, \sigma_\alpha^2]$ and $\varepsilon_{it} \sim [0, \sigma_\varepsilon^2]$ (Cameron and Trivedi, 2005, p. 700). The OLS estimation method can be applied to (3.29) with the new error term $u_{it} = \alpha_i + \varepsilon_{it}$ and produce consistent estimates. FE can also provide consistent estimates in the RE model. However, these estimators are not efficient. The OLS method is subject to serial correlation of the error terms for each individual over time, and the estimation methods for FE models can only estimate the coefficients of time-varying variables. The RE estimator, on the contrary, is both consistent and efficient when there is no correlation between unobserved heterogeneity effects and predictors. It is an OLS estimator for the following model derived from (3.29):

$$y_{it} - \hat{\lambda}\bar{y}_i = (1-\hat{\lambda})\mu + (x_{it} - \hat{\lambda}\bar{x}_i)'\beta + v_{it} \tag{3.31}$$

with $v_{it} = (1-\hat{\lambda})\alpha_i + (\varepsilon_{it} - \hat{\lambda}\bar{\varepsilon}_i)$ and $\hat{\lambda}$ is a consistent estimate of

$$\lambda = 1 - \frac{\sigma_\varepsilon}{\sqrt{\sigma_\varepsilon^2 + T\sigma_\alpha^2}}$$

(Cameron and Trivedi, 2005, p. 705)

The RE estimation method utilises both within- and between-people information, thus can avoid the FE models' problem. It allows consistent parameter estimations for all regressors, whether time-varying or time-invariant. An approach to decide on whether to use a FE or RE model is the Hausman test. The null hypothesis is that the difference between RE and FE coefficients is not systematic. Hence, if the null hypothesis is not rejected, then the RE approach should be used as it ensures consistent and efficient estimates.

In this study, with a large data set of respondents' demographic and economic information, the existence of individual heterogeneity is possible. Individual heterogeneity, such as personalities, childhood lifestyles, family background etc. can influence a person's health, SWB and job satisfaction, as well as their commuting choice. The assumption of independence between individual heterogeneity and the predictors in the RE models is a strong assumption and is perceived as implausible in microeconomic studies (Cameron and Trivedi, 2005). As it operates with both within and between-individual variation, this estimator is more efficient than FE. However, the RE estimator would be inconsistent if FE is the true underlying model, i.e. individual heterogeneity is correlated with one or more regressors. In a true FE model, estimation methods other than using the FE estimators would lead to inconsistent parameter estimation, including POLS and RE estimators. The literature on SWB has heavily incorporated the FE model and its assumption of potential correlation between individual effect $|_{i}$ and the predictors $\bullet_{i}$. Based on the literature, it is likely for the unobserved heterogeneity to correlate with the predictors in this thesis. Hausman tests will be applied to validate the choice of the FE model during the subsequent empirical chapter in this thesis.

3.6.2. Instrumental variables

Even though the FE model can remove the time-invariant unobserved heterogeneity effect, the models in this thesis are still exposed to other endogeneity sources, such as time-varying omitted variables. The most noticeable source is potential reverse causality due to the connections between the variables of interest, including SWB, health status and job satisfaction. As already explored in previous Sections 3.4 and 3.5, applying IV estimators is renowned in econometrics as a standard method to control for endogenous predictors (Cameron and Trivedi, 2005; Wooldridge, 2016). In fact, the use of IVs can be applied to different estimation approaches within the Generalized Method of Moments (GMM) estimator suite (Baum, Schaffer and Stillman, 2003). Because of its ability to deliver causal conclusions, there are tests to ensure the relevance and validity of the IVs used. Finding IVs that can satisfy the conditions can be difficult, but an advantage of panel data over cross-section data is that the exogenous lagged values from previous time periods can be used as IVs for the endogenous predictors in the current period (Cameron and Trivedi, 2005). This thesis is one of the first studies applying IVs and more specifically lagged values of endogenous predictors in this area of the literature. Previous studies in the topic of commuting effects on health and SWB tend to either use cross-section data (Gatersleben and Uzzell, 2007; Hansson *et al.*, 2011; Office for National Statistics, 2014; Wheatley and

Bickerton, 2016) or apply different versions of the FE and RE models (Künn-Nelen, 2015; Clark *et al.*, 2019).

Considering the same linear panel model from (3.29) in which it is assumed that the time-invariant heterogeneity α_i exists and correlates with the predictors in the vector $\mathbf{x}_{it}$, i.e. $E(\mathbf{x}_{it}\alpha_i) \neq 0$

$$y_{it} = \alpha_i + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} \qquad (3.32)$$

(Cameron and Trivedi, 2005, p. 726)

The error term u_{it} of (3.32) is a combination of the unobserved heterogeneity effect α_i and the idiosyncratic error ε_{it}. Assume that the predictors are endogenous, then $E(\mathbf{x}_{it}u_{it})$ = $E(\mathbf{x}_{it}(\alpha_i + \varepsilon_{it})) \neq 0$

With the existence of other endogeneity sources, a RE model is one in which instrument variables $\mathbf{z}_{it}$ meet the condition that they are uncorrelated with the error term $E(\mathbf{z}_{it}(\alpha_i + \varepsilon_{it})) = 0$. Then, panel GMM estimation methods should provide consistent estimates for all predictors in the model. However, if the instruments are uncorrelated with the idiosyncratic error $E(\mathbf{z}_{it}\varepsilon_{it}) = 0$, but they are linked with the unobserved heterogeneity $E(\mathbf{z}_{it}\alpha_i) \neq 0$, the model would be a FE model. In this thesis, it is possible that the instrument sets may include lagged values of the endogenous predictors, which will be discussed in detail in the subsequent Chapter 5. Given the above assumption of the correlation between the predictors $\mathbf{x}_{it}$ and the time-invariant heterogeneity α_i, the lagged values of $\mathbf{x}_{it}$ should also be correlated with α_i. Therefore, it is appropriate to assume a FE model. In this case the heterogeneity α_i is removed by within differencing transformation and only parameters of time-variant predictors will then be estimated with the Panel GMM estimation methods.

Incorporating the FE transformation into (3.32) to eliminate the unobserved heterogeneity

$$\tilde{y}_{it} = y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)'\beta + (\varepsilon_{it} - \bar{\varepsilon}_i) \qquad (3.33)$$

$$\text{or } \tilde{y}_{it} = \tilde{x}_{it}'\beta + \tilde{\varepsilon}_{it} \qquad (3.34)$$

(Cameron and Trivedi, 2005, p. 757)

where tilde represents the within differencing transformation.

As discussed earlier, it is possible that other endogeneity sources are present in the models, i.e. $E(x_{it}\varepsilon_{it}) \neq 0$. If it is the case, $E(\tilde{x}_{it}\tilde{\varepsilon}_{it}) \neq 0$ and a simple OLS estimation on (3.34) would be inconsistent, i.e. the FE estimation on the original model would not be sufficient to provide causal conclusions between variables.

If valid IVs z_{it} exist where $E(\tilde{z}_{it}\tilde{\varepsilon}_{it}) = 0$, panel GMM methods using z_{it}, including IV, 2SLS and two-step GMM (2SGMM) should produce consistent estimations for time-varying predictors in (3.34). The incorporated IVs should be excluded variables that are correlated with the endogenous predictors, but not the error term $\tilde{\varepsilon}_{it}$. The general panel GMM method will be applied to Equation (3.34) and discussed first and then different choices of IV estimation methods, including IV, 2SLS and 2SGMM will be followed.

If Equation (3.34) is rewritten by combining all the T periods together

$$\tilde{y}_i = \tilde{X}_i\beta + \tilde{\varepsilon}_i \qquad (3.35)$$

with $\tilde{X}_i$ being a $T \times K$ matrix, $\tilde{y}_i$ and $\tilde{\varepsilon}_i$ being $T \times 1$ vectors.

$$\tilde{y}_i = \begin{bmatrix} \tilde{y}_{i1} \\ \vdots \\ \tilde{y}_{iT} \end{bmatrix}, \quad \tilde{X}_i = \begin{bmatrix} \tilde{x}_{i1}' \\ \vdots \\ \tilde{x}_{iT}' \end{bmatrix}, \quad \tilde{\varepsilon}_i = \begin{bmatrix} \tilde{\varepsilon}_{i1} \\ \vdots \\ \tilde{\varepsilon}_{iT} \end{bmatrix}$$

The set of instruments for Equation (3.34) forms a $T \times r$ matrix $\tilde{Z}_i$ and contains r number of instruments. It is required that the number of instruments has to be at least equal to the number of endogenous variables, i.e. $r \geq K$, and the instruments in z_{it} meet the r moment conditions

$$E[Z_i' u_i] = 0 \tag{3.36}$$

The panel GMM estimator derived from these moment conditions should minimise the following associated quadratic function with an $r \times r$ weighting matrix W_N

$$Q_N(\beta) = \left[\sum_{i=1}^{N} Z_i' u_i\right]' W_N \left[\sum_{i=1}^{N} Z_i' u_i\right] \tag{3.37}$$

The panel GMM estimator is of the form

$$\hat{\beta}_{PGMM} = \left[\left(\sum_{i=1}^{N} X_i' Z_i\right) W_N \left(\sum_{i=1}^{N} Z_i' X_i\right)\right]^{-1} \left(\sum_{i=1}^{N} X_i' Z_i\right) W_N \left(\sum_{i=1}^{N} Z_i' y_i\right) \tag{3.38}$$

This estimator is consistent if the moment conditions (3.36) are satisfied. In compact notation, $\hat{\beta}_{PGMM}$ can be rewritten as

$$\hat{\beta}_{PGMM} = [X'ZW_N Z'X]^{-1} X'ZW_N Z'y \tag{3.39}$$

with $y = [y_1', \ldots, y_N']'$, $X = [X_1', \ldots, X_N']'$ and $Z = [Z_1', \ldots, Z_N']'$.

Its estimated asymptotic variance matrix is

$$\hat{V}[\hat{\beta}_{PGMM}] = N[X'ZW_N Z'X]^{-1}(X'ZW_N \hat{S} W_N Z'X)[X'ZW_N Z'X]^{-1} \tag{3.40}$$

This variance matrix produces standard errors that are robust for both autocorrelation and heteroskedasticity, i.e. panel-robust standard errors. $\hat{S}$ is a consistent estimation of

$$S = \operatorname{plim} \frac{1}{N} \sum_{i=1}^{N} Z_i' u_i u_i' Z_i \tag{3.41}$$

The matrix S is a $r \times r$ matrix and its robust estimate is of the form

$$\hat{S} = \frac{1}{N} \sum_{i=1}^{N} Z_i' \hat{u}_i \hat{u}_i' Z_i \tag{3.42}$$

where $\hat{u}_i$ is the residual estimated from $\hat{u}_i = y_i - X_i \hat{\beta}$.

When the number of IVs equals the number of endogenous predictors $L = K$, the equation is regarded as just-identified and the panel GMM estimator reduces to the panel IV estimator with any matrix W:

$$\hat{\beta}_{IV} = (Z'X)^{-1} Z'y \tag{3.43}$$

When $L > K$, the equation is over-identified and different weighting matrix W will yield different GMM estimators. The two-stage least-squares (2SLS) estimator is accompanied with the weighting matrix $W = (Z'Z)^{-1}$:

$$\hat{\beta}_{2SLS} = [X'Z(Z'Z)^{-1}Z'X]^{-1} X'Z(Z'Z)^{-1}Z'y \tag{3.44}$$

The $\hat{\beta}_{2SLS}$ can be achieved by applying OLS in two steps, and it also can be computed in one step by applying data in the above formula.

Meanwhile, the weighting matrix $W = \hat{S}^{-1}$ yields the most efficient GMM estimator. $\hat{S}$ here is the consistent estimate of S. The estimation $\hat{S}$ from (3.42) provides the two-step GMM (2SGMM) estimator

$$\hat{\beta}_{2SGMM} = (X'Z\hat{S}^{-1}Z'X)^{-1} X'Z\hat{S}^{-1}Z'y \tag{3.45}$$

This estimation method involves using a consistent estimation for β (e.g. $\hat{\beta}_{2SLS}$) to create $\hat{u}_i$ in Equation (3.42) for $\hat{S}$. The estimator $\hat{\beta}_{2SGMM}$ is more efficient than $\hat{\beta}_{2SLS}$ in case of heteroskedastic errors. In fact, it is the optimal estimator given the moment conditions in (3.36).

Given the use of 2SGMM estimator in controlling for endogeneity, there are three tests that are essential to ensure that only relevant and valid IVs are applied. The following summary of the three tests and their criteria follows from Baum, Schaffer and Stillman (2010).

The endogeneity test is to determine whether IV methods are necessary or OLS is preferred due to its higher efficiency. The test's null hypothesis is that the tested variables can be regarded as exogenous. The test statistic is distributed with a χ^{2} distribution and the degree of freedom is equal to the number of predictors tested for endogeneity.

As mentioned earlier in this subsection, an IV is required to satisfy two conditions: (1) to correlate with the endogenous variable that they are instrumenting for, and (2) not to correlate with the error terms. After an IV method is confirmed as necessary by the endogeneity test, the relevance test investigates whether the instruments are correlated with the endogenous predictor. It is a standard F-statistics testing the first stage regression in the 2SGMM estimation process. The test verifies whether the IVs are good enough instruments. If they are, they should be strongly correlated with the endogenous variable and thus jointly significant in a regression of the endogenous predictor.

Lastly, in the over-identified case, the number of instruments is greater than the number of endogenous predictors needed instrumenting, thus leading to ì ù number of overidentifying restrictions. The validity test examines whether the instruments are correlated with the error term. The null hypothesis states that the instruments used are valid, i.e. there is no correlation between them and the error term, and that it is correct to exclude those instruments from the original equation. This is essential to ensure consistency of the estimates. However, there is no available test for just-identified models where the number of IVs is equal to the number of endogenous variables. Model misspecification or instrument endogeneity can be reasons for rejection in this test. Cameron and Trivedi (2005) argue that the property of no connection between instruments and the error term can be difficult to test, and the decision on instrument exogeneity tend to be subjective and usually requires support from economic theories. Apart from satisfying the property of an instrument, an instrument's exogeneity is also important in the case of a weak instrument. With small level of instrument endogeneity, the IV estimator derived from a weak instrument can be more inconsistent than the already inconsistent OLS estimator. As the GMM estimator is used, together with a heteroskedasticity-robust standard error, STATA reports a Hansen’s J statistic for this validity test. This statistic is also distributed with a χ^{2} distribution with the degree of freedom being the number of overidentifying restrictions ( ). If the null hypothesis is rejected, then some components of z_i are correlated with the error term. Detail on the format of these three tests will be expanded in Chapter 5.

Apart from these two techniques of FE and IV, there are other econometric adjustments that will be made in estimation. As panel data is used in this thesis, the precision of regression estimation is improved due to the increase in the number of observations across time and individuals, compared to cross sectional data. However, it comes at a cost of serial correlation between standard errors for each respondent across time periods, which would result in downward bias in conventional standard errors (Cameron and Trivedi, 2005; Wooldridge, 2016). Hence, standard errors that are robust to autocorrelation by using cluster standard errors over the personal identification variable should be applied. Moreover, it is also possible that the error term is subject to heteroskedasticity, which means its variance varies across observations. Heteroskedasticity can yield bias in standard errors and it can be either upward or downward bias (Cameron and Trivedi, 2005). However, the “robust” option in STATA deals with heteroskedasticity, and in combination with the use of the FE models will tackle autocorrelation. Therefore, the standard errors used throughout the thesis will be panel-robust standard errors that are robust to both heteroskedasticity and autocorrelation whenever is possible.

3.7. Data and variables

This section explores the data used in the thesis. It will provide an overall description of the measurement chosen for the variables of interest, including the dependent variables, the predictors and controlling factors that have been discussed in Chapter 2. As the application of IVs is used in the subsequent empirical chapter, a list of potential IVs along with each variable's definition and measurement will also be reviewed in this section.

3.7.1. Data source

This thesis uses data extracted from the UK Household Longitudinal survey (UKHLS) or the Understanding Society survey (University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2017). This is an on-going panel survey collecting information of individuals from households residing in the United Kingdom, including England, Wales, Scotland and Northern Ireland, from Wave 1 in 2009.

This survey project is led by the Institute for Social and Economic Research (ISER) at the University of Essex and receives funding support from various governmental departments and institutions. ISER is responsible for the survey design whereas the field work is carried out by NatCen Social Research and Kantar Public in Great Britain and by their collaborating partners in Northern Ireland. It is intended to provide a quality data source for social and economic research in British households' daily life. The aim is to investigate the effects of social and economic change on well-being of British citizens (Institute for Social and Economic Research (ISER), no date a).

The main survey is comprised of four parts, including the General Population Sample, the Ethnic Minority Boost Sample, the Immigrant and Ethnic Minority Boost sample and the original sample from the former British Household panel survey (BHPS) (Knies Gundi (ed.), 2017). The BHPS started from 1991 as the first socioeconomic household panel survey in the UK. It first recorded 10,000 people from 5,500 households in Great Britain, and additional samples from Scotland, Wales and Northern Ireland were added in later waves (British

Household Panel Survey (BHPS), no date). The BHPS was carried out annually until 2009 with eighteen waves of data. Since 2010, the BHPS has been incorporated into the Understanding Society survey from the latter's second wave. The General Population sample includes 26,000 private households in the UK, whereas the Ethnic Minority Boost sample provides around 1000 respondents from different ethnic minorities, such as Indian and African, in England and Wales. The more recent Immigrant and Ethnic Minority Boost sample has been added since Wave 6 to include new immigrants and reflect the new ethnic minority structure in the UK.

Knies Gundi (ed.) (2017) provides details on how households among the UK have been chosen as potential survey respondents. Firstly, postcode sectors are grouped into regional strata, corresponding to the 10 regions in English and another two for Scotland and Wales. Within the twelve regions, sectors are sorted based on several demographic categories. A random sample of each sector was chosen systematically based upon the percentage of residential addresses within that postal sector, and then 18 households are selected from each sector by the method of systematic random sampling.

The first wave of data collection started in 2009 and members from approximately 40,000 households were recruited and interviewed about different socio-economic issues. They have been re-interviewed each year to record changes in their circumstances. The interviews are mainly face-to-face with interviewers but in more recent waves, interviews for a small part of the sample have been done via telephone or website. Each wave's data collection straddles over a 2-year period and each survey respondent is visited around the same time every year (Knies Gundi (ed.), 2017). The sample of households varies across waves with the highest number of households being observed in Wave 1 (Hannah Carpenter, 2017). Objective health assessment such as BMI, body fat, grip strength and several health-related data derived from blood samples were collected but only in waves 2 and 3 of the survey (Institute for Social and Economic Research (ISER), no date d).

The UKHLS survey possesses multiple strengths and the main rationale why this thesis chooses to analyse this data is because it is an on-going longitudinal dataset providing periodic information about a large sample of individuals in the UK. The large sample target of 40,000 households ensures that meaningful analysis of a certain group of people, for example: working people aged 16-65, could be carried out with sufficient data. Additionally, the survey strives to maintain continuity of interviewees and monetary incentives have been offered for respondents since Wave 3 (Knies Gundi (ed.), 2017). Moreover, the data from the UKHLS covers all four countries in the UK which enables controlling of regional trends in the studies. Most importantly, the survey offers information on various topics, including health, SWB, transport and employment characteristics of respondents which are the necessary data for this thesis. The main measures employed in this thesis have been recorded annually, such as measures about health status, current job characteristics and life satisfaction (Buck and McFall, 2011). However, there are variables that have only been collected either up to a certain wave or every few years. By offering such comprehensive data, the survey has been linked to more than 2,300 publications in various research fields according to the Understanding Society website (Institute for Social and Economic Research (ISER), no date e).

Even though the data are available from 1991 to 2018 (as of August 16th, 2019), the first 18 waves are exclusively from the BHPS, and this thesis only uses the next 7 waves of the UKHLS survey which include the combination of the BHPS. This is because there are several new variables available in the UKHLS but not in the BHPS's previous waves that are essential to the thesis's aims and objectives. At the time of empirical work for this thesis, the most recent wave, Wave 8, had not become available, thus the absence of the latest wave.

The seven waves of data from which the thesis extracts information cover the period January 2009 to June 2017.

For each wave, the main part of the Understanding Society is the mainstage survey for adults of age 16 or above. The main survey has five set of questionnaires, including two sets on grid information about the respondents, the household questionnaire, the individual questionnaire and a proxy questionnaire for respondents whose responses are given by someone else.

The individual questionnaire contains sections about a respondent's demographics, chronic health conditions, employment information, including commuting behaviours, etc. There are also several self-completed modules within the individual questionnaire about health, satisfaction, relationships and parenting styles. The early waves (i.e. wave 1 and 2) separate the self-completion modules from the mainstage questionnaires. Further details about each variable used in the thesis will be discussed in the next subsections.

3.7.2. Key variables

The key data sets for the thesis from the UKHLS are the household and individual data sets. They record information on responding household and individuals that are 16-year old or older. Each question in the UKHLS survey corresponds to a variable in the data files.

Households are distinguished by a specific household identifier variable, called hidp which assigns a specific value for each household. The same is applied for individuals in which each respondent is assigned a particular identifier value for the variable pidp. These personal identifiers are kept consistent across all waves. Together with the unique wave prefix in different waves, they aid the merge of data across individuals, households and waves to form a longitudinal data set ready to use. The data form an unbalanced panel data set and have missing observations in some years for some respondents in the same sample. Moreover, with

7 years of data and a maximum of approximately 40,000 households, the data set is a short panel data set, in which there is a large cross section of respondents observed over a short range of time periods. Observations associated with proxy, refusal responses and when interviewees do not know the answer have been removed. The removal of these observations is not likely to generate biases since they make up a low proportion of the sample. When respondents chose the option "Inapplicable", that response also tends to be removed, unless mentioned otherwise during this section.

Dependent variables

The effect of commuting on health, subjective well-being and job satisfaction is of interest in this thesis. The individual survey questionnaire includes a question about the level of satisfaction that the respondent has with their current job

"On a scale of 1 to 7 where 1 means 'Completely dissatisfied' and 7 means 'Completely satisfied', how dissatisfied or satisfied are you with your present job overall?"

(University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2015, p.420)

The potential responses are based on a 7-point Likert scale

"7-Completely satisfied
6-Mostly satisfied
5-Somewhat satisfied
4-Neither satisfied nor dissatisfied
3-Somewhat dissatisfied
2-Mostly dissatisfied
1-Completely dissatisfied"

(University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2015, p.420)

The responses for this question are chosen to be the measurement for the variable job satisfaction in this thesis, meanwhile there is not any other question available in the survey for the same purpose.

There are various measures of health that have been applied in the literature, including objective and subjective health measures. Studies incorporating the BHPS or UKHLS have used the following variables to examine health. Objective health measures can include whether the respondent has any diagnosed health problems and whether they had sick leave during last year, whereas health satisfaction and health status with Likert scale options are the subjective measures employed (Künn-Nelen, 2015). Health behaviour (e.g. sport participation, BMI) and healthcare utilisation (e.g. last year's GP visits and in-patient hospital visits) have also been applied (Künn-Nelen, 2015).

There are measures used in the literature from the BHPS but are not available in the UKHLS, such as a variable reporting sick leave from last year. Similarly, several measures employed in the literature are only available in the UKHLS. Some health measures are only available in a few waves. The BMI was only recorded once in wave 1, whereas any sport activities were only asked in Wave 2 and 5. The health service utilisation variable is only available in Wave 4, 6 and 7 and has a high response rate in the "Inapplicable" option. The diagnosed health conditions variable is available for all 7 waves and records whether an interviewee has any long-standing condition that has been confirmed by a qualified professional such as asthma, heart conditions, liver conditions, cancer, diabetes, blood conditions, etc. It is only asked once and then assumed to apply for each respondent, and in each new wave, the question is asked only to new respondents. However meaningful response rate for this variable is trivially low which makes it inappropriate as a useful dependent variable for the purpose of this thesis.

In contrast, the subjective health measures are recorded regularly in the UKHLS with higher meaningful response rates. A particular subjective measure of health has been considered for this thesis. It records the general health status that the respondents complete themselves without assessment from a medical professional. The variable is included in either the "General health" module or the "Self-completion SF12" module within the individual questionnaire, depending on the survey structure in each wave. Either way, it is a question taken from the 12-item short form health survey (SF-12) developed by Ware, Kosinski and Keller (1996) and licensed through QualityMetric, Inc. (part of Optum, Inc.). The SF-12 is the shortened version of the SF-36 survey (Ware and Sherbourne, 1992) and comprises of 12 questions on a person's physical and mental health and how their health limits or interferes with their normal daily activities. The question on general health from the SF-12 is chosen as the health measure for this thesis. It indicates how a respondent rates their own health status subjectively on a 5-point Likert scale

"In general, would you say your health is...

1-Excellent
2-Very good
3-Good
4-Fair
5-Poor"

(University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2015, p. 560)

The reason that this question is chosen as the sole measurement on health in the thesis is because it has been shown in the literature that this single-item general health measure can be a suitable alternative for the full SF-12 measure (Desalvo *et al.*, 2006a). It can be treated as a summary variable that has good reliability and correlations with both physical and mental health measures in a modified version of SF-12; and this variable can also separate interviewees who have different levels of physical abilities and mental health measured by the multiple-item measurement. Also Desalvo *et al.* (2006b) have shown that single-item general health measures can predict all-cause mortality, with higher scores of the health measures (i.e. worsened health) linked with higher mortality risk in all adults. It can ease off the burden of interpreting multiple-item measures in studies focusing on large populations. In order for the interpretation to be consistent with that of other dependent variables, the categories are rearranged in a reverse order, compared with the original variable, i.e. 1-'Poor', 2-'Fair', 3-'Good', 4-'Very good' and 5-'Excellent'. The same variable has been regarded in the literature as a continuous variable to be applied in linear FE models (Künn-Nelen, 2015), following the same approach as discussed in Subsection 3.5.2.

In this thesis, a single-item measure of SWB is analysed and that is the life satisfaction measure. In the UKHLS, the question recording this variable belongs to the Self-completion Satisfaction module and has been reported consistently throughout 7 waves of the UKHLS. The Self-completed Satisfaction module is included in the individual questionnaire, which reports respondents' own thoughts about components in their life, including health, income, leisure time and overall life. The question about life satisfaction asks respondents on how satisfied they feel with their life overall and presents 7 options in a Likert scale, and this is the same scale used for the job satisfaction variable, discussed earlier in this subsection.

"Please choose the number which you feel best describes how dissatisfied or satisfied you are with the following aspects of your current situation. Your life overall.

1-Completely dissatisfied
2-Mostly dissatisfied

3-Somewhat dissatisfied
4-Neither satisfied nor dissatisfied
5-Somewhat satisfied
6-Mostly satisfied
7-Completely satisfied

(University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2017, p. 573 & 575)

Fujiwara and Campbell (2011) argue that life satisfaction is applied the most in the literature among other SWB measurements because it is assumed as the closest to the concept of utility in economics. Indeed, frequently cited articles have been using life satisfaction as the measure of SWB (e.g. Stutzer and Frey, 2008). The use of single-item measures is also beneficial as the need to combine multiple-item measures and the burden of interpretation are avoided.

The thesis wishes to keep the dependent variables consistent, thus the choice of single-item measures with similar Likert categorical scales. With their ranges of options, all three variables can be considered as ordered variables. In each variable, say the Life satisfaction variable, there is a natural ordering in the options, but one cannot quantify the distances between two consecutive options meaningfully and say what the difference between 6-“Mostly satisfied” and 7-“Completely satisfied” is, and the same applies to other options.

Independent variables

The effects of commuting on SWB, health and job satisfaction are of interest, and according to the theoretical review section above, commuting can be represented by either commuting distance or duration. The potential heterogenous effects of mode choices are also of interest.

Thus, the independent variables for this thesis comprise of different transport modes that interviewees choose to commute and their commute duration. The thesis follows the approach in Roberts et al. (2011) and uses commuting time, rather than distance travelled as the principal commuting variable, even though distance travelled has been widely used in the transport and urban economics literature. Commuting time can be more suitable as an opportunity cost of commuting to workers (Stutzer and Frey, 2006). Besides, commuting time has been found as being strongly correlated with distance travelled (Small and Song, 1992). Moreover, commuting distance is available in the UKHLS, however its record has not been consistent throughout the whole sample period of 7 waves.

In terms of commuting information, the UKHLS survey has grouped respondents into two categories: employees and self-employed, and the commuting time and mode choices of the two groups have been recorded separately in the individual questionnaire. For the purpose of this research, the data on commuting is merged together for all respondents and no longer based on their employment types. A dummy variable of whether someone is an employee or self-employed is included to take account of any differential effect of the two categories of employment. Respondents working at home, no matter whether they are self-employed or employees would have a commuting time of 0 minutes. The commuting time variable is a cardinal variable measuring how many minutes a person spent on a one-way commuting journey to work, door-to-door. The commuting mode variable records the transport mode the respondent often uses to travel to work. There are 10 transport mode options with an additional ‘Other’ option, and respondents are encouraged to report the transport mode they use for the longest distance in the case that they commute with more than one mode.

“And how do you usually get to your place of work?

1-Drive myself by car or van
2-Get a lift with someone from household

3-Get a lift with someone outside the household

4-Motorcycle/moped/scooter

5-Taxi/minicab

6-Bus/coach

7-Train

8-Underground/Metro/Tram/Light railway {if region = England/Scotland/Wales}

9-Cycle

10-Walk

97-Other”

(University of Essex. Institute for Social and Economic Research. NatCen Social Research. Kantar Public, 2015, p.405 & p.419).

When dealing with different commuting mode choices, it is possible to re-categorise the transport modes into broader groups with similar characteristics. For example, one can separate mode choices into two categories: active modes and passive modes (e.g. Roberts, Hodgson and Dolan, 2011), or car, public transport and active modes (including walking, cycling) (e.g. Hansson *et al.*, 2011; Wheatley, 2014). The subsequent empirical chapters in this thesis will discuss in more detail how the commuting modes are regrouped to support the goal of each study.

3.7.3. Control variables

There is a need to control for variables that can influence the effects of the independent variables on the dependent variable. Control variables can help to reduce the omitted variable bias and yield better regression estimation. The set of control variables used in this thesis is based on a review of what may influence commuting mode choice and duration discussed in Chapter 2. It contains demographic (age, age squared, gender, ethnicity, number of children) and socioeconomic information (marital status, highest qualifications, social class based on job role, whether a person is self-employed or an employee, whether they live in an urban or rural area, and personal income).

Regarding the demographic control variables, the age of a person is reported by a derived variable from the UKHLS and this variable is computed in whole numbers with the unit of year. Derived variables in the UKHLS are computed after the data collection by ISER and based on one or more variables (Knies Gundi (ed.), 2017). The age variable's square term is also included as it has been illustrated in the literature that age and SWB can have a quadratic relationship (David G Blanchflower and Oswald, 2008). It is then scaled by 100 in Chapter 4 and 5's empirical models. The gender variable indicates if the respondent is a male or female. From the UKHLS, the question on the respondent's ethnicity has 18 options to choose from which are then grouped into 5 different categories: "White", "Mixed", "Asian or Asian British", "Black or Black British" and "Other ethnic group". The last demographic control variable counts how many under-16 children that the respondent has in their household, including natural, adopted or step- children.

Among all the socioeconomic variables employed in the thesis, personal income is the only continuous variable and the rest are categorical. The legal marital status of respondents is recorded by a question with 9 options which have been regrouped into 5 broader choices, comprising of "Single", "Married", "Separated", "Divorced" and "Widowed". These choices include both marriage and legally recognised partnership. To control for the education level of respondents, a derived variable is chosen, and it has been updated in every wave to identify the highest academic qualification achieved by respondents to date. The variable includes 17 options, which are re-categorised into 5 groups, based on a guideline from the Government (UK Government, no date). The 5 groups contain "GCSE or equivalent", "A Levels or equivalent", "First degree or equivalent", "Higher degree (e.g. Master's or PhD)" and one "None of the above" option.

The social class of respondents is included in the empirical models by employing a derived variable that classifies respondents' current employment positions in the labour market according to their company types, duties and training at work (Institute for Social and Economic Research (ISER), no date b). The classifications used in this variable are based on the National Statistics Socio-economic Classification (NS-SEC), which is developed by the ONS as a framework for socioeconomic positions. The variable consists of 35 values that are identical to the full operational categories of the NS-SEC, except that the NS-SEC includes additional classifications for unemployed, students and unclassifiable cases (Office for National Statistics, no date c). Instead, respondents who were not working at the time of the interview are not given any value for this derived variable. The value list is aggregated into 3 different categories, including "Higher managerial, administrative and professional", "Intermediate occupations" and "Routine and manual occupations", based on how studies in the literature using the same data set (BHPS or UKHLS) have regrouped their variables' option lists (Roberts, Hodgson and Dolan, 2011; Künn-Nelen, 2015). According to the ONS, the NS-SEC is constructed based on employment relations rather than skills of a person, and the differences are between employers who pay for and have some authority over labour, self-employed who do not pay for or offer labour to anyone else and employees who offer labour. The categories used in this thesis will put employers and self-employed together into the "Higher managerial, administrative and professional" group. Moreover, the thesis recognises potentially different effects between being an employee working for someone else and being a self-employed whereas a person is their own boss. Thus, a question of whether the respondent is "an employee or self-employed" in their current occupation is included in the control variable list, and its options are either "Employee" or "Self-employed" (University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2017, p. 386).

