LONG ROAD TO RUIN?

ESSAYS EXAMINING THE EFFECTS OF COMMUTING ON HEALTH AND WELL-BEING

Inauguraldissertation zur Erlangung des Doktorgrades des Fachbereichs IV

– Wirtschafts- und Sozialwissenschaften, Mathematik und Informatikwissenschaften –

der Universität Trier

vorgelegt von

Olga Lorenz

Trier, April 2017

Tag der Abgabe: 27. April 2017
Tag der mündlichen Prüfung: 19. Juli 2017

Promotionsausschuss:

Vorsitzender: J.-Professor Dr. Lars Hornuf
1. Gutachter: Professor Dr. Laszlo Goerke
2. Gutachter: Professor Dr. Normann Lorenz

Abstract

Flexibility and spatial mobility of labour are central characteristics of modern societies which contribute not only to higher overall economic growth but also to a reduction of interregional employment disparities. For these reasons, there is the political will in many countries to expand labour market areas, resulting especially in an overall increase in commuting. The picture of the various, unintended long-term consequences of commuting on individuals is, however, relatively unclear. Therefore, in recent years, the journey to work has gained high attention especially in the study of health and well-being. Empirical analyses based on longitudinal as well as European data on how commuting may affect health and well-being are nevertheless rare. The principle aim of this thesis is, thus, to address this question with regard to Germany using data from the Socio-Economic Panel.

Chapter 2 empirically investigates the causal impact of commuting on absence from work due to sickness-related reasons. Whereas an exogenous change in commuting distance does not affect the number of absence days of those individuals who commute short distances to work, it increases the number of absence days of those employees who commute middle (25 – 49 kilometres) or long distances (50 kilometres and more). Moreover, our results highlight that commuting may deteriorate an individual's health. However, this effect is not sufficient to explain the observed impact of commuting on absence from work.

Chapter 3 explores the relationship between commuting distance and height-adjusted weight and sheds some light on the mechanisms through which commuting might affect individual body weight. We find no evidence that commuting leads to excess weight. Compensating health behaviour of commuters, especially healthy dietary habits, could explain the non-relationship of commuting and height-adjusted weight.

In Chapter 4, a multivariate probit approach is used to estimate recursive systems of equations for commuting and health-related behaviours. Controlling for potential endogeneity of commuting, the results show that long distance commutes significantly decrease the propensity to engage in health-related activities. Furthermore, unobservable individual heterogeneity can influence both the decision to commute and healthy lifestyle choices.

Chapter 5 investigates the relationship between commuting and several cognitive and affective components of subjective well-being. The results suggest that commuting is related to lower levels of satisfaction with family life and leisure time which can largely be ascribed to changes in daily time use patterns, influenced by the work commute.

Deutsche Kurzfassung (German Abstract)

Flexibilität und regionale Mobilität von Arbeitskräften gelten heutzutage als zentrale Charakteristika der modernen Gesellschaft, die nicht nur zu einem wirtschaftlichen Wachstum sondern auch zum Abbau von Disparitäten zwischen regionalen Arbeitsmärkten beitragen können. Vor diesem Hintergrund versuchen politische Entscheidungsträger, die Mobilität von Arbeitskräften zu fördern, was in den letzten Jahrzehnten vor allem zu einer Intensivierung der Pendelmobilität geführt hat. Dabei rückt die Frage nach den möglichen, nicht intendierten Folgen berufsbedingter räumlicher Mobilität – insbesondere für das subjektive Wohlbefinden und die Gesundheit – immer mehr in den Mittelpunkt gesellschaftlicher Diskussionen sowie der Arbeitsmarkt- und Gesundheitsforschung. Während der Zusammenhang zwischen der berufsbedingten Mobilität und des Gesundheitszustands im US amerikanischen Kontext mit Querschnittsanalysen vergleichsweise häufig untersucht wurde, ist ein entsprechender Forschungsstand in Deutschland bislang kaum vorhanden. Hier setzt die vorliegende Dissertation an. Ziel ist es, basierend auf für Deutschland repräsentativen Längsschnittdaten des Sozio-ökonomischen Panels, den Zusammenhang zwischen der Pendelentfernung zum Arbeitsplatz und verschiedenen Indikatoren des Gesundheitszustandes und des subjektiven Wohlbefindens zu untersuchen.

In Kapitel 2 wird die Beziehung zwischen der Pendeldistanz zum Arbeitsplatz und krankheitsbedingten Fehlzeiten empirisch analysiert, indem eine exogen bedingte Veränderung der Distanz genutzt wird. Die Ergebnisse zeigen, dass insbesondere längere Pendelentfernungen (25 Kilometer und mehr), einen signifikanten Einfluss auf die Anzahl an Fehltagen ausüben. Obwohl das Pendeln zu einer schlechteren Gesundheit beiträgt, kann der Effekt der Pendeldistanz auf krankheitsbedingte Abwesenheit nicht vollständig durch den Gesundheitszustand erklärt werden.

In Kapitel 3 wird das Verhältnis zwischen der Pendelentfernung und dem Körpergewicht unter Berücksichtigung zahlreicher bisher in der Forschung vernachlässigter Aspekte untersucht. Darüber hinaus wird analysiert, welche Verhaltensweisen einen Zusammenhang zwischen Pendeln und Übergewicht fördern bzw. verhindern. Die Untersuchung führt zu Zweifeln an der in der Literatur vorherrschenden Vorstellung, dass ein langer Arbeitsweg die Entstehung von Übergewicht begünstigt. Vielmehr deuten die Resultate auf gesündere

Ernährungsgewohnheiten von Pendlern hin, welche der Entwicklung von Übergewicht entgegenwirken können.

Kapitel 4 betrachtet die Interdependenzen zwischen der Entfernung zum Arbeitsplatz und verschiedenen, gesundheitsrelevanten Verhaltensweisen (z.B. körperliche Aktivität, Nikotingenuss, Alkoholkonsum). Die auf einer Kausalanalyse mit Strukturgleichungs-modellen basierenden Ergebnisse zeigen, dass insbesondere Fernpendler einen insgesamt „ungesünderen" Lebensstil aufweisen. Jedoch dokumentieren die Analysen ebenfalls, dass nichtbeobachtbare Heterogenitäten existieren, die sich sowohl auf die Entscheidung zum Pendeln als auch auf eine gesunde Lebensführung positiv auswirken können.

Kapitel 5 setzt sich mit der Frage auseinander, ob Pendeln verschiedene affektive und kognitive Komponenten des subjektiven Wohlbefindens determiniert. Die Ergebnisse zeigen, dass insbesondere Erwerbstätige mit einem langen Arbeitsweg eine signifikant geringere Zufriedenheit mit ihrem Familienleben und ihrer Freizeit aufweisen. Zugleich bestätigen kausale Mediationsanalysen, dass die Unzufriedenheit mit diesen Lebensbereichen aufgrund des durch das Pendeln hervorgerufenen Zeitmangels entsteht, da die zeitlichen Ressourcen nicht mehr in genügendem Maße für andere Lebensbereiche, wie Freizeit und Familie, zur Verfügung stehen.

To the loving memory of my father

Acknowledgments

I have been on the road for some years now, working on my thesis. There are many people who helped me through the different stages of this long journey and I would like to take this opportunity to thank those who made this thesis possible.

First of all, I would like to express my greatest thanks to my supervisor, Professor Dr. Laszlo Goerke, for all his unwavering support, critical remarks, and encouragement. I greatly benefited from his experience and expertise. I am also indebted to my second supervisor, Professor Dr. Normann Lorenz, for his helpful suggestions concerning the interpretation and analysis of the data. Additionally, I owe many thanks to my colleagues and former colleagues for numerous talks, helpful feedback, an inspiring academic environment and a host of hilarious evenings. My appreciation also goes to my legal colleagues who have made the whole PhD experience enjoyable. Daniel, Mario, Marco, Adrian, Gabriel, Konstantin, Maike, Natalia, Anna and all the others I did not mention – Thank you all for the great time and your friendship or simply for being there! I really have derived enormous personal and scientific benefits from my time spent at the Institute for Labour Law and Industrial Relations in the European Union in Trier.

Finally, I wish to express sincere gratitude to my family. I am incredibly grateful to my parents, Maria and Anatoli, and to my sister, Vera, for their unconditional support – not just during the preparation of this thesis but also throughout my entire education and life. Their loving kind words and their caring hugs always gave me strength to continue my work in spite of many setbacks. I am also grateful to Marius for standing behind me, especially over the past weeks and months and for still believing in me. Thanks for keeping me grounded during all this time. Vera, Marius, Mom and Dad: Thank you for everything that you have done for me, for your patience, wisdom, encouragement and unconditional confidence. Words can't describe my gratitude. There is no better family.

Mama und Papa, seit ich denken kann, habt ihr mich gefördert, mich gelehrt meinen Träumen zu folgen und mir unbezahlbare Ratschläge gegeben. Ich danke euch von ganzem Herzen für eure bedingungslose Liebe und Unterstützung, die ein großes Geschenk für mich sind.

Trier, March 2017 *Olga Lorenz*

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Flexibility and geographic labour mobility are decisive factors for success in the European labour market and thus the foundation for an economically strong, wealthy and stable Europe (Eichhorst 2013). Geographic labour mobility describes the ability of the workforce to move within and between regions and can be achieved through either migration or commuting.[1] Mobility of labour contributes to higher overall economic growth as well as a reduction of interregional employment disparities since enlarged job regions create more opportunities for work. Economic growth increases if interregional mobility reduces, inter alia, the regional mismatch between labour supply and labour demand, thus leading to higher employment levels. Moreover, geographic mobility may also foster productivity and thus economic growth by improving the average matching quality (e.g., Kim 1989, Bonin 2008). For these reasons, there is the political will in many countries to expand labour market areas, with the specific result of an increase in commuting. This growth of work-related travel is especially accompanied and intensified by a complex set of developments that occurred in the last few decades: Particularly processes such as outsourcing, improvements in transportation and technological progress, decentralisation of economic and residential activities, rise in female labour participation and two-earner households as well as deregulation of the labour market including growth in part-time employment, job insecurity and the growing demands for employee flexibility have combined to create an 'imperative' of high mobility (Viry and Kaufmann 2015). Because most European labour markets are becoming increasingly more flexible, commuting distances as well as the percentage of individuals who need to commute in order to find or keep a job are likely to increase even further in the coming years.

[1] Commuting is a form of work-related circular mobility which occurs repeatedly when individuals are working in a place different from the place of residence. Work-related migration is a form of mobility which occurs when individuals change residential location because of a job offer in another region (Huber and Nowotny 2013).

National registry studies from several European countries indicate that Europeans are travelling more with each passing decade (e.g., Federal Statistical Office 2013, Office Fédéral de la Statistique 2014, Commissariat général au Développement durable 2015, Department for Transport 2016). Although commuting distances and commuting times are correlated, travel increase is mainly observed in the distance travelled, driven by higher travel speeds and the widespread use of personal cars, in turn fostering urban sprawl (e.g., Crozet and Joly 2004, Lyons and Chatterjee 2008, Viry and Kaufmann 2015). In Sweden, the average commuting distance has increased from 10 kilometres in 1970 to 15.6 kilometres in 2005 (Mattisson et al. 2015). In the UK, the average daily one-way commute of a typical worker has increased from 8 miles in 1997 to 9.3 miles in 2011 (Office for National Statistics 2014). In Germany, the average commuting distance has increased from 14 kilometres in 1999 to 17 kilometres in 2009 (Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) 2012). This trend is not unique to Europe. In the US, for example, average commuting distances increased from 8.9 miles in 1983 to 21 miles in 2009 (US Department of Transportation 2016).