A derived variable is chosen to represent personal income of respondents in the models. It is computed by the UKHLS as a total net monthly amount of income after taking away contributions for national insurance and earning taxes, measured in sterling pound. It is a total amount of 6 income elements, including net labour income (which is the sum of net earnings from main job, net earnings from second job and self-employed), miscellaneous income, private benefit income, income from investment, pension income and social benefit income (Fisher *et al.*, 2019). The variable may include data of non-working respondents. There is household income data available within the UKHLS data files, however household income includes not only information from each household's responding members, but also from proxy members and non-responding members (Fisher *et al.*, 2019). Dropping specific observations with such computation would add to the sample selection bias. Thus, the thesis excludes household income due to the unavailability of more reliable data. Furthermore, relative income has been rarely applied in this research area on the effects of commuting, and it involves various possible measurement approaches. Thus, relative income is also not included in the set of control variables used.

Regional and year dummy variables are included to account for the unobserved effects of living in a specific region and time period. The region variable is represented by a derived variable in the UKHLS which reports the region that a respondent is residing based on their postcode, including 12 following regions: "North East", "North West", "Yorkshire and the Humber", "East Midlands", "West Midlands", "East of England", "London", "South East", "South West", "Wales", "Northern Ireland" and "Scotland" (Institute for Social and Economic Research (ISER), no date c). The options in this derived variable follow the Government offices for the regions classifications in England by the ONS; Wales, Scotland and Northern Ireland are not regarded as regions but often included for country-wide research (Office for National Statistics, no date b).

Apart from regional dummy variables, a binary derived variable from the survey is also incorporated to separate individuals into whether they are residing in an urban or rural area. It is based on an individual's address and classifies them as living in an urban area if they currently reside in an area of 10,000 people or more (Institute for Social and Economic Research (ISER), no date f). This variable is developed from the ONS's rural/urban classification (Office for National Statistics, no date a).

3.7.4. Instrumental variables

As discussed in Chapter 2, the relationship of commuting on job satisfaction is hardly explored in the literature. And although, the relationships between commuting, health and SWB have been examined, this is carried out with the FE model that only controls for unobserved heterogeneity. The potential issue of simultaneity between the variables of interest has not been touched on in the commuting literature. As the thesis attempts to utilise the application of IVs to address this matter, the selection of potential IVs is built on the literature and data availability in the UKHLS. The identified set of instruments $'H_{it}$ include one-period lags ($\grave{\omega}_{it-1}$) and differences of the endogenous variables ($\grave{\omega}_{it} - \grave{\omega}_{it-1}$). Apart from that, the following additional variables from the UKHLS survey are possible choices for the IVs.

It has been found in the literature that weather can affect a respondent's life satisfaction answer and the score tends to be larger in nicer weather conditions (Schwarz and Clore, 1983). Additionally, there is a gender difference with women being more sensitive towards weather and giving lower life satisfaction score in rainier weather (Connolly, 2013). The same study also finds that satisfaction in more specific domains, such as job satisfaction, is less likely to be affected by rain. This can be argued using the hypothesis that a respondent is more likely to depend on their current mood when giving response to a more general evaluation question. Thus, a variable reflecting the weather at the time of the interview hopefully can act as an instrument variable that relates to the SWB variable but is not associated with the other dependent variables. With the data available from the UKHLS survey, it is assumed in the thesis that the interview's month could reflect the weather at the time of the data-collecting interview. Moreover, when SWB scores are recorded during a short time period and in a particular area, then month and region dummy variables would not be enough to control for daily weather conditions (Connolly, 2013). However, as the UKHLS data set is collected over a 24-month period throughout 12 different regions in the UK, the weather conditions can be assumed as random. Besides, the month of the interview variable can represent the passage of time over the year, in which travel and job conditions may vary. According to the User guide for UKHLS survey, each respondent is interviewed at the same time in every wave, and no areas of the UK are covered in a particular month (Knies Gundi (ed.), 2017). Hence, any effect from the interview month is consistent over 7 waves for every respondent, and there is no weather factor intertwined with the regional effects. Furthermore, the Wave 7 technical report reveals that a normal interview should last from 1 to 2 hours (Hannah Carpenter, 2017), hence an interviewee's response in one wave should not be recorded over separate occasions during the 24-month collection period for that wave. Thus, a value of the derived variable Month of the interview date should present the true month of the interview. The variable takes discrete numerical values from 1 to 12 representing the 12 months of a year.

Another instrumental variable is the number of caring hours for other people. This variable measures the number of hours that a respondent spent per week on caring for people who either live with them or do not live with them in the same household. It is available for the 7 waves used in the thesis. It can be expected that the more hours spent on caring for others, the less leisure time available for oneself. Leisure time is one of the non-work life domains in the context of SWB, and according to the spill-over hypothesis, the experiences in one domain can affect those of another life domain (Near, Rice and Hunt, 1978; Judge and Locke, 1993). As a respondent is not satisfied with leisure time, it is likely that they would not feel as satisfied in another domain such as marital or work domains. This would affect overall life satisfaction. The variable in the UKHLS is an ordinal variable having 10 options which represents a range of hours spent caring for people outside and within the respondent's household per week.

"Now thinking about everyone who you look after or provide help for, both those living with you and not living with you - in total, how many hours do you spend each week looking after or helping them?

1-0 - 4 hours per week
2-5 - 9 hours per week
3-10 - 19 hours per week
4-20 - 34 hours per week
5-35 - 49 hours per week
6-50 - 99 hours per week
7-100 or more hours per week/continuous care
8-Varies under 20 hours
9-Varies 20 hours or more
97-Other"

(University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2017, p. 264)

The number of respondents who spent time looking after other people only takes up a small fraction of the sample. Thus, the variable is recoded such that an additional option of "0 hours" is included to take into account those respondents who do not have to take care of anyone inside and outside their household. This option also accounts for respondents living alone. Furthermore, as the categorical dependent variables are treated as continuous, this caring hour variable is also considered as a linear variable, in order to keep consistent with the dependent variables. The variable is further recoded to ignore certain categories that do not conform with a continuously increasing structure that the thesis wishes to impose on this variable. Those are “Varies under 20 hours”, “Varies 20 hours or more” and “Other”. These categories only contribute to an insignificant percentage of the observations (less than 2% in total). Overall, the range of the variable runs from zero hours, then “0-4 hours per week” to “100 or more hours per week/continuous care”.

It is possible that the size of a firm can influence how satisfied an employee is with their job. Employees in larger firms are found to experience a lower job satisfaction (Clark, 1996; Gazioğlu and Tansel, 2006; Haile, 2009), which can be due to the inflexible working environment in larger firms (Idson, 1990) and weaker connection between employees and their managers (Gazioğlu and Tansel, 2004). Hence, the size of the company that a person works for or owns as a self-employed is regarded as a potential instrument variable. There are two relevant variables available in the UKHLS questionnaire. One is for respondents who are employees, and this measures the size of the company where they work.

“How many people are employed at the place where you work?

1-1 - 2
2-3 - 9
3-10 - 24
4-25 - 49
5-50 - 99
6-100 - 199
7-200 - 499
8-500 - 999

9-1000 or more
10-Don't know but fewer than 25
11-Don't know but 25 or more”

(University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2017, p. 391)

The second variable measures how many employees a respondent hires for their company, thus is for self-employed respondents.

“How many people do you employ?

1-1 - 2
2-3 - 9
3-10 - 24
4-25 - 49
5-50 - 99
6-100 - 199
7-200 - 499
8-500 - 999
9-1000 or more
10-Don't know but fewer than 25
11-Don't know but 25 or more”

(University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2017, p. 407)

After removing 2 insignificant categories that do not conform to an increasingly continuous value format, both variables initially had 9 categorical options for the size of workforce. These 2 categories are the last 2 options “Don't know but fewer than 25” and “Don't know but 25 or more”. The self-employed variable is further recoded to include any self-employed respondents with no employees, thus its categories increase to 10 options. Both variables are recorded consistently throughout the 7-year period. Being an employee in a company owned by someone else may have different effects on health, SWB and job satisfaction compared with being your own boss. Indeed, both theoretical models and empirical data studied by Blanchflower and Oswald (1998) advocate that being self-employed can improve one's life satisfaction and job satisfaction. Therefore, as the workplace size variables are combined into one, the presence of the binary control variable that categorises respondents into employees and self-employed is essential in the models, in order to distinguish any potential unique effects of these two types of employment. In addition, the value range of the instrument variable comprises of increasing categories ranging from zero, then "1-2" to "1000 or more". To keep it consistent throughout the thesis, this IV will be treated as a continuous variable, in the same way with the categorical dependent variables.

Furthermore, it is argued that a person's house tenure can be an indicator of how affluent they are, which in turn can be related to income and SWB. The housing tenure information is available as a variable in the household data file from the UKHLS for all 7 waves. Based on the 4 different housing tenure definitions from the Ministry of Housing, Communities & Local Government, the original variable is recoded from 8 categories to comprise of 3 different values: "Rented from local authorities and housing associations", "Rented privately" and "Owner-occupied" (Ministry of Housing, Communities & Local Government, 2012). The two groups "Rented from local authorities" and "Rented from housing associations" are grouped together as they both represent individuals who could not find a suitable accommodation with their means on the housing market. The variable is treated as a continuous variable, in which the values are recoded to follow an increasing level of affluence.

There are several other variables that have been considered to be possibly related with health and SWB, including the daily number of cigarettes smoked, the number of days someone eats vegetables in a week, the number of days having fruits each week and the standard of local medical facilities. However, these variables have a disadvantage that they have been only reported for a few years, not for the full period of interest. The number of cigarettes smoked per day is a numerical variable recording the average daily number of cigarettes that a respondent has (University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2015). The question belongs to a module on smoking habits within the UKHLS's individual questionnaire and has been included in Wave 2, 5, 6 and 7. This variable is also recoded in this thesis to include an option of 0 for those in the survey who do not smoke.

The UKHLS uses 2 variables to record the weekly number of days that a respondent has fruit and vegetable in the Nutrition module within their individual mainstage questionnaire. Fruit can be of different type, including fresh, tinned, dried or frozen, whereas vegetable can be fresh, tinned or frozen, but not potatoes. The two variables share the same 4 categories, including "Never", "1-3 days", "4-6 days" and "Everyday", and these options are kept the same in order for the two variables to be treated as continuous. Both variables are only available for Wave 2, 5 and 7 (University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2015, p. 214-215).

It is possible that the standard of local medical facilities can relate to health and SWB of a respondent, but not with their job satisfaction. The Understanding Society survey includes 5 questions on respondents' perceptions on 5 local service and facilities in the Local neighbourhood module. One of the questions asks how they would rate their local medical facilities using 4 options "Excellent", "Very good", "Fair" and "Poor" (University of Essex. Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2013, p. 149). This question was only asked during Wave 3 and 6. As before, the variable is recoded so that the option range is in reverse order of "Poor" being the lowest value to

"Excellent" being the highest value and then treated as a continuous variable to keep consistent with other variables in the analysis.

3.7.5. Descriptive analysis

The number of observations available from Wave 1 (January 2009- June 2011) to Wave 7 (January 2015- June 2017) for the thesis's empirical studies is 125,187 observations. The subjects of interest in this research are adults above 16 years old that are currently working either as self-employed or employees. Even though the data in the UKHLS include information from working-aged individuals from 16 years old, the job-related variables used throughout the thesis, such as job satisfaction, should restrict the sample to only individuals who at the time of the interview had had a job in the previous week. Table 3.1 displays the descriptive statistics of the dependent variables, the commuting variables, the set of control variables and the potential IVs that will be considered in this thesis. Frequencies and sample proportions for the responses of the dependent variables health, job satisfaction and life satisfaction over the years are provided in Tables 3.2, 3.3. and 3.4, respectively. Table 3.5 presents the proportions of respondents that commute with a particular transport mode, and the breakdown of the sample's commuting time is given in Table 3.6.

Table 3.1: Descriptive analysis

Variable	Description	Mean	Std. Dev.	Min	Max
Dependent variables					
Subjective health status	General health status	3.669	0.959	1	5
Job satisfaction	Satisfaction with current job overall	5.303	1.430	1	7
Life satisfaction	Satisfaction with life overall	5.215	1.383	1	7
Independent variables					
Commuting time	Minutes spent travelling to work, door-to-door (minutes)	25.274	24.385	0	997
Private mode duration	Minutes spent travelling to work by private modes (minutes)	15.754	20.124	0	833
Public mode duration	Minutes spent commuting by public transport modes (minutes)	6.939	20.507	0	660
Cycling duration	Minutes spent cycling to work (minutes)	0.642	4.306	0	120
Walking duration	Minutes spent walking to work (minutes)	1.719	6.281	0	150
Age	Age from date of birth (years)	41.162	12.978	16	88
Personal income (divided by 100)	Total net personal income (£)	17.186	13.149	0	150
Number of dependent children	Number of own children in the household, under the age of 16	0.617	0.946	0	8
Gender	Gender (Male/Female)	0.534	0.499	0	1
Residence location (urban/rural)	Residing in an urban or rural area	0.219	0.414	0	1
Ethnicity	Ethnic group	1.336	0.848	1	5
Marital status	Legal marital status	1.900	0.912	1	5
Education qualification	Current status highest educational qualification	3.063	1.310	1	5
Social class based on occupation	National Statistics Socio-economic Classification of current job	1.957	0.890	1	3
Self-employed/Employee	Whether someone is self-employed or an employee in current job	0.912	0.283	0	1
Regions	Government Office Region, based on household's postcode	6.432	3.080	1	12
Potential instrumental variables					
Month of interview	Month of the interview	6.320	3.439	1	12
Number of hours spent caring	Hours per week spent caring inside and outside household	0.308	0.924	0	7
Company size	Number of people employed at workplace, or Number of employees hired in current job	4.624	2.670	0	9
Housing tenure	Housing tenure	2.626	0.680	1	3
Number of cigarettes smoked daily	Usual number of cigarettes smoked per day	2.076	5.454	0	202

Number of days eating vegetables	Number of days in a usual week eating vegetables	3.252	0.834	1	4
Number of days eating fruits	Number of days in a usual week eating fruit	3.017	0.992	1	4

Table 3.2: Responses for the General health status question

Year	**Poor**	**Fair**	**Good**	**Very good**	**Excellent**	*Total*
2009	423	2,143	5,959	7,671	4,426	20,622
	2.05%	10.39%	28.90%	37.20%	21.46%	
2010	390	2,409	7,236	9,706	4,979	24,720
	1.58%	9.75%	29.27%	39.26%	20.14%	
2011	308	1,762	4,809	7,270	3,803	17,952
	1.72%	9.82%	26.79%	40.50%	21.18%	
2012	315	1,565	5,175	6,923	3,473	17,451
	1.81%	8.97%	29.65%	39.67%	19.90%	
2013	295	1,559	5,026	6,883	3,508	17,271
	1.71%	9.03%	29.10%	39.85%	20.31%	
2014	229	1,424	4,306	6,597	3,508	16,064
	1.43%	8.86%	26.81%	41.07%	21.84%	
2015	284	1,736	5,545	6,897	2,900	17,362
	1.64%	10.00%	31.94%	39.72%	16.70%	
Total	2,244	12,598	38,056	51,947	26,597	131,442
	1.71%	9.58%	28.95%	39.52%	20.23%	

Table 3.3: Responses for the Job satisfaction question

Year	**1- Completely dissatisfied**	**2- Mostly dissatisfied**	**3- Somewhat dissatisfied**	**4- Neither satisfied nor dissatisfied**	**5- Somewhat satisfied**	**6- Mostly satisfied**	**7- Completely satisfied**	*Total*
2009	634 (3.07%)	838 (4.06%)	1,644 (7.97%)	1,503 (7.29%)	3,486 (16.90%)	8,832 (42.83%)	3,685 (17.87%)	20,622
2010	520 (2.10%)	855 (3.46%)	1,949 (7.88%)	1,775 (7.18%)	4,812 (19.47%)	10,802 (43.70%)	4,007 (16.21%)	24,720
2011	404 (2.25%)	608 (3.39%)	1,455 (8.10%)	1,654 (9.21%)	4,117 (22.93%)	6,678 (37.20%)	3,036 (16.91%)	17,952
2012	362 (2.07%)	608 (3.48%)	1,315 (7.54%)	1,648 (9.44%)	4,011 (22.98%)	6,612 (37.89%)	2,895 (16.59%)	17,451
2013	389 (2.25%)	561 (3.25%)	1,339 (7.75%)	1,633 (9.46%)	4,263 (24.68%)	6,308 (36.52%)	2,778 (16.08%)	17,271
2014	286 (1.78%)	498 (3.10%)	1,095 (6.82%)	1,438 (8.95%)	3,872 (24.10%)	5,872 (36.55%)	3,003 (18.69%)	16,064
2015	300 (1.73%)	507 (2.92%)	1,147 (6.61%)	1,500 (8.64%)	4,413 (25.42%)	6,213 (35.79%)	3,282 (18.90%)	17,362
Total	2,895 (2.20%)	4,475 (3.40%)	9,944 (7.57%)	11,151 (8.48%)	28,974 (22.04%)	51,317 (39.04%)	22,686 (17.26%)	131,442

Table 3.4: Responses for the Life satisfaction question

Year	**1- Completely dissatisfied**	**2- Mostly dissatisfied**	**3- Somewhat dissatisfied**	**4- Neither satisfied nor dissatisfied**	**5- Somewhat satisfied**	**6- Mostly satisfied**	**7- Completely satisfied**	*Total*
2009	312 (1.51%)	736 (3.57%)	1,475 (7.15%)	1,978 (9.59%)	4,045 (19.61%)	9,760 (47.33%)	2,316 (11.23%)	20,622
2010	384 (1.55%)	1,042 (4.22%)	1,891 (7.65%)	2,099 (8.49%)	4,615 (18.67%)	12,213 (49.41%)	2,476 (10.02%)	24,720
2011	316 (1.76%)	1,087 (6.06%)	1,426 (7.94%)	1,499 (8.35%)	3,396 (18.92%)	8,631 (48.08%)	1,597 (8.90%)	17,952
2012	322 (1.85%)	1,033 (5.92%)	1,558 (8.93%)	1,679 (9.62%)	3,274 (18.76%)	8,111 (46.48%)	1,474 (8.45%)	17,451
2013	309 (1.79%)	988 (5.72%)	1,497 (8.67%)	1,691 (9.79%)	3,419 (19.80%)	7,926 (45.89%)	1,441 (8.34%)	17,271
2014	202 (1.26%)	775 (4.82%)	1,181 (7.35%)	1,389 (8.65%)	3,039 (18.92%)	7,904 (49.20%)	1,574 (9.80%)	16,064
2015	231 (1.33%)	687 (3.96%)	1,224 (7.05%)	1,605 (9.24%)	3,422 (19.71%)	8,254 (47.54%)	1,939 (11.17%)	17,362
Total	2,076 (1.58%)	6,348 (4.83%)	10,252 (7.80%)	11,940 (9.08%)	25,210 (19.18%)	62,799 (47.78%)	12,817 (9.75%)	131,442

Table 3.5: Commuting mode use within the sample

Year	Private modes	Public modes	Cycle	Walk	Others	*Total*
2009	14,075	3,197	670	2,521	159	20,622
	68.25%	*15.50%*	*3.25%*	*12.22%*	*0.77%*	
2010	16,422	2,910	658	2,842	214	23,046
	71.26%	12.63%	2.86%	12.33%	0.93%	
2011	12,557	2,512	611	2,147	125	17,952
	69.95%	13.99%	3.40%	11.96%	0.70%	
2012	12,238	2,451	562	2,033	167	17,451
	70.13%	14.05%	3.22%	11.65%	0.96%	
2013	11,958	2,483	568	2,117	145	17,271
	69.24%	14.38%	3.29%	12.26%	0.84%	
2014	11,351	2,272	562	1,761	118	16,064
	70.66%	14.14%	3.50%	10.96%	0.73%	
2015	12,096	2,627	533	2,010	96	17,362
	69.67%	15.13%	3.07%	11.58%	0.55%	
Total	90,697	18,452	4,164	15,431	1,024	129,768
	69.89%	14.22%	3.21%	11.89%	0.79%	

Table 3.6: Commuting time spent across the sample

Time(mins)/ Year	**0**	**1-29**	**30-59**	**60-89**	**90-119**	**120**	*Total*
2009	850	12,160	5,381	1,647	380	204	20,622
	4.12%	58.97%	26.09%	7.99%	1.84%	0.99%	
2010	2,799	13,871	5,769	1,636	450	195	24,720
	11.32%	56.11%	23.34%	6.62%	1.82%	0.79%	
2011	928	10,753	4,374	1,413	319	165	17,952
	5.17%	59.90%	24.36%	7.87%	1.78%	0.92%	
2012	952	10,275	4,390	1,374	314	146	17,451
	5.46%	58.88%	25.16%	7.87%	1.80%	0.84%	
2013	896	10,087	4,482	1,312	342	152	17,271
	5.19%	58.40%	25.95%	7.60%	1.98%	0.88%	
2014	830	9,512	4,080	1,170	303	169	16,064
	5.17%	59.21%	25.40%	7.28%	1.89%	1.05%	
2015	973	9,811	4,691	1,387	347	153	17,362
	5.60%	56.51%	27.02%	7.99%	2.00%	0.88%	
Total	8,228	76,469	33,167	9,939	2,455	1,184	131,442
	6.26%	58.18%	25.23%	7.56%	1.87%	0.90%	

In this sample, respondents on average felt "Good" to "Very good" for their health status, "Somewhat satisfied" for both their job and overall life. They spent approximately 25.5 minutes on a one-way commuting journey. In terms of sociodemographic backgrounds, the average age of respondents is 41 years old and the sample is balanced between men and women with 53.4% of respondents being women. 78% of the sample reside in urban areas. The average monthly net personal income is £1,700 with 91.2% of the sample working as an employee, while the highest education qualification achieved on average is A-Levels.

3.8. Research design

The previous sections have provided a broad consideration of the underlying theoretical and methodological approaches for this thesis. Conceptual issues are also analysed, together with possible econometric techniques to control those issues. Given the longitudinal nature of the data available in this thesis, this section will propose a research design that takes account of the matters discussed in the preceding sections.

The effects of individuals' commuting mode choices and duration on their own utility is of interest in the context of the utility-maximising assumption. Unlike conventional approaches with the application of indirect utility, the thesis follows Stutzer and Frey (2008) and uses SWB as the direct proxy measurement for experienced utility. The variables of interest health, SWB and job satisfaction are measured by one-item measures that each has categorical options to choose from. In essence, these variables should be treated as ordinal variables and ordered choice modelling could be incorporated to analyse data from the UKHLS survey. Firstly, the distribution for the random part of the random utility function would be decided to take on the normal distribution or the logistic distribution. This assumption would in turn determine whether a probit or logit ordered choice model would be used, respectively. However, the ordinal variable SWB can be regarded as a continuous cardinal variable and there are advantages in doing so (Ferrer-i-Carbonell and Frijters, 2004), especially with respect to flexibility in dealing with unobserved heterogeneity and simultaneity.

The estimation strategy will be as follows. The thesis involves a system of simultaneous equations with four variables of interest: health, SWB, job satisfaction and active commuting. Simultaneity bias exists in each equation due to potential reverse causality between each pair of the four variables as reviewed in Chapter 2. Each equation within the system will be estimated separately as a reduced-form equation and of the same form as the following equation for health.

[illegible] (3.46)

where [illegible] denotes the individual time-fixed unobserved heterogeneity effect and [illegible] is a matrix of exogenous control variables. According to Wooldridge (2016), in general, the unobserved heterogeneity [illegible] could be assumed to correlate with every predictor in the model, even the components of [illegible]. But the idiosyncratic error [illegible] is assumed to be uncorrelated with [illegible] to maintain the notion of exogeneity of [illegible]. Apart from that, the main predictors job satisfaction, SWB and active commute should be correlated with the error term [illegible] due to simultaneity.

The first step is to eliminate unobservable individual heterogeneity effect that is intrinsic in sociodemographic surveys such as the UKHLS survey in this thesis. The unobserved heterogeneity effects can be controlled in the equation of interest by applying either the FE or RE estimation method. FE method is illustrated for the Health equation (3.46) as follows

[illegible] (3.47)

The unobserved heterogeneity effect is removed along with any time-constant variables. Thus, Δx_{it} is truly exogenous with no correlation with the new error term $\Delta \varepsilon_{it}$. However, the main predictors after transformation are still likely to correlate with the error $\Delta \varepsilon_{it}$ due to simultaneity and render OLS estimations inconsistent. Hence, the second step involves the IV method being applied to the transformed equation using valid instrumental variables for the endogenous variables. Cameron and Trivedi (2005, p. 754) specify that the differencing transformation is likely to impose serial correlation into the error term even when ε_{it} is assumed to be iid. Thus, together with the reasons discussed at the end of Section 3.6, panel-robust standard error will be applied throughout models in the subsequent empirical chapters.

To answer the research questions, the thesis will carry out two empirical studies in Chapter 4 and 5. Chapter 4 will provide preliminary results by performing linear panel FE models for health, SWB and job satisfaction. The effects of different commuting modes will be investigated in this chapter, together with any effect from longer commuting duration. The heterogenous effects of commuting on SWB and health between the two genders have been documented in the literature. The chapter will revisit these gender effects and explore whether there is such differential effect for job satisfaction. Apart from including regional dummy variables, observations for London will be taken out to have a clearer examination of the commuting effect for the rest of British population since London has significantly different transport structure and demographic characteristics. Moreover, as mentioned in Chapter 1, with the health and environmental benefits of active transport modes, the thesis would like to focus on the causal effects of active commuting on commuters, with the hope to yield more justifications for its advocacy in daily lifestyle and institutional policies. Also, it is clear from the literature review in Chapter 2 that different transport modes have unique impacts on health and SWB, and finding valid and relevant IVs can be a challenging task for models of different commuting modes. Thus, the thesis would like to then focus exclusively on active transport modes and explore whether they can causally improve health, SWB and job satisfaction. Therefore, the subsequent Chapter 5 will explore the causal relationships between health, SWB, job satisfaction and active commuting. The causal inference will be supported by identifying suitable IVs for the endogenous variables and the 2SGMM approach is chosen as the most suitable GMM method for this empirical study because of the likelihood of heteroskedastic errors. To the best of the researcher's knowledge, no studies in the transport literature have evaluated the causal relationships between commuting and either health, SWB or job satisfaction using the application of IVs. The thesis hopes to contribute to the literature empirical evidences of various potential IVs for the variables health, SWB, job satisfaction and active commuting.

3.9. Conclusions

This chapter has delivered a review of methodological framework, theories used in the literature of commuting and methodological approaches for causal inference. Considering available alternatives and the thesis's own topic of interest, a quantitative research framework based on Realism and Deductive approach is regarded as the best fit. As SWB is one of the main variables of interest, the utility maximisation theory from microeconomics together with the direct utility approach is the underlying theory for the thesis.

However, the empirical studies in this thesis are subject to endogeneity issues that limit causal inference for the relationships of interest. Due to the nature of sociodemographic studies, individual heterogeneity is unavoidable and needs controlling for. The use of a panel dataset helps control for unobservable time-fixed heterogeneity effect and the FE estimation approach integrated in the empirical models should eliminate this endogeneity issue.

Furthermore, when the models of health, job satisfaction, SWB and active commute each contains the other three variables of interest as the main predictors, the dependent and independent variables are jointly determined and expose the models to simultaneity bias. As these dependent variables are considered as cardinal variables, this endogeneity issue can be controlled for with the use of IVs. This chapter considered several estimation approaches from the GMM framework for the application of IVs. In addition, the data source and potential variables used in this thesis have been discussed, and a research design is established for the following empirical chapters.

4 - ASSOCIATIONS BETWEEN COMMUTING, HEALTH, SWB AND JOB SATISFACTION

4.1. Introduction

In Chapter 2, it has been identified that there is a lack of research on the relationship between commuting and job satisfaction. Moreover, studies exploring the effect of commuting on health and SWB have been based on cross-sectional data; and the small number of studies that use longitudinal observations do not take into account the possible reverse causality between the variables of interest. In this chapter, linear FE models will be used to estimate the preliminary impacts of commuting time and different modes of transport on commuters' health, SWB and job satisfaction. As discussed in Chapter 3, FE panel models are employed throughout the thesis to eliminate unobserved heterogeneity. Several sub-samples will be examined to explore the potential gender and regional differences that are still under-researched in the literature. The chapter is organised as follows. Section 4.2 explains the use of linear panel FE models for this study and provides additional details on the variables used in the study apart from those already discussed in Chapter 3. The panel FE models estimated on the main data set and various sub-samples are presented in Section 4.3, and the subsequent Section 4.4 offers intuitive discussions of the results and how the findings are related to the existing literature. Section 4.5 concludes the chapter and suggests several limitations and potential remedy that will be considered in the next chapter.

4.2. Methods and Data

This section describes the empirical methods and variables used in this study. As it is likely that unobserved heterogeneity exists in the data set, models that take into account its presence are introduced along with their strengths and weaknesses. Then the rationale of choosing one model over the other is provided, based on the objective Hausman tests and inductive reasons.

As presented in Chapter 2, the literature has been dominated with cross section studies which use information on a sample of population recorded at a specific point in time, thus cannot capture fixed individual heterogeneity. Individual heterogeneity is unique characteristics of an individual that are unobservable and assumed to be invariant over time. Examples of individual heterogeneity can be personality and preferences (Ferrer-i-Carbonell and Frijters, 2004). Cross section data also cannot take into account changes over time and distinguish the temporal ordering of event (Office for National Statistics, 2014). Alternatively, a sample of the population is recorded periodically over a time span in panel data. If an individual's heterogeneity can be assumed to be fixed over time, panel data econometric techniques would remove the individual heterogeneity without the need to record those unobservable factors directly. Thus, the use of a panel data set such as the UKHLS survey facilitates the control of unobservable heterogeneity in this thesis. Moreover, the dependent variables in this study, i.e. health, job satisfaction and SWB, are treated as continuous variables, as explained in Chapter 3. Linear panel models with the application of either FE or RE method to control for time-invariant unobserved heterogeneity are developed in this chapter as benchmark estimates.

To be more specific, the unobserved heterogeneity issues can be controlled for using individual-specific effects model, including both the FE and RE models. The two types of models contrast in their main assumptions: whereas the FE models assume that the individual heterogeneity is correlated with the independent variables, the RE models' main assumption is that they are unrelated. An OLS estimation does not control the heterogeneity effect and can lead to biased parameter estimations. The FE estimator can provide consistent and efficient estimation but only focuses on the within-people variation and excludes the between-people variation. Alternatively, the RE estimation method uses both within- and between-people information and can avoid the FE models’ problem. With information on subjective measurements such as feelings of individuals, the existence of individual heterogeneity has been considered to be of importance (Clark and Oswald, 2002). Individual heterogeneity, such as personalities, childhood lifestyles, family background etc. can influence a person’s commuting choice and duration. Thus, RE estimation with its assumption of no correlation between predictors and unobserved heterogeneity may be too restrictive. Moreover, Hausman test can be conducted to confirm the models’ assumptions and validate the recommended use of the FE versus the RE model. The test results will be provided together with the main results in Section 4.3. The Hausman test aims to examine whether the difference between the FE and RE estimators is statistically significant enough that the FE estimator is the better choice. If the RE model’s assumption of independence between the unobserved individual effects and the predictors is true, the FE estimator is consistent but inefficient, whereas the RE estimator is both consistent and efficient.

In this chapter, the dependent variables of interest are regressed against the commuting predictors to test the relations between commuting and health, job satisfaction and SWB. The model is presented in Equation 4.1.

$$y_{it} = \beta' Comm_{it} + \gamma' X_{it} + \varepsilon_{it} \qquad (4.1)$$

in which y_{it} is either the dependent variable health, job satisfaction or SWB treated as continuous. The term $\gamma' X_{it}$ contains the set of control variables discussed above in Subsection 3.7.3; and the error term ε_{it} includes the unobserved heterogeneity α_i and the individual idiosyncratic error u_{it}. Moreover, the study is interested in the effects of both commuting time and different transport modes, hence the covariates in $\beta' Comm_{it}$ will be either (1) commuting time on its own, (2) binary variables representing different modes, or (3) interactions between commuting time and different transport modes. From the UKHLS survey, the commuting time is measured in minutes, whereas the commuting mode variable is recorded with 11 categories. The mode variable is thus separated into 11 binary commuting mode variables to form the predictors in group (2), which are then multiplied with the commuting time variable to produce 11 duration variables for different commuting modes in group (3). It is necessary to separate commuting modes because the effects of commuting time on health and SWB have been found to be heterogeneous across different modes. Including them as one single commuting time can offset the underlying commuting effects on the dependent variables (Künn-Nelen, 2015). Furthermore, with some of the modes being of small sample sizes, the modes are aggregated into 4 categories based on their similar characteristics, which are Private modes, Public modes, Cycle and Walk. The private modes consist of the following modes: "Drive myself by car or van", "Get a lift with someone from household", "Get a lift with someone outside the household", "Motorcycle/moped/scooter", "Taxi/Minicab", whereas the public options contain modes that are for sharing with other citizens, including "Bus/coach", "Train", "Underground/Metro/Tram/Light railway". The "Other" option is dropped, which makes up only 0.80% of sample population. The choices of categorising into larger, more representative groups are supported by the literature (e.g. Laverty *et al.*, 2013; Martin, Goryakin and Suhrcke, 2014; Wheatley, 2014). Overall, in group (1) there is one single commuting time variable, while in group (2) there are four binary mode variables, including private modes, public modes, cycling and walking, that indicate what transport modes out of the four mode groups a commuter has chosen for their journey. For example, the binary variable walking is 1 if the respondent walks to work, and 0 if they use other transport modes. Group (3) consists of four commuting duration variables for four different groups of modes. These variables measure the separate commuting duration of each commuting mode group.