International and interregional work-related migration rates, in contrast, have remained fairly constant and rather low, since migration is often perceived as decision full of risks (e.g., Eichengreen 1993, Puga 1999, European Policy Brief 2008, Gruber 2010, Mattisson et al. 2015). Total migration costs include not only the costs to move the household, but also social and psychological costs associated with leaving family and friends behind (e.g., Mills and Hazarika 2001, Clark et al. 2007, Shuai 2012). Commuting, however, can be a mobility strategy to avoid migration and thereby sustain existing social relationships. It can give individuals and families the opportunity to maintain a social network built up during years of living at the same place, which would be lost if they moved (e.g., Fisher and Malmberg 2001). Thus, the decision to commute is strongly linked to residential and job location choices. As argued by Patuelli et al. (2007), commuting is the result of a network economy in which individuals look for earning opportunities outside their place of residence. Thereby, decisions of where to live and where to work, and consequently commuting, might foster individuals' income and career achievements (e.g., Krieger and Fernandez 2006, Russo et al. 2007, Sandow and Westin 2010), lower rents or housing prices (e.g., Renkow and Hoover 2000), pleasant living environments as well as desired housing and neighbourhood characteristics (e.g., Plaut 2006) and an intrinsically or financially rewarding job (e.g., Zax 1991, van Ommeren et al. 2000, So et al. 2001).

Although commuting has its advantages, it also imposes significant costs. The monetary costs of commuting, such as fuel prices, depreciation of the car due to its use or costs for public transit are acknowledged (e.g., van Ommeren and Fosgerau 2009, McArthur et al. 2013). The environmental effects of commuting, such as air pollution, urban sprawl and traffic congestion are also well known (e.g., Tolley 1996, Brueckner 2000, Travisi et al. 2010) as is the detrimental effect of commuting on individuals' social networks (e.g., Cassidy 1992, Green et al. 1999, Besser et al. 2008, Mattisson et al. 2015) as well as family ties (e.g., van der Klis and Mulder 2008, van der Klis and Karsten 2009, Sandow 2014). Regardless of the individuals' motives, commuters must often spend less time socialising with family, missing vital parts of everyday family life. The neglect of family activities has been shown to be associated with children's social and emotional problems (Li and Pollmann-Schult 2016) and higher separation rates among long-distance commuting couples (Sandow 2014). Additionally, lengthy commutes, which leave fewer hours for spare-time activities, also have a direct negative impact on individuals' involvement in community affairs, such as political activism, as well as on social participation and informal social interaction, such as participating in union meetings, attending public meetings or church services (e.g., Putnam 2000, Pocock 2003, Lindström 2006, Mattisson et al. 2015). Besides the out-of-pocket costs, environmental impact and the costs to personal and social relationships, commuting is also found to affect individuals' subjective well-being and health. Analyses dealing with commuting and well-being suggest that commuting is negatively associated with well-being in terms of life satisfaction (e.g., Stutzer and Frey 2008, Hilbrecht et al. 2014, Morris 2015, Nie and Sousa-Poza 2016). Studies addressing the relation between health and commuting indicate that commuting is related to fatigue symptoms (e.g., Kageyama et al. 1998), less nocturnal sleep (e.g., Walsleben et al. 1999) and reduced sleep time in general (e.g., Costal et al. 1988). Moreover, commuting is associated with self-perceived stress (e.g., Schaeffer et al. 1988, Hennessy and Wiesenthal 1999, Wener et al. 2003, Gottholmseder et al. 2009), increased pulse rate and systolic blood pressure (e.g., White and Rotton 1998), musculoskeletal disorders and increased anxiety (e.g., Koslowsky et al. 1995).

The literature relating commuting to health is dominated by empirical studies from social medicine. However, data availability on the relationship between commuting and health is in general rather scarce as it is limited primarily to cross-sections from the United States or northern Europe (especially Sweden and the UK), for which very detailed micro-data on commuting is available.[2] Empirical studies based on German data on how commuting may affect health are rare. As the attitudes towards work, mobility and health are very different between countries, findings relating to the US or Sweden cannot directly be applied to other countries, such as Germany (Giuliano and Dargay 2006, Bassett et al. 2008). Moreover, there are few, if any, longitudinal studies that investigate the long-term effects of commuting on health. Hence, research on this topic is still in its infancy. In contrast to the relatively large number of mainly cross-sectional studies on commuting and health, the relationship between commuting and subjective well-being is more or less unexplored since subjective well-being has usually been assessed by judgements of overall life satisfaction, although subjective well-being covers a wider range of concepts than just life satisfaction. One possible explanation for this apparent reluctance by economists to use subjective well-being as an outcome measure could be the fact that subjective well-being is such a loosely defined term. Its origins lie within psychology and sociology, and it is defined broadly as "people's cognitive and affective evaluations of their lives" (Diener 2000). Nevertheless, subjective well-being is stated to be a suitable proxy for an individual's level of utility and a more representative measure of people's life as a whole (e.g., Kahneman and Krueger 2006, Clark et al. 2008, Oswald and Wu 2010).

For individuals, understanding the factors that impact health and well-being is relevant because health is a key condition for enjoying many pleasures in life. Moreover, health is probably the most fundamental necessity and essential element of quality of life. For various reasons, identifying aspects that influence health is also important from a policy-maker's perspective. First, health is a crucial contributor to economic growth (e.g., Barro 2013). Second, as the growth in health expenditures challenges the functioning of health care systems around the world, knowledge about factors that influence health is indispensable. In almost all developed countries, spending on health care has increased substantially in the last decades (Chernew and Newhouse 2012). In Germany, for example, health care expenditures have increased from 4.8% of the total gross domestic product (GDP) in 1960 to 11.3% in 2014 and, hence, have almost doubled (Zweifel et al. 2009, World Health Organization (WHO) 2014). Third, in recent years, indicators of population health play an important role in the discussion about alternatives and supplements to GDP as a measure for social progress and economic performance (e.g., Stiglitz et al. 2009). Hence, policy-makers need to know about determinants of health. Since work-related circular mobility is currently a central

[2] This focus in the literature on the US and the northern European countries is apparent when looking at the sections on related literature in the subsequent empirical chapters.

feature of contemporary societies and appears to be increasing at a steady rate, it is important to see what impact longer commuting distances have on individuals, when measured against a number of various measures for health and well-being.

The objective of this thesis is, thus, to analyse how commuting affects health and subjective well-being in Germany. We therefore aim to look at the relationship between commuting distance, health and well-being, by using longitudinal data and different proxies for health outcomes (sickness absence, body mass index), health behaviours (sleep patterns, nutritional habits, physical activity, tobacco and alcohol consumption, health care utilisation) and subjective well-being (affective and cognitive evaluation of life). Generally, in empirical and non-experimental analyses, identification of the effects of commuting on health and health-related behaviour is often difficult, since serious econometric problems arise: endogeneity, heterogeneity and selection-bias. To address the potential biases, this dissertation applies a set of different state-of-the art econometric research and identification strategies, such as multivariate models, causal mediation analyses and fixed-effects panel estimation or exploits exogenous variation in commuting distance.

The theoretical foundations for these analyses are broadly related to two approaches of urban (labour) and health economics: Firstly, from a classical urban economic theory, commuting may be viewed as both an economic ‘good’ and an economic ‘bad’ and is just one of numerous decisions rational individuals make. If commuting has extra pecuniary and non-pecuniary costs, then travelling longer distances to and from work is only chosen if it is either compensated by an intrinsically or financially rewarding job or by additional welfare gained from pleasant housing and neighbourhood characteristics (e.g., Alonso 1964, Becker 1965, Stutzer and Frey 2008). Accordingly, individuals are expected to freely optimise and, hence, maximise their utility. Secondly, the concept of health capital provides another theoretical foundation. In particular, health capital is assumed to be both a consumption and an investment good and depends on the amount of resources the individual allocates to the production of health, in our case using, among others, commuting as input (e.g., Grossman 1972, Contoyannis and Jones 2004). Both of these theoretical frameworks echo through this thesis.

This thesis consists of four stand-alone empirical studies, partially written with co-authors. The data used for the subsequent empirical analyses of individual commuting behaviour, health and well-being is taken from the German Socio-Economic Panel (SOEP), which is a representative longitudinal micro-dataset for Germany (Wagner et al. 2007).

Moreover, the SOEP is the only person-level dataset for Germany which provides information on both commuting distance and various health and well-being measures over many years. The availability of a broad range of further individual and household characteristics allows not only the examination of a variety of different health outcomes, but also enables ruling out many potential alternative explanations.

The latter is especially true for the first empirical chapter. **Chapter 2**, which is joint work with Laszlo Goerke, investigates the association between commuting distance and sickness absence from work. Due to the potential reverse causal nature of this relationship, we focus on a subset of employees who experience an exogenous shock to their commuting distance. This shock is brought about by a change in workplace location, given the employee neither changes residence location nor employer. Our results indicate that employees who commute middle (between 25 and 49 kilometres) or long distances (50 kilometres and more), are absent more often than comparable employees who do not commute or who travel shorter distances. Moreover, we obtain no evidence that the observed effect of commuting on the number of sickness absence days is due to working hours mismatch, lower work effort, reduced leisure time or solely caused by differences in health status. Our results have important implications since they, for example, indicate how a firm's employment and location decisions may be influenced by its (prospective) employees' commuting behaviour.

Since several cross-sectional studies claim that commuting is one of the main causes for the rapid rise in obesity rates, **Chapter 3**, which is again joint work with Laszlo Goerke, explores the relationship between commuting distance and height-adjusted weight (BMI). In contrast to previous papers, we find no evidence that longer commutes are associated with excessive weight. The non-existence of a relationship between BMI and commuting distance is consistently found across various sub-samples and prevails regardless of included control variables (e.g., physical activity and eating habits). Again, by considering a subset of individuals who experience an exogenous shock to their commuting distance, we find further evidence to support our finding that there is no significant relationship between commuting and BMI. Moreover, we demonstrate that compensating health behaviours of commuters could explain the non-relationship of commuting and BMI. Since studies that explicitly deal with the association between the travel to work and excess weight are fairly common in the US, where mobility, commuting, car dependence and suburbanisation are extensive, we deduce that our results may be specific to Germany, and that further cross-country comparisons may be needed before a general consensus can be agreed upon.

While Chapter 2 and Chapter 3 investigate the effect of commuting on health outcomes, **Chapter 4** focuses on different health behaviours and, hence, supplements the previous paper. Although commuting has long been recognised as risk factor for health, there is little knowledge of how commuting affects lifestyles like smoking, alcohol consumption, physical activity or nutritional habits. However, it is widely accepted that lifestyle has an effect on individual health and that variations in health among individuals may depend upon differences in health-related behaviours. Therefore, the aim of Chapter 4 is to elucidate the relationship between commuting long distances and several health-related lifestyles by using a recursive system of equations for commuting and healthy lifestyles which has the advantage of accounting for methodological problems, such as unobservable heterogeneity, endogeneity and omitted variables. The results show that long distance commutes have significant effects on lifestyle choices, especially decreasing the propensity to physical activity, healthy diet and sleep patterns as well as prudent alcohol consumption. Furthermore, unobservable individual heterogeneity can influence both the decision to commute and healthy lifestyle choices. These findings highlight that previous studies underestimate the true causal effect of commuting on health behaviours since the effect of commuting on lifestyle choices is likely to be masked when unobservable heterogeneity and endogeneity are ignored. Since longer commutes are increasingly associated with behavioural patterns which, over time, may contribute to poor health outcomes, the effects of commuting on lifestyle choices should receive more attention in public discussions on population health.

Chapter 5 looks at the effect that commuting has on levels of subjective well-being. In the limited number of previous analyses, subjective well-being has usually been assessed by judgements of overall life satisfaction although subjective well-being covers a wider range of concepts than just life satisfaction. Therefore, in order to derive a more comprehensive measure of people’s quality of life and to gain further insights beyond those from the life satisfaction studies about the general consequences of commuting for well-being, Chapter 5 focuses on several cognitive (i.e., satisfaction with life and life domains) and affective (i.e., emotions and feelings) well-being measures. The results show that whereas affective well-being is barely influenced by commuting distance, cognitive well-being is lower for people who commute longer distances. Particularly, the findings suggest that commuting is related to lower levels of satisfaction with family life and leisure time. These results turn out to be robust against several specifications and sub-samples. A bootstrapping-based causal mediation analysis reveals that commuting decreases levels of satisfaction with these two life domains mainly through shaping the timing and the patterns of private daily activities, such as childcare or housework. Hence, longer commuting distances have led to a situation that complicates daily life which obviously comes at the expense of utility derived from family life and leisure time. Consequently, although enlarged job regions create more opportunities for work and strengthen the economy, policy makers should not lose sight of the fact that increased mobility of individuals is detrimental to well-being and, thus, to quality of life.

Finally, **Chapter 6** summarises the most important results derived in the previous chapters of the thesis and contains an outlook on future research needs.

Chapter 2

Commuting and sickness absence*

We investigate the causal effect of commuting on sickness absence from work using German panel data. To address reverse causation, we use changes in commuting distance for employees who stay with the same employer and who have the same residence during the period of observation. In contrast to previous papers, we do not observe that commuting distances are associated with higher sickness absence, in general. Only employees who commute long distances are absent about 20% more than employees with shorter commutes. We explore various explanations for the effect of long distance commutes to work and can find no evidence that it is due to working hours mismatch, lower work effort, reduced leisure time or differences in health status.

* This chapter is joint work with Laszlo Goerke. An earlier version of this paper appeared under the same title in the German Economic Association (VfS) working paper series 'Beiträge zur Jahrestagung des Vereins für Socialpolitik 2015: Ökonomische Entwicklung – Theorie und Politik'. We thank the participants of the 2016 Annual Conference of the European Society for Population Economics (ESPE) in Berlin, the 2016 CESifo Area Conference on Employment and Social Protection in Munich, the 7th Economic Workshop in Trier, the 2015 Colloquium on Personnel Economics (COPE) in Vienna, the 2015 Spring Meeting of Young Economists (SMYE) in Ghent, the 2015 Annual Conference of the Verein für Socialpolitik (VfS) in Münster, the Lüneburg Workshop in Economics and a seminar at U Trier for helpful comments and suggestions.

2.1 Introduction

Each day millions of employees commute between home and work. The frequency of commuting and the average distance of commutes have risen in the last decades (Kirby and LeSage 2009). According to the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR), in Germany, the average commuting distance has increased from 14 kilometres in 1999 to 17 kilometres in 2009 (BBSR 2012). Moreover, the percentage of commutes which took less than 10 minutes to work is declining, while the share of those people who commute 30 to 60 minutes to work has risen from 17% in 1996 to 23% in 2012 (Federal Statistical Office 2013). This trend is not unique to Germany. In the UK, for example, commuting times have increased from 48 to 54 minutes per day, the average commuting trip length has increased by 1.3 kilometres between the mid-nineties and 2012 to reach 14.5 kilometres (Department for Transport 2013). In Spain and Italy, commuting times have increased from 31 to 34 minutes and 22 to 35 minutes, respectively, over the period 1997 – 2006, according to the European Survey on Working Conditions (EWCS). These facts show that commuting is an important and growing component of daily life.

On the one hand, commuting may be viewed positively as it increases the density of labour markets and, hence, allows for better matches between jobs and individuals. Moreover, commuting enables employees to live in places where there are no adequate jobs, without forsaking their income. On the other hand, commuting is usually argued to be problematic from an environmental point of view and to be detrimental to the health of employees.[3]

The aim of this paper is to empirically examine the impact of commuting distance on the number of sickness absence days. If commuting is negatively related to health, employees who commute are more likely to be absent from work (Zenou 2002). In addition, the gain from absence in terms of hours which can be used for other purposes than work, such as recuperation, is likely to be higher for individuals who commute. However, from a theoretical vantage point, the effect of commuting on sickness absence may also be negative. Individuals

[3] Several predominantly US studies have found that work commutes induce stress due to their unpredictability and the perceived loss of control (e.g., Gottholmseder et al. 2009). Furthermore, commuting has been shown to be associated with increased heart rate and blood pressure (e.g., Novaco et al. 1979, Schaeffer et al. 1988). Moreover, commuting translates into shorter sleeping times and sleep disorders (e.g., Costa et al. 1988, Walsleben et al. 1999, Hansson et al. 2011), a lower social capital and participation (e.g., Mattisson et al. 2015), which has in turn been associated with health outcomes (e.g., Putnam 2000, Lindström 2004, Besser et al. 2008), negative mood (e.g., Gulian et al. 1989), emotional arousal (e.g., Hennessy and Wiesenthal 1997), lower general well-being and life satisfaction (e.g., Stutzer and Frey 2008, Olsson et al. 2013) as well as higher levels of workplace aggression (e.g., Hennessy 2008), poor concentration levels (e.g., Matthews et al. 1991) and a higher risk of mortality (e.g., Sandow et al. 2014).

would not choose to have a longer commute unless they were compensated for it, for example, in the form of improved job characteristics (including pay) or better housing prospects (Stutzer and Frey 2008). Hence, individuals who commute may have better, more motivating jobs and be able to achieve a better work-life balance. Furthermore, willingness to travel to work may be associated positively with work effort. Accordingly, the net effect of the commute to work on sickness absence is theoretically ambiguous.

An understanding of this relationship is important for a number of reasons: First, if absence affects productivity and profitability, a firm's employment and location decision may be influenced by its (prospective) employees' commuting behaviour. Second, since absence can cause externalities, for example, if absent employees are entitled to sick pay, health policy requires knowledge of the relationship between commuting and absence from work. Third, policies which alter the mobility of the workforce and the integration of economic regions need to take into account the effects of commuting on absence. Finally, an analysis of the relationship between the work commute and sickness absence enhances our knowledge of the economic costs of commuting.

Despite this imminent importance, few studies have analysed the effect of commuting on sickness absence thus far. Early contributions, surveyed by Kluger (1998), are often based on cross-sectional, firm-specific data and tend to find positive correlations. More recently, panel data have been utilised. Magee et al. (2011), for example, employ data from the Australian household, income, and labour dynamics data set (HILDA) for the years 2005 and 2008. They find a positive correlation between commuting time and absence. Künn-Nelen (2016) uses the British Household Panel Survey (BHPS) data for 1991 to 2008 and detects no robust correlation between commuting time and being absent.[4] The study most relevant to our analysis is that by van Ommeren and Gutiérrez-i-Puigarnau (2011). Using data from the German Socio-Economic Panel (SOEP), they examine the impact of changes in commuting distance on workers' productivity as manifested through higher levels of sickness absence days. van Ommeren and Gutiérrez-i-Puigarnau (2011) find that commuting distance induces illness-related absence, which they interpret as shirking behaviour by employees, with an elasticity of about 0.07 to 0.09.

Against this background, our paper makes a number of contributions: First, by analysing the impact of employer-induced changes in commuting distance on absence and by using a

[4] Moreover, there are some empirical analyses of absence behaviour which include an indicator of commuting as covariate, without looking at the relationship in detail. Allen (1981) and De Paola (2010), for example, report no correlation.

fixed-effects (FE) framework that includes important predictors of sickness absence and – novel to the literature – measures of compensation for commuting in the labour or housing market, e.g. indicators of satisfaction with the job, leisure and housing situation, we present a more integrated approach for explaining the relationship between sickness absence and commuting. We hence, provide a more precise analysis of the effects of the work commute. Second, we are able to ascertain whether absence behaviour of employees who do not commute differs from that of employees who make short, middle or long distance commutes. Third, we allow for discontinuities in the effect of commuting on absence. Finally, we investigate potential channels determining the relationship between commuting and sickness absence. This enables us to obtain a fuller picture of how commuting affects behavioural (lifestyle) factors that, in turn, influence absence behaviour.

Our empirical analyses are conducted using data from the German Socio-Economic Panel (SOEP) for the period 2002 – 2011. First, an ordinary least squares and a negative binomial model are estimated. Second, fixed-effects models are used to remove time invariant unobserved heterogeneity. One major issue in the empirical study of the effect of commuting on sickness absence is reverse causation. In order to address this issue, we employ an identification strategy where we focus on the impact of employer-induced changes in commuting distance, because these changes are exogenous from an employee's perspective. In particular, we look at employees who stay with the same employer and have the same place of residence during the period of observation.[5] We show that employees who commute middle (between 25 and 49 kilometres) or long distances (more than 50 kilometres), are absent more often than comparable employees who do not commute or who travel shorter distances. In particular, the average number of absence days amounts to 10.36 days for the entire sample, while long (middle) distance commuters exhibit 11.86 (10.43) absence days. These descriptive findings are confirmed when accounting for observable characteristics in a pooled sample as well as in the panel structure of our data. In contrast to previous papers in the literature, we do not observe that shorter commuting distances are associated with higher sickness absence. Moreover, we find no evidence that the effect of commutes on absence

[5] This identification strategy has been used by other authors, as well, looking at different issues. Zax (1991) and Zax and Kain (1996) analyse job and residential moving behaviour. Gutiérrez-i-Puigarnau and van Ommeren (2010) investigate labour supply patterns. van Ommeren and Gutiérrez-i-Puigarnau (2011) examine the impact of commuting on workers' productivity and Roberts et al. (2011) consider the effect of an exogenous change in commuting time on psychological health in a robustness check. Finally, Carta and De Philippis (2015) investigate the impact of commuting on the labour supply of couples.

from work is due to working hours mismatch (respectively, a lower work effort or shirking), reduced leisure time or differences in health status.

The remainder of this paper is organised as follows: Section 2.2 describes the data and variables. Section 2.3 focuses on our identification strategy and outlines the econometric method. Section 2.4 reports the results, including several robustness checks and the analysis of mechanisms through which commuting might affect individual's absence behaviour. Section 2.5 concludes the study.