Apart from the main commuting predictors, the same set of demographic and socioeconomic control variables are included in each regression equation. The set of control variables is applied frequently in the literature and could potentially have confounding effects on the relationships between the predictors and dependent variables if not controlled for. The demographic control variables are age, gender and ethnicity. The squared term for age is also included because of the existence of a quadratic relationship between age and SWB found in a study by David G Blanchflower and Oswald (2008). The commuting literature frequently includes the two age terms together (for example: Roberts, Hodgson and Dolan, 2011; Dickerson, Hole and Munford, 2014; Martin, Goryakin and Suhrcke, 2014; Wheatley, 2014; Künn-Nelen, 2015; Morris, 2015). Additionally, the socioeconomic factors controlled for are personal income (in pounds sterling, divided by 100), number of own under-16 children in the household (including natural, adopted and step- children), whether a person resides in an urban or rural area, marital status, highest educational qualifications, social class (based on job types) and employment type (employee or self-employed). Moreover, year dummy variables are also incorporated in the analysis to take account of any trends emerging over time. Similarly, regional characteristics are controlled for by the presence of regional dummy variables.

The error term ε_{it} may be correlated for the same respondent over the observed time periods. A standard error that is robust to serial correlation should be used in place of the usual standard error from cross section models, which in this case can be biased downward and affect hypothesis testing's results (Cameron and Trivedi, 2005). Thus, panel-robust standard errors are employed to control for both serial correlation and heteroskedasticity and included in all estimation result tables in this chapter.

4.3. Results

This section applies the linear panel FE model to test for the relationships between commuting time and health, SWB and job satisfaction, using a panel data set on respondents across the UK. Firstly, Section 4.3.1 examines the impact of commuting time as a whole, without separating out the potential heterogeneous effects of different commuting modes. The second Section 4.3.2 explores the effects of transport modes by using binary mode variables. Then, the commuting durations spent on various transport modes are investigated in the subsequent Section 4.3.3. As the transport system and demographic and socioeconomic characteristic of London are significantly different from the rest of the UK, respondents residing in London are excluded for a robustness check in Section 4.3.3. The data set is then divided into male and female respondents to consider whether the effects of different commuting modes are still preserved and also explore the potential heterogenous effects on different genders. As mentioned in Section 4.2, the standard errors used in this study will be robust to heteroskedasticity and serial correlation by clustering over the respondents' personal identifiers set by the UKHLS survey.

Hausman tests are provided to facilitate the decision of whether a FE or RE model should be applied to investigate each specific relationship. Note that as the STATA software cannot perform the Hausman test when the standard errors are robust to heteroskedasticity and serial correlation, the results of the Hausman tests in this chapter are based on the FE and RE models with conventional standard errors.

4.3.1. The effects of overall commuting time

This section presents the empirical result of how overall commuting time can impact health, SWB and job satisfaction, without considering any potential effects from using different types of transport modes. The independent variable is a continuous cardinal variable measuring the commuting time of respondents in minutes. The results of Hausman tests are given in Table 4.1, where the linear panel FE models are supported over the RE models. The results of the linear panel FE models are provided in Table 4.2.

Table 4.1: Hausman tests

Model	χ^2 statistic	χ^2 d.f.	p-value
Health	459.04	34	0.000
Job satisfaction	333.66	34	0.000
Life satisfaction	323.91	34	0.000

Table 4.2: The effects of overall commuting time

Variable	General health	Job satisfaction	Life satisfaction
Commuting time	-0.0004707***	-0.0003801	-0.0003338
	(0.00012)	(0.0002443)	(0.0002027)
Age	0.030792***	-0.0411533**	0.0144143
	(0.0102436)	(0.0201173)	(0.0165006)
Age squared (divided by 100)	-0.0359593***	0.0206576**	0.0303482***
	(0.0056093)	(0.0103761)	(0.0091884)
Monthly net personal income (divided by 100)	0.0004054	0.0024607***	0.001299***
	(0.0002726)	(0.0004647)	(0.0004667)
Number of own children in household	-0.0210099***	-0.0261932**	0.0124412
	(0.00685)	(0.0123141)	(0.0109777)
Gender (Female) (Base level: Male)	(omitted)	(omitted)	(omitted)
Whether living in a rural area (Base level: Urban area)	0.0048698	-0.0273137	0.0562999
	(0.0213239)	(0.0417511)	(0.034767)
Ethnicity: (Base level: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base level: Married)			
Á Single	0.0271197*	-0.0019333	-0.0113725
	(0.0154644)	(0.0296405)	(0.0263279)
Á Separated	-0.0041607	0.0264898	-0.1989803***
	(0.0253551)	(0.0463031)	(0.0477365)
Á Divorced	0.0195795	-0.0814347**	-0.0411076
	(0.0217526)	(0.0410455)	(0.0385052)
Á Widowed	0.0134696	-0.0959689	-0.3290507***
	(0.0520818)	(0.0905613)	(0.1022976)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0171214	-0.1358623*	-0.0353023
	(0.0437707)	(0.0822661)	(0.0734329)

Á First degree or equivalent	0.0076699	-0.0937061	0.0026921
	(0.0331594)	(0.0611636)	(0.0549866)
Á A Levels	-0.0595336*	-0.0930123	-0.0098149
	(0.0312723)	(0.0584023)	(0.0540965)
Á None of the above	0.0177407	0.0319061	0.2476195**
	(0.0544659)	(0.1083606)	(0.1048338)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	-0.0156236	0.1338195***	-0.0185159
	(0.0141672)	(0.0306538)	(0.0233535)
Á Intermediate occupations	-0.0130913	0.100399***	0.0029961
	(0.0155657)	(0.0335375)	(0.0263115)
Employment type (Employee) (Base level: Self-employed)	-0.0100172	-0.3336962***	-0.0124548
	(0.020368)	(0.0421887)	(0.0353296)
Region: (Base level: London)			
Á North East	-0.0156177	-0.071293	0.1367335
	(0.1317334)	(0.2132407)	(0.1993053)
Á North West	-0.1283481*	0.01635	-0.1390032
	(0.0669381)	(0.1496386)	(0.1018769)
Á Yorkshire and the Humber	-0.0751932	-0.0422658	-0.0377928
	(0.0719495)	(0.1606879)	(0.1143746)
Á East Midlands	-0.1023979	0.0786718	0.0206573
	(0.0670967)	(0.1285855)	(0.1119305)
Á West Midlands	-0.0525372	0.1795494	-0.0202699
	(0.0735061)	(0.1478699)	(0.113485)
Á East of England	-0.0676353	0.00338	-0.0895361
	(0.0615673)	(0.108904)	(0.0788812)
Á South East	-0.1000002*	0.0999401	0.0785362
	(0.0530564)	(0.0984219)	(0.0804571)
Á South West	-0.1670065**	0.1814534	-0.006056
	(0.0663795)	(0.1426022)	(0.104464)
Á Wales	-0.0593314	0.1394594	0.1083901
	(0.1155086)	(0.1927768)	(0.1649898)

Á Scotland	-0.025355	-0.1134416	-0.2263556
	(0.1011188)	(0.212947)	(0.1560977)
Á Northern Ireland	0.4387666**	-0.2283436	0.0992626
	(0.1843499)	(0.517263)	(0.3666633)
Year: (Base level: 2009)			
Á 2010	0.004528	0.0021972	-0.0886598***
	(0.0117031)	(0.0224942)	(0.0188533)
Á 2011	0.0185066	-0.0551472	-0.2385399***
	(0.020203)	(0.0389858)	(0.0322272)
Á 2012	-0.0258251	-0.0320451	-0.3467672***
	(0.0291746)	(0.0568343)	(0.046424)
Á 2013	-0.0196659	-0.0352193	-0.3868659***
	(0.0381995)	(0.0746977)	(0.0607885)
Á 2014	0.0150134	0.0621398	-0.2819514***
	(0.0474882)	(0.0928474)	(0.0755255)
Á 2015	-0.1298731**	0.0949904	-0.2960086***
	(0.0567395)	(0.1110626)	(0.0900809)

Observations: 123,505. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Commuting time has a negative association with all three variables health, job satisfaction and life satisfaction, but the effect is only significant in the model of health. As a person spends an additional 10 minutes on commuting to work, their health is likely to worsen by 0.0047 units. Although the coefficient is of small magnitude, it is strongly significant, thus provides strong evidence for a negative relation between commuting time and health. As a person only has 24 hours in a day, if working time is fixed and their commuting duration increases, the time spent on other activities must reduce. Hence, this negative relation between commuting time and health can be potentially explained by the trade-off between commuting time and time spent on activities that contribute to health, such as sleeping, recreational physical activities and preparing more nutritious foods (Christian, 2012). A margins plot is provided in Figure 4.1 for this significant relationship between overall commuting time (in minutes) and general health status.

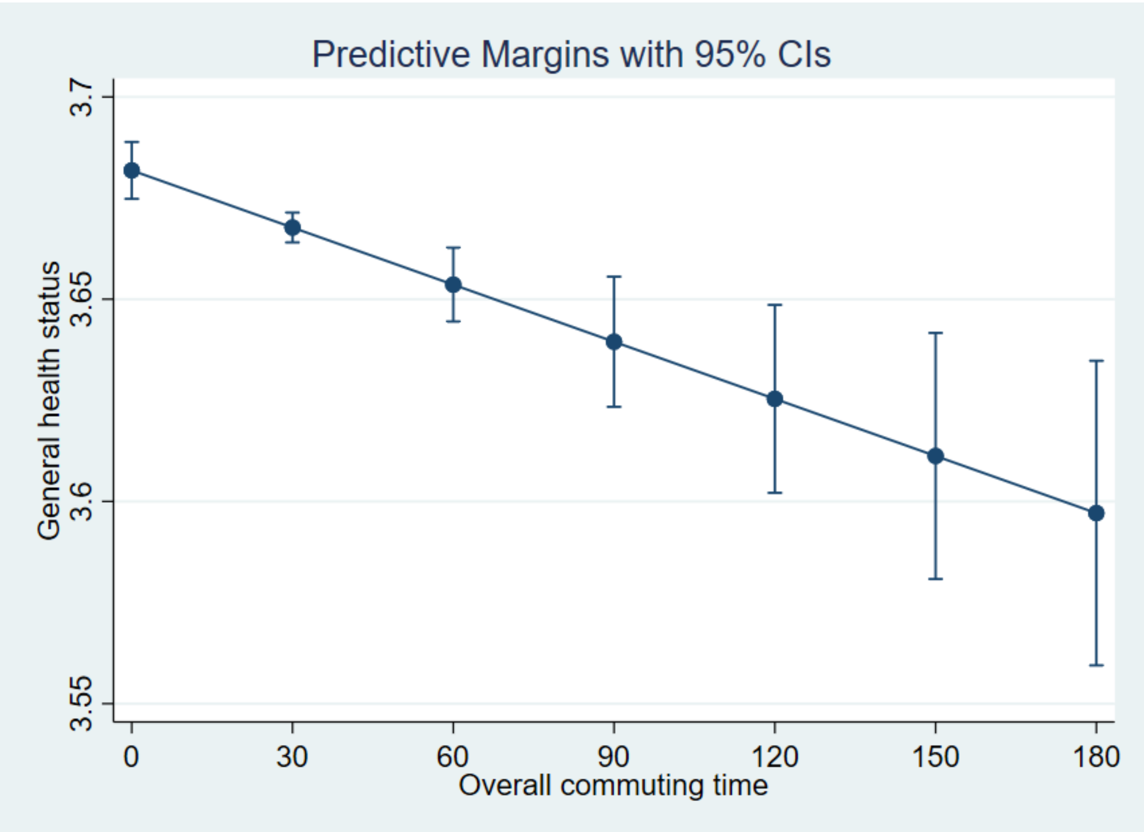

Figure 4.1: Margins plot between overall commuting time and general health status

4.3.2. The effects of commuting mode choices

In this subsection, the commuting variables are the binary mode choice variables reporting whether a respondent uses a particular transport mode to commute to work. Separating out the effect of commuting time can give a clearer perspective on how different transport mode choices may link with the dependent variables. There are four binary mode variables representing four groups of transport modes: private modes, public modes, cycling and walking. The private modes are applied as the base level, because the more active and sustainable transport modes are of interest in this thesis, and it would be useful to study whether the changes from private modes to public modes, walking or cycling will significantly improve health, SWB and job satisfaction. The choice of the base level is also consistent with what has been done in the literature, such as in a longitudinal study by Martin, Goryakin and Suhrcke (2014). Table 4.3 provides the results of Hausman tests which strongly suggest that FE models should be applied rather than the RE models. The results of the FE models studying the relationships between binary commuting modes and health, job and life satisfaction are presented in Table 4.4.

Table 4.3: Hausman tests

Model	χ^2 statistic	χ^2 d.f.	p-value
Health	491.72	36	0.000
Job satisfaction	306.86	36	0.000
Life satisfaction	321.48	36	0.000

Table 4.4: The effects of different commuting modes

Variable	General health	Job satisfaction	Life satisfaction
Commuting modes: (Base level: Private modes)			
Á Public modes	-0.023695*	0.0005502	-0.0267273
	(0.0125183)	(0.0245898)	(0.0215992)
Á Cycle	0.059933***	-0.0163292	0.0648496**
	(0.0199751)	(0.0375414)	(0.0314307)
Á Walk	0.0049593	0.0133709	0.0231712
	(0.012679)	(0.0238929)	(0.0214228)
Age	0.0304373***	-0.0417392**	0.0138184
	(0.0102746)	(0.0201274)	(0.016508)
Age squared (divided by 100)	-0.0351534***	0.0209252**	0.0304549***
	(0.0056246)	(0.0104242)	(0.0092192)
Monthly net personal income (divided by 100)	0.0003835	0.0025021***	0.0011982**
	(0.0002724)	(0.0004696)	(0.0004673)
Number of own children in household	-0.0214631***	-0.0268825**	0.0120128
	(0.0068591)	(0.0123533)	(0.0110018)
Gender (Female) (Base level: Male)	(omitted)	(omitted)	(omitted)
Whether living in a rural area (Base level: Urban area)	0.0046836	-0.0252846	0.0543303
	(0.0214096)	(0.0419073)	(0.0346597)
Ethnicity: (Base level: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base level: Married)			
Á Single	0.0274184*	-0.0001336	-0.0120972
	(0.0154859)	(0.0296888)	(0.0263817)
Á Separated	-0.0038541	0.0275143	-0.1988173***
	(0.0254579)	(0.0464472)	(0.0478646)
Á Divorced	0.020394	-0.080428*	-0.0418961
	(0.0218149)	(0.0411498)	(0.0384643)

Á Widowed	0.011999	-0.0939851	-0.3205841***
	(0.0526069)	(0.0913004)	(0.1028451)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0129839	-0.1364512*	-0.0451617
	(0.0433489)	(0.0824494)	(0.0733406)
Á First degree or equivalent	0.0052103	-0.0945807	-0.0064398
	(0.033122)	(0.0613198)	(0.0546925)
Á A Levels	-0.0632768**	-0.0964204	-0.0155993
	(0.031255)	(0.0585629)	(0.0541564)
Á None of the above	0.015953	0.0307149	0.230799**
	(0.0545674)	(0.1088339)	(0.1044356)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	-0.0149611	0.1341499***	-0.0149332
	(0.0142085)	(0.0306909)	(0.0233891)
Á Intermediate occupations	-0.0130628	0.0979516***	0.0055504
	(0.0156299)	(0.033662)	(0.0264237)
Employment type (Employee) (Base level: Self-employed)	-0.003749	-0.3316995***	-0.0179344
	(0.0206312)	(0.0430603)	(0.0359377)
Region: (Base level: London)			
Á North East	-0.0185178	-0.0743865	0.1488079
	(0.1327956)	(0.2149559)	(0.201659)
Á North West	-0.1302406*	0.0088062	-0.136463
	(0.066967)	(0.1497805)	(0.102075)
Á Yorkshire and the Humber	-0.0792625	-0.0502696	-0.0386159
	(0.0718269)	(0.1609845)	(0.1146218)
Á East Midlands	-0.1052873	0.0721654	0.0216704
	(0.0673475)	(0.1292733)	(0.1125246)
Á West Midlands	-0.0530964	0.1811788	-0.0260658
	(0.0736805)	(0.1482274)	(0.1138395)
Á East of England	-0.0710565	-0.0020495	-0.0881904
	(0.0617364)	(0.1088793)	(0.079051)
Á South East	-0.1064989**	0.0902181	0.0797476

	(0.0531233)	(0.0984921)	(0.0806004)
Á South West	-0.171597**	0.1667372	-0.0147579
	(0.0661982)	(0.1426402)	(0.1039948)
Á Wales	-0.0709542	0.1422811	0.1098683
	(0.1163653)	(0.1937458)	(0.1662652)
Á Scotland	-0.0293179	-0.1361145	-0.2233707
	(0.1022135)	(0.2153451)	(0.1546468)
Á Northern Ireland	0.4370228**	-0.239046	0.1102487
	(0.1846413)	(0.5206795)	(0.3685052)
Year: (Base level: 2009)			
Á 2010	0.0034458	0.0016242	-0.085565***
	(0.0117494)	(0.0225304)	(0.0188789)
Á 2011	0.0177181	-0.0557129	-0.2369273***
	(0.0202606)	(0.0389813)	(0.0322306)
Á 2012	-0.0269384	-0.0321937	-0.3442219***
	(0.0292618)	(0.0568239)	(0.046414)
Á 2013	-0.0211964	-0.035126	-0.3842605***
	(0.0383139)	(0.074683)	(0.0607761)
Á 2014	0.0130399	0.062819	-0.2788001***
	(0.0476315)	(0.0928339)	(0.0755148)
Á 2015	-0.1321722**	0.0956541	-0.2921689***
	(0.0569145)	(0.111039)	(0.0900654)

Observations: 123,039. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

The change from commuting by private modes to public modes is significantly associated with a reduction in a respondent's health status by 0.024 units, whereas switching to cycling can improve the same health measure by 0.060 units. By shifting from using private modes to cycling, respondents may potentially see an improvement in how they perceive their life with an increase in life satisfaction score by 0.065 units. Furthermore, switching to walking to work from private commuting has positive but nonsignificant improvements on these three dependent variables. Figures 4.2 and 4.3 provide a graphical illustration of the effect of switching from private modes to public modes and cycling on general health, respectively.

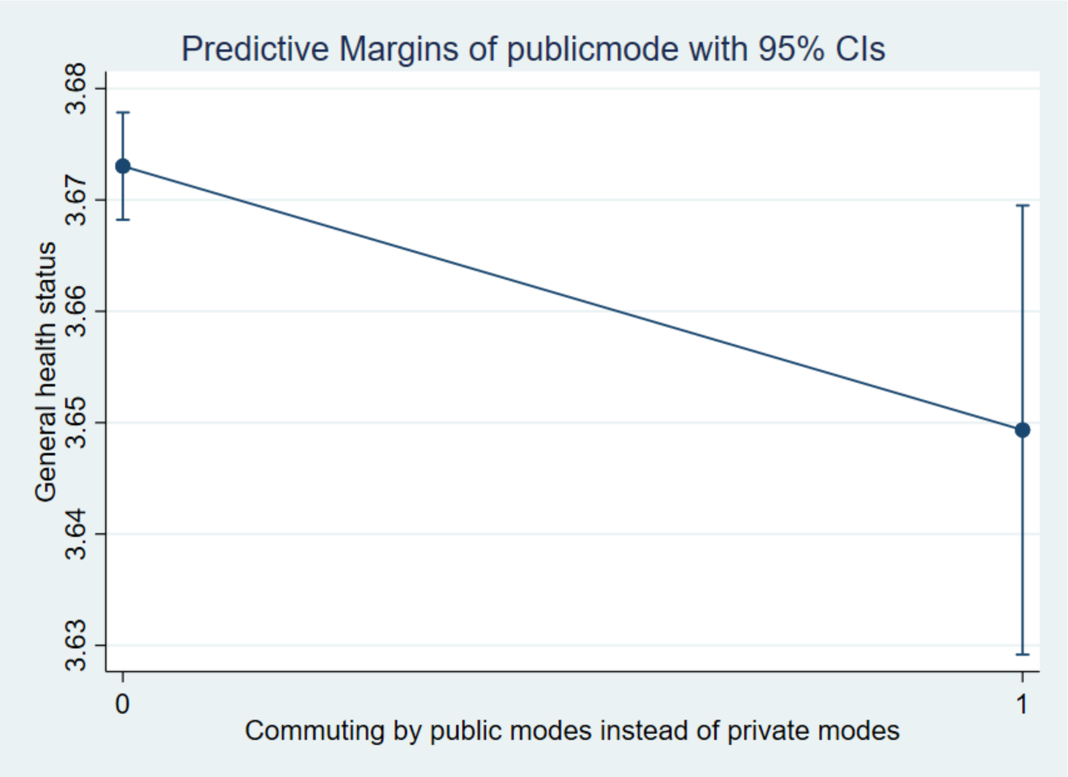

Figure 4.2: The effect on general health of switching from private modes to public modes

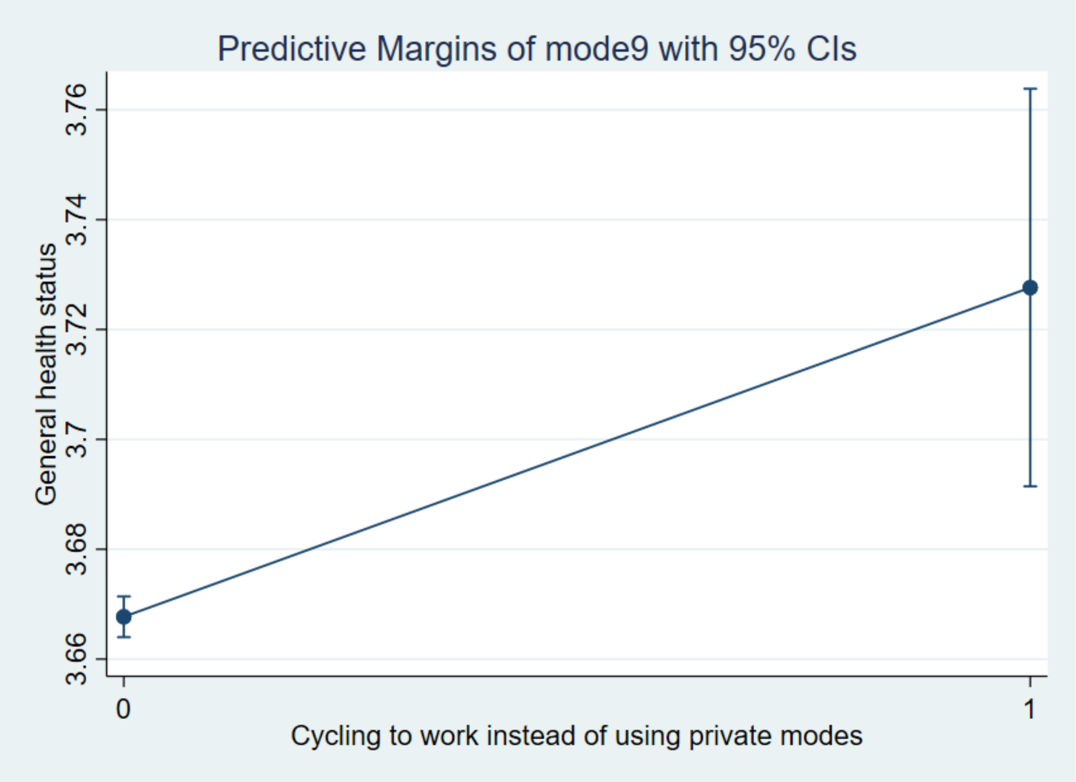

Figure 4.3: The effect on general health of switching from private modes to cycling

4.3.3. The effects of commuting time across transport modes

In this subsection, the empirical results from the linear panel FE models examine whether there is any systematic difference between the effects of commuting duration across multiple transport modes on health, job satisfaction and life satisfaction of commuters. The commuting variables in the models are four different commuting duration variables for four groups of commuting modes: Private modes, Public modes, Cycling and Walking. Similar to the method carried out in the study by Stutzer and Frey (2008), these four commuting duration variables are interaction terms formed by the commuting time variable and the four binary mode variables.

Firstly, three models for the three dependent variables are performed on the original dataset, whose results are shown in Table 4.6. Then, the study recognises that London has a significantly different transport infrastructure and experiences higher usage of public transport, and active modes are used more than any other parts of the country (Laverty *et al.*, 2013). Laverty *et al.* (2013) attributes the difference in public transport usage between different parts of the UK to the substandard public transport services in some areas. In addition, the number of commuting trips in London is greater than other areas in the UK (Sullivan, Kershaw and Cummings, 2016). Therefore, the observations for London are taken out of the original sample, and the three dependent variables are regressed in the absence of the London observations. By doing so, a clearer and more representative view of the commuting effects on workers across the UK should be extracted from the models. The literature recognises this geographical difference and estimates models on sub-samples which exclude London (Künn-Nelen, 2015). The results from this smaller sample are reported in Table 4.7.

Table 4.5: Hausman tests

Model	χ^2 statistic	χ^2 d.f.	p-value
Health	495.99	37	0.000
Job satisfaction	346.69	37	0.000
Life satisfaction	327.36	37	0.000

Table 4.5 presents the Hausman tests' results which suggest for all three dependent variables, the FE model is more suitable than the RE model.

Table 4.6: The effects of commuting time across transport modes

Variable	General health	Job satisfaction	Life satisfaction
Commuting time for transport modes:			
Á Private modes	-0.0004666***	0.0000453	-0.0001548
	(0.0001615)	(0.0003256)	(0.0002691)
Á Public modes	-0.0005465***	-0.000812**	-0.0007223**
	(0.0001832)	(0.0003534)	(0.0003213)
Á Cycle	0.0016805**	-0.0004247	0.0019513
	(0.0007394)	(0.0015049)	(0.0011857)
Á Walk	-0.0005264	-0.0010566	0.0005974
	(0.0005446)	(0.001006)	(0.0008908)
Age	0.0307456***	-0.0423251**	0.0138269
	(0.010278)	(0.0201196)	(0.0165049)
Age squared (divided by 100)	-0.0355848***	0.0215773**	0.0303974***
	(0.0056263)	(0.0104179)	(0.0092138)
Monthly net personal income (divided by 100)	0.0003845	0.0025038***	0.0012002**
	(0.0002725)	(0.0004698)	(0.000467)
Number of own children in household	-0.0215736***	-0.0272635**	0.0118654
	(0.0068583)	(0.0123554)	(0.0110002)
Gender (Female) (Base level: Male)	(omitted)	(omitted)	(omitted)
Whether living in a rural area (Base level: Urban area)	0.0050438	-0.0271544	0.0536567
	(0.0214038)	(0.0419104)	(0.0346588)
Ethnicity: (Base level: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base level: Married)			
Á Single	0.0274675*	0.0001026	-0.0122056
	(0.0154935)	(0.0296841)	(0.0263851)
Á Separated	-0.0042249	0.0280569	-0.1988895***
	(0.0254617)	(0.0464272)	(0.047869)

Á Divorced	0.0201258	-0.0802809*	-0.0420645
	(0.0218093)	(0.0411233)	(0.0384719)
Á Widowed	0.011489	-0.0937532	-0.3206976***
	(0.0525994)	(0.0912537)	(0.1028861)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0144606	-0.1359815*	-0.0449193
	(0.0433143)	(0.0824749)	(0.0733288)
Á First degree or equivalent	0.0054324	-0.0953363	-0.006702
	(0.0330735)	(0.0613002)	(0.0546961)
Á A Levels	-0.0632487**	-0.0967111*	-0.0159832
	(0.031234)	(0.0584891)	(0.054126)
Á None of the above	0.0153896	0.0304797	0.2298674**
	(0.0545514)	(0.1088186)	(0.1044184)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	-0.0139351	0.1341221***	-0.0148237
	(0.0142066)	(0.0307035)	(0.0233976)
Á Intermediate occupations	-0.0123638	0.0982924***	0.0053201
	(0.0156272)	(0.0336724)	(0.0264277)
Employment type (Employee) (Base level: Self-employed)	-0.0016042	-0.3302964***	-0.0168458
	(0.0206412)	(0.0430955)	(0.0359171)
Region: (Base level: London)			
Á North East	-0.0169908	-0.083732	0.1485632
	(0.1329799)	(0.2151476)	(0.2011466)
Á North West	-0.1257016*	0.0025127	-0.1369453
	(0.0669731)	(0.1497952)	(0.1020596)
Á Yorkshire and the Humber	-0.0752522	-0.0569417	-0.0373065
	(0.0720312)	(0.1610392)	(0.1146438)
Á East Midlands	-0.1006445	0.0633939	0.0224679
	(0.0673182)	(0.1293646)	(0.1125215)
Á West Midlands	-0.050707	0.170824	-0.0249306
	(0.0736095)	(0.1482066)	(0.1137391)
Á East of England	-0.0660781	-0.0065537	-0.085501

	(0.0616343)	(0.1090708)	(0.0791215)
Á South East	-0.1009902*	0.0875036	0.0834725
	(0.053155)	(0.0986078)	(0.0806033)
Á South West	-0.1710744**	0.1607066	-0.0149754
	(0.0663337)	(0.1427736)	(0.103914)
Á Wales	-0.0675224	0.1312131	0.1092886
	(0.1164639)	(0.1937056)	(0.1662371)
Á Scotland	-0.0233545	-0.1392115	-0.2210864
	(0.1019405)	(0.2155174)	(0.1542016)
Á Northern Ireland	0.4390521**	-0.2396421	0.107262
	(0.1843154)	(0.5186685)	(0.3673582)
Year: (Base level: 2009)			
Á 2010	0.0035119	0.0019243	-0.0856438***
	(0.0117538)	(0.0225266)	(0.0188804)
Á 2011	0.0176795	-0.0557867	-0.2369548***
	(0.0202697)	(0.0389684)	(0.0322356)
Á 2012	-0.0268931	-0.0323566	-0.3442451***
	(0.029276)	(0.0568065)	(0.0464219)
Á 2013	-0.0209102	-0.0349219	-0.3842264***
	(0.0383348)	(0.0746606)	(0.0607879)
Á 2014	0.0133137	0.0623684	-0.2788132***
	(0.0476567)	(0.0928032)	(0.0755296)
Á 2015	-0.1316946**	0.095379	-0.2923565***
	(0.0569461)	(0.111003)	(0.0900836)

Observations: 123,039. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

In the full sample, the results indicate that different commuting modes have significant effects on health status even though the effect sizes are small. If someone commutes by a private mode for 10 minutes longer, then it is likely that their health will deteriorate and their health score be reduced by 0.0047 units. Public transport modes also have a negative effect on respondents' self-reported health status. If a public mode is used to commute for 10 additional minutes, the commuter's health status will be decreased by 0.0055 units. Compared with the relation between commuting time and health in section 4.3.1, it can be said that private and public transport modes contribute to the negative association between commuting time and health status. However, not all commute modes impact self-reported health negatively. As a respondent cycles to work for 10 more minutes, it can have a significantly positive effect on their health and increases their health status score by 0.017 units. Also, the magnitude of the positive impact from cycling is approximately three times the size of the negative influence from either public or private modes. Graphical illustrations of these effects on general health status from commuting by private modes, public modes and cycling are given in Figures 4.4, 4.5 and 4.6, respectively.