2.2 Data and variables

The current study is based on information from the German Socio-Economic Panel (SOEP) for the years 2002 – 2011. The SOEP is a longitudinal, nationally representative survey of private households in Germany. Currently around 30,000 people in approximately 15,000 households participate in the survey. The SOEP includes rich information on labour market status, wealth, income and standard of living, health and life satisfaction as well as on family life and socio-economic variables.[6] To the best of our knowledge, the SOEP is the only person-level dataset for Germany providing detailed information on both absence from work and commuting distance.

The SOEP provides a self-reported measure of the annual number of days absent from work due to sickness in the previous year. The exact question reads as follows: "How many days were you unable to work in 20XX due to illness? Please state the total number of days, not just the number of days for which you had an official note from your doctor: (a) None, (b) A total of X days." The advantage of this question is that it provides information on the total number of absence days, and not only with respect to those, for example, for which a medical certificate is required.[7] However, there is no data in the SOEP on the annual number and the duration of specific sickness spells. Therefore, in the following multivariate regressions we use 'days absent', i.e. the total number of days the employee has been absent during the previous year, as our dependent variable. We also consider the incidence of absence in a robustness check (cf. Section 2.4.4).

---

[6] Further information about the SOEP is provided by Wagner et al. (2007) and can also be found at: http://www.diw.de/english/soep/29012.html. We use the SOEP long v29 dataset.

[7] In Germany, dependent employees with a minimum tenure of four weeks can basically take sick leave without a durational restriction. From the fourth day of the sickness spell onwards, employees are legally required to present an official note by a doctor. During the first six weeks of an absence period, the employer has to continue to pay wages. Once an employee's absence period exceeds six weeks, the mandatory health insurance will cover the cost of sick pay which drops to at most 90% of the net wage.

The SOEP, furthermore, requires respondents to report on commuting distance. The question reads: "How far (in kilometres) is it from where you live to where you work? (a) X km, (b) Difficult to say, location of workplace varies, (c) Workplace and home are in the same building/same property." We define all respondents for whom either part (c) of the question applies or who state that the distance between home and workplace is less than ten kilometres (part (a) of the question) as non-commuters. All respondents who travel ten or more kilometres to work are defined as commuters. Of these respondents, those who travel to work between ten kilometres and less than 25 kilometres are short distance, those who travel more than 25 kilometres and less than 50 kilometres are middle distance and those who cover 50 or more kilometres are long distance commuters.[8] This approach allows for qualitatively different effects of, for example, shorter and longer commuting distances on absence. Moreover, it is not sensitive to minor reporting errors. As robustness check we have experimented with several functional forms and categorisations for commuting distance (cf. Section 2.4.4). Finally, those who report working in different places (part (b) of the question) are excluded from the analysis as it is difficult to determine their actual commuting distance.

It is worth mentioning that the SOEP provides direct information about commuting time and commuting mode only in 2003. In other years, it is possible to imprecisely ascertain commuting time by calculating the difference between daily working hours, including travel time to and from work, and the usual daily working hours. We use this information in a robustness check (cf. Section 2.4.4).

The choice of the other explanatory variables is informed by the literature on the determinants of sickness absence as well as on commuting. Correlates or determinants of absence can be categorised as follows (e.g., Dionne and Dostie 2007, Frick and Malo 2008, Ziebarth and Karlsson 2010, Livanos and Zangelides 2013, Block et al. 2014). The first group contains variables on personal characteristics such as gender, marital status, children, age, current health status as well as educational attainment. The second set incorporates variables on job-related aspects: Tenure, working time, type of employment contract (temporary), occupational position, size of company, sector information, industry dummies, and income. We also include region as well as year dummies. Furthermore, studies on commuting (e.g., Costa et al. 1988, Stutzer and Frey 2008, Lyons and Chatterjee 2008) suggest that compensation for commuting may be provided in the housing or labour market. Hence, we

[8] No standard definition of commuting is used internationally or in Germany. We build our categories in line with definition used by the Federal Statistical Office of Germany.

also include indicators of satisfaction with dwelling and the amount of leisure time, job satisfaction and a household crowding index as explanatory variables.

Our estimation sample consists of 18 to 65-year-old individuals in paid employment and does not include self-employed.[9] As information on sickness absence refers to the year before the interview date $(t-1)$ and commuting distance is measured at the interview date (t), we ensure that the commuting distance reported at the interview date applies to the same year for which sickness absence days are reported. Furthermore, to affirm that information on commuting distance and sickness absence refers to the same employer we additionally confine our sample to workers who have a minimum tenure of two years.[10] As part of our identification strategy explained in the next section we focus on workers who stay with the same employer and have the same residence. Our working sample then consists of 6,459 individuals with 31,567 observations.

Tables A.1 and A.2 in Appendix A show our variable definitions and a complete list of covariates and descriptive statistics.

2.3 Identification strategy and econometric methods

2.3.1 Identification strategy

A worker's commuting distance is often self-chosen and may, thus, be affected by the endogenously determined residence and employer. In order to derive a causal effect, commuting distance needs to fluctuate for exogenous reasons. Such an exogenous variation will occur if a firm alters its location. To identify such a change in commuting distance, we focus on respondents who did not change employer or residence during the period of observation. It is plausible that in such circumstances the worker must have changed workplace location because e.g. of a firm relocation.[11] Such changes in workplace location due to firm relocation have been shown to be quite common (e.g., Gutiérrez-i-Puigarnau and van Ommeren 2010, Gutiérrez-i-Puigarnau et al. 2016). For example, about 16.5% of firms in

[9] See, for example, Roberts et al. (2011) for a comparable approach.

[10] Since we estimate worker fixed-effect specifications, there is unlikely to be a selection bias because the FE specification controls for worker-specific time-invariant heterogeneity.

[11] It is important to note that in the data available there is no information on whether the worker's firm relocated or not. So it is not possible to distinguish between true changes (because of firm relocation) and misreporting. Since we are treating commuting distance as a categorical variable, our results are not sensitive to minor reporting errors. Hence, the downward bias in our estimate is likely to be small. We additionally address this problem by excluding observations referring to absolute changes in commuting distance smaller than two kilometres (cf. Section 2.4.4).

Germany are involved in relocation decisions each year (Federal Statistical Office 2008). Using this approach, in our sample, about 10% of the observations incur employer-driven changes in commuting distance. We will explicitly address the potential bias of this selection by comparing results of different samples (cf. Section 2.4.4).

2.3.2 Models for cross-sectional data

Since absence days can only take on non-negative integer values we estimate a negative binomial model with heteroskedasticity robust standard errors, which is also a convenient way for dealing with overdispersed data, such as we are examining.[12] Additionally, we make use of an OLS regression model with heteroskedasticity robust standard errors. This approach is feasible since we need not get the functional form perfectly right to obtain valid estimates of the average partial effects. The idea for the empirical test is captured in the following regression equation:

$$A_i = \alpha + \beta D_i + \gamma X_i + \theta T_i + \delta R_i + \varepsilon_i. \tag{2.1}$$

A_i equals the total number of days absent from work for individual i. D_i is an indicator for commuting distance and X_i represents a vector of independent variables (e.g., relating to personal and job characteristics and compensation for commuting). In order to capture region and time specific effects we also consider region (R_i) and year dummies (T_i). β, γ, θ and δ are coefficients, and ε_i denotes the error term. Our main interest lies in β. The pooled estimators identify the effect of commuting on the reported number of days absent, based on the variation in these variables between people and for each individual over time. It is assumed that unobserved characteristics, as well as measurement errors, are captured in the error term of the estimation.

2.3.3 Models for panel data

Additionally, we assess the impact of a change in commuting distance on a change in the outcome variable using fixed-effects models because causal inference is better supported using panel data, rather than cross-sectional data (Wooldridge 2010). Accordingly, we

[12] The overdispersion parameter corresponds to α = 2.73.

eliminate the risk that time-invariant variables confound the relationship between commuting and sickness absence.

Since our dependent variable is a count variable, we employ a conditional fixed-effects negative binomial regression model as a benchmark.[13] Conditional estimation of the fixed-effects model is obtained using maximisation of the log likelihood conditional on the sum of the number of counts during the period during which the individual is observed. Although this method is used frequently, it has been criticised for not being a true fixed-effects approach since it fails to control for all of its stable predictors (Allison 2009, Allison and Waterman 2002). The unconditional negative binomial model and the multinomial model have been suggested as alternatives. Since the former model is unsuitable for large data sets with lots of variables and the latter fails to handle overdispersion, we additionally revert to the fixed-effects OLS regression.[14] Furthermore, a fixed-effects OLS regression is less contingent on distributional assumptions and easier to interpret than the alternatives. The basic model specification can be denoted by:

$$A_{it} = \beta D_{it} + \gamma X_{it} + \iota_i + \mu_t + \varepsilon_{it}, \tag{2.2}$$

where A_{it} is a measure of the number of days absent for a worker i in year t, D_{it} is an indicator for commuting distance, X_{it} are a set of conditioning variables, β and γ refer to parameters to be estimated. μ_t are defined as year fixed-effects and ι_i are individual fixed-effects for each residence and employer combination.

2.4 Results

2.4.1 Sample description

Table 2.1 reports the associations between commuting distance, the number of days absent and the incidence of absence. The average number of days lost through sickness absence amounts to 10.36 days. The standard deviation of 24.7 days indicates that there is a lot of cross-sectional variation. The distribution of absence days is heavily skewed with a mass point at zero. The full distribution of sickness absence days is depicted in Appendix A, Figure A.1.

[13] For detailed explanation, see Hilbe (2007).
[14] The unconditional negative binomial model leads to an underestimation of standard errors, which yields biased estimates.

About half of the individuals in our dataset (54%) are short, middle or long distance commuters. The annual number of days absent increases by about two days, as one-way commute distance increases from under 10 kilometres (non-commuter) to over 50 kilometres (long distance commuter). Those workers who commute long distances have on average 11.9 absence days. The incidence rate is also higher. Approximately 70% of long distance commuters have stayed home sick at least once in the last 12 months, whereas only 63% of non-commuters did so. Hence, the descriptive evidence suggests that being a commuter is associated with a higher incidence of absence and more absence days per year.

Table 2.1. Descriptive statistics for full sample and for commuter categories.

	Full sample				Non-Commuter		Short distance commuter		Middle distance commuter		Long distance commuter	
	Mean	SD	Min	Max	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Absence:												
# of days	10.36	24.70	0	365	9.96	24.31	10.59	25.12	10.43	23.72	11.86	27.62
Incidence	0.65	0.47	0	1	0.63	0.48	0.65	0.47	0.67	0.46	0.70	0.45
N	31,567				14,113		10,435		5,129		1,890	
%	100%				46%		33%		16%		5%	

Notes: Summary statistics only for key variables. SD = Standard deviation. Appendix A shows the detailed descriptive statistics in Table A.2.

The descriptive statistics furthermore indicate that commuters are more often male, are better educated, work longer hours, and are less likely to work part time. In addition, they have a higher labour income, shorter tenure and tend to work more often in large firms. Finally, commuters appear to be less satisfied with their leisure time and work than non-commuters.

In our data, the average commuting trip length has increased by 2.3 kilometres between 2002 and 2011 to reach 20.13 kilometres. The average one-way commuting distance of workers is 19 kilometres. This is in line with a range of other studies employing German data (OECD 2007, Schulze 2009). Hence, our sample selection is likely unrelated to commuting behaviour. The full distribution of commuting distances can be found in Appendix A, Figure A.2.

2.4.2 Cross-sectional evidence

Table 2.2 reports results for cross-sectional, multivariate regression models. Model I estimates a pooled negative binomial regression (NEGBIN). While the estimated coefficient of being a short distance commuter is insignificant, being a middle distance commuter instead of a non-commuter is associated with a 7.05% change in the expected number of days absent, or equivalently, the conditional mean is 1.07 times larger.[15] Being a long distance commuter leads to a 0.201 proportionate change or 20% change in the number of sickness absence days. The effect is, for example, comparable to the impact due to being a female (Model I: $\beta_{\text{female}} = 0.191,\ p < 0.001$; Model II: $\beta_{\text{female}} = 2.073,\ p < 0.001$, see Appendix A, Table A.3).[16]

Table 2.2. Estimation results using cross-sectional data.

	Model I Pooled NEGBIN	Model II Pooled OLS
Short distance commuter	0.038	0.572
	(1.45)	(1.86)
Middle distance commuter	0.070^{*}	0.846^{*}
	(2.17)	(2.17)
Long distance commuter	0.201^{***}	2.173^{***}
	(3.72)	(3.36)
N	31,567	31,567

Notes: Only the coefficients for the commuting variables are reported. Non-commuters are treated as the reference category. The following control variables are included: female, age, age squared, married, children, college degree, education, health status, working hours, regular part-time, temporary job, blue-collar worker, firm size, public sector, tenure, tenure squared, log(monthly wage), satisfaction with work, leisure and dwelling, household crowding index, business sector dummies, region dummies, year dummies. Appendix A shows the results for control variables in Table A.3. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Model II estimates a pooled least squares regression (OLS). The regression results are almost identical to the ones reported above, indicating that greater commuting distances are associated with more sickness absence. For example, long distance commuters are on average about 2.17 days more absent than those who commute less than 10 kilometres. Since the raw difference in the duration of absence observed between long distance commuters and non-commuters is 1.90 days (Table 2.1), this difference tends to underestimate the impact of commuting.

[15] Recall that the dependent variable is a count variable, and negative binomial regression models the log of the expected count as a function of the predictor variables. We can interpret the negative binomial regression coefficients as follows: for a one unit change in the predictor variable, the difference in the logs of expected counts is expected to change by the respective regression coefficient, given the other predictor variables in the model are held constant. Hence, the coefficients displayed are equal to the proportionate change in the conditional mean if the regressors change by one unit. For indicator variables the coefficient reflects a proportionate change from the base level. For a detailed explanation, see Cameron and Trivedi (2008).

[16] There is a huge body on literature showing that sex is a strong predictor of sickness absence rates with higher incidence and duration of sickness absence for women predominantly due to the high total workload and the double-exposure situation, e.g. responsibility for household chores and child care, see Leigh (1983), Vistnes (1997), Krantz et al. (2006).

2.4.3 Fixed-effects analyses

We next present the findings from fixed-effects estimations to cater for the potential impact of time-invariant, unobservable characteristics on absence behaviour. In Table 2.3, Model III reports the results for a fixed-effects negative binomial estimation (FE NEGBIN).

Table 2.3. Estimation results using panel data.

	Model III FE NEGBIN	Model IV FE OLS
Short distance commuter	0.044	1.305
	(1.91)	(1.94)
Middle distance commuter	0.109^{***}	2.607^{**}
	(3.65)	(2.79)
Long distance commuter	0.191^{***}	3.370^{*}
	(4.35)	(2.56)
N	31,567	31,567

Notes: Only the coefficients for the commuting variables are reported. Non-commuters are treated as the reference category. The following control variables are included: age, age squared, married, children, college degree, education, health status, working hours, regular part-time, temporary job, blue-collar worker, firm size, public sector, tenure, tenure squared, log(monthly wage), satisfaction with work, satisfaction with leisure, satisfaction with dwelling, household crowding index, business sector dummies, region dummies, year dummies and being female (in Model III). Appendix A shows the results for control variables in Table A.3. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The overall effect of commuting distance on the number of days absent is positive and statistically significant.[17] Further, the expected number of days absent is about 11% higher for middle distance and 20% higher for long distance commuters compared to non-commuters.

Since the conditional negative binomial method has been criticised for not being a true fixed-effects model, we also estimate a fixed-effects least squares model (FE OLS; Model IV). Model IV in Table 2.3 shows that the overall effect of commuting distance is positive and statistically significant.[18] Comparing the magnitudes of the estimated coefficients in Models II and IV clarifies that controlling for time-invariant characteristics tends to increase the effect of being a middle or long distance commuter on the number of days absent. Hence, cross-section estimation of the effect of commuting on sickness absence negatively biases the results. One plausible explanation for this bias is that individuals with unobserved positive attitudes towards work are more likely to accept jobs which require commuting longer distances and are also less likely to be absent. So, the conditional method estimates reported above are conservative. In consequence, being a long distance commuter instead of a non-commuter is associated with 3 absence days more on average ($p < 0.05$), while being a middle

[17] The three degree-of-freedom chi-square test indicates that commuting distance is a statistically significant predictor of absence ($\chi^2(3) = 25.27; \mathrm{p} = 0.0000$).

[18] The F-test indicates that commuting distances are jointly significant at the 5% level ($\mathrm{F}(3, 6458) = 3.38; \mathrm{p} = 0.0175$).

distance commuter goes along with 2 more absence days on average ($p < 0.01$). The relationship between commuting short distances and the number of sickness absence days is either not significant or at the borderline of being weakly significant in the main models (see Table 2.2 and Table 2.3). Additionally, the sensitivity checks provide no evidence of a link for short distance commuters (see Section 2.4.4).

Thus, the descriptive evidence and the results of the pooled estimations are confirmed: While short distance commutes have no impact on sickness absence, middle and long distance commutes increase the duration of absence. For completeness, we run separate fixed-effects negative binomial regressions for long, middle, short distance commuters and non-commuter to analyse whether determinants of sickness absence differ between commuter and non-commuter and to test for differences in relationships between variables across these sub-samples. Our findings indicate that the determinants of sickness absence are broadly the same for commuters and non-commuters and do not contribute much to explaining the difference in absence between long, middle, short distance commuters and non-commuter.[19]

2.4.4 Robustness checks

In Table A.4 (Appendix A) we report a number of robustness checks on our results of the fixed-effects negative binomial model. The first two models ((i) and (ii)) are estimated for men and women separately as the determinants of absence may be gender-specific (e.g., Leigh 1983, Vistnes 1997). The estimated coefficients of the commuting variables are not statistically different from each other. Hence, we obtain no evidence that the effect of commuting distance on absence is gender-specific.

The third model (iii) is estimated for those individuals who do not work in the public sector as sickness absence in the public sector is higher than in the private sector (e.g., Winkelmann 1999, Frick and Malo 2008). For this sample, the results are almost identical to the ones in the main model, indicating that the observed impact of commuting distance on absence is certainly not a public sector phenomenon.

The next two models ((iv) and (v)) are estimated for rural and urban communities. There are a number of reasons why the relationship between commuting and absence may vary with such spatial characteristics (e.g., Eibich and Ziebarth 2014). First, employees living in rural regions may be healthier, have a higher quality of life compared to individuals living in urban

[19] Results are not documented and available upon request.

regions (e.g., Ziersch et al. 2009, Zeng et al. 2015) and may commute longer distances. Second, in small, rural communities the observability of the behaviour of others is likely to be more pronounced than in urban communities characterised by greater anonymity. Hence, the impact of commuting on absence may be weaker in rural communities. We indeed find that individuals who are living in rural regions have less sickness absence days (results not documented). Table A.4 indicates that the effects of long distance commutes are similar to those reported in the main model for both regions. Further, the coefficient of short distance commutes becomes significant for the urban community sample, whereas it loses its significance for individuals who commute middle distances. Therefore, our main finding – long distance commutes increase absence – holds for individuals who live in rural and urban communities. The evidence for other distances reveals no clear spatial pattern.

In a further robustness check, we exclude all observations for which sickness absence amounts to more than 30 days annually (model (vi)). Excluding such observations (outliers) makes the sample more homogeneous because workers who are continuously absent for more than six weeks no longer receive a wage replacement but a lower level of sick pay instead. The results for this restricted sample are virtually identical to those presented for the baseline. This suggests that unobserved wage reductions due to long sickness absence periods do not affect our results.

Model (vii) tests the sensitivity of our results to reporting error by excluding observations that refer to small distance changes (less than 2 km). We see that the effect of commutes is very similar to that reported in the main model, indicating that the effect of commuting to work on sickness absence is not due to measurement error.[20]

In models (viii) and (ix) we have experimented with several functional forms and categorisations for commuting distance. In model (viii) we classify commuting distance as a dummy variable (equals 1 if individual commutes 50 km and more) and in model (ix) we estimate a log-linear specification of commuting distance. In model (viii) the coefficient of the dummy variable indicates that the expected number of days absent is about 14% higher for those who travel 50 kilometres and more compared to those who travel fewer kilometres. In

[20] Another attempt to deal with measurement error is to calculate a proxy for commuting time. To obtain the commuting time we built the difference between the daily working hours including travel time to and from work (taken from the question: "How many hours per normal workday do you spend on job, apprenticeship, second job (including travel time to and from work)?") and the usual daily working hours (taken from the question: "And how many hours do you generally work, including any overtime?") divided by 5 workdays. Again, we only find a positive and statistically significant effect of long commutes, particularly of commutes which take more than 45 minutes ($\beta_{46\,\min\,and\,more} = 0.0559, p = 0.013$). We do not use this measure of commuting time as our focal explanatory variable as it is calculated in an imprecise manner. Further, commuting time may be influenced by many factors, for instance by the chosen commuting mode.

model (ix) the point estimate of the continuous commuting distance variable (in log), and therefore the elasticity, is 0.046 (s.e. 0.009). Thus, if the average logarithm of commuting distance, 2.24 in our data, falls to about 0, sickness absence days will decline by about 10% (0.046×2.24). van Ommeren and Gutiérrez-i-Puigarnau (2011) use a similar measure of commuting distance and find that commuting distance induces absence or shirking behaviour with an elasticity twice as large as the one we find (0.07 to 0.09). Since they also use data from the SOEP and employ a similar identification strategy, we can test whether it is the choice of the explanatory variables that is driving the difference in the results. To do this we re-run our analysis including only explanatory variables similar to those used by van Ommeren and Gutiérrez-i-Puigarnau (2011) (not reported). We find a point estimate of 0.062, indicating that failure to include additional confounders into the estimations is likely to result in overestimates of the strength of the association between commuting and sickness absence. We also estimate the latter model using the categorical commuting distance variable instead of the continuous measure. We find that only middle and long distance commutes are associated with higher sickness absence days, while short distance commutes are not. It is thus apparent that the effect documented by van Ommeren and Gutiérrez-i-Puigarnau (2011) does not hold in general, as we find no evidence of an impact of short distance commutes on absence in our application.[21]

The next models ((x) to (xiv)) are an attempt to address a potential selection bias since our estimates are, thus far, based on a sample of workers who change neither their employer nor residence. In our setting, endogeneity might, first, result from the self-selection of employees in a group of workers who do not change residence or employer.[22] Strictly speaking we cannot exclude the possibility that individuals with unobserved positive attitudes towards work are more likely to accept jobs at longer distances and are also less likely to be absent. Second, employees may move residence or job as a reaction to employer-induced workplace relocation. Third, if an employer needs some employees to move to a different part of the firm at a different location, employees are usually asked whether they are willing to move or not. To tackle the potential bias resulting from these issues, we additionally employ two strategies. The first is to estimate the fixed-effects negative binomial model on other,

[21] Our main results remain robust when we use more fine grained commuting classes or models with linear splines: Individuals who commute less than 20 to 25 km do not have a higher number of absence days than non-commuters. These additional robustness checks are available upon request.