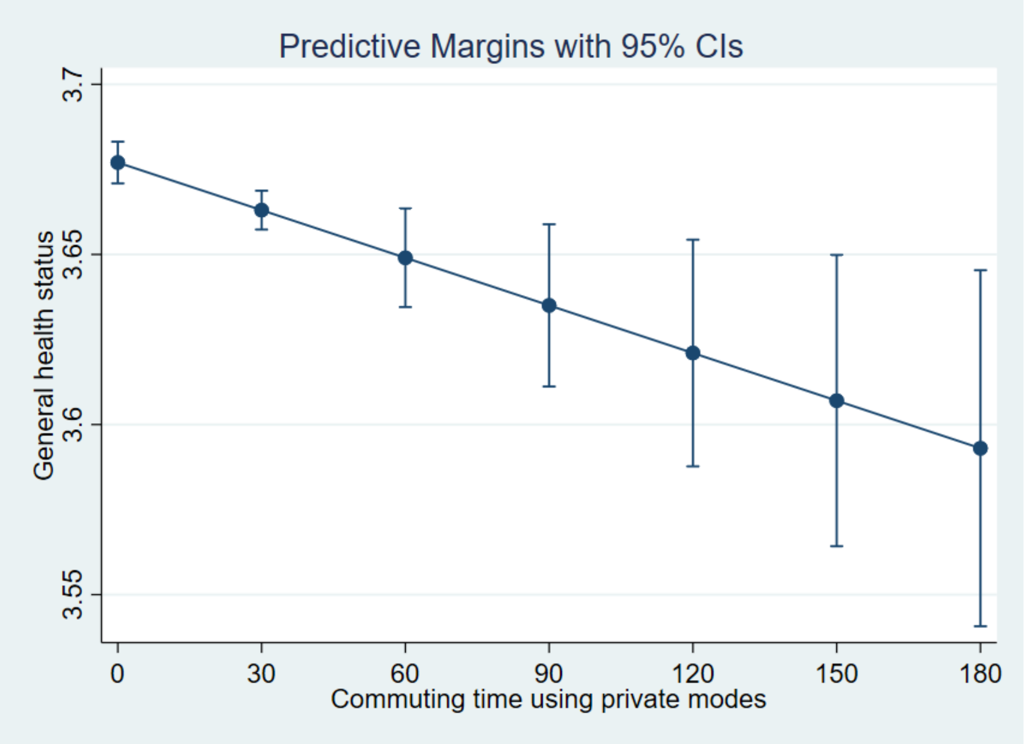

Figure 4.4: The effect of commuting time using private modes on general health

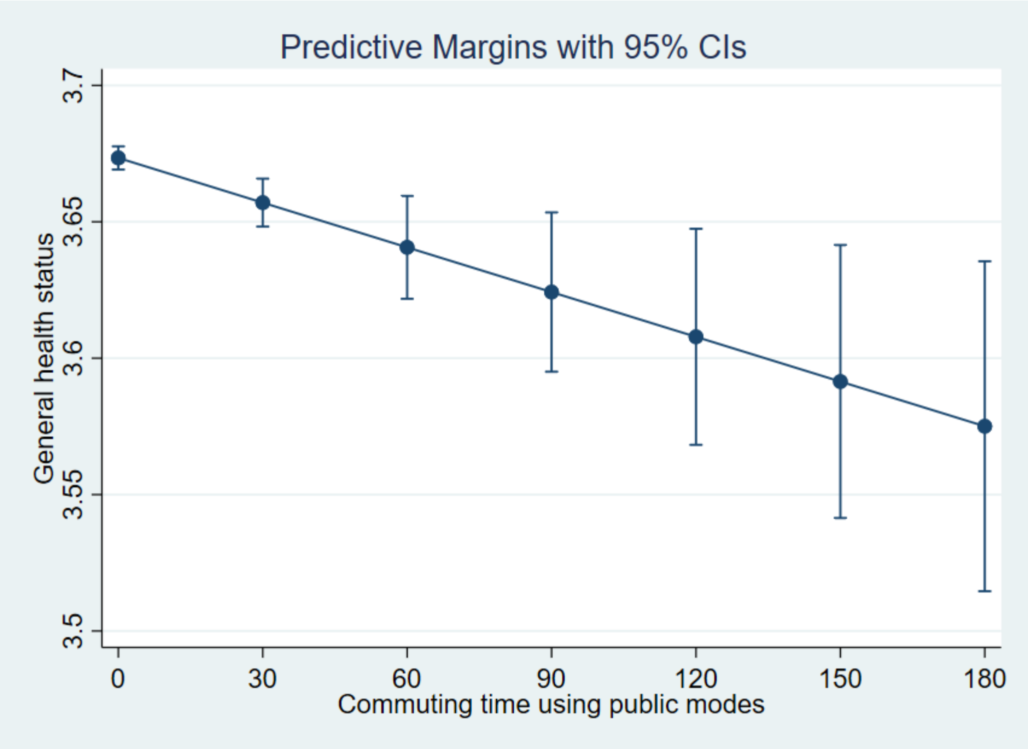

Figure 4.5: The effect of commuting time using public modes on general health

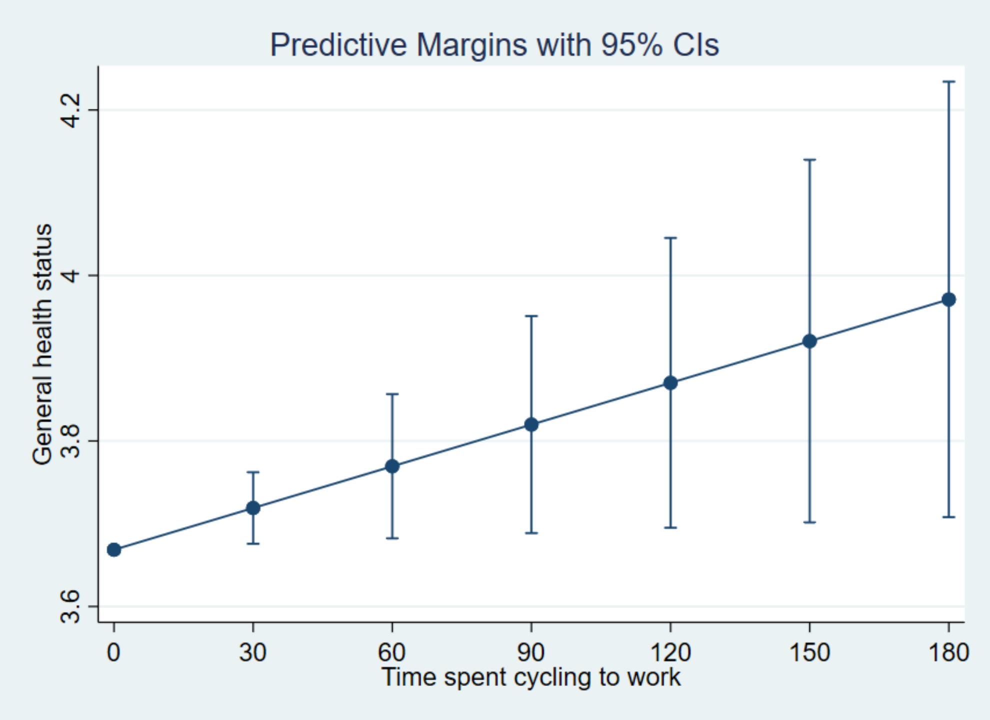

Figure 4.6: The effect of cycling time to work on general health

Apart from having a deteriorating effect on health, using public modes is linked with lowered levels of a person's job satisfaction and SWB. By spending 10 more minutes using public transport, a commuter can experience a decrement in job satisfaction by 0.0081 units and in SWB by 0.0072 units. In the literature, it has been found that people having high income will be able to switch to other transport modes more easily, and the income elasticity of bus demand is substantially negative in the range of -0.5 to -1 (Paulley *et al.*, 2006). The same study also argues that there is a strong link between income and car ownership in the UK and car ownership can impose negative effect on both bus and rail. This is consistent with the estimation in Table 4.6, in which personal income is found to be significantly linked with higher scores for job satisfaction and life satisfaction. Also, workers with high and intermediate level occupations have better satisfaction at work than those with routine and manual roles. Thus, it is likely that public transport users in this study tend to earn less income, have lower level jobs and are associated with having lower job satisfaction and life satisfaction. Figures 4.7 and 4.8 present margins graphs for the effects of commuting duration using public modes on job satisfaction and life satisfaction, respectively.

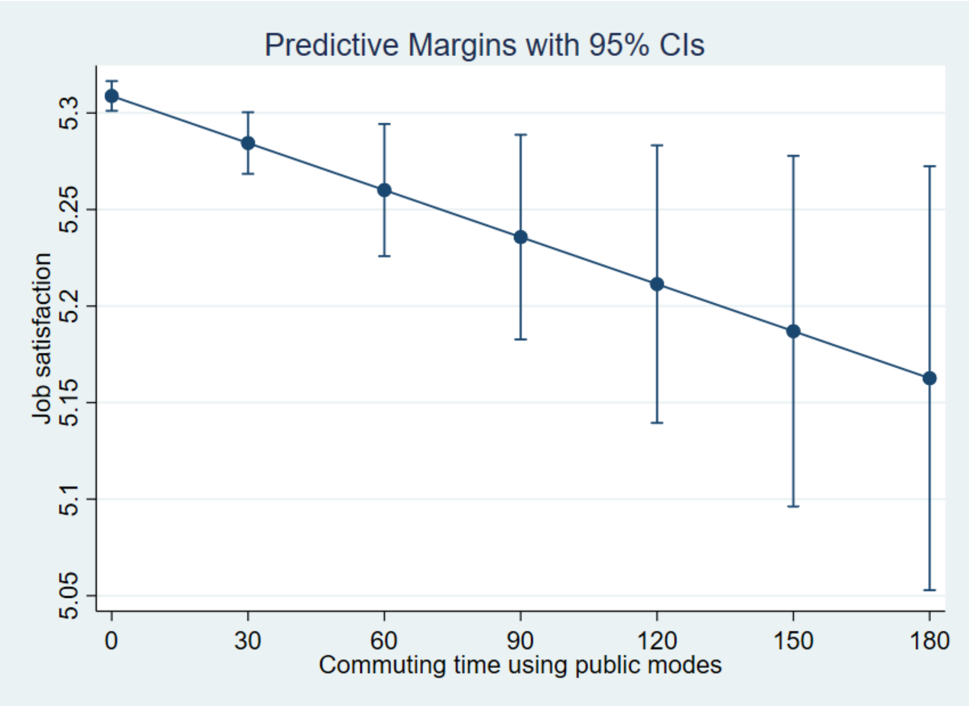

Figure 4.7: The effect of commuting duration using public modes on job satisfaction

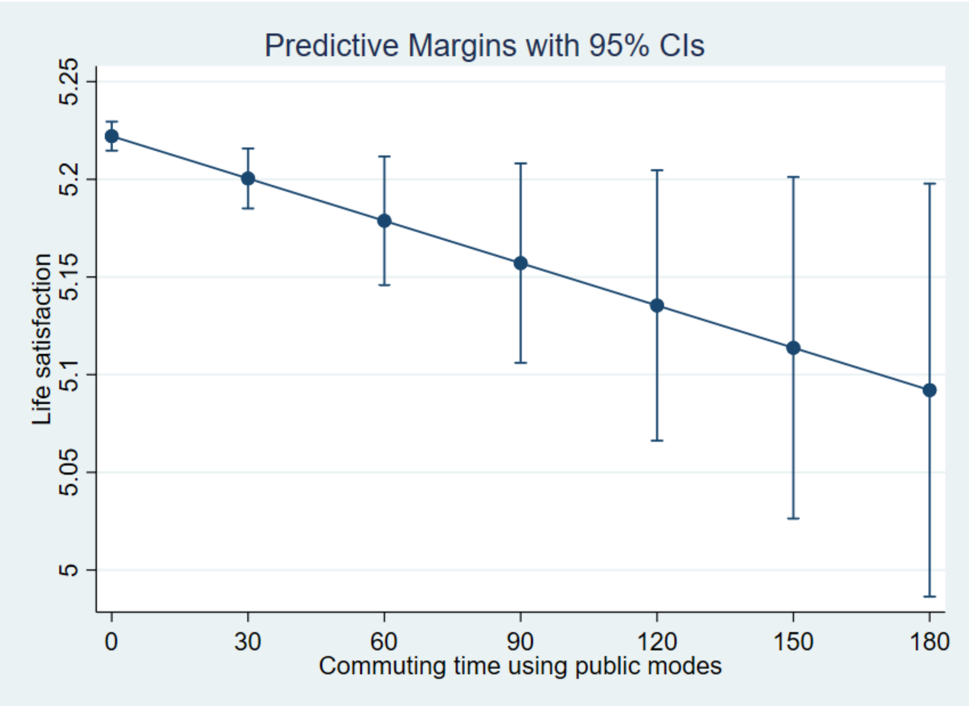

Figure 4.8: The effect of commuting duration using public modes on life satisfaction

Table 4.7: The effects of commuting time across transport modes (without London)

Variable	General health	Job satisfaction	Life satisfaction
Commuting time for transport modes:			
Á Private modes	-0.000535***	0.0000306	-0.0002781
	(0.0001702)	(0.0003414)	(0.0002798)
Á Public modes	-0.0007366***	-0.0009562**	-0.0007599**
	(0.0002115)	(0.0004002)	(0.0003525)
Á Cycle	0.001032	-0.0014869	0.0015603
	(0.0008999)	(0.0017907)	(0.0014426)
Á Walk	-0.0005933	-0.0011304	0.0008407
	(0.0005963)	(0.0010995)	(0.0009884)
Age	0.0350013***	-0.0551476**	0.0124252
	(0.0115662)	(0.0223037)	(0.0184612)
Age squared (divided by 100)	-0.0381416***	0.0263406**	0.0304877***
	(0.0059408)	(0.0110532)	(0.0097531)
Monthly net personal income (divided by 100)	0.0005174*	0.0027366***	0.0014409***
	(0.0002999)	(0.0005129)	(0.0005124)
Number of own children in household	-0.019714***	-0.0260148**	0.0145601
	(0.0073649)	(0.0131986)	(0.0115738)
Gender (Female) (Base level: Male)	(omitted)	(omitted)	(omitted)
Whether living in a rural area (Base level: Urban area)	0.0003367	-0.0181886	0.0548226
	(0.0218169)	(0.0425581)	(0.0354801)
Ethnicity: (Base level: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base level: Married)			
Á Single	0.0328602**	0.0192289	-0.0183674
	(0.0165905)	(0.0315658)	(0.0274918)
Á Separated	0.0020503	0.0032192	-0.197048***
	(0.0269826)	(0.048564)	(0.0507485)

Á Divorced	0.0264612	-0.0835302*	-0.0574213
	(0.0230001)	(0.0433134)	(0.0405659)
Á Widowed	0.0670364	-0.1135474	-0.3006401***
	(0.0554622)	(0.0905753)	(0.1108973)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0149755	-0.1601867*	-0.0266813
	(0.0451495)	(0.0867888)	(0.0773137)
Á First degree or equivalent	0.0009114	-0.0992345	0.0079264
	(0.0347365)	(0.0639124)	(0.057465)
Á A Levels	-0.0775003**	-0.1033471*	0.0026041
	(0.0325695)	(0.060459)	(0.0557556)
Á None of the above	0.027717	-0.0031404	0.2342642**
	(0.0567195)	(0.1149513)	(0.110151)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	-0.0084482	0.1189379***	-0.0143982
	(0.0151332)	(0.0325004)	(0.0247043)
Á Intermediate occupations	-0.00633	0.0782047**	0.0010873
	(0.0167036)	(0.0363274)	(0.0285249)
Employment type (Employee) (Base level: Self-employed)	0.0050868	-0.3741168***	-0.0252655
	(0.0226113)	(0.0470939)	(0.0387216)
Region: (Base level: North East)			
Á North West	-0.1688724	0.1398637	-0.3389986*
	(0.1341055)	(0.2171074)	(0.2021416)
Á Yorkshire and the Humber	-0.0945885	-0.010077	-0.2038211
	(0.1371083)	(0.222172)	(0.1943563)
Á East Midlands	-0.1115875	0.1538004	-0.1475723
	(0.1434626)	(0.2301434)	(0.2212614)
Á West Midlands	-0.0654815	0.2813681	-0.2169531
	(0.1419207)	(0.2319516)	(0.2195646)
Á East of England	-0.0801445	0.0649446	-0.2442618
	(0.1472892)	(0.2429571)	(0.2242305)
Á South East	-0.0976394	0.2272847	-0.0468933

	(0.1434425)	(0.2349971)	(0.2116737)
Á South West	-0.1780226	0.3036072	-0.1530442
	(0.1482217)	(0.2529763)	(0.2229455)
Á Wales	-0.0835739	0.2486281	-0.064174
	(0.1894913)	(0.2592078)	(0.245167)
Á Scotland	-0.0164419	-0.1197072	-0.3734042
	(0.1615583)	(0.2809582)	(0.2402623)
Á Northern Ireland	0.3091028	-0.5446983	-0.4120489
	(0.2386445)	(0.6226753)	(0.3376484)
Year: (Base level: 2009)			
Á 2010	0.0037331	-0.0068585	-0.0854893***
	(0.0129675)	(0.0245886)	(0.0207389)
Á 2011	0.0165511	-0.0558083	-0.2295132***
	(0.0227068)	(0.0431413)	(0.0358999)
Á 2012	-0.0266138	-0.022516	-0.339217***
	(0.0329167)	(0.0630161)	(0.0519359)
Á 2013	-0.0231593	-0.0157965	-0.3824583***
	(0.0432012)	(0.0830014)	(0.0682241)
Á 2014	0.0072628	0.0882566	-0.2800102***
	(0.0537583)	(0.1032679)	(0.0849136)
Á 2015	-0.1429351**	0.1315545	-0.2938114***
	(0.0643236)	(0.1236632)	(0.1013393)

Observations: 107,861. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

After extracting the observations for London from the sample, the results do not change markedly from the previous set of models. In terms of health, private and public transport modes are still found to impact respondents' health status negatively. A respondent's health status would worsen by 0.0054 units and 0.0074 units if they spend extra 10 minutes commuting by private and public modes, respectively. However, the positive impact of cycling on health is no longer significant which indicates that cyclists in London are the main recipients of the health benefit coming from cycling to work. Apart from the negative effect on health, the deteriorating influence from commuting with public modes persists and increase in magnitude for job satisfaction and life satisfaction. The satisfaction with life score for a respondent will be likely to reduce by 0.0076 units and the satisfaction with job 0.0096 units if that person uses public transport modes for an additional 10 minutes in their daily one-way commute journey. Comparing the results of the two samples, the sample without London's observations produce larger coefficients than when the full sample is used. This may suggest that with its more developed and intricate public transport system, commuters in London may bear less of the negative effect of commuting. Perhaps, the variety of choices has lightened the perceived lack of control intrinsic to private and public transport for London commuters. This difference advocates for the fact that London has significantly unique characteristics compared to the rest of the UK, and it would be necessary to remove London's observations to have a clearer perspective of the UK.

Commuting effects across genders

As FE models are employed throughout this study, estimations for time-invariant covariates such as genders and ethnicity are not available. However, it would be of interest to explore the differences between male and female commuters that are documented in the literature, for instance: the gender differences in effects of commuting on health (Künn-Nelen, 2015) and SWB (Roberts, Hodgson and Dolan, 2011). In this subsection, the full sample including London is divided into two subsamples for male and female respondents so that the potentially heterogenous effects of different genders on the association between commuting and health, SWB and job satisfaction can be examined. The results can contribute to the literature on how commuting can impact job satisfaction between different genders on which there is little to no research. Table 4.8 provides the results for female commuters, then the models for their male counterparts are included in Table 4.9.

Table 4.8: The effects of commuting time across transport modes for female commuters

Variable	General health	Job satisfaction	Life satisfaction
Commuting time for transport modes:			
Á Private modes	-0.0006769**	-0.000579	-0.000427
	(0.0002714)	(0.000571)	(0.0004415)
Á Public modes	-0.0004895*	-0.0008792	-0.0014285***
	(0.000286)	(0.0005947)	(0.0005061)
Á Cycle	-0.0005274	-0.0039699	0.0040284*
	(0.0014747)	(0.0029178)	(0.0023829)
Á Walk	-0.0010138	-0.0027103*	0.0005341
	(0.0007169)	(0.0014031)	(0.0012082)
Age	0.0347466**	-0.057551**	0.0419957**
	(0.0138791)	(0.0277061)	(0.0203957)
Age squared (divided by 100)	-0.0414268***	0.0308953**	-0.00059
	(0.007787)	(0.0144308)	(0.012821)
Monthly net personal income (divided by 100)	0.0004613	0.001463*	0.0014907*
	(0.0004334)	(0.0007784)	(0.0007844)
Number of own children in household	-0.0171203*	-0.0177871	0.0135654
	(0.0098454)	(0.0173287)	(0.0154726)
Whether living in a rural area (Base level: Urban area)	-0.0125818	0.0302624	0.0292219
	(0.0292095)	(0.0583265)	(0.0486836)
Ethnicity: (Base level: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base level: Married)			
Á Single	0.0192103	0.0161598	-0.011509
	(0.0213472)	(0.0416204)	(0.0373165)
Á Separated	0.0101595	0.0487269	-0.1986891***
	(0.0330959)	(0.0589554)	(0.0608371)
Á Divorced	0.0018192	-0.0624109	-0.0413847

	(0.0290239)	(0.0557957)	(0.0505408)
Á Widowed	0.0233615	-0.0657978	-0.4334164***
	(0.0618895)	(0.1053522)	(0.1299889)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0106741	-0.0696985	-0.0462847
	(0.0580931)	(0.1113654)	(0.0995682)
Á First degree or equivalent	0.0624139	-0.1261496	0.0271095
	(0.0427013)	(0.0810684)	(0.074487)
Á A Levels	-0.054296	-0.1255331	-0.0411562
	(0.0409783)	(0.0771116)	(0.0717036)
Á None of the above	0.0772353	0.052115	0.3140695**
	(0.0733983)	(0.1495233)	(0.1426455)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	0.0032964	0.1658347***	0.0072064
	(0.0192349)	(0.0418915)	(0.0321363)
Á Intermediate occupations	-0.0093485	0.1504329***	0.0256223
	(0.0202475)	(0.0445061)	(0.0341847)
Employment type (Employee) (Base level: Self-employed)	0.0048105	-0.3047503***	-0.0496252
	(0.0320633)	(0.0654369)	(0.0535106)
Region: (Base level: London)			
Á North East	0.0225644	-0.3137673	0.0534101
	(0.1919862)	(0.26402)	(0.2990727)
Á North West	-0.2072534**	-0.0590601	-0.2218741
	(0.0858606)	(0.194402)	(0.1464665)
Á Yorkshire and the Humber	-0.1432446	-0.2215251	-0.2414737
	(0.1055834)	(0.227056)	(0.1527816)
Á East Midlands	-0.119533	0.0136716	0.0392513
	(0.090678)	(0.1727926)	(0.155227)
Á West Midlands	-0.0873795	0.07976	-0.0735948
	(0.0978581)	(0.1948466)	(0.1614124)
Á East of England	-0.0794446	0.0739684	-0.0548901
	(0.0888978)	(0.1485119)	(0.1120735)

Á South East	-0.0777244	0.0512641	0.0612907
	(0.0739803)	(0.1386181)	(0.111514)
Á South West	-0.0943331	0.3381429*	0.0658185
	(0.0923102)	(0.2016331)	(0.1574436)
Á Wales	-0.0900955	-0.0139854	0.1694517
	(0.1576353)	(0.2849742)	(0.2820857)
Á Scotland	-0.1819949	-0.0681952	-0.1144348
	(0.1315742)	(0.2828043)	(0.196051)
Á Northern Ireland	0.5327449**	-0.4002109	0.0445353
	(0.2312508)	(0.652797)	(0.5011648)
Year: (Base level: 2009)			
Á 2010	0.0113768	-0.0063547	-0.1219739***
	(0.0157355)	(0.0312099)	(0.0242707)
Á 2011	0.0165305	-0.0584474	-0.2692607***
	(0.0270859)	(0.054322)	(0.0403006)
Á 2012	-0.0317235	-0.047812	-0.3850868***
	(0.0391672)	(0.0793628)	(0.057579)
Á 2013	-0.0209644	-0.0340094	-0.4234758***
	(0.0513209)	(0.1045093)	(0.0748176)
Á 2014	-0.0103279	0.0529521	-0.3039593***
	(0.063811)	(0.1297844)	(0.0927753)
Á 2015	-0.1454051*	0.0831009	-0.3425551***
	(0.07614)	(0.1552711)	(0.1106322)

Observations: 65,750. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

For female commuters, results are consistent with the full sample that both public and private modes have negative relations with women's health. By spending an extra 10 minutes using private or public commuting modes, a female respondent will be likely to have worsening health score by 0.0068 units and 0.0049 units, respectively. However, the significance level is lower for public modes at 10%. Public modes preserve their negative effect on life satisfaction from the full sample, however the negative impact on how a person views their job is no longer significant in the case for female workers. The magnitude of the negative relation between public modes and life satisfaction is remarkedly larger than in full sample with SWB decreasing by 0.014 units if 10 additional minutes are spent using public modes. This illustrates that women are the main contributor to this negative relation from using public modes in the full sample.

Unlike in the full sample, cycling to work does not have a significant association with women's health, but there is a significantly positive association with life satisfaction at the 10% significance level in which 10 more minutes spending on cycling to work will yield an increase of 0.04 units in how satisfied a female respondent feels about their overall life. However, the other active commuting modes – walking has a negative impact on job satisfaction, also at the 10% significance level. The job satisfaction score would reduce by 0.027 units if a female worker walks 10 more minutes to work.

Table 4.9: The effects of commuting time across transport modes for male commuters

Variable	General health	Job satisfaction	Life satisfaction
Commuting time for transport modes:			
Á Private modes	-0.0003407*	0.0003782	0.0000205
	(0.0002007)	(0.0003937)	(0.0003397)
Á Public modes	-0.0005798**	-0.0007927*	-0.0001325
	(0.0002363)	(0.0004243)	(0.0003954)
Á Cycle	0.0027092***	0.0008451	0.0014843
	(0.0008433)	(0.0017532)	(0.0013588)
Á Walk	0.0000509	0.0010805	0.00055
	(0.0008463)	(0.0014213)	(0.0013192)
Age	0.026222*	-0.0209283	-0.0202421
	(0.0151548)	(0.025868)	(0.0288942)
Age squared (divided by 100)	-0.0298633***	0.0081613	0.0659622***
	(0.0081198)	(0.0150782)	(0.0132267)
Monthly net personal income (divided by 100)	0.0002704	0.0029684***	0.0010109*
	(0.0003485)	(0.0005887)	(0.0005798)
Number of own children in household	-0.0277425***	-0.0420492**	0.0094017
	(0.009579)	(0.0175616)	(0.0156106)
Whether living in a rural area (Base level: Urban area)	0.0268155	-0.0964551	0.0840695*
	(0.0313962)	(0.0601648)	(0.0489034)
Ethnicity: (Base level: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base level: Married)			
Á Single	0.0362007	-0.0140262	-0.0113421
	(0.0224293)	(0.0422818)	(0.0371763)
Á Separated	-0.0336611	-0.0069764	-0.1838098**
	(0.0395158)	(0.0749927)	(0.079735)
Á Divorced	0.0387715	-0.0989057	-0.0481473

	(0.03331)	(0.060342)	(0.0594388)
Á Widowed	-0.006141	-0.1240186	-0.0346579
	(0.0998744)	(0.1822173)	(0.151185)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0174835	-0.2111276*	-0.0590809
	(0.0644471)	(0.1226284)	(0.1078577)
Á First degree or equivalent	-0.0868735*	-0.017896	-0.0874731
	(0.0521553)	(0.0950777)	(0.0795835)
Á A Levels	-0.0725066	-0.0533729	0.0235448
	(0.04783)	(0.089793)	(0.0826482)
Á None of the above	-0.0645403	0.0057083	0.1173247
	(0.0807472)	(0.1559902)	(0.1518584)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	-0.030094	0.1027283**	-0.0321301
	(0.0210885)	(0.0451714)	(0.0341792)
Á Intermediate occupations	-0.0094497	0.0197429	-0.0161007
	(0.024857)	(0.0516127)	(0.0425656)
Employment type (Employee) (Base level: Self-employed)	-0.000401	-0.3711976***	-0.0003327
	(0.0279138)	(0.0582063)	(0.0494736)
Region: (Base level: London)			
Á North East	-0.0548716	0.3247377	0.3644763
	(0.15409)	(0.365482)	(0.2396477)
Á North West	-0.0250397	0.0977673	-0.0192448
	(0.1041569)	(0.2317621)	(0.1354185)
Á Yorkshire and the Humber	0.0243203	0.1342306	0.2147098
	(0.0963368)	(0.2204283)	(0.1669847)
Á East Midlands	-0.0801726	0.142557	-0.0055883
	(0.0988477)	(0.1930376)	(0.1642726)
Á West Midlands	-0.0038222	0.2852938	0.005081
	(0.1085283)	(0.2219204)	(0.1587933)
Á East of England	-0.0520238	-0.066518	-0.1091275
	(0.0832308)	(0.1598262)	(0.1122017)

Á South East	-0.1246034	0.1305417	0.1214891
	(0.0758938)	(0.1396483)	(0.117424)
Á South West	-0.2409296**	-0.0215542	-0.0880244
	(0.0952045)	(0.1988976)	(0.1356063)
Á Wales	-0.0096115	0.2509143	0.0557516
	(0.1709136)	(0.2583358)	(0.1744854)
Á Scotland	0.2581918*	-0.2137116	-0.3917959
	(0.1551402)	(0.3178413)	(0.2544447)
Á Northern Ireland	0.1360962	0.0476709	0.3291778
	(0.2467188)	(0.7572674)	(0.2499308)
Year: (Base level: 2009)			
Á 2010	-0.0032027	0.0165037	-0.0376583
	(0.0175732)	(0.0297731)	(0.0312379)
Á 2011	0.0217721	-0.0486423	-0.1932381***
	(0.0303119)	(0.0490884)	(0.0557071)
Á 2012	-0.0176657	-0.0105698	-0.2901746***
	(0.0436612)	(0.0705282)	(0.0811562)
Á 2013	-0.0165567	-0.0355479	-0.3288907***
	(0.0571099)	(0.0918671)	(0.1071707)
Á 2014	0.0456417	0.0731656	-0.2361779*
	(0.0709485)	(0.1141141)	(0.1335259)
Á 2015	-0.1085522	0.108362	-0.2202023
	(0.0849255)	(0.1360346)	(0.1594719)

Observations: 57,389. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

The results for male respondents are also consistent with those of the full sample data set, compared to their female counterpart. In terms of health, commuting by private modes and public modes are associated with more detrimental health status which is reduced by 0.0034 and 0.0058 units, respectively, if 10 more minutes of commuting by such modes are added into the normal routine. Meanwhile, at a strong significance level of 1%, cycling can have a positive effect on health by a larger improvement of 0.027 units if a male commuter cycles for 10 extra minutes. Only public modes are found to have a significant relation with job satisfaction in which for every 10 additional minutes spending on public transport, there is a reduction of 0.0079 units in how a person views their job. Active commuting choices can have positive effects on both job and life satisfaction for men, however unlike in the case for female commuters, these effects are not found to be statistically significant.

Comparing between female (Table 4.8) and male commuters (Table 4.9) in the UK, private and public modes both have significantly negative associations with both genders' general health status. However, the potential benefit from cycling on health found in the full sample is only retained for male respondents. The literature has shown that cycling tends to be a male activity (Downward and Rasciute, 2015). Men are more likely to cycle for commuting and recreational purposes than women, and for longer durations (Heesch, Sahlqvist and Garrard, 2012). Thus, with the renowned health benefits of cycling, it is reasonable that male cyclists in this study are associated with better health. Furthermore, it is suggested in the literature that there is a significant gender inequality in household responsibilities; the data for Great Britain indicates that women spend on average nearly 14 hours for housework per week, whereas that of their male partners is roughly 5.6 hours (Knudsen and Waerness, 2007). It is likely that women would tend to choose more convenient modes of transport, such as cars, to combine several household tasks in one trip (Roberts, Hodgson and Dolan, 2011). Therefore, the potential health benefit from cycling may not be enjoyed by women. Apart from the negative relations with health for both genders, public modes are also negatively associated with job satisfaction of male commuters and life satisfaction of female commuters.