[22] Endogenous selection, namely, that commuting distance can only be observed for individuals who are healthy enough to work and thus to commute, can only bias the relation between commuting distance and the number of sickness absence days downward. In that case, our estimates can be seen as a lower bound.

less-selective samples. In particular, we include data on employees who change the employer only (model (x)), employees who change the residence only (model (xi)), and employees who change both employer and residence (model (xii)). Second, we replace commuting distance with lagged values of commuting distance, in order to avoid the influence of sickness absence on contemporaneous commuting distance (model (xiii) and (xiv)). This strategy is based on the assumption that lagged commuting distance is uncorrelated with the current sickness absence residual, which assumes no serial correlation in the sickness absence residuals for the two periods. This approach reveals that especially commuting long distances translates into higher sickness absence days for the next two years. Overall, none of these analyses yields any other qualitative finding than those reported above, indicating that the effect of commuting long distances to work on sickness absence is not due to self-selection based endogeneity bias.[23]

Finally, in model (xv) we alter the methodology to see whether the choice of the dependent variable affects the results. We therefore estimate a random-effects probit model where we only distinguish between 'never having been absent' and 'having been absent at least once'. The results indicate that being a middle or long distance commuter increases the probability of being absent at least once in a given year. This finding also supports the hypothesis that only longer commuting distances positively affect sickness absence from work.

2.4.5 Transmission channels

The previous analysis has uncovered a robust impact of commuting longer distances on the number of days of absence from work. In this subsection, we investigate various hypotheses concerning the cause of this relationship.

As outlined in the introduction, there is substantial evidence that commuting is associated with increased levels of illness. Since absence is negatively related to health (e.g., Puhani and Sonderhoff 2010 as well as Goerke and Pannenberg 2015, for example, present according evidence for Germany), the impact of commuting on absence may be due to health effects. To accommodate this possibility, the estimations presented thus far include a subjective measure of health. We further analyse health as transmission mechanism by, first, omitting the health

[23] Given that commuting long distances is positively associated with absence days, we would expect someone who stops commuting long distances to have fewer sickness absence days. Hence, we also investigated the effect of quitting commuting on absence. Stopping to commute long distances decreases the number of sickness absence days significantly by about 16%. This evidence supports our identification strategy.

variables included in the estimations depicted in Table 2.3. Second, we include additional health indicators, such as satisfaction with health, concern about individual's own health, degree of disability, the number of overnight hospital stays and the number of annual doctor visits.[24]

Table 2.4 depicts the results for the fixed-effect specifications and reveals that more healthy people are indeed less absent from work. Moreover, we see that the magnitudes of the estimated coefficients of the commuter variables decline to some extent if health indicators are included. Therefore, commuting may deteriorate an individual's health. However, this effect does not explain the observed impact of commuting on absence. Otherwise, the significant coefficients of the commuting covariates would become statistically insignificant when controlling for health.

While health-related absence may be regarded as involuntary, the standard labour-supply perspective on absence views such behaviour as voluntary adjustment to predetermined and overly long or insufficiently flexible working hours (Allen 1981). Since commuting increases the length of the total workday while simultaneously reducing time for private use, the need to adjust total working time to the preferred amount is likely to be greater for individuals who commute. In order to scrutinise this transmission channel, we estimate extended specifications of Models III and IV, as depicted in Table 2.3, and add two dummy variables which indicate whether individuals would like to work less or more hours than they actually do. The estimated coefficients of the commuter variables (not documented) are basically unaffected compared to those in the main model. This is also true if we include further working time indicators, such as the number of actual hours worked, overtime hours per week or having a second job. Therefore, commuting does not result in greater voluntary absence, which is often interpreted as shirking.[25]

In a substantial number of empirical studies, job (in-) security has been found to affect absence from work (e.g., Staufenbiel et al. 2010, Bratberg et al. 2015). Moreover, reduced job security has a disciplining effect, suggesting that workers are more likely to accept jobs at longer distances and are also less likely to be absent. Hence, job insecurity may influence both the probability of becoming a commuter and of being absent from work. We investigate this

[24] We have also analysed the effect of interactions of distance with health indicators, but have not found any significant effects. This indicates that an employee's marginal costs of commuting do not depend on the individual's state of health.

[25] In a further step, we have also included information on private time use, for instance, the average time per day spent on running errands, housework, child care, care for people with disabilities and other dependants living in the household, leisure time, time for repairs and garden work. The estimated coefficients of the commuter variables are basically unaffected by the inclusion of the private time use variables.

transmission channel by including a variable in extended specifications of Models III and IV that indicates whether the respondent is concerned about its own job security. Individuals who are not concerned about their job indeed have higher absence (results not documented).[26] However, the estimated coefficients of the commuting variables are basically the same as shown for the baseline. Alternatively, we use the unemployment rate (at the level of federal states) as a proxy of job insecurity. Its inclusion does not substantially alter the estimated coefficients of interest. Consequently, the impact of commuting on absence does not arise because commuters are concerned about their jobs.

Table 2.4. Transmission channels. Fixed-effects estimates.

	Baseline (see Table 2.3)		Baseline without subjective health measures		Baseline with additional health measures	
	FE NEGBIN	FE OLS	FE NEGBIN	FE OLS	FE NEGBIN	FE OLS
Focal variable:						
Short distance commuter	0.044	1.305	0.057^{*}	1.363	0.037	0.946
	(1.91)	(1.94)	(2.49)	(1.89)	(1.62)	(1.42)
Middle distance commuter	0.109^{***}	2.607^{**}	0.121^{***}	2.809^{**}	0.104^{***}	2.339^{*}
	(3.65)	(2.79)	(4.04)	(2.91)	(3.46)	(2.55)
Long distance commuter	0.191^{***}	3.370^{*}	0.205^{***}	4.094^{**}	0.195^{***}	2.971^{*}
	(4.35)	(2.56)	(4.67)	(2.89)	(4.42)	(2.29)
Health status: very good (ref.)						
good	0.157^{***}	1.242^{**}			0.104^{**}	0.255
	(4.67)	(3.18)			(3.02)	(0.66)
acceptable	0.343^{***}	2.577^{***}			0.200^{***}	-0.323
	(9.52)	(4.93)			(5.10)	(-0.59)
less good	0.581^{***}	10.871^{***}			0.308^{***}	4.422^{***}
	(14.20)	(10.48)			(6.37)	(4.09)
bad	0.947^{***}	47.503^{***}			0.503^{***}	35.685^{***}
	(14.08)	(9.90)			(6.53)	(7.76)
Health satisfaction					-0.041^{***}	-0.947^{***}
					(-6.67)	(-5.44)
Life satisfaction					0.003	-0.285
					(0.56)	(-1.80)
Concerned about health: very (ref.)						
somewhat					-0.017	-1.735^{*}
					(-0.69)	(-2.20)
not at all					-0.039	-1.253
					(-1.25)	(-1.50)
Invalidity level					0.0003	-0.172^{**}
					(0.50)	(-2.77)
# of hospital stays					-0.006^{***}	-0.082
					(-4.13)	(-1.16)
# of doctor visits					0.008^{***}	0.272^{***}
					(18.21)	(9.63)
N	31,567	31,567	31,567	31,567	31,354	31,354

Notes: Only the coefficients for the commuting variables and those of potential health channels are reported. Non-commuters are treated as the reference category. The baseline models correspond to Model III and Model IV of Table 2.3. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[26] These results complement findings by Ichino and Riphahn (2005) who find that average absence substantially rises, once the probability of being fired decreases.

Research on the determinants of sickness absence has shown that higher wages are associated with lower sickness absence rates (e.g., Drago and Wooden 1992, Piha et al. 2009). Further, standard urban economic theory (e.g., Lucas and Rossi-Hansberg 2002) suggests that workers should be willing to accept longer commutes only if they are compensated by higher wages. Hence, wages may influence both the probability of commuting long distances and of being absent from work, which could mean that the impact of commuting on absence is due to wage effects (Ross and Zenou 2008). To account for this possibility, the estimations presented thus far include information on monthly labour income. We further analyse income as transmission mechanism by, first, omitting the income variable included in the estimations depicted in Table 2.3. Second, we include an additional variable, indicating whether income increased, decrease or remained constant in comparison to the previous year (e.g., due to promotion). Excluding or adding further income controls does not change our main results.[27]

We conclude that long distance commuting raises absence. This effect is partially due to health consequences but cannot be explained by it. Moreover, it does not arise because of a change in job security or because commuters face a greater mismatch between actual and desired working time. One reason why absence from work is much lower for those travelling shorter distances might be that they more frequently show up at work, despite anticipating an upcoming illness. Such behaviour could arise because short distance commuters can more easily return home if their health condition deteriorates than employees who have to travel longer distances to reach their place of residence. Consequently, we might expect long distance commuters to exhibit lower levels of presenteeism. Unfortunately, we are not able to investigate to which extent employees with different commuting distances go to work although being sick. This is the case since our data does not provide information on presenteeism days. This limitation may be worth addressing in future research.

Alternatively, one may hypothesise that commuting is associated with lower work effort and, hence, more absenteeism. Our data does not enable us to directly provide further evidence on this kind of transmission mechanism. However, when we consider weekly overtime or actual weekly work time as proxies for work effort and as our dependent variables, we find that commuting distance has a positive effect on working overtime or working more hours than the number which has been contractually agreed upon. Hence, one

[27] A full set of the results of the specification described in this subsection are available upon request.

should be cautious with the interpretation of sickness absence as inverse measure of productivity or work effort.[28]

2.5 Conclusion

In summary, in this paper we enrich the literature on the relationship between commuting distance and sickness absence using panel data for Germany. Empirically, we know very little about this linkage. We address a possible reverse causality bias by exploiting variation of commuting distance within individuals when there are no changes in residence and employer. For Germany, we find a causal effect of commuting distance on sickness absence. We show that long distance commutes increase the numbers of days absent by about 20%. The effect of middle distance commutes is much lower, i.e. about 11%. The effect becomes zero at commuting distances of less than 25 kilometres. The results are robust across specifications and when accounting for selection effects. Furthermore, we explore potential explanations for the effect of commutes to work on absence. We find that the impact is not due to working hours mismatch or poor health. A deeper investigation of the determinants shows that differences in personnel characteristics, job-related aspects and factors compensating for commuting are not able to explain the gap in sickness absence from work either.