Table 4.10: Main result summary

Model/Variable	General health	Job satisfaction	Life satisfaction
(1) Overall commuting time			
Commuting time	-0.0004707***	-0.0003801	-0.0003338
	(0.00012)	(0.0002443)	(0.0002027)
(2) Commuting mode choices			
Base level: Private modes			
Á Public modes	-0.023695*	0.0005502	-0.0267273
	(0.0125183)	(0.0245898)	(0.0215992)
Á Cycle	0.059933***	-0.0163292	0.0648496**
	(0.0199751)	(0.0375414)	(0.0314307)
Á Walk	0.0049593	0.0133709	0.0231712
	(0.012679)	(0.0238929)	(0.0214228)
(3) Commuting time across transport modes			
a) Full sample			
Á Private modes	-0.0004666***	0.0000453	-0.0001548
	(0.0001615)	(0.0003256)	(0.0002691)
Á Public modes	-0.0005465***	-0.000812**	-0.0007223**
	(0.0001832)	(0.0003534)	(0.0003213)
Á Cycle	0.0016805**	-0.0004247	0.0019513
	(0.0007394)	(0.0015049)	(0.0011857)
Á Walk	-0.0005264	-0.0010566	0.0005974
	(0.0005446)	(0.001006)	(0.0008908)
b) Sample without London			
Á Private modes	-0.000535***	0.0000306	-0.0002781
	(0.0001702)	(0.0003414)	(0.0002798)
Á Public modes	-0.0007366***	-0.0009562**	-0.0007599**
	(0.0002115)	(0.0004002)	(0.0003525)
Á Cycle	0.001032	-0.0014869	0.0015603
	(0.0008999)	(0.0017907)	(0.0014426)
Á Walk	-0.0005933	-0.0011304	0.0008407

	(0.0005963)	(0.0010995)	(0.0009884)
c) Sample of female commuters			
Á Private modes	-0.0006769**	-0.000579	-0.000427
	(0.0002714)	(0.000571)	(0.0004415)
Á Public modes	-0.0004895*	-0.0008792	-0.0014285***
	(0.000286)	(0.0005947)	(0.0005061)
Á Cycle	-0.0005274	-0.0039699	0.0040284*
	(0.0014747)	(0.0029178)	(0.0023829)
Á Walk	-0.0010138	-0.0027103*	0.0005341
	(0.0007169)	(0.0014031)	(0.0012082)
d) Sample of male commuters			
Á Private modes	-0.0003407*	0.0003782	0.0000205
	(0.0002007)	(0.0003937)	(0.0003397)
Á Public modes	-0.0005798**	-0.0007927*	-0.0001325
	(0.0002363)	(0.0004243)	(0.0003954)
Á Cycle	0.0027092***	0.0008451	0.0014843
	(0.0008433)	(0.0017532)	(0.0013588)
Á Walk	0.0000509	0.0010805	0.00055
	(0.0008463)	(0.0014213)	(0.0013192)

*p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

4.4. Discussions

Overall, the findings in this study indicate that commuting time can influence health status, but not how satisfied individuals are with their job and life overall. This negative effect of longer commuting time on subjective health measures is consistent with findings in the literature (e.g. Hansson *et al.*, 2011 for cross-section data; Künn-Nelen, 2015 for longitudinal data). The longitudinal study by Künn-Nelen (2015) is based on the BHPS data, which is the preceding survey data set of the UKHLS employed in this thesis. However, the author only includes the separate commuting time of cars and public transport. The current study takes account of all available modes and still find similar findings, which may signify the importance of the negative associations between private, public transport modes and subjective health status. This result can be due to the positive connection between commuting and fatigue (Lyons and Chatterjee, 2008) and stress levels (Gottholmseder *et al.*, 2009). Further explanations can be found in Hansson *et al.* (2011), in which commuting is negatively associated with subjective sleep quality, self-reported health and exhaustion level. Nevertheless, this study does not find any significant relationship between commuting time and life satisfaction, which contrasts with findings in Stutzer and Frey (2008) of "a commuting paradox". The authors use similar measurement of commuting time and a life satisfaction question with a 10-point Likert scale, while the one employed in this study is a 7-point Likert scale. A potential explanation can be because Stutzer and Frey (2008) use data for Germany from the German Socio-Economic Panel survey whereas this study's data are about British workers in the UK. Thus, there can be cultural differences that influence factors evolving around respondents in each survey, such as their lifestyles, commuting choice preferences and how they perceive their life, etc. This study's findings are also in conflict with Roberts, Hodgson and Dolan (2011) who advocate for a significant negative relation between commuting and SWB. However, although the authors employ the BHPS data, i.e.

the preceding survey of this study's data source, they apply the GHQ score as the measurement for SWB (Roberts, Hodgson and Dolan, 2011), which is sometimes used as a proxy for mental illness. This difference in measurement can potentially explain the contradiction in findings between the studies. Alternatively, the finding is consistent with a study by Dickerson, Hole and Munford (2014) in which the data source is the preceding BHPS survey and SWB is measured by the same life satisfaction question as in this study. Their findings are also robust for both linear FE and ordered models. A cross-sectional study by Hansson *et al.* (2011) for Sweden also finds no association between mental health and a combination variable of commuting time and modes. In terms of job satisfaction, there is no significant relationship between commuting time and job satisfaction. However, the commute effect on job satisfaction is revealed once different commute modes and genders are separated.

Regarding different transport mode choices, private modes and public modes are consistently related to detrimental health status of a respondent. The results are robust over the study's sub-samples, whether that person is a female or male commuter or whether they live outside London. Public modes, such as using bus, train and the underground, can also have a negative impact on job and life satisfaction of commuters, no matter whether they live in London or elsewhere in the UK. Moreover, the above estimations in Section 4.3 can be interpreted in terms of monetary equivalents. They can be used to derive respondents' implicit willingness-to-pay (WTP) in relation to changes in commuting duration and transport mode choice (Brenig and Proeger, 2018). The WTP is in essence the monetary amount required to keep a person's life satisfaction unchanged if their commuting duration using a particular transport mode increases. In terms of job satisfaction and life satisfaction, a respondent in the full sample would be willing to commute for 10 more minutes by public transport if they are compensated with £324.3 and £601.8 per month, respectively. However, these effects are divided when different genders are taken into account, in which public modes are found to have negative associations with life satisfaction of female commuters and job satisfaction of male commuters. Regarding more active commuting modes, cycling can improve a commuter's health, especially if that commuter is male and resides within London. Furthermore, female commuters are found to be positively impacted in terms of how they view their life if they cycle to work. Walking is not found to have significant effect on health in general, but this transport mode can potentially reduce job satisfaction of women. Even though cycling is associated with higher health status, it does not have significant connections with life and job satisfaction. This finding is similar with a study by Rasciute and Downward (2010), in which the authors propose that a trade-off in utility may be needed for a positive benefit of cycling on health.

This study supports the findings that commuting effects on health are heterogeneous across different modes. In the main sample, private and public modes have a negative effect on health while cycling improves it. This can be because cycling can contribute significantly to a person's physical activity requirement (Shephard, 2008; Crane *et al.*, 2016) and provide pronounced health effects (Oja *et al.*, 2011). The same findings are established for male commuters. If a respondent changes from commuting by private modes to public modes, it would affect their health status negatively. Public transport in England has been found to have negative income elasticity with citizens' income, thus it is an inferior good (Bresson *et al.*, 2003). Indeed, compared to using a car, public transport, and especially bus services are regarded as unreliable, whereas a car can provide freedom, security and facilitate daily planning in a study (Hiscock *et al.*, 2002). The same study also mentions that people with poor health would be more likely to find waiting and travelling in public transport more uncomfortable. Alternatively, Table 4.4 shows that changing from using private modes to cycling would improve both health and life satisfaction of respondents. With its sedentary nature, car commuting can be related with health conditions such as obesity, diabetes and cardiovascular diseases even for physically active commuters (Thorp *et al.*, 2011). Thus, switching to cycling, which is a more vigorously intense physical activity compared to walking (Haskell *et al.*, 2007), will bring pronounced benefits for commuters' health. While car use can involve unreliability and lack of control during traffic congestion, these characteristics are rarely linked with cycling to work (Gatersleben and Uzzell, 2007). Moreover, cycling is reported to be more exciting, whereas more passive transport modes, such as cars and public transportation, are viewed as more exhausting or boring (Gatersleben & Uzzell, 2007). Because of its benefits on subjective health status together with its characteristics of being more exciting, changing from private modes to cycling is also connected with improved SWB in this study.

Unlike in Künn-Nelen (2015) where the negative effects of commuting on subjective health measure is stronger for female commuters, the effects of different commuting modes on male and female respondents' health in this study are not as clear-cut. Private modes seem to have a larger effect on female commuters than their male counterpart, whereas male respondents would potentially bear more deteriorations for their health if public transport modes are used. However, a closer look at the coefficient sizes reveals that the effect of private modes on female's health is almost double that of male respondents. The size of the influence from public modes on men's health is only about 0.001 unit higher than for women. With car being the dominant transport mode, it can be argued that commuting time affects women more than men. This may be attributable to the gender inequality in household responsibilities, in which British women spend more than double the time that their male partners on housework (Knudsen and Waerness, 2007). These responsibilities limit the time availability of women and may make them more sensitive to longer commute time (Roberts, Hodgson and Dolan, 2011) which can link to stress and lower perceived health.

In terms of SWB, women are affected if using public modes whereas male commuters show no effects from any mode choices. The literature has found similar findings when the effect of commuting on SWB of females and males are compared and only female commuters are found to have a significantly negative result (Roberts *et al.*, 2011; Dickerson *et al.*, 2014). It is possible that unreliable service (Gatersleben and Uzzell, 2007) and inflexible timetables (Hansson *et al.*, 2011) make women struggle to schedule their daily routine which is already subject to time constraints due to unbalanced household responsibilities. The effect of public modes only affects women's life satisfaction but not their satisfaction at work.

In the model for job satisfaction, the use of public modes for commuting is associated with reduced job satisfaction score. The effect persists after London observations are removed, but only exists for male workers. There can be some spill over effect of inconvenient experience during commuting trip by public modes which remains and transforms into feelings later when arriving at work.

As the literature has recognised the remarkable difference in commuting time between London and the rest of the UK with London consistently having much longer commuting time (Roberts, Hodgson and Dolan, 2011; Künn-Nelen, 2015), a robustness check is carried out without the observations for London. The findings do not differ substantially for the subsample without London, which is consistent with studies by Roberts, Hodgson and Dolan (2011) and Künn-Nelen (2015), however the magnitude of coefficient estimates tend to be larger in this sub-sample. Also, the positive impact of cycling on health is no longer significant when London is removed. This could be because during the time period of interest (2009-2015), London areas experienced a high level of cycling. Two boroughs of London, namely Richmond upon Thames and Wandsworth, were within the five local authorities with the largest proportions of adults cycling once a month or more; their percentages were both more than 30%, whereas England's national average was less than half of that at 14.7%

(Department for Transport, 2016). Unsurprisingly, Cambridge and Oxford held the first and second ranks for the highest percentages at 58% and 43.2%, respectively, however this is likely due to their large populations of students. In addition, the use of cycling in London has been raising with a growth rate of 31.9% from 2008 to 2014 (Transport for London, 2015). This is further supported by a bike hire scheme in central London which was launched in 2010 and reached 10.1 million hires in 2015.

The findings for control variables are largely consistent across all models using different commuting variables and subsamples. In the models for health and job satisfaction, age and age squared have significant coefficients, meanwhile age squared is found to be significant in the life satisfaction model. This represents a quadratic relationship between age and the dependent variables. The coefficient of age squared in the model for health is negative which suggests age and health share an upward-sloping curvilinear relationship, demonstrating that as respondents in this survey get older, health increases up until a certain age, and then it starts diminishing. The same coefficients are positive for job and life satisfaction models, indicating a U-shaped parabola relationship. This supports findings in the literature that there should be U-shaped relationships between age and SWB reaching minimum at mid-life (Blanchflower and Oswald, 2004; Blanchflower and Oswald, 2008), and between age and job satisfaction with a minimum around the ages of 30s (Clark, Oswald and Warr, 1996; Gazioğlu and Tansel, 2006). In this chapter, the age variables are consistently significant at 1% significance level in the models for health. Respondents in the full sample are found to reach their best health around 43 years; more specifically women have the best health at around 42, while men reach the stage a few years later at 44. Meanwhile, people living outside London seem to stay healthy for longer and reach their peak at the age of 46. For the rest of the demographic control variables, one additional child is likely to associate with decreasing health status and job satisfaction of a person, whereas it does not have a significant effect on respondents' SWB. This could be because children give parents a sense of meaning, even though their existence could impose increased stress level on the parents' health and careers.

In terms of socioeconomic information, compared with married respondents, people who are separated and widowed are less satisfied with their life overall, thus have lower SWB score by 0.2 and 0.32 units, respectively. Alternatively, being single can improve a person's health, compared to married respondents by a small effect size of 0.027 units. Respondents with higher degrees (e.g. PhD or Masters) than a first degree are found to have lower job satisfaction than GCSE qualifications holders. In addition, respondents of higher social positions in society are found to be more satisfied with their careers: those with higher managerial, administrative and professional jobs and intermediate jobs are more likely to score their job satisfaction scores higher by 0.13 and 0.10 units compared to those of routine and manual workers. Regarding job types, respondents who are employees have consistently lower job satisfaction scores than self-employed. Personal income level is found to be significant in improving the job and life satisfaction of workers, and the effect sizes are similar across models. As a respondent's monthly personal income increases by £1000, their job satisfaction increases by 0.25 units and life satisfaction by 0.12 units. This result supports the arguments that income can be a determinant of SWB (Diener, 1984).

The study recognises the potential influence of personal income on a person's daily commuting mode choice, hence its indirect effect on the three dependent variables. Thus, four interaction terms between the durations spent on four commuting modes and personal income are created and included in the models for health, SWB and job satisfaction (Table A7 in Appendix 1). Similar to Section 4.4.2, the models are estimated on a sub-sample without London observations to achieve a better understanding of the UK's population (Table A8). In both sets of results, none of the interaction terms were statistically significant, demonstrating that any potential relationships between a commuter's mode duration and the three variables health, SWB and job satisfaction are not conditional on their personal income. This finding is similar to findings in a study by Morris (2015) in which the interaction terms between travel and household income do not contribute to the relationship between travel and life satisfaction.

4.5. Conclusions

In this chapter, the effects of commuting time and different commuting modes on health, SWB and job satisfaction are investigated for a sample of British workers. Cardinality has been assumed for the dependent variables which enables linear FE models to be applied on the study. Heterogeneous gender effects are also studied, together with a closer perspective of the rest of the UK when London is taken out of the sample studied.

It has been found that commuting time is negatively associated with self-reported health status of a respondent. In particular, private modes and public modes, when combining with commuting time, have consistently negative links with health, whether the person is female or male, and whether they live in or outside London. For the active commuting modes, cycling is found to benefit health, specifically if a respondent is male and lives in London. Cycling can also improve women's life satisfaction. Consistent with the literature, changing from using private modes to cycling is associated with improving health and life satisfaction in the full sample of respondents.

To the best of the researcher's knowledge, this study is one of the first studies looking at the effects of commuting on job satisfaction, even though commuting is an essential part of a person's daily life. It finds that longer commuting time is not associated with job satisfaction, however when combined with different commuting modes, commuting by public modes can be associated with lower job satisfaction. The chapter also contributes a panel study into the relationships between commuting and health and SWB as well as job satisfaction, specifically comparing between genders, and between passive and active modes. The literature is dominated with cross-sectional studies which cannot incorporate investigations of over-time changes, thus only give preliminary results about associations between variables. This study utilises a large longitudinal survey of 40,000 households in the UK for 7 years of data, thus panel models could be applied and provide more detailed findings based on changes across time dimension for a large sample of respondents.

However, there are a few limitations in this study. The study looks at respondents with unique individual characteristics which if unobserved can correlate with predictors and yield inconsistent OLS estimations. The use of FE models facilitates the control of such unobserved individual heterogeneity. But the FE models can only provide estimations for time-varying variables. Time-invariant variables, such as gender and ethnicity in this case, are omitted from the FE estimation models, as seen in Tables 4.2, 4.4, 4.6, 4.7, 4.8 and 4.9, together with the unobserved individual heterogeneity. Although the variable gender is eliminated, the potential gender effects have been studied in Subsection 4.3.3. by separating the sample into two groups of gender. Moreover, the effects of commuting on health, job and life satisfaction are of interest in this study. Thus, consistent $\hat{\beta}$ estimates of the associations between the dependent variables and the main commuting predictors are more important, whereas the individual heterogeneity α_i can be regarded as nuisance parameter and removed during the estimation process.

This study does not take account of the potential associations between health, job and life satisfaction. SWB can improve health and longevity of society and the size of this effect is clear and nontrivial (Diener and Chan, 2011). Boyce (2010) finds that health can help explain the heterogeneity in SWB models, whereas job satisfaction has a causal effect on workers' health and SWB, according to a meta-analysis by Faragher, Cass and Cooper (2005). As the literature has illustrated, the three variables are likely to link together and the causal directions can even be reciprocal, such as the relationship between SWB and job satisfaction found in Bowling, Eschleman and Wang (2010). While including job satisfaction as a control variable in the linear FE models for SWB, Roberts, Hodgson and Dolan (2011) recognise the potential endogenous relationship between job satisfaction and SWB, but due to the difficulty in finding valid IVs, they cannot control for the potential reverse causality. Therefore, even though this study's panel data models give better causal investigation than cross-sectional studies, there are potential correlations between the dependent variables in this chapter. Adding these variables into models of each other as predictors would yield a clearer picture on the effects of commuting, and the use of IVs can control for the endogenous relationships between them. As cardinality is assumed for the categorical dependent variables, the GMM method for linear models with the use of valid IVs can be incorporated into the study to provide definite conclusions about causal relationships between the variables of interest and the directions of causality. This will be the main objective for the next chapter of this thesis.

5 - CAUSAL RELATIONSHIPS BETWEEN ACTIVE COMMUTING, HEALTH, SWB AND JOB SATISFACTION

5.1. Introduction

In the previous chapter, the associations between commuting time, different commuting modes and the dependent variables health, SWB and job satisfaction have been investigated. Gender differences and the contrast between London and the rest of the UK are noted. The FE estimation approach is used to control for omitted variable bias that stems from time-fixed unobserved individual characteristics. The results indicate that commuting time is associated with only deteriorating health, but not significantly with job and life satisfaction. In terms of different transport modes, commuting by private and public modes can be detrimental to commuters' health. Public modes are also negatively connected with job and life satisfaction. When genders are considered, it is discovered that the negative effects of private and public modes on health persist, and public modes are further associated with lower women's life satisfaction and men's job satisfaction. For active commuting modes, only cycling can improve subjective health in general, but especially for male respondents residing in London. The results support the literature on the relationships between commuting and health and SWB and explore more about the potential effect of commuting on job satisfaction.

However, health, SWB and job satisfaction are linked, and the literature has examined these in pair-wise relationships. It would be logical to include these variables as predictors in each model to achieve a clearer view of commuting effects on health, SWB and job satisfaction and account for potential reverse causality. As in the previous chapter, panel FE models are employed to acknowledge the existence and correlation of individual heterogeneity with the models' covariates. Nevertheless, the models are estimated making use of Generalized Method of Moments (GMM) with the help of valid instrumental variables (IV) to enable identification of causal relationships among the variables. Active commuting can contribute to public health directly by incorporating physical activities into daily life and also indirectly via reduction in air and noise pollution. Thus, unlike the previous empirical chapter, only active commuting will be investigated in this chapter to explore the causal effects and contribute to the evidence of active commuting's benefits on commuters' welfare. This chapter is structured as follows: The empirical methods are discussed in Section 5.2, whereas Section 5.3 presents the study's data, including the choice of IVs employed. Section 5.4 will report the estimation results of the 2SGMM models, together with the discussion on the findings. Section 5.5 concludes the chapter.

5.2. Methods

This methodology section contains estimation methods and their applications which are synthesised in Cameron and Trivedi (2005).

The simultaneous relationships between active commuting duration, health, life and job satisfaction are of interest here. The study investigates 4 models with dependent variables being these variables of interest. In each model, the other three variables are included as predictors. Due to the potential simultaneity between the predictors and the dependent variable in each model, these predictors will be assumed as endogenous variables.

The variable reporting the amount of time a person spent on commuting actively is a cardinal variable measured in minutes. On the contrary, as discussed in previous chapters, health, job satisfaction and life satisfaction are measured in the UKHLS in such a way that they can be classified as ordinal variables. In Chapter 4, these three dependent variables have been regarded as continuous variables. There is an additional benefit of cardinality assumption over ordinality. Both linear and ordered models can be adapted to control for individual heterogeneity through FE and “Blow-up and Cluster” estimators, respectively. However, if reverse causality is taken into account in ordered models, each categorical covariate would need transforming into several dummy variables, depending on how many categories there are. This can be complex to instrument for, compared to a more straightforward yet still robust use of IVs in linear models. Hence, to keep estimates consistent, the variables health, job satisfaction and life satisfaction are all treated as continuous variables in this chapter. As mentioned in Section 3.4, a structural framework, in other words, a system of structural equations should have been ideal for causal inference, however the literature has not developed an underlying theory that can support the inclusion of necessary predictors required for a system of simultaneous equations. Therefore, the thesis will adopt the structural specification with the incorporation of each variable of interest in the models of the others, but the equations will be estimated separately, instead of in a system of equations.

Similar to the previous empirical chapter, the models employed in this chapter are linear FE models controlling for individual heterogeneity. The four models used for testing the simultaneous effects of active commuting on health, job satisfaction, SWB are as follows:

[illegible] (5.1)

[illegible] (5.2)

[illegible] (5.3)

[illegible] (5.4)

in which the parameters [illegible] and [illegible] are assumed to be constant across time and individuals, whereas [illegible] represents time-fixed individual heterogeneity effects which is regarded to be unobserved and correlated with the predictors. As [illegible] is unobserved, the error terms will be transformed into [illegible]

Unlike in Chapter 4, this chapter recognises that simultaneity, or reverse causality, is another endogeneity problem existing in the data. Figure 5.1 depicts the idea of potential simultaneous relationships between the main variables of interest in this chapter. Each arrow represents potential effect and its direction. An example of reverse causality is that an intrinsically happy and healthy person may be more likely to choose more active commute modes, thus their life satisfaction and health status would improve even further.

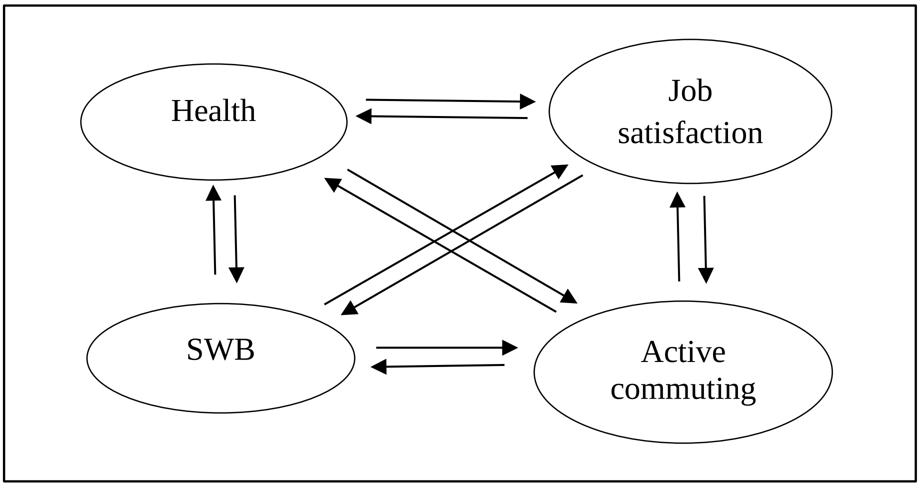

Figure 5.1: Simultaneity between health, SWB, job satisfaction and active commuting.

Both endogeneity sources make the predictors in the models endogenous, i.e. correlated with the error term, thus OLS estimations are inconsistent.

As discussed in Chapter 3, the FE estimation approach can control for unobserved heterogeneity. However, simultaneity requires the more advanced GMM estimator with valid IVs to compute consistent parameter estimation. The IV sets Z_i for the four models contain one-period lagged values $x_{i,t-1}$ and the difference values $(x_{it} - x_{i,t-1})$ of the endogenous variable x_{it}. Because x_{it} is assumed to be correlated with the time fixed unobserved heterogeneity effect η_i, it is likely that its lagged and difference values should be correlated with η_i also. Thus, the assumption $E(Z_i|\eta_i) \neq 0$ is more suitable for the models in this study, and a FE model with the presence of endogenous variables should be employed. The IVs are required to be correlated with the endogenous regressors while having no relation with the dependent variable unless indirectly via the endogenous regressors.

The IV list in each model (discussed in more detail in Section 5.3) is more than the number of endogenous variables, thus each model is overidentified with the standard errors assumed to be heteroskedastic. Therefore, as discussed in Subsection 3.6.2, the 2SGMM estimator will be used for models in this study, instead of an IV or a 2SLS estimator. The 2SGMM estimation approach is applied to the four equations 5.1, 5.2, 5.3 and 5.4 using the user-written command xtivreg2 (Schaffer, 2010) in the STATA software.

Apart from that, additional methods are incorporated to control for other econometric issues that may exist. The same set of sociodemographic and economic variables from Chapter 4 is included to control for confounding factors. In addition, panel-robust standard errors are applied in all models to control for heteroskedatiscity, as well as serial correlation between error terms of the same respondent across different waves.

As explained above, for each variable of either health, job satisfaction, life satisfaction and active commuting duration, the other three variables are included as predictors. Due to the potential simultaneity between the variables of interest, these predictors are treated as endogenous variables. The IVs employed in each model are required to pass several IV tests, including the relevance and validity tests. Meanwhile, an additional test, the endogeneity test, is required to verify whether the variables being regarded as endogenous are indeed endogenous. The three tests have been discussed in Section 3.6, and the following summary serves as a reminder.

The endogeneity test determines whether an IV approach is necessary using the null hypothesis that the tested variables can be regarded as exogenous. The test statistics is distributed with a χ^2 distribution and the degree of freedom is equal to the number of predictors tested for endogeneity. With a common 95% confidence level in social science, if the p-value is smaller than 0.05, it is concluded that the predictors are endogenous.

The relevance test investigates whether the instruments are correlated with the endogenous predictor. It employs a standard F-statistics to test the first stage regression in the 2SGMM estimation process and verify whether the IVs are relevant instruments. If they are, they should be strongly correlated with the endogenous variable and thus jointly significant in a regression of the endogenous predictor. Although a low p-value should determine that one can reject the hypothesis, Staiger and Stock (1997, cited in Cameron and Trivedi, 2005) propose a rule-of-thumb that a F statistics of more than 10 should be safe enough to avoid finite-sample bias. Finite sample bias is when the IV estimator can be biased, especially when the IVs used are weak instruments, i.e. they are weakly correlated with the endogenous variables. The more instruments there are, the larger the bias which will approach the bias of the OLS estimator. However, a large enough sample can mitigate the problem of finite sample bias. The finite sample bias of the IV estimator in relation with the OLS estimator can be approximated using the ratio $1/F$, where F is the F statistics of the first-stage model (Cameron and Trivedi, 2005, p. 109). A figure of F greater than 10 will guarantee that the bias is at most 10% that of the OLS estimator. Any figures less than 10 can be an issue, and statistics of 5 or smaller indicates a problem of extreme finite-sample bias.

Lastly, the third test is regarded as the validity test, or the Sargan-Hansen test, which can only be applied for over-identified models. It examines the overidentifying restrictions to see whether the instruments are correlated with the error term. The null hypothesis checks that the instruments used are valid, i.e. there is no correlation between them and the error term. The purpose is to ensure that the instruments should not be predictors of the dependent variable in the original equation. The IV sets have satisfied all of the three tests, as shown in Section 5.4, i.e. endogeneity is present as well as the instruments are valid and relevant.

5.3. Data

The outcome variables of interest are health, job satisfaction, SWB and duration spent commuting actively. The measurement for the variables health, job satisfaction and SWB is kept the same as in the previous chapter, with SWB being measured by the UKHLS's question on satisfaction with life. In addition, a new variable is introduced in this chapter to measure the duration of active commuting done by a respondent, by combining the commuting time variables for walking and cycling modes. It is a continuous variable measured in minutes. If a person commutes by any transport mode, other than walking and cycling, or do not commute at all, they are assigned a value of 0.

Apart from the main independent variables, a common set of control variables is applied for each model. The control variables are the same as in Chapter 4, including demographic (age, age squared, gender, ethnicity) and socioeconomic information (marital status, number of children, highest education qualifications, social class based on job role, whether a person is self-employed or an employee, whether they live in an urban or rural area, and personal income). Regional and year dummy variables are also included to take into account the effects of living in a specific region and time period.

In terms of the instrumental variables used, the IV lists are not the same for each model. The potential IVs Ἠ comprise of one-period lags of the endogenous variables (ὼ), differences of the endogenous variables (ὼ ὼ), 4 other variables from the UKHLS survey ᾳ and their one-period differences (ᾳ ᾳ). The 4 other variables that will be used as IVs include month of interview, number of caring hours for other people living within and outside the household, the size of the company that a person works for or owns as a self-employed, and housing tenure. The constructions of these instrumental variables have been discussed in Subsection 3.7.4. Apart from the variable month of interview recording numerical values, the other three variables are categorical variables and will be regarded as continuous variables to remain consistent with the dependent variables. As mentioned in Subsection 3.7.4, the month of the interview is assumed to reflect the weather, as well as the passage of time over the year in which job and travel conditions may vary. These factors could have an impact on the mood of a respondent and in turn their answers for the questions on life and job satisfaction. In addition, the number of hours spent caring for people inside and outside household can reduce time that could have been spent on doing recreational physical activities, leisure and family. Thus, it can influence a person's health status, as well as their satisfaction with life domains, such as leisure and family, which can in turn have a spill-over impact on the satisfaction in other life domains, such as work, and on overall life satisfaction. Moreover, a worker's satisfaction at work can be influenced by the size of their employer. Also, to distinguish any potential difference for self-employed people running their own companies, the binary control variable of whether someone is an employee or self-employed is included in all models. Lastly, the housing tenure of a respondent can be an indicator of their wealth and sense of security which can be related to their life satisfaction. The measurement and descriptive analysis of the instrumental variables applied in this chapter are available in Subsections 3.7.4 and 3.7.5, respectively.

5.4. Results and Discussions

The endogenous predictors satisfy the required endogeneity test, and all the IV sets employed in the following subsections have been tested and satisfied the relevance and validity tests. The relevance tests are reported in Table 5.1, whereas the first stage results in Appendix 2.

The results of endogeneity and validity tests are included in Table 5.2, together with the estimation results of the four panel FE models with 2SGMM estimations. In each of these four models, there are three endogenous variables and the set of IVs contains more than three instruments, i.e. all four models are overidentified. Within parentheses are panel-robust standard errors.

The IV set for the model (5.1) for health has 6 variables including one-period lagged values of job satisfaction and life satisfaction, and the following instruments: the month of the interview, number of hours spent caring for people, size of someone's employer or their own company, and housing tenure. The lagged variable for active commuting duration is not added in this IV set because active commuting from one period before may have some influence on the dependent variable health. In model (5.2) for job satisfaction, the IVs comprise of 5 variables: the one-period differences of the three endogenous variables health, life satisfaction and active commuting duration, and the one-period differences of the 2 variables month of the interview and hours spent caring for people. The endogenous variables in the model (5.3) for life satisfaction are instrumented with 7 variables, including the one-period differences of the endogenous variables health, job satisfaction and active commuting duration, as well as the one-period differences of the variables month of the interview, hours spent caring for people, company size and housing tenure. The model (5.4) for active commuting duration contains 7 IVs which are the one-period lagged values of the endogenous variables health, job satisfaction and life satisfaction, as well as the variables month of interview, hours spent caring for people, and the one-period differences of these two variables.

Table 5.1: Relevance tests

Model	Endogenous variable	F	p-value
Health	Job satisfaction	F (6, 17,697) = 53.79	0.000
	Life satisfaction	F (6, 17,697) = 151.31	0.000
	Active commute duration	F (6, 17,697) = 5.46	0.000
Job satisfaction	Health	F (5, 17,765) = 23449.05	0.000
	Life satisfaction	F (5, 17,765) = 20655.97	0.000
	Active commute duration	F (5, 17,765) = 1247.07	0.000
Life satisfaction	Health	F (7, 17,344) = 16059.84	0.000
	Job satisfaction	F (7, 17,344) = 10046.69	0.000
	Active commute duration	F (7, 17,344) = 849.10	0.000
Active commute duration	Health	F (7, 17,809) = 64.51	0.000
	Job satisfaction	F (7, 17,809) = 47.62	0.000
	Life satisfaction	F (7, 17,809) = 135.68	0.000

Table 5.2: Causal relationships between health, job satisfaction, SWB & active commuting

	Health	Job satisfaction	Life satisfaction	Active commute duration
	(5.1)	(5.2)	(5.3)	(5.4)
Health		0.0826437***	0.1192035***	-0.6008237*
		(0.0111605)	(0.0113246)	(0.3461881)
Job satisfaction	0.0092542		0.089734***	-0.1300624
	(0.0294543)		(0.0064333)	(0.2411966)
Life satisfaction	0.011345	0.086411***		-0.2803667**
	(0.0174248)	(0.005994)		(0.1260733)
Active commute duration	0.0396922**	-0.0002734	0.0007701	
	(0.0186301)	(0.0014445)	(0.0013874)	
Age	0.0255512	-0.0549515*	0.0093576	-0.0311807
	(0.0164991)	(0.0309113)	(0.0251639)	(0.1064799)
Age squared (divided by 100)	-0.0340782***	0.0218973	0.0289624**	0.011372
	(0.0088607)	(0.0149087)	(0.0139035)	(0.0760165)
Personal income (divided by 100)	0.0003962	0.0020087***	0.0013138**	-0.0054419*
	(0.0003879)	(0.0005933)	(0.0005904)	(0.0028797)
Number of own children	-0.025366**	-0.0264513	-0.0065161	-0.0761581
	(0.0101486)	(0.0165024)	(0.0152546)	(0.0840768)
Gender (Base: Male)	(omitted)	(omitted)	(omitted)	(omitted)
Living in a rural area (Base: Urban)	0.023647	-0.0234446	0.1001276**	-0.6553353**
	(0.032148)	(0.0567706)	(0.0498423)	(0.2732798)
Ethnicity: (Base: White)				
Á Mixed	(omitted)	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)	(omitted)
Marital status: (Base: Married)				
Á Single	0.0188653	0.0157326	-0.0218296	0.0596142
	(0.0216983)	(0.0369187)	(0.0352561)	(0.1783649)
Á Separated	-0.0434237	0.017269	-0.234417***	0.4962149*
	(0.0370493)	(0.0613602)	(0.0665061)	(0.2998926)

Á Divorced	0.0056504	-0.0482939	-0.0912713*	0.1855904
	(0.0306978)	(0.0535348)	(0.0525241)	(0.2289811)
Á Widowed	0.0446919	-0.0379137	-0.3910251***	-0.0630496
	(0.0693786)	(0.131437)	(0.1201105)	(0.3485849)
Education qualification: (Base: GCSE)				
Á Higher degrees, e.g. PhD, Masters	0.0111674	-0.0634085	0.0881589	0.3101529
	(0.0746509)	(0.1169374)	(0.1240856)	(0.4677795)
Á First degree or equivalent	-0.0160174	-0.0407478	0.0884301	0.0425562
	(0.0573554)	(0.0939919)	(0.0942677)	(0.3756353)
Á A Levels	-0.093444	0.0293297	0.0717303	0.4329755
	(0.0605505)	(0.1054705)	(0.1095367)	(0.4843134)
Á None of the above	-0.0363022	0.057414	-0.0386569	0.0185333
	(0.0835444)	(0.15554)	(0.1736887)	(0.4338776)
Social class: (Base: Routine, manual)				
Á Higher managerial	-0.0042209	0.1447539***	-0.047053	-0.695446***
	(0.0252245)	(0.0429119)	9(0.033183)	(0.1981704)
Á Intermediate occupations	-0.0241313	0.1130494**	0.0149328	-0.3461718*
	(0.0240655)	(0.0461342)	(0.0379231)	(0.2052947)
Employment type (Base: Self-employed)	-0.0229399	-0.434014***	0.0342645	0.3982624
	(0.0332926)	(0.0597545)	(0.0498709)	(0.2708906)
Region: (Base: London)				
Á North East	0.1840346	-0.0862947	0.1658321	-1.689488
	(0.1706015)	(0.2930487)	(0.2822979)	(1.93733)
Á North West	0.0672609	0.2125587	-0.1502089	-3.150543***
	(0.1335671)	(0.2076155)	(0.1763948)	(1.212252)
Á Yorkshire and the Humber	0.0440896	-0.1520342	0.1840273	-3.021485**
	(0.133018)	(0.2212191)	(0.1760711)	(1.252507)
Á East Midlands	0.0176737	0.1154938	-0.0320581	-3.652437***
	(0.1273674)	(0.1850064)	(0.1627436)	(1.160678)
Á West Midlands	-0.0523728	0.3593911*	0.0381267	-2.026479
	(0.1269952)	(0.2065398)	(0.1823513)	(1.298086)
Á East of England	0.0499469	-0.0253591	0.0428433	-2.841979*
	(0.1267522)	(0.1439406)	(0.1261846)	(1.452836)
Á South East	-0.0959667	0.1901412	0.0358458	-1.590563*
	(0.0887454)	(0.1456434)	(0.1170014)	(0.9377477)

Á South West	-0.1775535	0.1891664	0.1514532	-1.489182
	(0.1179907)	(0.2114839)	(0.1510781)	(1.269274)
Á Wales	-0.1297362	0.4830544*	0.1959998	-2.231582
	(0.1895203)	(0.2849277)	(0.2594648)	(1.830343)
Á Scotland	0.2468361	-0.1345628	0.0314492	-5.760243**
	(0.2127711)	(0.3035613)	(0.2295148)	(2.372622)
Á Northern Ireland	0.5964226***	0.225466	-0.5448485	-6.067395**
	(0.2079248)	(0.7524323)	(0.5752832)	(2.667083)
Year: (Base: 2009)				
Á 2010	0.1112555	-0.1550923	0.1431013	0.0802307
	(0.0742699)	(0.1417132)	(0.1145434)	(0.4405346)
Á 2011	0.1325853**	-0.2128885*	0.0140064	-0.0590459
	(0.0598968)	(0.1140611)	(0.0923817)	(0.3594462)
Á 2012	0.0990442**	-0.1626007*	-0.0860544	-0.2345934
	(0.0456933)	(0.0857651)	(0.0698892)	(0.2732709)
Á 2013	0.1018214***	-0.1518566***	-0.1393591***	-0.0236642
	(0.0313807)	(0.0584004)	(0.0482532)	(0.1940949)
Á 2014	0.14765***	-0.0531192*	-0.0137973	-0.189655
	(0.0175723)	(0.0313926)	(0.0267884)	(0.1194327)
Á 2015	(omitted)	(omitted)	(omitted)	(omitted)
Hansen's ὐc˙	0.873	1.414	4.334	3.150
p-value	0.8318	0.4930	0.3627	0.5330
Endogeneity test	11.796***	24.224***	20.152***	8.699**
p-value	0.0081	0.0000	0.0002	0.0336
Observations	68,233	68,680	66,468	68,916

*p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table 5.3: Main result summary

V	Health	Job satisfaction	Life satisfaction	Active commute duration
	(5.1)	(5.2)	(5.3)	(5.4)
Health		0.0826437***	0.1192035***	-0.6008237*
		(0.0111605)	(0.0113246)	(0.3461881)
Job satisfaction	0.0092542		0.089734***	-0.1300624
	(0.0294543)		(0.0064333)	(0.2411966)
Life satisfaction	0.011345	0.086411***		-0.2803667**
	(0.0174248)	(0.005994)		(0.1260733)
Active commute duration	0.0396922**	-0.0002734	0.0007701	
	(0.0186301)	(0.0014445)	(0.0013874)	

*p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

5.4.1. Health

The IV list in the first model in Table 5.2 comprises of the one-period lagged variables of the endogenous variables Job satisfaction and Life satisfaction, the interview month, the number of caring hours for other people, workplace size and housing tenure. The lagged variable for active commuting duration is not included as an IV because of the potential relation between it and the dependent variable. Among the main predictors of interest, only the relationship between active commute duration and health is statistically significant, whereas there are no significant causal relations from job satisfaction and life satisfaction to subjective health. As a respondent spends an additional 10 minutes on commuting actively to work, it is likely that their health would increase by 0.4 units of measurement. This finding is consistent with the previous empirical chapter – Chapter 4, in which cycling is associated with better health, and switching from private modes to cycling has a positive connection with improved health status. Even though active commuting here comprises of both walking and cycling, based on Chapter 4's findings, it is likely that cycling contributes more to this positive causal effect of active modes on an individual's perceived health status.

Whereas long commute journeys are linked with loss of time for health-related activities, such as taking recreational activities (Lyons and Chatterjee, 2008; Wheatley and Bickerton, 2016), active commuting incorporates physical activities into daily commute, thus contributes to the weekly physical activity requirement proposed by WHO (World Health Organization, 2010). This is likely to be the pathway from active commuting to health in this study. Moreover, the literature has found that active commuting is linked to several objective health conditions, such as lower chance of being obese, overweight, having diabetes, high blood pressure, cardiovascular diseases, etc (Hamer and Chida, 2008; Woodcock *et al.*, 2009; Laverty *et al.*, 2013). Objective health measures are not available for the current study, but the subjective health status variable has been confirmed throughout the literature as having a strong correlation with the ultimate health event - mortality (DeSalvo *et al.*, 2006). Moreover, objective measures may not be able to fully capture certain extent of a person's state of health, which can only be reflected in the subjective health status, such as the degree, duration and outcome predictions of health conditions (Jylhä, 2009).

Commuting can normally associate with stress due to lack of control and unpredictability (Koslowsky, Kluger and Reich, 1995), however, commuters tend not to mention about those problems if they commute by active modes (Gatersleben and Uzzell, 2007). Instead, cycling is often described at providing excitement for the journey and walking allowing commuters to relax after work. It is likely that active commuting can contribute to subjective health because commuters are less subject to delays and uncontrollable events such as traffic congestion, thus regain more control over their daily schedule.

5.4.2. Job satisfaction

The second model in Table 5.2 is the model for job satisfaction. It is explored with the IVs including the first-differences of the 3 endogenous variables health, SWB and active commuting duration, and the first-differences of the interview month and caring hours variables. In the model for job satisfaction, health has a strongly significant effect after having controlled for reverse causality. As a person gets healthier by 1 unit, they are more likely to be satisfied at work and the job satisfaction score is raised by 0.083 units. The same can be argued for SWB. As job satisfaction is a domain-specific factor of SWB, it is reasonable for a significantly positive relationship between them, and the coefficient is slightly greater (0.086 units), compared to that of health.

The literature has found a positive relationship between job satisfaction and health (e.g. Ramirez *et al.*, 1996; Fischer and Sousa-Poza, 2009; Dirlam and Zheng, 2017), even though studies are mainly based on cross-section data with small sample sizes. When the same subjective health status variable is examined in a panel data setting, it is found to be positively associated with job satisfaction (Fischer and Sousa-Poza, 2009). The authors suggest a causal direction from job satisfaction to health, even though they recognise the weakness in not controlling for the potential reverse causality from health to job satisfaction due to the lack of valid IVs. With the use of panel data and instrumental variables, this finding of a positive causal relation from general health status to job satisfaction can be regarded as a novel finding for the literature.

A possible explanation for the causal relation from health status to job satisfaction is that health is likely to be associated with workers' self-rated performance, absenteeism and productivity (Pelletier, Boles and Lynch, 2004; Merrill *et al.*, 2013; Mitchell, Ozminkowski and Serxner, 2013). Several meta-analyses of the literature has confirmed that job satisfaction has been found to be related with one's performance at work (e.g. Iaffaldano and Muchinsky, 1985). However, several theoretical models and studies suggest that higher job performance could result in a person feeling more satisfied with their work (Judge *et al.*, 2001; Aziri, 2011). They argue that job satisfaction is derived from intrinsic and extrinsic rewards gained by the person's performance at work. Thus, it is possible that job performance is a pathway for the positive causal relation from subjective health to job satisfaction.

5.4.3. SWB

The third model (5.3) is the model for Life satisfaction and the IV set employed in this model comprises of 7 variables, including the first-differences of the endogenous variables health, job satisfaction, active commuting duration, as well as the first-differences of the month of interview, the caring hours for other people, workplace size and housing tenure. The result in

Table 5.2 indicates that health and job satisfaction can have positive influences on SWB, both with a strong 1% significance level. A person who is healthy and satisfied with their work will perceive their life with a more positive perspective.

This result of a positive relation from job satisfaction to SWB is consistent with the literature. SWB measured by life satisfaction is positively correlated with global job satisfaction (Bowling *et al.*, 2010). It has also been found in the same review across the literature that life satisfaction has a positive relationship with any of the components of job satisfaction, including satisfaction with work itself, with supervision, with co-workers, with pay and with promotion, which could eventually translate into an improvement in overall life satisfaction. As discussed in Chapter 2, job satisfaction is one of SWB specific life domains (Near, Rice and Hunt, 1978; Diener, 1984; Judge and Locke, 1993). Thus, the bottom-up theory can explain the causal direction from job satisfaction to SWB in which feelings in several life domains, including satisfaction at workplace, can be summed up into the overall life satisfaction (Bowling, Eschleman and Wang, 2010; Diener, Lucas and Oishi, 2018).

This result, in combination with the result for the job satisfaction model in 5.4.2., illustrates the reciprocal relation between SWB and job satisfaction (Figure 5.2). A causal effect from SWB to job satisfaction could be an example of the dispositional approach or top-down theory. Diener (1984) suggests that SWB illustrates a person's tendencies to have certain emotions (e.g. being an optimistic and happy person) and those tendencies can dictate how satisfied a person would feel in a particular life domain, for example at work. Hence, that explains the possible causal relation from SWB to job satisfaction. Moreover, the reciprocal relationship between SWB and job satisfaction can also be supported by the spill-over hypothesis. It proposes that the experiences a person acquire in one life domain can affect, i.e. spill over to how they feel in another domain (Near *et al.*, 1978). Positive emotions gained from work can carry forward when the person interacts later on with family and friends, thus influence the satisfaction with marriage or leisure time.

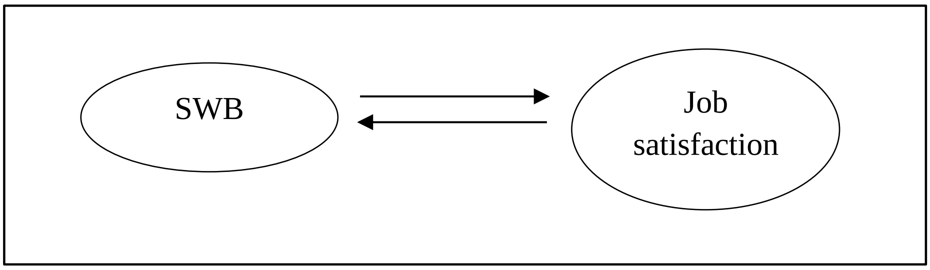

Figure 5.2: Reciprocal relationship between SWB and job satisfaction

Within the reciprocal relation between SWB and job satisfaction, the influence of SWB over job satisfaction tends to be stronger than that of job satisfaction towards SWB. It is not the case for the results in Model 2 and 3 from Table 5.2. Rather, the two coefficients are approximately similar: the coefficient for SWB in Model 2 for job satisfaction is about 0.086, whereas it is 0.09 for job satisfaction in Model 3 for SWB.

A better health status can also increase the extent to which a person is happy with their overall life. This finding is consistent with the literature, in which health is argued to be a determinant of SWB (Dolan, Peasgood and White, 2008; Diener, Lucas and Oishi, 2018).

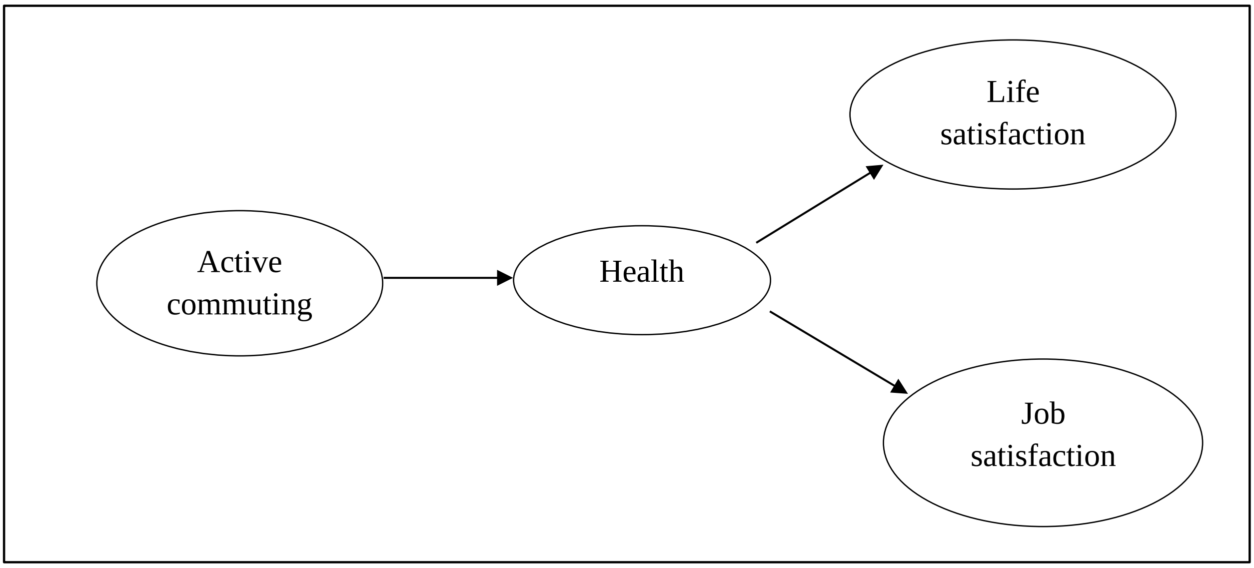

Figure 5.3: Health as a pathway for active commuting

Even though active commuting does not have any causal relations with both life and job satisfaction, it can improve subjective health. From Subsection 5.4.2 and 5.4.3, better health can raise life and job satisfaction. Thus, it can be plausible that active commuting can boost life and job satisfaction via the pathway of health (Figure 5.3).

5.4.4. Duration spent on active commuting

The fourth model looks at the active commuting duration of respondents, with health, job satisfaction and SWB being the endogenous variables. There are 7 IV used to instrument for the endogenous variables in this model, including the lagged values of the endogenous variables health, life and job satisfaction and the variables month of the interview, caring hours and their first-differences. The result in Model 4 from Table 5.2 suggests that health and job satisfaction do not have a strong influence on how much time commuters spent on walking and cycling to work. Only the coefficient of life satisfaction is strongly significant at

5% significance level. Contrary to the suggestion that happy people will choose active commuting modes, the causal connection of SWB towards the duration of active commuting is identified as a negative one. However, the coefficient's magnitude is of trivial size: an increase of one unit in the life satisfaction score will reduce an amount of 0.28 minutes in overall time spent on active commuting.

Standard error is an indication of how close the estimate is to the true parameter value. The panel-robust standard errors of the main predictors' coefficients are trivially small, especially in the first three models for health status, job satisfaction and life satisfaction. This suggests that the parameter estimations for the endogenous variables are likely to be accurate.

5.5. Conclusions

With the use of panel data and valid IVs, this chapter has identified several causal relationships between the variables of interest. Active commuting is the focus of this study and it has been found to causally improve subjective health status. This is consistent with not only the literature, but also Chapter 4's findings in which cycling is associated with better health, whereas private and public modes are likely to reduce it. Combining the results from both empirical chapters, it is reasonable to suppose that cycling is the main contributor towards a better perceived health. Moreover, there are no significant causal relationships between active commuting and job and life satisfaction. This is similar with Chapter 4's results in which time spent cycling and walking in both the full and without-London samples are not connected with either job satisfaction or life satisfaction. However, it is possible for active commuting to improve both job and life satisfaction via the health pathway. In this study, health is found to significantly ameliorate the satisfaction at work and overall life satisfaction for commuters.

Apart from the relationships between active commuting and health, job and life satisfaction, this chapter's findings confirm the reciprocal relationship between job satisfaction and life satisfaction found in the literature. Both the bottom-up and top-down theories are at play in this study.

To summarise, with linear panel FE models and the use of 2SGMM estimation approach, this study has controlled for endogeneity issues to offer causal conclusions on the relations between active commuting, health, job and life satisfaction. Similar with other studies in the literature, panel FE models have been employed to control for individual unobserved heterogeneity. While studies in the literature have noted on the possibility of reverse causality, this study is one of the first studies that find and apply relevant and valid IVs to explore the causal relations between the variables of interest. The findings illustrate that active commuting can causally boost subjective health status and potentially raise the satisfaction at work and with overall life via health. Organisations can introduce approaches to encourage active commuting, such as installing shower facilities and secured bike racks for employees.

The positive results of active commuting can also advocate for national transport system developments that are friendly for walking and cycling. Recognising the benefits of active travelling on general health and well-being, England's local and national Government bodies have launched various programmes to boost the use of active transport, improve public health and tackle environmental issues. Inspired by London's integrated and convenient transport network, the Greater Manchester authority in early 2020 issued their 10-year plan of embedding sustainable travel (i.e. walking, cycling and public transport) to transform the region into a living community where their citizens are happier and healthier (Transport for Greater Manchester, 2020a). The plan has initially received £160m from the Government's Transforming Cities Fund to build a 1,800-mile network of active travelling routes which would be the largest in the UK. The network would provide a protective and convenient experience for travelling actively with the best transport standards and a transforming perspective where car travelling does not mean the highest social value. The aim is to have at least 50% of all journeys done by sustainable modes by 2040, and this target can generate a potential benefit of £6bn towards public health. The authority also announced a new bike hire scheme launching in early 2021 to support daily commuting and short trips linking residential areas and contribute to the active transport movements of the region (Transport for Greater Manchester, 2020b).

Moreover, in May 2020, the UK Government has issued an investment plan worth of £2bn to encourage active transport (Department for Transport, Office for Low Emission Vehicles and The Rt Hon Grant Shapps MP, 2020). Launching during the coronavirus pandemic in which citizens walk and cycle significantly more to ensure social distancing and as part of their daily exercises, this programme also hopes to ease off the strains on public transport and the general transport system. The first stage of the investment plan is issuing a £250m Emergency Active Travel fund to local authorities across the country to implement measures that can tackle the capacity restrictions of public transport during the pandemic while promoting active travel habits for the long-term (City of York Council, 2020). A range of cycling-friendly measures would be installed across England, including cycle-only paths, wider pavements, as well as initiatives such as bike repairs, discount schemes. While the first stage involves temporary measures to address transport needs emerging during the pandemic, the second stage would support more permanent projects (Department for Transport, 2020a). In July 2020, the current British Prime Minister - Boris Johnson set out a new vision for England as "a great walking and cycling nation" in which active travel would become people's first choice of transport mode thanks to safer environment and more convenient transport system (Department for Transport, 2020b, p. 12). The steps required from the

Government and local authorities to achieve this vision follow four themes: (1) Creating better routes for cycling, (2) Keeping active travelling at the centre of decision-making in transport planning, health policies, housing and business developments, (3) Delegating power and distributing funds to local authorities to transform their towns and cities to be cycle-friendly, and (4) Enabling citizens to cycle (by providing cycling training and tackling bike theft) while providing protection for those who do (by issuing legal changes to protect vulnerable road users). With such substantial initiatives and investments, it would be interesting to observe the changes in public health and general well-being in short-, medium- and long-term and compare with before the vision was established.

6 - CONCLUSIONS

6.1. Introduction

Commuting is an essential activity that people take part in during their daily life to connect between home and work. People may not pay much attention to the act of commuting, however, on average they spend an hour every day for commuting between home and work (Department for Transport, 2017). It represents a substantial amount of time in everyday life. The commuting experience can impose impacts on commuters' health, SWB and moods at the workplace. These are factors that can influence a labour workforce's performance and productivity, which in turn can reflect on an organisation's profitability. Thus, the commuting effects on health, SWB and job satisfaction are of interest in this thesis. By investigating how commuting may influence the three factors, this research hopes to contribute towards a better understanding of the welfare of working-aged people and support transport policies and initiatives at workplace. This chapter concludes the thesis by summarising and reflecting on how the empirical findings in the previous chapters meet the aim and research questions of the thesis. Section 6.2 recalls the aim, research questions and objectives of the thesis and provides a brief summary of the empirical findings. Then Section 6.3 considers in more detail how the empirical findings meet the aim and research questions and the implications for the literature. Section 6.4 concludes the chapter with discussions about the strengths and limitations of the thesis.

6.2. Research questions, aim and objectives

Chapter 2 synthesises the current literature on the impacts of commuting on health, SWB and job satisfaction. When considering overall impacts, commuting time has negative connections with health conditions, whereas there are mixed findings for the overall influence of commuting time on SWB. Also, transport modes with different characteristics may have distinct effects on commuters' health and SWB. Commuting by car and public transport is often associated with deteriorating health and SWB ratings, owing to the unpredictability and lack of control that are linked with these modes, for example traffic congestion, delayed services. Commuting by car can indirectly affect health by producing air and noise pollutions. In contrast, active commuting modes incorporate physical activities and have connections with better health outcomes. Their effects on SWB are also positive. Apart from the heterogenous effects between different transport modes, there exist contrasting findings between female and male commuters which can be attributed to gender inequality in domestic responsibilities.

The literature has studied how commuting is connected with commuters' health and SWB; however, little has been done on job satisfaction. In addition, the three variables health, SWB and job satisfaction are likely to relate to one another and including them as predictors in the models of each other could improve the findings of commuting effects. There are only a few studies that have done so and the usual method employed is FE models. FE models can eliminate the individual unobserved heterogeneity, for example: people that have been raised with healthier lifestyle may have higher tendencies to choose active modes. However, the potential reversed causality between the variables of interest is another source of endogeneity which requires attention before causal inference can be deduced. The literature has acknowledged but failed to eliminate this endogeneity source because of difficulties in finding valid IVs. Moreover, active commuting with its health and environmental benefits is of interest as potential findings can contribute to advocacy for more sustainable transport.

Therefore, the aim in this thesis is to explore the relationships between commuting and health, SWB and job satisfaction. The research questions based on the gaps identified from the literature are whether commuting time can affect health, SWB and job satisfaction of commuters, and what effects different commuting modes, especially active modes, can have on health, SWB and job satisfaction. Based on the aim and research questions derived, the objectives are set as a plan for the thesis. Firstly, panel data from the UKHLS are employed. Cross sectional data only observe individuals at a specific point in time, whereas panel data allow researchers to identify time and individual trends. Panel data also permit the use of FE models to eliminate the unobserved heterogeneity effect. Thus, the second step involves using separate linear FE models to explore the associations between commuting duration and health, SWB and job satisfaction. As the literature has identified heterogeneous impacts between different modes and genders, the models separate the commuting time predictor into different transport mode groups and are also rerun on several sub-samples to examine possible variations across genders and regions. Lastly, the variables are treated as covariates together with active commuting duration within the linear FE models of one another. Valid and relevant IVs with the GMM estimation approach are applied to control for reverse causality bias.

The thesis has found that commuting time in general is associated with lower health status, but not with job satisfaction and SWB. Looking more closely into different transport mode groups, public transport modes can be linked with reduced scores of all three measures health status, job satisfaction and SWB, and this finding is consistent across sub-samples of different genders and regions. Private modes are also connected with deteriorating health status, whereas cycling is associated with better health. Furthermore, when considering the causal effects of active transport modes, it is revealed that active modes can increase general health status directly, and potentially improve job satisfaction and SWB indirectly via the interconnections between the variables of interest.

6.3. Contributions

The UKHLS data from Wave 1 to 7 covering around 40,000 households is the main data source throughout the thesis. In the first empirical chapter, linear FE models are implemented to explore the associations between commuting and health, SWB and job satisfaction. It finds that overall commuting time, regardless of the mode used, is linked with lowered subjective health status, but not with satisfaction at work or overall life satisfaction. When commuting time is separated between different transport modes, it is revealed that both public and private modes have a negative connection with health whereas cycling tends to be linked with better health. Apart from health, public modes are related with lowered satisfaction at work and overall life. There are heterogenous differences across genders and regions, however, in general, these findings persist throughout several sub-samples tested. Moreover, when being compared with private modes, public modes are associated with more deteriorating health status whereas cycling is more likely to improve it. FE models can control for heterogeneity but are unable to eliminate reverse causality, thus the results can only be regarded as association inference. These findings validate the detrimental effect of longer commute time and private and public modes on subjective health. The positive association of cycling on health is as expected from the literature. Moreover, the findings on job satisfaction can contribute to the gap in the literature. The study finds that public modes are consistently linked with lowered satisfaction in the workplace in the full samples and when London observations are removed. Unpredictability from unreliable services and crowded carriage are likely to contribute to this negative association between commuting by public modes and satisfaction at workplace via the spill-over effect.

With the literature missing causal inferences on the commuting effects on health, SWB and job satisfaction, the second empirical chapter in this thesis makes use of valid and relevant IVs to derive causal relations between the variables of interest. With a focus on active commuting, it has been found that longer time spent on walking and cycling can lead to an improved health status. This confirms association inferences in the literature on the connection between active commuting and health indicators. Furthermore, the chapter reveals that better perceived health status can causally generate higher satisfaction with overall life and satisfaction at workplace. These causal relations can act as pathways for the positive effects of active commuting on SWB and job satisfaction. In addition, the chapter verifies a bidirectional relationship between life satisfaction and one of its life domains – job satisfaction. The reciprocity between the two variables confirms the presence of both the bottom-up and top-down theories in the relationships between life satisfaction and its domains.

Therefore, the thesis with its findings has contributed in an empirical context to the literature. By answering the research questions, it has filled a gap in the literature, namely the finding that active commuting can causally increase health status and potentially influence job satisfaction and life satisfaction via health. Also, public modes of transport are associated with reduced satisfaction in the workplace. With such positive findings for active commuting, the thesis could advocate for initiatives aiming at increasing the use of daily active commuting. For private policies, companies could introduce and expand their Cycle to Work scheme, in which companies can receive tax exemption for lending bicycles and equipment to their employees. Secure bike sheds, shower facilities and a cycling buddy scheme can also encourage employees to cycle more. With such pronounced influences from active commuting on health, SWB and job satisfaction, more investment should be spent on local and national transport infrastructure and network to ensure that pedestrians and cyclists could be confident to commute daily, for example: introducing cycle-only lanes, keep pavements clean and well-lit. Ways to improve the public transport's quality standards should also be investigated, such as: updating journey routes, improving timetables and punctuality.

6.4. Strengths and limitations

An advantage that this thesis has is the rich panel data set from the UKHLS, covering a substantial sample of the British populations. The variables available permit the investigation of the research questions and also the control of important confounding factors. The UKHLS survey does not focus exclusively on any of the variables of interest, thus the thesis can rule out the reporting bias. Moreover, the rich data set from the UKHLS can reduce any potential finite-sample issue of the GMM estimator.

The thesis is not without limitations. One limitation is the use of self-reported measures for the dependent and main independent variables. Responses from measures can be subject to measurement errors, and measures that are devised from similar (or common) concepts or methods, such as the dependent variables in this study, may introduce the common-method variance. This is when the measurement errors from two variables covary and make the correlation between them spurious and biased (Sharma, Yetton and Crawford, 2009). However, self-reported measures are advocated based on the self-reflective nature of several concepts of interest in this study, such as job satisfaction and life satisfaction. Thus, measurements that require respondents to reflect and respond themselves may be regarded as appropriate to assess such concepts. Also, even if the study could suffer from the common-method variance, previous literature indicates that it may not be damaging (Spector, 2006; Spector and Brannick, 2010). Although the variance can inflate the estimated relationships, it can also attenuate them, and the bias is reduced if more predictors that are subject to the common-method variance are added into the model (Siemsen, Roth and Oliveira, 2010).

Even though the GMM method with IV is adequate to deliver causal inference, it is based on the crucial assumption of cardinality for health, SWB and job satisfaction. These variables are measured on Likert scales and could be regarded as ordinal variables. Non-linear models that can control for simultaneity bias could have been employed to explore the differences in measurement assumptions, but there is no ordered model available to solve the simultaneity issues. Moreover, in the context of linear models, the variables of interest are potentially connected with one another and the connections can be subject to reverse causality, a system of simultaneous equations would be a better choice. However, a system of simultaneous equations would require an underlying theory to support its structure (Wooldridge, 2016) which has not been developed for the variables of interest in this thesis. Furthermore, an intrinsic issue with the FE model is that any time-invariant predictor, such as gender and ethnicity in this thesis, is eliminated during the differencing process. Thus, parameter estimation is not available for those variables and the empirical results are driven by the majority of determinants discussed in Chapter 2. However, Chapter 4 has investigated gender-specific models to compensate for the lack of a gender control variable. Also, it can be argued that controlling for heterogeneity is more essential. In a panel GMM estimation approach, using IVs alone would not yield consistent parameter estimation without proper control for unobserved heterogeneity. Thus, using FE models is of necessity and the removed time-invariant predictors can be argued to be of less importance than controlling for individual unobservable heterogeneity. In addition, there are possible heterogeneity factors that can vary over time, but the thesis has not controlled for such heterogeneity. The urban economic theory argues that longer commuting is compensated with either higher salary or better housing. And although personal income has been applied throughout the thesis as a control variable, housing quality is missing from the studies as it is not available from the survey data.

Countries may have significantly different transport policies and land use (Morris, 2015), and also their various cultures may have different impacts on the relationships of interest in this thesis (Dickerson, Hole and Munford, 2014). Thus, findings on one particular country like the UK in this thesis should not be generalised for other countries. However, with the large representative data set of the British households and strong econometric techniques that allows for causal inference, this thesis hopes that the empirical findings of improved health, SWB and job satisfaction could contribute to the advocacy of active transport modes in commuting and everyday life in general.

As mentioned in Chapter 1 – Introduction, at the time of writing this thesis, commuting represented a large proportion of working life that was not likely to disappear in the near future. However, the on-going coronavirus (i.e. COVID-19) pandemic has caused an unprecedented situation where nearly half of the British workforce experienced working from home as of April 2020 (Office for National Statistics, 2020). There are sociodemographic differences in the home working pattern, for example, the option of working from home is more likely to be available in positions that need higher education qualifications and longer seniority than for those routine and manual roles. With such an unprecedented and substantial change in the pattern of working and commuting, there are many possible research questions that can link to the variables of interest in this thesis, for example: the effects of remote working on general health, SWB and job satisfaction; comparisons between pre-COVID-19 commuting and remote working during the pandemic, etc. These potential research topics can be beneficial for private and public organisations in transforming their workplace policies temporarily during the pandemic and permanently in the future to embrace remote working with the aid of rapid technological advancements.

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APPENDIXES

Appendix 1

This appendix presents alternative approaches to the primary models in Chapter 4, including the RE, POLS models' estimation results and the FE models with the additional interaction variables between commuting modes and income. Firstly, Tables A1 and A2 provide the corresponding RE and POLS models respectively for the FE model in Subsection 4.3.1 where the effects of overall commuting time are studied. After that, the RE and POLS models for Subsection 4.3.2 with the effects of binary commuting mode choices are given in Tables A3 and A4, respectively. For the effects of commuting duration between different modes in Subsection 4.3.3, the RE and POLS models applied on the full sample are demonstrated in Tables A5 and A6. Lastly, the FE models for health, SWB and job satisfaction in Subsection 4.3.3 are re-estimated with the inclusion of four interaction terms between personal income and the variables representing the commuting durations spent on the four commuting modes. The inclusion explores the indirect impact of personal income on the three dependent variables, via its influence on a person's daily commuting mode choice. Table A7 presents the models with interaction terms on the full sample, whereas observations for London are excluded in Table A8.