Our findings have a number of implications. First, we demonstrate that sickness absence due to commuting is an important characteristic of the (German) labour market, which is in line with a range of theoretical models. Second, the present study suggests that commuting may have far-reaching consequences for both employees and the financial performance of employers. Hence, evidence of an absence-commute relationship puts a price on the work commute and should be considered in cost-benefits assessments, since absence from work causes sizeable costs not only for the employer but also for the employee. Consequently, our findings point to the economic benefit from transport infrastructure improvements as well as to potential costs savings for the health care system. Third, it is important to consider the positive effect of commuting on sickness absence when discussing the expansion of economic regions or increasing the mobility of the workforce. Hence, there is a need for integrating

[28] One additional hypothesis we considered is that income, working hours or the desired working hours (work more or less hours) might be proxy indicators of work effort. Since, the coefficient of long distance commutes is basically unaffected by the inclusion of these variables one may argue that the impact of commuting on absence does not arise because commuters provide lower work effort. However, as with other proxy indicators, there is a difficulty in ensuring that the claimed relationship is not confounded by other variables. Nevertheless, there is a growing body of literature showing that commuting increases the number of working hours and, hence, labour supply (Gutiérrez-i-Puigarnau and van Ommeren 2010, 2015).

different policy areas concerning commuting, such as planning policy, transport policy, policies at the workplace, social policies and innovative policies.

2.6 Appendix A

Table A.1. Variable definitions.

Variable	*Definition*
Dependent variable	
Days absent	Number of sickness absence days.
Focal variable	
Commuter	Commuting distance measured one-way in kilometres. Categorical variable: 0 = "non-commuter (< 10 km)", 1 = "short distance commuter (10 – 24 km)", 2 = "middle distance commuter (25 – 49 km)", 3 = "long distance commuter (> 49 km)".
Personal characteristics	
Female	Dummy equals 1 for female.
Age	Age in years.
Age^2	Age squared.
Married	Dummy equals 1 if individual is living together with partner (either as a married or unmarried couple).
Children	Dummy equals 1 if children live in the household.
Education	A five point scale measuring highest level of education attainment: 0 = "no or other school certificate", 1 = "secondary general school certificate", 2 = "intermediate school degree", 3 = "leaving certificate from vocational high school", 4 = "college entrance exam".
College Degree	Dummy equals 1 if individual has completed college education.
Health status	A five point indicator of self-reported health status: 1 = "very good", 2 = "good", 3 = "acceptable", 4 = "less good", 5 = "bad".
Job-related aspects	
Tenure	Number of years in present job.
$Tenure^2$	Job tenure squared.
Working hours	Contractually agreed hours of work per week.
Regular part-time	Dummy equals 1 if individual works part-time.
Temporary job	Dummy equals 1 if individual has a fixed-term employment contract.
Blue-collar worker	Dummy equals 1 if individual is a blue-collar worker.
Firm size	Size of company: 0 = "< 5 employees", 1 = "5 – 19 employees", 2 = "20 – 99 employees", 3 = "100 – 199 employees", 4 = "200 – 1999 employees", 5 = "2000 employees and over".
Public sector	Dummy equals 1 if individual works in the public sector.
Log (monthly wage)	Current gross labor income, being corrected by purchasing power parity and harmonised by consumer price index. Variable expressed in natural logarithms.
Variables compensating for commuting	
Satisfaction with work	Satisfaction with main job measured on an eleven point scale from 0 = "completely dissatisfied" to 10 = "completely satisfied".
Satisfaction with leisure	Satisfaction with leisure time measured on an eleven point scale from 0 = "completely dissatisfied" to 10 = "completely satisfied".
Satisfaction with dwelling	Satisfaction with dwelling measured on an eleven point scale from 0 = "completely dissatisfied" to 10 = "completely satisfied".
Household crowding index	Household crowding index defined as the number of usual residents in a dwelling divided by the number of rooms in the dwelling.
Industry	9 dummies equalling 1 for individuals working in the named industry: agriculture, energy, mining, manufacturing, construction, trade, transport, bank or insurance, services.
Region	Dummy variables for the 16 federal states of Germany.
Year	Dummy variables for each year covered by the sample.

Table A.2. Descriptive statistics for full sample and for commuter categories.

	Full sample				Non-Commuter		Short distance commuter		Middle distance commuter		Long distance commuter	
	Mean	SD	Min.	Max.	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Number of days absent	10.36	24.70	0	365	9.96	24.31	10.59	25.12	10.43	23.72	11.86	27.62
Incidence of absence	0.6529	0.47	0	1	0.6328	0.48	0.6589	0.47	0.6786	0.46	0.7005	0.45
Female	0.47	0.49	0	1	0.54	0.49	0.45	0.49	0.37	0.48	0.30	0.46
Age	45.25	9.00	19	64	45.64	9.00	45.08	9.01	44.71	8.82	44.87	9.34
Married	0.74	0.43	0	1	0.73	0.44	0.75	0.43	0.74	0.43	0.76	0.42
Children	0.40	0.48	0	1	0.38	0.48	0.41	0.49	0.39	0.48	0.40	0.49
Education:												
No school certificate (ref.)	0.09	0.25	0	1	0.07	0.27	0.09	0.25	0.07	0.21	0.05	0.15
Sec. general school certificate	0.25	0.43	0	1	0.27	.044	0.26	0.44	0.22	0.41	0.18	0.38
Intermediate school degree	0.38	0.48	0	1	0.39	0.48	0.37	0.47	0.38	0.48	0.40	0.49
Vocational high school	0.06	0.24	0	1	0.05	0.22	0.06	0.24	0.07	0.26	0.07	0.27
College entrance exam	0.22	0.41	0	1	0.19	0.39	0.22	0.41	0.26	0.43	0.30	0.45
College degree	0.25	0.43	0	1	0.23	0.42	0.22	0.41	0.30	0.45	0.34	0.47
Health status:												
Very good (ref.)	0.09	0.25	0	1	0.07	0.26	0.09	0.25	0.08	0.24	0.11	0.27
Good	0.46	0.49	0	1	0.47	0.49	0.45	0.49	0.45	0.49	0.44	0.49
Acceptable	0.34	0.47	0	1	0.33	0.47	0.35	0.47	0.36	0.48	0.33	0.47
Less good	0.10	0.30	0	1	0.09	0.29	0.10	0.31	0.10	0.30	0.11	0.31
Bad	0.01	0.10	0	1	0.01	0.11	0.01	0.10	0.01	0.10	0.01	0.12
Working hours	35.18	7.74	1.5	72.5	33.94	8.65	35.55	7.25	36.75	6.10	38.14	4.73
Regular part-time	0.21	0.40	0	1	0.27	0.44	0.19	0.39	0.12	0.33	0.06	0.25
Temporary job	0.02	0.15	0	1	0.02	0.14	0.02	0.15	0.02	0.14	0.03	0.17
Blue-collar worker	0.29	0.45	0	1	0.30	0.46	0.31	0.46	0.26	0.44	0.20	0.40
Firm size:												
< 5 employees (ref.)	0.06	0.19	0	1	0.05	0.22	0.06	0.16	0.04	0.13	0.05	0.14
5 – 19 employees	0.12	0.32	0	1	0.14	0.35	0.11	0.32	0.08	0.27	0.06	0.25
20 – 99 employees	0.19	0.39	0	1	0.22	0.41	0.18	0.39	0.15	0.36	0.15	0.36
100 – 199 employees	0.10	0.31	0	1	0.11	0.32	0.10	0.30	0.09	0.29	0.08	0.27
200 – 1999 employees	0.26	0.43	0	1	0.24	0.43	0.27	0.44	0.26	0.44	0.27	0.44
2000 employees and over	0.27	0.44	0	1	0.20	0.40	0.28	0.45	0.38	0.48	0.39	0.48
Public sector	0.34	0.47	0	1	0.37	0.48	0.33	0.47	0.32	0.46	0.31	0.46
Tenure	14.95	9.52	2	49.80	15.06	9.60	15.23	9.49	14.45	9.32	13.51	9.48
Log (monthly wage)	7.76	0.57	4.23	10.23	7.62	0.60	7.80	0.53	7.94	0.51	8.06	0.47
Satisfaction with work	6.95	1.86	0	10	7.04	1.86	6.90	1.85	6.88	1.84	6.79	1.99
Satisfaction with leisure	6.61	2.01	0	10	6.77	1.98	6.56	1.99	6.46	1.97	5.99	2.19
Satisfaction with dwelling	7.82	1.72	0	10	7.80	1.73	7.84	1.68	7.83	1.70	7.80	1.81
Household crowding index	0.70	0.28	0.09	10	0.71	0.29	0.70	0.28	0.67	0.28	0.69	0.27
N	31,567				14,113		10,435		5,129		1,890	
%	100%				46%		33%		16%		5%	

Table A.3. Estimation results. Dependent variable: Days absent.

	Model I Pooled NEGBIN	Model II Pooled OLS	Model III FE NEGBIN	Model IV FE OLS
Focal variable				
Non-commuter (ref.)				
Short distance commuter	0.038 (1.45)	0.572 (1.86)	0.044 (1.91)	1.305 (1.94)
Middle distance commuter	0.070* (2.17)	0.846* (2.17)	0.109*** (3.65)	2.607** (2.79)
Long distance commuter	0.201*** (3.72)	2.173*** (3.36)	0.191*** (4.35)	3.370* (2.56)
Personal characteristics				
Female	0.191*** (6.52)	2.073*** (6.11)	0.256*** (8.77)	
Age	-0.036*** (-3.33)	-0.374** (-2.96)	-0.097*** (-9.11)	-1.917*** (-5.09)
Age^2	0.0005*** (4.20)	0.005*** (3.69)	0.0008*** (6.92)	0.023*** (5.39)
Married	0.013 (0.44)	0.064 (0.17)	0.009 (0.37)	0.654 (0.62)
Children	-0.056 (-1.91)	0.087 (0.27)	0.065** (2.75)	0.326 (0.48)
Education: No school certificate (ref.)				
Secondary general school certificate	0.066 (1.36)	0.454 (0.67)	-0.001 (-0.04)	7.260*** (5.86)
Intermediate school degree	-0.086 (-1.78)	-0.535 (-0.81)	0.129* (2.53)	3.153** (2.85)
Vocational high school	-0.072 (-1.08)	-1.000 (-1.30)	0.239*** (3.56)	0.932 (0.60)
College entrance exam	-0.151** (-2.73)	-1.231 (-1.83)	0.322*** (5.55)	5.702*** (4.60)
College degree	-0.181*** (-5.01)	-1.245** (-3.18)	-0.025 (-0.69)	-1.622 (-0.95)
Health status: Very good (ref.)				
Good	0.270*** (5.80)	1.386*** (5.33)	0.157*** (4.67)	1.242** (3.18)
Acceptable	0.661*** (13.47)	4.557*** (13.36)	0.343*** (9.52)	2.577*** (4.93)
Less good	1.335*** (23.28)	15.650*** (19.74)	0.581*** (14.20)	10.871*** (10.48)
Bad	2.381*** (26.99)	58.930*** (13.43)	0.947*** (14.08)	47.503*** (9.90)
Job-related aspects				
Working hours	0.017*** (6.29)	0.165*** (5.30)	0.007*** (3.67)	0.073 (1.18)
Regular part-time	0.149** (3.23)	1.244* (2.12)	0.046 (1.30)	-0.555 (-0.61)
Temporary job	-0.101 (-1.39)	-1.471* (-2.43)	-0.092 (-1.59)	-2.156* (-2.39)
Blue-collar worker	0.286*** (8.36)	2.787*** (6.67)	-0.033 (-1.18)	1.350 (1.39)
Firm size: < 5 employees (ref.)				
5 – 19 employees	0.127 (1.64)	0.987 (1.55)	0.249*** (3.99)	-0.835 (-0.67)
20 – 99 employees	0.293*** (3.87)	2.608*** (4.00)	0.371*** (5.95)	2.459 (1.62)
100 – 199 employees	0.366*** (4.52)	3.304*** (4.60)	0.383*** (5.87)	2.338 (1.47)
200 – 1999 employees	0.444*** (5.87)	4.428*** (6.76)	0.454*** (7.25)	3.626* (2.45)
2000 employees and over	0.468*** (6.15)	4.578*** (6.90)	0.446*** (7.10)	2.700 (1.80)
Public sector	0.158*** (4.76)	1.487*** (3.98)	0.177*** (6.31)	0.388 (0.50)
Tenure	-0.005 (-1.15)	0.025 (0.46)	-0.0005 (-0.13)	0.462** (3.21)

Table A.3. cont. Estimation results. Dependent variable: Days absent.