Table A1: The effects of overall commuting time (RE model)

Variable	General health	Job satisfaction	Life satisfaction
Commuting time	-0.0003763***	-0.0012049***	-0.0004518***
	(0.0001045)	(0.0002026)	(0.0001679)
Age	-0.0148551***	-0.0475121***	-0.0593894***
	(0.0019527)	(0.0027448)	(0.002732)
Age squared (divided by 100)	0.0041052*	0.0587095***	0.0648611***
	(0.0023134)	(0.0032009)	(0.0031793)
Monthly net personal income (divided by 100)	0.0021526***	0.0045195***	0.0035193***
	(0.0002374)	(0.0003658)	(0.0003622)
Number of own children in household	-0.0001682	0.0286548***	0.0038328
	(0.0043124)	(0.0064295)	(0.0060813)
Gender (Female) (Base level: Male)	-0.0355703***	0.1690672***	0.0133981
	(0.0086543)	(0.011976)	(0.0114983)
Whether living in a rural area (Base level: Urban area)	0.0617783***	0.0534262***	0.0476294***
	(0.0100532)	(0.0144417)	(0.0133498)
Ethnicity: (Base level: White)			
Á Mixed	-0.0501446	-0.095292**	-0.2257714***
	(0.031921)	(0.0420454)	(0.0443089)
Á Asian	-0.1217067***	0.0979739***	-0.222964***
	(0.0150949)	(0.0208155)	(0.0212508)
Á Black	0.0118705	-0.1621152***	-0.1938979***
	(0.0210176)	(0.0303458)	(0.0303324)
Á Other ethnic groups	-0.0820648*	-0.0611976	-0.2453746***
	(0.0462714)	(0.0639827)	(0.0629108)
Marital status: (Base level: Married)			
Á Single	-0.0562053***	-0.1000269***	-0.2397855***
	(0.0098974)	(0.0154144)	(0.014542)
Á Separated	-0.0752464***	-0.0260967	-0.3975646***
	(0.0204222)	(0.0325112)	(0.0343588)
Á Divorced	-0.0711948***	-0.0891939***	-0.2642008***
	(0.0138571)	(0.0212097)	(0.0201026)

Á Widowed	-0.0466948	0.0306384	-0.3009843***
	(0.0342343)	(0.0486061)	(0.0509801)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.226657***	-0.0724883***	0.1147048***
	(0.014442)	(0.0203459)	(0.0191323)
Á First degree or equivalent	0.1457343***	-0.0705834***	0.0660516***
	(0.0112244)	(0.0158599)	(0.0150246)
Á A Levels	0.0681751***	-0.0806607***	0.0207547
	(0.0130502)	(0.0192042)	(0.0182326)
Á None of the above	-0.0652087***	0.0397908**	-0.0164777
	(0.0133006)	(0.0187308)	(0.0182385)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	0.091331***	0.1064675***	0.1005652***
	(0.0091666)	(0.0150164)	(0.0131081)
Á Intermediate occupations	0.0493285***	0.0189961	0.0541382***
	(0.0104645)	(0.0174322)	(0.015262)
Employment type (Employee) (Base level: Self-employed)	-0.0130752	-0.3301954***	0.0408776**
	(0.0135479)	(0.0212053)	(0.0197258)
Region: (Base level: London)			
Á North East	-0.0440328*	-0.0435037	0.089752***
	(0.0256027)	(0.0366378)	(0.0334099)
Á North West	-0.0068019	0.0054562	0.0867194***
	(0.0176745)	(0.0253153)	(0.0239988)
Á Yorkshire and the Humber	-0.029473	0.0633108**	0.0591806**
	(0.0190968)	(0.0273132)	(0.0260618)
Á East Midlands	-0.0597654***	0.045613*	0.041227
	(0.0196957)	(0.0269965)	(0.026441)
Á West Midlands	-0.0754323***	-0.0171688	-0.0017093
	(0.0185656)	(0.0261519)	(0.0255594)
Á East of England	-0.0536912***	0.0118372	0.0272321
	(0.0186716)	(0.0255084)	(0.0244621)

Á South East	-0.0231407	0.0612236***	0.0560616**
	(0.0170018)	(0.0234874)	(0.0226791)
Á South West	-0.0199612	0.0652975**	0.0623481**
	(0.0193561)	(0.0272484)	(0.0260033)
Á Wales	-0.0183057	0.0512653	0.0607497**
	(0.0225151)	(0.0314015)	(0.0300166)
Á Scotland	0.0390569**	-0.0030831	0.0547949**
	(0.0197452)	(0.0279853)	(0.026707)
Á Northern Ireland	0.0902719***	0.1660445***	0.2032808***
	(0.0244107)	(0.0315702)	(0.0303427)
Year: (Base level: 2009)			
Á 2010	0.0128928*	-0.0048698	-0.0349996***
	(0.0068325)	(0.0125582)	(0.011064)
Á 2011	0.0350302***	-0.0737028***	-0.1453073***
	(0.0072556)	(0.0130261)	(0.0121247)
Á 2012	0.0029294	-0.0699411***	-0.2068743***
	(0.0074759)	(0.0132775)	(0.0123803)
Á 2013	0.0160367**	-0.1010377***	-0.2065307***
	(0.0076791)	(0.0135166)	(0.0124997)
Á 2014	0.0599903***	-0.0230903*	-0.0651767***
	(0.0079678)	(0.0137834)	(0.012517)
Á 2015	-0.0738819***	-0.0087549	-0.0282915**
	(0.0079895)	(0.0137754)	(0.0121861)

Observations: 123,505. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table A2: The effects of overall commuting time (Pooled OLS model)

Variable	General health	Job satisfaction	Life satisfaction
Commuting time	-0.000244	-0.0018581***	-0.0006841***
	(0.0001526)	(0.0002286)	(0.000203)
Age	-0.0254873***	-0.0522688***	-0.065635***
	(0.0022723)	(0.0028513)	(0.0028796)
Age squared (divided by 100)	0.0160323***	0.0639924***	0.0701859***
	(0.0026799)	(0.0032992)	(0.0033238)
Monthly net personal income (divided by 100)	0.0045703***	0.0062334***	0.0050501***
	(0.0003309)	(0.0004394)	(0.0004129)
Number of own children in household	0.0121493**	0.0346629***	-0.0049584
	(0.0052831)	(0.0070277)	(0.006777)
Gender (Female) (Base level: Male)	-0.0005807	0.1797344***	0.0282593**
	(0.0094805)	(0.0125783)	(0.0120173)
Whether living in a rural area (Base level: Urban area)	0.0649169***	0.0650933***	0.0374324***
	(0.0115272)	(0.0150275)	(0.0141859)
Ethnicity: (Base level: White)			
Á Mixed	-0.0653269*	-0.0834652*	-0.195373***
	(0.0357026)	(0.0440467)	(0.0461327)
Á Asian	-0.1528341***	0.1140273***	-0.2493288***
	(0.0170343)	(0.0218424)	(0.022264)
Á Black	-0.0050503	-0.1636049***	-0.2075093***
	(0.0238064)	(0.0319542)	(0.0325941)
Á Other ethnic groups	-0.1617461***	-0.050675	-0.2143877***
	(0.0523703)	(0.0676088)	(0.061525)
Marital status: (Base level: Married)			
Á Single	-0.0928054***	-0.1242481***	-0.3079594***
	(0.0124984)	(0.0169571)	(0.0163963)
Á Separated	-0.1065211***	-0.0791809**	-0.503996***
	(0.027906)	(0.0378427)	(0.0392776)
Á Divorced	-0.0993402***	-0.0984291***	-0.3136932***
	(0.0169941)	(0.0231782)	(0.0220573)

Á Widowed	-0.0352886	0.1024744**	-0.2817463***
	(0.0416516)	(0.051295)	(0.0535562)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.2000914***	-0.0705833***	0.0879178***
	(0.0165197)	(0.0212578)	(0.0202093)
Á First degree or equivalent	0.1253789***	-0.0699135***	0.0482913***
	(0.0128511)	(0.0167265)	(0.016049)
Á A Levels	0.0581958***	-0.085784***	0.0070875
	(0.0154935)	(0.0205817)	(0.0196492)
Á None of the above	-0.0675404***	0.0425311**	-0.0272214
	(0.0145639)	(0.0196307)	(0.0189696)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	0.1337588***	0.0818251***	0.131304***
	(0.0114956)	(0.0156624)	(0.0147475)
Á Intermediate occupations	0.0766498***	-0.012781	0.0626555***
	(0.0133292)	(0.0181864)	(0.0170183)
Employment type (Employee) (Base level: Self-employed)	-0.025565	-0.3476063***	0.0425202**
	(0.0168401)	(0.0222097)	(0.0215289)
Region: (Base level: London)			
Á North East	-0.0309878	-0.0471496	0.1015482***
	(0.0279227)	(0.0376911)	(0.0352304)
Á North West	0.0219814	0.0012567	0.0900867***
	(0.0201857)	(0.0265369)	(0.0255644)
Á Yorkshire and the Humber	-0.0114205	0.0670129**	0.0747199***
	(0.0216374)	(0.0285207)	(0.0274803)
Á East Midlands	-0.0420194*	0.0405625	0.0408171
	(0.022355)	(0.0283604)	(0.0282075)
Á West Midlands	-0.0514646**	-0.0371197	0.001826
	(0.0208622)	(0.0273067)	3(0.0267607)
Á East of England	-0.0370397*	0.015699	0.0417126
	(0.0210771)	(0.0268155)	(0.0261168)

Á South East	-0.0062882	0.0572868**	0.0560944**
	(0.0193608)	(0.0243795)	(0.0241459)
Á South West	0.0143481	0.079492***	0.0861389***
	(0.0217716)	(0.0282825)	(0.0273769)
Á Wales	0.0096073	0.0717088**	0.0782617**
	(0.0248828)	(0.0324426)	(0.0313166)
Á Scotland	0.0628638***	-0.0030861	0.0766481***
	(0.0221128)	(0.0293113)	(0.0279286)
Á Northern Ireland	0.0964113***	0.147917***	0.2053751***
	(0.0270536)	(0.0329929)	(0.0314816)
Year: (Base level: 2009)			
Á 2010	0.0096793	-0.0028363	-0.0287461**
	(0.0075563)	(0.0130495)	(0.0115945)
Á 2011	0.0375355***	-0.0565759***	-0.1362114***
	(0.0081558)	(0.0135793)	(0.0127275)
Á 2012	0.0105688	-0.0473894***	-0.1921192***
	(0.0083923)	(0.013853)	(0.0130422)
Á 2013	0.0200005**	-0.0767837***	-0.1904819***
	(0.0085937)	(0.0140826)	(0.0131479)
Á 2014	0.0690524***	0.0132019	-0.0504212***
	(0.0089638)	(0.0143629)	(0.013212)
Á 2015	-0.0615603***	0.0278157*	-0.007017
	(0.0088951)	(0.0141707)	(0.0128661)

Observations: 123,505. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table A3: The effects of different commuting modes (RE model)

Variable	General health	Job satisfaction	Life satisfaction
Commuting modes: (Base level: Private modes)			
Á Public modes	-0.0387467***	-0.024305	-0.0527384***
	(0.0094933)	(0.0159194)	(0.0146552)
Á Cycle	0.1116301***	0.0124971	0.0597884**
	(0.0161955)	(0.0265907)	(0.0235157)
Á Walk	-0.0126101	0.0518153***	-0.0020771
	(0.0097145)	(0.0158571)	(0.0148299)
Age	-0.0155815***	-0.0479755***	-0.0599624***
	(0.001958)	(0.002751)	(0.0027436)
Age squared (divided by 100)	0.0049182**	0.0593343***	0.065473***
	(0.0023197)	(0.0032044)	(0.0031919)
Monthly net personal income (divided by 100)	0.002133***	0.0044532***	0.0034529***
	(0.0002374)	(0.0003686)	(0.0003635)
Number of own children in household	-0.0006531	0.0292196***	0.0031904
	(0.0043139)	(0.0064451)	(0.0060943)
Gender (Female) (Base level: Male)	-0.0299184***	0.1715213***	0.0171373
	(0.0086771)	(0.0120368)	(0.0115057)
Whether living in a rural area (Base level: Urban area)	0.0614101***	0.0553371***	0.0456313***
	(0.0100941)	(0.0145212)	(0.0134035)
Ethnicity: (Base level: White)			
Á Mixed	-0.04772	-0.0972506**	-0.219897***
	(0.0319433)	(0.042229)	(0.0444883)
Á Asian	-0.1154318***	0.1000127***	-0.2180342***
	(0.0151277)	(0.0208811)	(0.0213078)
Á Black	0.0191719	-0.1644939***	-0.1856536***
	(0.0210985)	(0.0304777)	(0.0304433)
Á Other ethnic groups	-0.078202*	-0.0609137	-0.2352026***
	(0.046287)	(0.0639939)	(0.0631323)
Marital status: (Base level: Married)			
Á Single	-0.0551335***	-0.1017721***	-0.2401838***

	(0.0099087)	(0.0154701)	(0.014576)
Á Separated	-0.073885***	-0.0265348	-0.3980129***
	(0.0204586)	(0.0325996)	(0.0344769)
Á Divorced	-0.0694067***	-0.0902801***	-0.264613***
	(0.013868)	(0.0212699)	(0.0201329)
Á Widowed	-0.0458377	0.0330908	-0.2977409***
	(0.0343957)	(0.0487785)	(0.0510534)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.2241324***	-0.0795548***	0.1127888***
	(0.0144221)	(0.0204188)	(0.0191536)
Á First degree or equivalent	0.1441042***	-0.0748571***	0.0645343***
	(0.0112234)	(0.0158885)	(0.0150256)
Á A Levels	0.0674582***	-0.0843302***	0.0195186
	(0.0130518)	(0.0192413)	(0.0182704)
Á None of the above	-0.0652539***	0.0390085**	-0.0170357
	(0.0133014)	(0.0187619)	(0.0182533)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	0.0906721***	0.1035021***	0.0998346***
	(0.0091808)	(0.0149983)	(0.0130978)
Á Intermediate occupations	0.0486956***	0.0185077	0.0542011***
	(0.0104867)	(0.017481)	(0.0153004)
Employment type (Employee) (Base level: Self-employed)	-0.0118158	-0.3360743***	0.0392826**
	(0.0136479)	(0.0214196)	(0.019912)
Region: (Base level: London)			
Á North East	-0.0491875*	-0.0377304	0.0788429**
	(0.0257135)	(0.0369677)	(0.0337747)
Á North West	-0.0133762	0.0072385	0.0731912***
	(0.0179405)	(0.0258872)	(0.0245911)
Á Yorkshire and the Humber	-0.036225*	0.0659056**	0.0455187*
	(0.0192845)	(0.0278013)	(0.0265594)

Á East Midlands	-0.0663962***	0.0486104*	0.0276356
	(0.0199516)	(0.0276513)	(0.027067)
Á West Midlands	-0.0810083***	-0.0119508	-0.0144745
	(0.0188662)	(0.0267954)	(0.0261572)
Á East of England	-0.0613032***	0.0106741	0.0136391
	(0.0188377)	(0.0260242)	(0.0248867)
Á South East	-0.0304722*	0.0588851**	0.0429866*
	(0.0172379)	(0.0241401)	(0.0232712)
Á South West	-0.028763	0.0680329**	0.0494558*
	(0.01961)	(0.0278763)	(0.0265181)
Á Wales	-0.0246383	0.0571911*	0.0467558
	(0.0227441)	(0.0320201)	(0.03061)
Á Scotland	0.0348579*	-0.0000982	0.0445937
	(0.0198966)	(0.0283822)	(0.0271216)
Á Northern Ireland	0.0842119***	0.1750159***	0.1918955***
	(0.0246273)	(0.0321162)	(0.0308817)
Year: (Base level: 2009)			
Á 2010	0.0120926*	-0.0066809	-0.0336165***
	(0.0068731)	(0.0126452)	(0.0111343)
Á 2011	0.0349768***	-0.0739589***	-0.1453538***
	(0.0072598)	(0.0130286)	(0.0121284)
Á 2012	0.0030667	-0.0700254***	-0.2066272***
	(0.0074796)	(0.0132788)	(0.0123772)
Á 2013	0.0161829**	-0.101638***	-0.2064955***
	(0.0076843)	(0.013519)	(0.0125008)
Á 2014	0.0598837***	-0.022995**	-0.0651525***
	(0.0079704)	(0.0137875)	(0.0125178)
Á 2015	-0.0738185***	-0.00929	-0.0282971**
	(0.0079905)	(0.013779)	(0.0121889)

Observations: 123,039. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table A4: The effects of different commuting modes (Pooled OLS model)

Variable	General health	Job satisfaction	Life satisfaction
Commuting modes: (Base level: Private modes)			
Á Public modes	-0.0496957***	-0.0295405*	-0.0701521***
	(0.0126973)	(0.0172577)	(0.0167589)
Á Cycle	0.2178981***	0.0243777	0.0739758***
	(0.0220772)	(0.0300828)	(0.02844)
Á Walk	-0.0157876	0.0833068***	0.004317
	(0.0126986)	(0.0173539)	(0.0168448)
Age	-0.0263326***	-0.05275***	-0.0663883***
	(0.0022768)	(0.002861)	(0.0028928)
Age squared (divided by 100)	0.0169426***	0.0646389***	0.0709963***
	(0.0026861)	(0.0033089)	(0.0033384)
Monthly net personal income (divided by 100)	0.0046143***	0.0060026***	0.0049946***
	(0.0003312)	(0.0004413)	(0.0004131)
Number of own children in household	0.0108326**	0.035826***	-0.0056761
	(0.0052791)	1(0.0070507)	(0.0067856)
Gender (Female) (Base level: Male)	0.0083425	0.1833089***	0.0332013***
	(0.0095198)	(0.0126208)	(0.0120131)
Whether living in a rural area (Base level: Urban area)	0.0660137***	0.0664093***	0.0358723**
	(0.0115757)	(0.0151109)	(0.0142499)
Ethnicity: (Base level: White)			
Á Mixed	-0.062503*	-0.0860081*	-0.1868954***
	(0.0355866)	(0.0442023)	(0.0460719)
Á Asian	-0.1416855***	0.1150023***	-0.2434888***
	(0.0171016)	(0.0218912)	(0.0223325)
Á Black	0.0078471	-0.1687835***	-0.1984383***
	(0.0239451)	(0.0320287)	(0.0326596)
Á Other ethnic groups	-0.1570421***	-0.0526494	-0.2055599***
	(0.052658)	(0.0674475)	(0.0617998)
Marital status: (Base level: Married)			
Á Single	-0.0923258***	-0.1279557***	-0.3085952***

	(0.0125024)	(0.0170153)	(0.0164243)
Á Separated	-0.104117***	-0.0798247**	-0.5032017***
	(0.0279134)	(0.0379069)	(0.0393953)
Á Divorced	-0.0970052***	-0.1000172***	-0.3141341***
	(0.0169826)	(0.0232427)	(0.022082)
Á Widowed	-0.0335353	0.1060177**	-0.2803806***
	(0.0415712)	(0.0514635)	(0.0536239)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.1973094***	-0.0798683***	0.0867816***
	(0.0164783)	(0.0213348)	(0.0202313)
Á First degree or equivalent	0.1232479***	-0.0744749***	0.0474606***
	(0.0128369)	(0.0167497)	(0.016061)
Á A Levels	0.0581057***	-0.09031***	0.0062663
	(0.0154848)	(0.0206327)	(0.0196888)
Á None of the above	-0.0671626***	0.0420141**	-0.027424
	(0.0145619)	(0.0196728)	(0.0189857)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	0.1338739***	0.07708***	0.1284216***
	(0.0114844)	(0.0156376)	(0.0147365)
Á Intermediate occupations	0.0768021***	-0.0143534	0.0614688***
	(0.0133361)	(0.0182314)	(0.0170339)
Employment type (Employee) (Base level: Self-employed)	-0.0287445*	-0.3630244***	0.0381494*
	(0.0169234)	(0.0223329)	(0.0216414)
Region: (Base level: London)			
Á North East	-0.0371006	-0.0347054	0.0880494**
	(0.0281491)	(0.038086)	(0.0357128)
Á North West	0.0141846	0.008569	0.073044***
	(0.0205901)	(0.0271425)	(0.0263678)
Á Yorkshire and the Humber	-0.0192806	0.0740226**	0.0582578**
	(0.0219888)	(0.0290164)	(0.0281976)

Á East Midlands	-0.0512973**	0.0508862*	0.0237686
	(0.0227556)	(0.0290993)	(0.0290466)
Á West Midlands	-0.0578716***	-0.0266677	-0.0144228
	(0.0213423)	(0.0280967)	(0.0275916)
Á East of England	-0.0487067**	0.0184989	0.0236325
	(0.0213545)	(0.0273715)	(0.026723)
Á South East	-0.014305	0.0586751**	0.0395327
	(0.0197606)	(0.0251493)	(0.024994)
Á South West	0.0019546	0.0878277***	0.0688301**
	(0.022214)	(0.0289993)	(0.0281287)
Á Wales	0.0032628	0.0845251**	0.0619558*
	(0.0252791)	(0.0331473)	(0.0321374)
Á Scotland	0.0581023***	0.005509	0.0649822**
	(0.0223553)	2(0.0297518)	(0.0285468)
Á Northern Ireland	0.0913465***	0.1635202***	0.1917724***
	(0.0274728)	(0.0337283)	(0.0322826)
Year: (Base level: 2009)			
Á 2010	0.0082416	-0.0052214	-0.0277522**
	(0.0076211)	(0.0131572)	(0.0116872)
Á 2011	0.0368174***	-0.0557999***	-0.1365692***
	(0.0081506)	(0.013581)	(0.0127274)
Á 2012	0.0102678	-0.0463654***	-0.1922604***
	(0.0083909)	(0.0138544)	(0.0130401)
Á 2013	0.0196827	-0.0767281***	-0.1907702***
	(0.0085942)	(0.0140858)	(0.0131473)
Á 2014	0.0680852***	0.0146495	-0.0506269***
	(0.0089595)	(0.0143681)	(0.013213)
Á 2015	-0.0617855***	0.0283876**	-0.0072455
	(0.0088897)	(0.0141743)	(0.0128675)

Observations: 123,039. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table A5: The effects of commuting time across transport modes (RE model)

Variable	General health	Job satisfaction	Life satisfaction
Commuting time for transport modes:			
Á Private modes	-0.0001922	-0.0010977***	-0.0001236
	(0.0001398)	(0.0002618)	(0.0002175)
Á Public modes	-0.0005795***	-0.0014231***	-0.0009631***
	(0.0001487)	(0.0002645)	(0.0002422)
Á Cycle	0.003831***	-0.0018589*	0.0016561*
	(0.0006331)	(0.0010968)	(0.0009031)
Á Walk	-0.0011349**	-0.0020749***	-0.0008404
	(0.0004555)	(0.0007788)	(0.0006945)
Age	-0.0152992***	-0.0478913***	-0.0597598***
	(0.001958)	(0.0027491)	(0.0027421)
Age squared (divided by 100)	0.0046101**	0.0591424***	0.0652497***
	(0.0023204)	(0.0032032)	(0.0031912)
Monthly net personal income (divided by 100)	0.0021337***	0.004513***	0.0034668***
	(0.0002376)	(0.0003696)	(0.0003637)
Number of own children in household	-0.0005484	0.0282742***	0.0032523
	(0.0043123)	(0.0064431)	(0.0060935)
Gender (Female) (Base level: Male)	-0.032008***	0.1698422***	0.0155755
	(0.0086744)	(0.0120476)	(0.0115291)
Whether living in a rural area (Base level: Urban area)	0.0612478***	0.052751***	0.0453116***
	(0.0100847)	(0.0145224)	(0.0134059)
Ethnicity: (Base level: White)			
Á Mixed	-0.0494995	-0.0950786**	-0.2211227***
	(0.0319448)	(0.0421972)	(0.0444636)
Á Asian	-0.1178139***	0.0994288***	-0.2198821***
	(0.0151219)	(0.020867)	(0.0212919)
Á Black	0.016635	-0.1610498***	-0.187538***
	(0.0210739)	(0.0304537)	(0.0304062)
Á Other ethnic groups	-0.0803893*	-0.0592143	-0.2366001***
	(0.0462257)	(0.0640419)	(0.0631707)

Marital status: (Base level: Married)			
Á Single	-0.0554258***	-0.0996018***	-0.2402907***
	(0.009911)	(0.0154559)	(0.014572)
Á Separated	-0.0746919***	-0.0255999	-0.3985379***
	(0.0204712)	(0.0325569)	(0.0344774)
Á Divorced	-0.0699416***	-0.0896397***	-0.2650913***
	(0.0138705)	(0.0212605)	(0.0201298)
Á Widowed	-0.0464054	0.0331441	-0.2982853***
	(0.034384)	(0.048688)	(0.0510801)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.2248616***	-0.073395***	0.1138695***
	(0.0144315)	(0.0204158)	(0.0191621)
Á First degree or equivalent	0.1446687***	-0.0725072***	0.0651724***
	(0.0112276)	(0.015892)	(0.0150347)
Á A Levels	0.067718***	-0.0823789***	0.0198878
	(0.0130536)	(0.019226)	(0.0182682)
Á None of the above	-0.0654167***	0.0392415**	-0.017143
	(0.0133019)	(0.0187569)	(0.0182546)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	0.0913798***	0.1057272***	0.1004873***
	(0.0091958)	(0.0150468)	(0.0131554)
Á Intermediate occupations	0.0489323***	0.019577	0.0544134***
	(0.0104914)	(0.0174806)	(0.015313)
Employment type (Employee) (Base level: Self-employed)	-0.0105738	-0.3264546***	0.0408192**
	(0.0136694)	(0.021461)	(0.0199384)
Region: (Base level: London)			
Á North East	-0.0453741*	-0.0487788	0.0804863**
	(0.0256709)	(0.0368544)	(0.0336441)
Á North West	-0.0082582	-0.0007558	0.075828***
	(0.0178318)	(0.025693)	(0.0243817)
Á Yorkshire and the Humber	-0.0306259	0.059403**	0.0486427*
	(0.0192073)	(0.0276289)	(0.0263788)

Á East Midlands	-0.0601774***	0.0393474	0.0310369
	(0.0198504)	(0.0273916)	(0.0268122)
Á West Midlands	-0.0755879***	-0.0214575	-0.0115514
	(0.0187214)	(0.0265242)	(0.0259277)
Á East of England	-0.0536248***	0.0074487	0.0192167
	(0.0187351)	(0.0257863)	(0.0246762)
Á South East	-0.0236254	0.0559241**	0.0480367**
	(0.017121)	(0.0238277)	(0.0229998)
Á South West	-0.0221345	0.0616504**	0.0537572**
	(0.0194978)	(0.0276057)	(0.0263163)
Á Wales	-0.0192969	0.0463766	0.0496398
	(0.0226364)	(0.0317687)	(0.0303864)
Á Scotland	0.0389984**	-0.0079452	0.046722*
	(0.0198349)	(0.0282577)	(0.0269701)
Á Northern Ireland	0.0893142***	0.163609***	0.1945547***
	(0.0245199)	(0.031877)	(0.0306454)
Year: (Base level: 2009)			
Á 2010	0.0121816*	-0.006075	-0.0333349***
	(0.006874)	(0.0126486)	(0.0111365)
Á 2011	0.0349592***	-0.0741523***	-0.1452567***
	(0.0072601)	(0.0130299)	(0.0121288)
Á 2012	0.0030492	-0.0704513***	-0.2066225***
	(0.0074795)	(0.0132787)	(0.012378)
Á 2013	0.0163583**	-0.1012038***	-0.2062141***
	(0.0076838)	(0.0135208)	(0.0125024)
Á 2014	0.059793***	-0.0236231*	-0.0653221***
	(0.0079694)	(0.0137837)	(0.0125178)
Á 2015	-0.0736978***	-0.0090206	-0.0281932**
	(0.0079901)	(0.013779)	(0.0121903)

Observations: 123,039. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table A6: The effects of commuting time across transport modes (Pooled OLS model)

Variable	General health	Job satisfaction	Life satisfaction
Commuting time for transport modes:			
Á Private modes	0.0000849	-0.0021121***	-0.0003615
	(0.0002029)	(0.0002994)	(0.0002609)
Á Public modes	-0.0006002***	-0.0017726***	-0.0012126***
	(0.0002056)	(0.0002948)	(0.0002798)
Á Cycle	0.0085746***	-0.0032834***	0.0017616
	(0.0008408)	(0.001184)	(0.0010789)
Á Walk	-0.0013574**	-0.0029756***	-0.001224
	(0.0006042)	(0.0008873)	(0.0008011)
Age	-0.0261906***	-0.0522399***	-0.0660485***
	(0.0022775)	(0.0028628)	(0.0028922)
Age squared (divided by 100)	0.0167971***	0.0639671***	0.0706275***
	(0.0026875)	(0.0033122)	(0.0033387)
Monthly net personal income (divided by 100)	0.0045768***	0.0061717***	0.0050319***
	(0.0003322)	(0.0004432)	(0.0004136)
Number of own children in household	0.011091**	0.0345494***	-0.0055066
	(0.0052781)	(0.0070481)	(0.0067849)
Gender (Female) (Base level: Male)	0.0071685	0.1790261***	0.0309222**
	(0.0095095)	(0.0126548)	(0.0120551)
Whether living in a rural area (Base level: Urban area)	0.0647571***	0.0646312***	0.0358617**
	(0.0115654)	(0.0151075)	(0.0142614)
Ethnicity: (Base level: White)			
Á Mixed	-0.0649109*	-0.0840686*	-0.1889309***
	(0.0356104)	(0.0442514)	(0.0460623)
Á Asian	-0.1438579***	0.1131873***	-0.2459771***
	(0.0170813)	(0.0218737)	(0.0223225)
Á Black	0.0052935	-0.1659416***	-0.2013618***
	(0.0239059)	(0.0320436)	(0.0326608)
Á Other ethnic groups	-0.1587665***	-0.0494775	-0.207176***
	(0.0524329)	(0.0674908)	(0.0618205)

Marital status: (Base level: Married)			
Á Single	-0.0929124***	-0.1243852***	-0.30861***
	(0.0124979)	(0.0170008)	(0.0164216)
Á Separated	-0.1056627***	-0.0784859**	-0.5039533***
	(0.0279348)	(0.0378782)	(0.0393835)
Á Divorced	-0.0977613***	-0.0992227***	-0.3147098***
	(0.0169824)	(0.0232488)	(0.0220855)
Á Widowed	-0.0349473	0.1049605**	-0.2817513***
	(0.0415827)	(0.051276)	(0.0536472)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.1968512***	-0.0704118***	0.0881927***
	(0.0165024)	(0.0213351)	(0.0202557)
Á First degree or equivalent	0.1233426***	-0.0701928***	0.0485961***
	(0.0128483)	(0.0167585)	(0.0160732)
Á A Levels	0.058305***	-0.0864735***	0.0070762
	(0.0154835)	(0.0206196)	(0.0196881)
Á None of the above	-0.0669667***	0.0424137**	-0.0274888
	(0.0145558)	(0.019667)	(0.0189925)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	0.1320163***	0.0825186***	0.1296183***
	(0.0115184)	(0.0157138)	(0.0148157)
Á Intermediate occupations	0.0749539***	-0.0117379	0.0618133***
	(0.0133365)	(0.0182355)	(0.0170607)
Employment type (Employee) (Base level: Self-employed)	-0.0291091*	-0.3455679***	0.0411664*
	(0.0169478)	(0.0223951)	(0.0217125)
Region: (Base level: London)			
Á North East	-0.029375	-0.0468987	0.0921427**
	(0.0280353)	(0.0379619)	(0.0355585)
Á North West	0.0224806	0.0021841	0.0787962***
	(0.020416)	(0.0269653)	(0.0260907)
Á Yorkshire and the Humber	-0.0101957	0.0697057**	0.0645566**

	(0.0218399)	(0.028886)	(0.0279723)
Á East Midlands	-0.0412285*	0.0417702	0.0302419
	(0.0225941)	(0.0288528)	(0.0287317)
Á West Midlands	-0.049241**	-0.0349331	-0.00831
	(0.0211215)	(0.027791)	(0.0272926)
Á East of England	-0.0364837*	0.017924	0.0328751
	(0.0211964)	(0.0271337)	(0.0264493)
Á South East	-0.0040275	0.0584957**	0.0482096*
	(0.019584)	(0.0248066)	(0.0246527)
Á South West	0.0141446	0.0828573***	0.0768937***
	(0.0220144)	(0.028693)	(0.0278487)
Á Wales	0.0122959	0.0737064**	0.0677775**
	(0.0251048)	(0.0328655)	(0.0318427)
Á Scotland	0.0660602***	-0.0032868	0.0693715**
	(0.0222299)	(0.0296356)	(0.0283526)
Á Northern Ireland	0.0998213***	0.1517959***	0.1972222***
	(0.0272706)	(0.033448)	(0.0319627)
Year: (Base level: 2009)			
Á 2010	0.0083692	-0.0044076	-0.0271511**
	(0.0076236)	(0.0131595)	(0.0116915)
Á 2011	0.0369958***	-0.0563316***	-0.1363639***
	(0.0081542)	(0.0135816)	(0.0127283)
Á 2012	0.0105401	-0.0472439***	-0.1921997***
	(0.0083914)	(0.0138544)	(0.0130414)
Á 2013	0.020188**	-0.0764231***	-0.1902914***
	(0.0085957)	(0.0140879)	(0.0131487)
Á 2014	0.068211***	0.0132185	-0.050831***
	8(0.0089583)	(0.0143641)	(0.0132119)
Á 2015	-0.0615393***	0.0284419**	-0.0070038
	(0.0088935)	(0.0141745)	(0.0128683)

Observations: 123,039. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table A7: The effects of commuting time across transport modes with income interaction terms (full sample)

Variable	General health	Job satisfaction	Life satisfaction
Commuting time for transport modes:			
Á Private modes	-0.0005651**	0.0003253	-0.0002291
	(0.0002512)	(0.0004809)	(0.0004604)
Á Public modes	-0.0005688**	-0.0007571	-0.0005436
	(0.0002508)	(0.000468)	(0.0004256)
Á Cycle	0.0012803	-0.0015172	0.0011308
	(0.00113)	(0.0021326)	(0.0020478)
Á Walk	-0.0001853	-0.0022275	-0.0000673
	(0.0007981)	(0.0014756)	(0.0013086)
Monthly net personal income (divided by 10,000)	0.0308084	0.2631143***	0.1128242*
	(0.0343131)	(0.0588384)	(0.0580035)
Private modes*Personal income	0.0004513	-0.001292	0.0003478
	(0.0008398)	(0.001533)	(0.0017569)
Public modes*Personal income	0.0000967	-0.0002184	-0.0007182
	(0.0006946)	(0.0011095)	(0.0011041)
Cycle*Personal income	0.001885	0.0054314	0.0040148
	(0.0040063)	(0.0066431)	(0.0071858)
Walk*Personal income	-0.0024463	0.0082436	0.0046565
	(0.0038719)	(0.0067421)	(0.0056704)
Age	0.0308033***	-0.0425545**	0.0138475
	(0.0102808)	(0.0201231)	(0.0165069)
Age squared (divided by 100)	-0.035665***	0.0218881**	0.0304059***
	(0.0056301)	(0.0104222)	(0.009216)
Number of own children in household	-0.0215629***	-0.0271981**	0.0118575
	(0.0068572)	(0.0123569)	(0.0110016)
Gender (Female) (Base level: Male)	(omitted)	(omitted)	(omitted)
Whether living in a rural area (Base level: Urban area)	0.0050826	-0.0274843	0.0536168
	(0.0214042)	(0.0419104)	(0.0346606)
Ethnicity: (Base level: White)			

Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base level: Married)			
Á Single	0.0275726*	-0.0003792	-0.0124595
	(0.0154933)	(0.0296862)	(0.0263929)
Á Separated	-0.0042144	0.0277699	-0.1992008***
	(0.0254576)	(0.0464318)	(0.0478822)
Á Divorced	0.020125	-0.0805376*	-0.0423788
	(0.0218062)	(0.0411298)	(0.0384754)
Á Widowed	0.0115799	-0.0939533	-0.3207124***
	(0.0525961)	(0.0912671)	(0.1028916)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0151058	-0.1376998*	-0.0456076
	(0.0433033)	(0.0824728)	(0.0733507)
Á First degree or equivalent	0.0060486	-0.0968575	-0.0070532
	(0.033059)	(0.0612868)	(0.0547333)
Á A Levels	-0.0629098**	-0.0978104*	-0.0163335
	(0.031225)	(0.0584696)	(0.0541459)
Á None of the above	0.0155151	0.0302412	0.2299538**
	(0.0545495)	(0.1087983)	(0.1043928)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	-0.0136436	0.1333343***	-0.0149357
	(0.0142107)	(0.0307102)	(0.0234203)
Á Intermediate occupations	-0.0121687	0.0977569***	0.0051166
	(0.0156281)	(0.0336722)	(0.0264301)
Employment type (Employee) (Base level: Self-employed)	-0.0015	-0.3304447***	-0.0168559
	(0.0206462)	(0.0431048)	(0.0359041)
Region: (Base level: London)			
Á North East	-0.0171012	-0.0822542	0.1503413
	(0.1329506)	(0.2151876)	(0.2010772)

Á North West	-0.1258712*	0.0041534	-0.1351409
	(0.0669813)	(0.1497947)	(0.102062)
Á Yorkshire and the Humber	-0.0753736	-0.0556725	-0.0355276
	(0.0720381)	(0.1611095)	(0.1146272)
Á East Midlands	-0.1004406	0.0657014	0.0243344
	(0.0673131)	(0.1293076)	(0.1125723)
Á West Midlands	-0.0511911	0.1731394	-0.02264
	(0.0736291)	(0.1482411)	(0.1138027)
Á East of England	-0.0657798	-0.0055662	-0.0838733
	(0.0616605)	(0.1090859)	(0.0791573)
Á South East	-0.1009376*	0.0882944	0.0843061
	(0.0531665)	(0.0985104)	(0.0805094)
Á South West	-0.1706316**	0.1605487	-0.0138286
	(0.0663356)	(0.1428798)	(0.1039038)
Á Wales	-0.0674681	0.1320142	0.1117294
	(0.1164369)	(0.1938483)	(0.1662305)
Á Scotland	-0.023594	-0.1380944	-0.2185625
	(0.1020282)	(0.2157518)	(0.154184)
Á Northern Ireland	0.4397078**	-0.2410537	0.1077516
	(0.1842108)	(0.5185894)	(0.3672591)
Year: (Base level: 2009)			
Á 2010	0.0035354	0.0017448	-0.0857252***
	(0.0117548)	(0.0225296)	(0.0188819)
Á 2011	0.0177323	-0.0560215	-0.2370386***
	(0.0202724)	(0.0389735)	(0.0322372)
Á 2012	-0.0267996	-0.0326802	-0.3443735***
	(0.0292799)	(0.0568134)	(0.0464237)
Á 2013	-0.0208297	-0.0353069	-0.3844392***
	(0.0383399)	(0.0746698)	(0.0607903)
Á 2014	0.0134524	0.061815	-0.2790138***
	(0.0476628)	(0.0928151)	(0.0755345)

Á 2015	-0.1315116**	0.0946648	-0.2926333***
	(0.0569538)	(0.111017)	(0.0900893)

Observations: 123,039. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table A8: The effects of commuting time across transport modes with income interaction terms (sample without London)

Variable	General health	Job satisfaction	Life satisfaction
Commuting time for transport modes:			
Á Private modes	-0.000637**	0.0004478	-0.0004234
	(0.0002642)	(0.0005004)	(0.0004839)
Á Public modes	-0.0006655**	-0.00097*	-0.0006898
	(0.0002816)	(0.0005246)	(0.0004605)
Á Cycle	-0.0002212	-0.0015637	-0.0003711
	(0.0014521)	(0.0027602)	(0.0023043)
Á Walk	0.0000452	-0.0022719	-0.000251
	(0.0009364)	(0.0017248)	(0.0015078)
Monthly net personal income (divided by 10,000)	0.0455068	0.3007232***	0.1203301*
	(0.0373191)	(0.0638232)	(0.0632132)
Private mode*Personal income	0.0004633	-0.0019136	0.0006991
	(0.0008807)	(0.0015987)	(0.001874)
Public mode*Personal income	-0.0003052	0.000051	-0.0002495
	(0.0007115)	(0.0010824)	(0.0010666)
Cycle*Personal income	0.0070562	0.0005589	0.0108466
	(0.0062045)	(0.0119123)	(0.008138)
Walk*Personal income	-0.0049115	0.0088689	0.0079696
	(0.0053783)	(0.0092551)	(0.0076016)
Age	0.0351032***	-0.0555321**	0.0123917
	(0.011571)	(0.0222969)	(0.0184689)
Age squared (divided by 100)	-0.0382616***	0.0267046**	0.0305235***
	(0.0059454)	(0.0110596)	(0.0097569)
Number of own children in household	-0.0196923***	-0.0259707**	0.0145434
	(0.0073631)	(0.0132008)	(0.0115755)
Gender (Female) (Base level: Male)	(omitted)	(omitted)	(omitted)
Whether living in a rural area (Base level: Urban area)	0.0003231	-0.0184297	0.0548366
	(0.021816)	(0.042559)	(0.0354798)
Ethnicity: (Base level: White)			
Á Mixed	(omitted)	(omitted)	(omitted)

Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base level: Married)			
Á Single	0.0328706**	0.0188278	-0.0186245
	(0.0165906)	(0.0315703)	(0.0275048)
Á Separated	0.0020807	0.0029213	-0.1974468***
	(0.0269712)	(0.0485734)	(0.0507627)
Á Divorced	0.026491	-0.0835704*	-0.0576162
	(0.0229977)	(0.0433202)	(0.0405662)
Á Widowed	0.0672988	-0.1138965	-0.300525***
	(0.0554591)	(0.09059)	(0.1109172)
Education qualification: (Base level: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0158285	-0.1620229*	-0.0270951
	(0.045119)	(0.0867874)	(0.0773351)
Á First degree or equivalent	0.0020083	-0.101386	0.0076822
	(0.0346953)	(0.0638895)	(0.0575154)
Á A Levels	-0.0769073**	-0.1046718*	0.0021817
	(0.0325451)	(0.0604372)	(0.0557835)
Á None of the above	0.0283888	-0.0041732	0.2341151**
	(0.0567318)	(0.1149685)	(0.110099)
Social class: (Base level: Routine and manual occupations)			
Á Higher managerial, administrative and professional	-0.0080978	0.1177917***	-0.0145236
	(0.0151379)	(0.0325101)	(0.0247278)
Á Intermediate occupations	-0.0061786	0.0775214**	0.0008355
	(0.0167032)	(0.0363317)	(0.0285287)
Employment type (Employee) (Base level: Self-employed)	0.0050229	-0.3742645***	-0.0250812
	(0.0226136)	(0.0471118)	(0.0387114)
Region: (Base level: North East)			
Á North West	-0.1688729	0.1403583	-0.3381402*
	(0.133956)	(0.2170602)	(0.2020877)
Á Yorkshire and the Humber	-0.0946775	-0.0101041	-0.2034239

	(0.1369681)	(0.2221927)	(0.1943015)
Á East Midlands	-0.1114722	0.154222	-0.1474086
	(0.1433015)	(0.2301757)	(0.2212257)
Á West Midlands	-0.0666622	0.2829018	-0.2157239
	(0.1417116)	(0.2319827)	(0.2195014)
Á East of England	-0.0800889	0.0646314	-0.243424
	(0.1471243)	(0.242943)	(0.2241738)
Á South East	-0.0974004	0.2269101	-0.0476557
	(0.1433044)	(0.2350112)	(0.2116583)
Á South West	-0.1772971	0.3014199	-0.1535031
	(0.1480742)	(0.2531471)	(0.2229911)
Á Wales	-0.0833688	0.2476464	-0.0631335
	(0.1892091)	(0.2593436)	(0.2452079)
Á Scotland	-0.0158002	-0.120389	-0.3726218
	(0.1614164)	(0.2811576)	(0.2402496)
Á Northern Ireland	0.3101643	-0.5475522	-0.4127176
	(0.2385236)	(0.6226715)	(0.3377877)
Year: (Base level: 2009)			
Á 2010	0.0037163	-0.0069112	-0.0856221***
	(0.0129686)	(0.0245794)	(0.0207415)
Á 2011	0.016602	-0.0558061	-0.2295803***
	(0.0227118)	(0.0431183)	(0.0359056)
Á 2012	-0.0265679	-0.0225016	-0.3393363***
	(0.0329241)	(0.0629808)	(0.0519452)
Á 2013	-0.0231314	-0.0156743	-0.3826026***
	(0.0432111)	(0.0829546)	(0.0682377)
Á 2014	0.0073644	0.0882906	-0.2800653***
	(0.0537711)	(0.1032076)	(0.0849314)
Á 2015	-0.1428019**	0.1315431	-0.2939982***
	(0.0643387)	(0.1235901)	(0.1013608)

Observations: 107,861. *p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Appendix 2

This appendix presents the first stage results of the corresponding relevance tests from Table 5.1 in Section 5.4. Tables B1, B2, B3 and B4 report the first stage regression estimations regressing each endogenous variable from the models of health, job satisfaction, life satisfaction and active commute duration, respectively, on their instrumental variables.

Table B1: First stage result for dependent variable Health

	Job satisfaction	Life satisfaction	Active commute duration
Job satisfaction ρ	-0.0940068***	0.0228734***	0.0063062
	(0.0052812)	(0.0047448)	(0.02259)
Life satisfaction ρ	0.0130008***	-0.1646526***	0.0378431*
	(0.004622)	(0.0055173)	(0.0206382)
Month of interview	-0.0026189	-0.0045616**	0.0036316
	(0.0021934)	(0.0021859)	(0.0101086)
Caring hours	0.0135369	-0.0235156***	-0.0246363
	(0.0083759)	(0.0089498)	(0.0311045)
Company size	0.0043746	0.0094417	-0.00000791
	(0.0077202)	(0.0058675)	(0.0351146)
Housing tenure	-0.0099801	-0.0590785**	-0.8757119***
	(0.0295451)	(0.0277226)	(0.16716)
Age	-0.0542171	0.0008971	-0.0532709
	(0.0345223)	(0.0213108)	(0.1029375)
Age squared (divided by 100)	0.0261445*	0.0317835**	0.0155733
	(0.0157325)	(0.0147268)	(0.0739698)
Personal income (divided by 100)	0.0022554***	0.001702***	-0.0049915*
	(0.0006022)	(0.0005975)	(0.0027795)
Number of own children	-0.0325662*	-0.0066885	-0.0433674
	(0.0172086)	(0.0159892)	(0.0844063)
Gender (Base: Male)	(omitted)	(omitted)	(omitted)
Living in a rural area (Base: Urban)	-0.0225694	0.103712**	-0.6859376**
	(0.0587523)	(0.0516128)	(0.2811921)
Ethnicity: (Base: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base: Married)			

Á Single	0.0205893	-0.0371609	0.0140038
	(0.0385701)	(0.0366561)	(0.1817763)
Á Separated	0.0091351	-0.2869646***	0.4142009
	(0.0632414)	(0.0688316)	(0.2996132)
Á Divorced	-0.0595289	-0.1269537**	0.1704196
	(0.0551774)	(0.0541401)	(0.2263721)
Á Widowed	-0.0213428	-0.43773***	0.0199381
	(0.1302091)	(0.1215173)	(0.337708)
Education qualification: (Base: GCSE)			
Á Higher degrees, e.g. PhD, Masters	-0.0865848	0.0630725	0.1732965
	(0.1205067)	(0.1266622)	(0.4613141)
Á First degree or equivalent	-0.0472634	0.0579167	-0.0163368
	(0.0987027)	(0.0945563)	(0.3692996)
Á A Levels	0.0091935	0.0513021	0.1718416
	(0.1092377)	(0.1085054)	(0.4648157)
Á None of the above	0.1210417	0.0126069	-0.0854472
	(0.1597146)	(0.1798791)	(0.4326067)
Social class: (Base: Routine, manual)			
Á Higher managerial	0.1399708***	-0.0506515	-0.6968984***
	(0.0445654)	(0.0344802)	(0.1961566)
Á Intermediate occupations	0.1229913**	0.0125025	-0.3670812*
	(0.0477993)	(0.0391294)	(0.206934)
Employment type (Base: Self-employed)	-0.458275***	-0.0443153	0.4175441
	(0.0664591)	(0.0565751)	(0.2780319)
Region: (Base: London)			
Á North East	0.0415985	0.1863656	-1.183274
	(0.2994268)	(0.2785963)	(1.956052)
Á North West	0.3720105*	-0.1208427	-3.012801**
	(0.2128851)	(0.1803939)	(1.274038)
Á Yorkshire and the Humber	-0.084893	0.0996923	-2.793432**
	(0.2309201)	(0.187539)	(1.265364)
Á East Midlands	0.1054641	-0.0305584	-3.138576***

	(0.1936635)	(0.1705871)	(1.161411)
Á West Midlands	0.3934575*	0.07824	-1.553466
	(0.2124251)	(0.1807431)	(1.363794)
Á East of England	0.00578	0.0641889	-2.767754*
	(0.1513589)	(0.1268774)	(1.502939)
Á South East	0.1913271	0.0719299	-1.330044
	(0.1493553)	(0.1227997)	(0.9531577)
Á South West	0.1760742	0.1978779	-1.137921
	(0.2150339)	(0.1576945)	(1.266039)
Á Wales	0.411335	0.1780658	-1.627924
	(0.275188)	(0.3073871)	(1.901452)
Á Scotland	-0.1680781	-0.0093965	-5.986128**
	(0.320055)	(0.2471305)	(2.414707)
Á Northern Ireland	0.3426807	-0.0294996	-3.361528**
	(0.9064173)	(0.6977687)	(1.690466)
Year: (Base level: 2009)			
Á 2010	-0.1207719	0.1422038	-0.0933719
	(0.1591736)	(0.0913799)	(0.4306558)
Á 2011	-0.1928231	0.0081202	-0.1827646
	(0.1279952)	(0.0738734)	(0.3484711)
Á 2012	-0.1660885	-0.1052414*	-0.301267
	(0.0962407)	(0.0562268)	(0.265171)
Á 2013	-0.1594905	-0.1664938***	-0.057184
	(0.0653144)	(0.0394707)	(0.1842422)
Á 2014	-0.0476606**	-0.0254584	-0.2580975**
	(0.0345309)	(0.0224961)	(0.1058759)
Á 2015	(omitted)	(omitted)	(omitted)
	F (6, 17697) = 53.79	F (6, 17697) = 151.31	F (6, 17697) = 5.46
	Prob > F = 0.000	Prob > F = 0.000	Prob > F = 0.000

*p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table B2: First stage result for dependent variable Job satisfaction

	Health	Life satisfaction	Active commute duration
Ў(Å Á Ì Ô È	0.4917863***	-0.0006262	-0.0086053
	(0.0014414)	(0.003112)	(0.0143237)
ЎLife satisfaction	0.0015406	0.5029077***	0.0015214
	(0.000996)	(0.0015721)	(0.0079007)
ЎActive commute duration	-0.0000222	0.0005197	0.4943055***
	(0.0002453)	(0.0004013)	(0.0062974)
ЎMonth of interview	0.0000148	-0.0010549	-0.0038401
	(0.0004809)	(0.0008409)	(0.0039183)
ЎCaring hours	0.0019219	0.003316	-0.0188907
	(0.0019762)	(0.0035216)	(0.013842)
Age	0.0199615*	-0.0202305	-0.0882884
	(0.0119588)	(0.014969)	(0.0843761)
Age squared (divided by 100)	-0.0347256***	0.0347624***	0.0563056
	(0.0070531)	(0.0114897)	(0.0663732)
Personal income (divided by 100)	0.0002392	0.0010234***	-0.0053807**
	(0.000239)	(0.0004116)	(0.0024345)
Number of own children	-0.0234209***	0.0128309	-0.0009215
	(0.0074895)	(0.0119278)	(0.0682011)
Gender (Base: Male)	(omitted)	(omitted)	(omitted)
Living in a rural area (Base: Urban)	-0.0053403	0.0800444**	-0.4304536**
	(0.0228938)	(0.0355973)	(0.19752)
Ethnicity: (Base: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)
Marital status: (Base: Married)			
Á Single	0.0091067	-0.0646709**	0.1713308
	(0.0161946)	(0.0263793)	(0.1447522)

Á Separated	-0.0206094	-0.230385***	0.4724847*
	(0.025208)	(0.0493084)	(0.2470444)
Á Divorced	-0.0025723	-0.1252377***	0.1401369
	(0.0229869)	(0.0389624)	(0.2126388)
Á Widowed	0.0225997	-0.3383404***	0.0983684
	(0.0554151)	(0.09444)	(0.3196845)
Education qualification: (Base: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.033712	-0.0861869	0.2885909
	(0.0542116)	(0.0903071)	(0.3884651)
Á First degree or equivalent	0.0129775	-0.0056599	-0.2163099
	(0.0410644)	(0.0688233)	(0.3171507)
Á A Levels	-0.0883497*	-0.0388071	0.207373
	(0.046225)	(0.0757099)	(0.3926838)
Á None of the above	0.0189098	0.0974297	0.2886186
	(0.0612924)	(0.1217185)	(0.634373)
Social class: (Base: Routine, manual)			
Á Higher managerial	-0.0198082	-0.0072127	-0.4070309***
	(0.0153805)	(0.0248213)	(0.1530783)
Á Intermediate occupations	-0.0137556	0.0040202	-0.147085
	(0.0166719)	(0.0281211)	(0.1637093)
Employment type (Base: Self-employed)	0.023116	0.0091148	0.3335215
	(0.0226851)	(0.0388103)	(0.1954541)
Region: (Base: London)			
Á North East	0.0060974	0.174625	0.2201241
	(0.1433938)	(0.1872329)	(1.341858)
Á North West	-0.1084757	-0.0093519	-1.524245
	(0.0817213)	(0.1229916)	(0.9483914)
Á Yorkshire and the Humber	-0.0911196	-0.0712397	-1.711449*
	(0.0861385)	(0.1346608)	(1.016359)
Á East Midlands	-0.1742311**	0.0164413	-2.026787**
	(0.071634)	(0.1169854)	(0.9608335)
Á West Midlands	-0.1278832	0.1320817	-0.4265035

	(0.0830819)	(0.1146692)	(1.288588)
Á East of England	-0.1565319**	0.0031257	-1.877637
	(0.0631225)	(0.084113)	(1.176566)
Á South East	-0.1523721***	0.1528819*	-0.7417869
	(0.0574021)	(0.0898933)	(0.7906421)
Á South West	-0.2417341***	0.1399003	0.1459266
	(0.0817155)	(0.1207904)	(1.137506)
Á Wales	-0.1106696	0.1690801	-1.088789
	(0.1370216)	(0.2141845)	(1.237869)
Á Scotland	-0.0534259	0.0011665	-3.964552**
	(0.1103927)	(0.1878937)	(1.693132)
Á Northern Ireland	0.4055885**	0.1799551	-6.601849***
	(0.197901)	(0.5455009)	(2.317309)
Year: (Base level: 2009)			
Á 2010	0.0024778	0.0819918	-0.0356312
	(0.0524953)	(0.0593831)	(0.3117148)
Á 2011	0.0223022	0.0006132	0.0501154
	(0.0421824)	(0.0479645)	(0.2525987)
Á 2012	0.019405	-0.0900644**	-0.0878404
	(0.0318701)	(0.0367387)	(0.1927095)
Á 2013	0.0116329	-0.1509726***	-0.0203068
	(0.0218319)	(0.0259518)	(0.1344693)
Á 2014	0.042951***	-0.0830804***	-0.0207287
	(0.0113582)	(0.0142789)	(0.0722815)
Á 2015	(omitted)	(omitted)	(omitted)
	F (5, 17765) = 23449.05	F (5, 17765) = 20655.97	F (5, 17765) = 1247.07
	Prob > F = 0.000	Prob > F = 0.000	Prob > F = 0.000

*p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table B3: First stage result for dependent variable Life satisfaction

	Health	Job satisfaction	Active commute duration
ЎHealth	0.4918276***	0.002339	-0.0078775
	(0.0014714)	(0.0032808)	(0.0145265)
ЎJob satisfaction	0.0009093	0.4919864***	-0.0009711
	(0.0010535)	(0.0018611)	(0.0083695)
ЎActive commute duration	-0.0000822	0.0002873	0.4949724***
	(0.0002508)	(0.0004698)	(0.0065068)
ЎMonth of interview	0.0001078	0.0002223	-0.0032252
	(0.0004891)	(0.0008486)	(0.0039409)
ЎCaring hours	0.0025451	-0.0002898	-0.0151336
	(0.0020169)	(0.0036625)	(0.0141528)
ЎCompany size	0.0005788	0.0086533**	-0.0168568
	(0.0017525)	(0.0034998)	(0.0176281)
ЎHousing tenure	-0.0030922	-0.0205119	0.0052097
	(0.0081897)	(0.0153873)	(0.0734705)
Age	0.0318341***	-0.0073694	-0.1518903
	(0.0110903)	(0.0209857)	(0.1013009)
Age squared (divided by 100)	-0.0340633**	0.020985	0.0711711
	(0.0072129)	(0.0128878)	(0.0669052)
Personal income (divided by 100)	0.0002469	0.0015711***	-0.0046813*
	(0.0002399)	(0.0004308)	(0.0024542)
Number of own children	-0.0236601***	-0.0124788	-0.0065989
	(0.0075792)	(0.0135859)	(0.069686)
Gender (Base: Male)	(omitted)	(omitted)	(omitted)
Living in a rural area (Base: Urban)	-0.0008861	0.0032784	-0.452571**
	(0.0231794)	(0.0452047)	(0.2049591)
Ethnicity: (Base: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)

Marital status: (Base: Married)			
Á Single	0.0087014	0.0088299	0.182663
	(0.0165669)	(0.030392)	(0.1476816)
Á Separated	-0.0274366	0.0005932	0.4574799*
	(0.0257886)	(0.047768)	(0.2556173)
Á Divorced	0.0017016	-0.0623752	0.1299878
	(0.0229052)	(0.0424504)	(0.2190462)
Á Widowed	0.0195318	0.0056085	0.097208
	(0.0576352)	(0.102378)	(0.3354714)
Education qualification: (Base: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0225407	-0.0794935	0.2758849
	(0.0555983)	(0.0981773)	(0.3981989)
Á First degree or equivalent	0.0101004	0.0036461	-0.2227828
	(0.0421792)	(0.0775719)	(0.3260141)
Á A Levels	-0.1032709**	0.0508361	0.1126209
	(0.0483082)	(0.0848882)	(0.3980816)
Á None of the above	0.0180073	0.1342636	0.2118133
	(0.0632458)	(0.124945)	(0.6314304)
Social class: (Base: Routine, manual)			
Á Higher managerial	-0.0200935	0.1228345***	-0.398043**
	(0.0155827)	(0.0321451)	(0.1572777)
Á Intermediate occupations	-0.0180082	0.0799537**	-0.1496869
	(0.0169473)	(0.0346823)	(0.1689435)
Employment type (Base: Self-employed)	0.0117549	-0.2935721***	0.3848462*
	(0.0237092)	(0.0469873)	(0.2035635)
Region: (Base: London)			
Á North East	-0.0549994	0.3500004	0.3650033
	(0.1488061)	(0.2371058)	(1.407695)
Á North West	-0.1412332*	0.4836874***	-1.575923
	(0.0851827)	(0.1548933)	(0.9950894)
Á Yorkshire and the Humber	-0.1175376	-0.0078965	-1.571048
	(0.0892514)	(0.1668858)	(1.066311)

Á East Midlands	-0.2161022***	0.1521642	-1.741677*
	(0.0750308)	(0.140447)	(0.9948942)
Á West Midlands	-0.1666455*	0.4322452***	-0.0080088
	(0.0864089)	(0.1631144)	(1.312884)
Á East of England	-0.1633479**	0.0108617	-2.105417*
	(0.0660293)	(0.1226672)	(1.236375)
Á South East	-0.1725898***	0.0768527	-0.916033
	(0.0604272)	(0.1079675)	(0.826147)
Á South West	-0.2915449***	0.0466308	0.6544609
	(0.0871925)	(0.1595856)	(1.18852)
Á Wales	-0.1990253	0.3912841**	-0.6573478
	(0.1415364)	(0.1818003)	(1.34795)
Á Scotland	-0.1021759	-0.1717321	-4.008567**
	(0.1144531)	(0.2562731)	(1.802665)
Á Northern Ireland	0.4777803**	0.4608734	-5.469769*
	(0.2029464)	(0.5695894)	(3.15489)
Year: (Base level: 2009)			
Á 2010	0.0667677	0.1074321	-0.284694
	(0.0468474)	(0.0901443)	(0.4135723)
Á 2011	0.0753553**	0.0220354	-0.1423058
	(0.0376703)	(0.0726327)	(0.3341296)
Á 2012	0.058626**	-0.0297603	-0.2344324
	(0.0285705)	(0.0548739)	(0.252978)
Á 2013	0.0372591*	-0.0598492	-0.1159645
	(0.0197459)	(0.0373939)	(0.1740571)
Á 2014	0.0567948***	-0.0428211**	-0.071974
	(0.0104586)	(0.0194922)	(0.0912688)
Á 2015	(omitted)	(omitted)	(omitted)
	F (7, 17344) = 16059.84	F (7, 17344) = 10046.69	F (7, 17344) = 849.10
	Prob > F = 0.000	Prob > F = 0.000	Prob > F = 0.000

*p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.

Table B4: First stage result for dependent variable Active commute duration

	Health	Job satisfaction	Life satisfaction
Health ρ	-0.1053175***	0.0104156	0.0276312***
	(0.0049659)	(0.0083777)	(0.0081802)
Job satisfaction ρ	0.0021991	-0.0949315***	0.0226037***
	(0.0025941)	(0.0052502)	(0.0047339)
Life satisfaction ρ	0.0037948	0.0140618***	-0.1682363***
	(0.0026346)	(0.0046441)	(0.0054804)
Month of interview	0.0015742	-0.0026508	-0.005282
	(0.0019188)	(0.003456)	(0.0034156)
Caring hours	-0.0053004	0.0157924	-0.0302254**
	(0.0081446)	(0.0131677)	(0.013493)
ЎMonth of interview	-0.000234	0.0005146	0.0005813
	(0.0012651)	(0.0022198)	(0.0022357)
ЎCaring hours	0.0040454	-0.0033229	0.0075782
	(0.0051332)	(0.008755)	(0.008753)
Age	0.02547	-0.0536163	0.0042565
	(0.0155053)	(0.032932)	(0.0215944)
Age squared (divided by 100)	-0.0361619***	0.0237058	0.0312364**
	(0.0086465)	(0.0156282)	(0.0147574)
Personal income (divided by 100)	0.0002381	0.0023038***	0.001539***
	(0.000355)	(0.0005994)	(0.0005911)
Number of own children	-0.0327893***	-0.0291092*	-0.0073734
	(0.009705)	(0.0171018)	(0.0158497)
Gender (Base: Male)	(omitted)	(omitted)	(omitted)
Living in a rural area (Base: Urban)	-0.0050059	-0.0155757	0.101041**
	(0.0288939)	(0.0583997)	(0.0505007)
Ethnicity: (Base: White)			
Á Mixed	(omitted)	(omitted)	(omitted)
Á Asian	(omitted)	(omitted)	(omitted)
Á Black	(omitted)	(omitted)	(omitted)
Á Other ethnic groups	(omitted)	(omitted)	(omitted)

Marital status: (Base: Married)			
Á Single	0.0200391	0.0187134	-0.0380888
	(0.0211002)	(0.0381575)	(0.036477)
Á Separated	-0.0167263	0.0028429	-0.2690094***
	(0.033408)	(0.0628443)	(0.0677139)
Á Divorced	0.0148009	-0.0590174	-0.1129496**
	(0.0293488)	(0.0551442)	(0.0534174)
Á Widowed	0.0277066	-0.0542819	-0.5151991***
	(0.0674476)	(0.1334156)	(0.1261778)
Education qualification: (Base: GCSE)			
Á Higher degrees, e.g. PhD, Masters	0.0436308	-0.0618002	0.0550985
	(0.0718288)	(0.1186738)	(0.1271595)
Á First degree or equivalent	0.002635	-0.0354998	0.0640389
	(0.0551149)	(0.0958273)	(0.0935823)
Á A Levels	-0.0711287	0.0451326	0.079381
	(0.0587024)	(0.1068078)	(0.1065789)
Á None of the above	-0.0087789	0.0531163	0.0116922
	(0.0822123)	(0.1589824)	(0.1780857)
Social class: (Base: Routine, manual)			
Á Higher managerial	-0.0252467	0.1478915***	-0.0401902
	(0.0202917)	(0.0440829)	(0.0340383)
Á Intermediate occupations	-0.0238753	0.1127447**	0.0113303
	(0.0220341)	(0.0473545)	(0.0384985)
Employment type (Base: Self-employed)	0.0062534	-0.4418643***	-0.0071448
	(0.0298172)	(0.0608353)	(0.0518293)
Region: (Base: London)			
Á North East	0.1304779	-0.0154	0.1627663
	(0.149516)	(0.2997573)	(0.2757319)
Á North West	-0.0694262	0.2458813	-0.1381639
	(0.1105471)	(0.210147)	(0.1723198)
Á Yorkshire and the Humber	-0.0767772	-0.1338743	0.0986263
	(0.1118585)	(0.2303545)	(0.1858158)

Á East Midlands	-0.1301338	0.1055816	-0.0670243
	(0.0949562)	(0.1914502)	(0.1649842)
Á West Midlands	-0.1187931	0.3891012*	0.0633711
	(0.1053797)	(0.2113897)	(0.1759839)
Á East of England	-0.0962652	-0.0333388	0.026652
	(0.0914057)	(0.147937)	(0.1243832)
Á South East	-0.1653243**	0.1724513	0.0783154
	(0.0759907)	(0.1475247)	(0.1203048)
Á South West	-0.2280042**	0.1949266	0.1726212
	(0.1039025)	(0.2140473)	(0.1573772)
Á Wales	-0.1175213	0.4726743	0.1605748
	(0.1787501)	(0.2872468)	(0.2965172)
Á Scotland	-0.0019395	-0.1713325	0.0397172
	(0.1380735)	(0.3116364)	(0.2631929)
Á Northern Ireland	0.3579409	0.2179808	-0.7331964
	(0.2573844)	(0.7562788)	(0.9086396)
Year: (Base level: 2009)			
Á 2010	0.1037066	-0.1233007	0.1616956*
	(0.0694789)	(0.1510571)	(0.0919061)
Á 2011	0.1178921**	-0.1960884	0.0236353
	(0.0557673)	(0.1215165)	(0.0743162)
Á 2012	0.085369**	-0.1650952*	-0.0915034
	(0.0421597)	(0.0913981)	(0.0565746)
Á 2013	0.092295***	-0.1571831**	-0.1578067***
	(0.028935)	(0.0620945)	(0.0396456)
Á 2014	0.1338486***	-0.0479508	-0.0209396
	(0.0155926)	(0.0329214)	(0.0225406)
Á 2015	(omitted)	(omitted)	(omitted)
	F (7, 17809) = 64.51	F (7, 17809) = 47.62	F (7, 17809) = 135.68
	Prob > F = 0.000	Prob > F = 0.000	Prob > F = 0.000

*p<0.1; **p<0.05; ***p<0.01. Panel-robust standard errors in parentheses.