	Model I Pooled NEGBIN	Model II Pooled OLS	Model III FE NEGBIN	Model IV FE OLS
Tenure^2	0.00007	-0.001	0.00008	-0.006
	(0.64)	(-0.69)	(0.84)	(-1.61)
Log (monthly wage)	-0.072	-1.107*	0.184***	-1.344
	(-1.88)	(-2.58)	(6.43)	(-1.44)
Variables compensating for commuting				
Satisfaction with work	-0.049***	-0.566***	-0.034***	-0.401**
	(-7.11)	(-5.46)	(-7.29)	(-2.69)
Satisfaction with leisure	0.013*	0.263***	0.013**	0.202
	(2.25)	(3.35)	(3.01)	(1.71)
Satisfaction with dwelling	0.006	0.176	-0.002	-0.049
	(0.84)	(1.80)	(-0.53)	(-0.37)
Household crowding index	-0.033	-0.418	-0.082*	-0.926
	(-0.70)	(-0.76)	(-2.08)	(-0.96)
Business sector dummies	Included	Included	Included	Included
Region dummies	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included
constant	1.962***	10.480*	-0.893**	51.101***
	(5.23)	(2.38)	(-2.72)	(4.22)
N	31,567	31,567	31,567	31,567

Notes: *t* statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.4. Robustness checks.

	(Baseline) Sample used for Table 3	(i) Female	(ii) Male	(iii) Excluding public sector	(iv) Rural region	(v) Urban Region	(vi) Excluding 'sickness absence days outliers'	(vii) Excluding small distance changes	(viii) Commuting distance as dummy variable	(ix) Commuting distance as log-linear specification	(x) Including employer change
Short distance commuter	0.044	0.036	0.055	0.027	-0.004	0.062*	0.049	0.026			0.039
	(1.91)	(1.12)	(1.68)	(0.93)	(-0.10)	(2.37)	(1.93)	(1.00)			(1.74)
Middle distance commuter	0.109***	0.120**	0.102*	0.153***	0.235***	0.063	0.113***	0.078*			0.110***
	(3.65)	(2.65)	(2.54)	(4.04)	(3.75)	(1.86)	(3.39)	(2.38)			(3.72)
Long distance commuter	0.191***	0.162*	0.212***	0.258***	0.242**	0.167**	0.223***	0.154***			0.181***
	(4.35)	(2.19)	(3.84)	(4.66)	(3.05)	(3.14)	(4.56)	(3.35)			(4.24)
Commutes: 50 km and more (ref.: 0 – 49 km)									0.142***		
									(3.44)		
Commuting distance (in log)										0.046***	
										(4.96)	
N	31,567	14,942	16,625	20,279	7,673	23,848	28,968	25,370	31,567	31,190	32,178

Table A.4 cont. Robustness checks.

	(xi) Including residence change	(xii) Including employer and residence change	(xiii) 1-year-lag	(xiv) 2-year-lag	(xv) Dependent variable: incidence of absence
Short distance commuter	0.038	0.036	0.031	0.004	0.045
	(1.90)	(1.84)	(1.01)	(0.13)	(1.75)
Middle distance commuter	0.088***	0.092***	0.132***	0.060	0.078*
	(3.41)	(3.66)	(3.23)	(1.29)	(2.32)
Long distance commuter	0.177***	0.175***	0.233***	0.199**	0.141**
	(4.74)	(4.84)	(3.69)	(2.83)	(2.82)
N	39,181	40,289	18,369	14,321	31,567

Notes: Only the coefficients for the commuting variables are reported. Models (i) – (xiv) are fixed-effects negative binomial models with the number of 'days absent' as dependent variable. Model (xv) is a random effects probit model with the 'incidence of absence' as dependent variable. In models (i) – (vii) and models (x) – (xv) non-commuters are treated as the reference category. Like in the main table, all control variables are included in all specifications. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure A.1. Distribution of absence days.

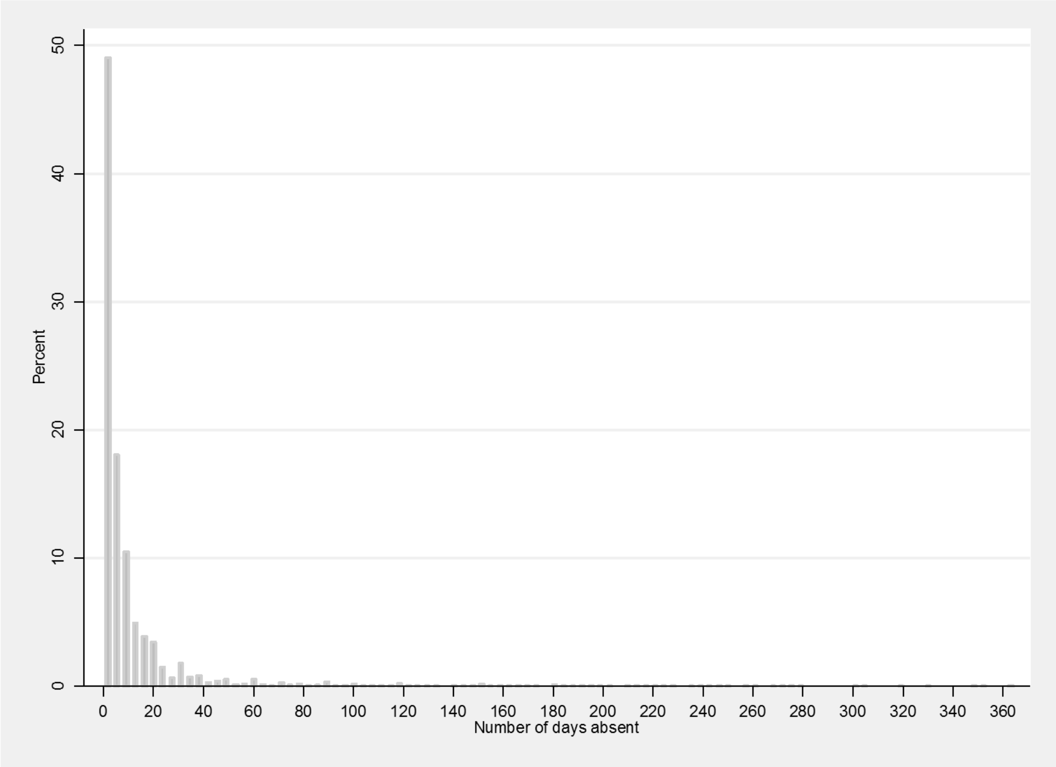
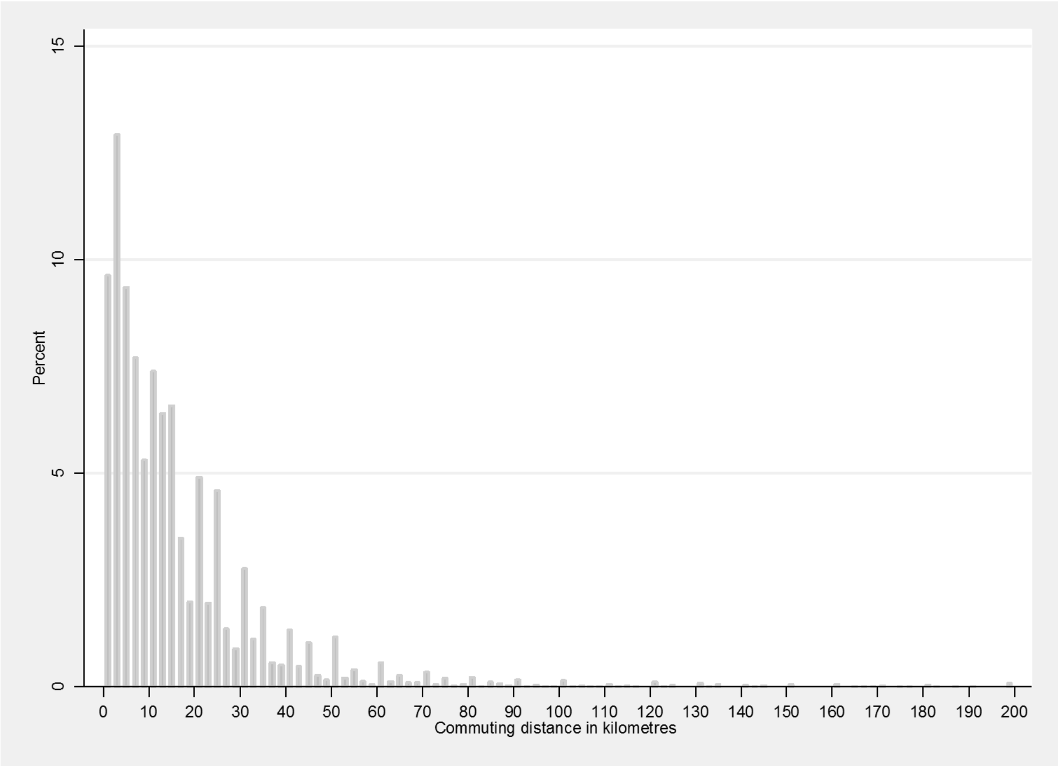


Figure A.2. Distribution of commuting distances.



Chapter 3

Is your commute really making you fat?

The effect of commuting distance on height-adjusted weight*

Commuting has become an increasingly important feature of modern life. Several studies claim that commuting is one of the causes for the rapid rise in obesity rates. However, empirical studies based on European data on how commuting may affect body weight are rare. Therefore, this paper explores the relationship between commuting distance and height-adjusted weight (BMI) in Germany, using micro-level data for the period 2002 – 2012. In contrast to previous papers, we find no evidence that longer commutes are associated with a higher BMI. The non-existence of a relationship between BMI and commuting distance prevails when physical activity and eating habits are adjusted for.

* This chapter is joint work with Laszlo Goerke. An earlier version of this paper appeared in the German Economic Association (VfS) working paper series 'Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel'. We thank the participants of the 2016 Lüneburg Workshop on Microeconomics, the 2016 Colloquium on Personnel Economics (COPE) in Aachen, the 2016 Spring Meeting of Young Economists (SMYE) in Lisbon, the 2016 International German Socio-Economic Panel User Conference in Berlin, the 2016 Annual Conference of the Verein für Socialpolitik (VfS) in Augsburg and a seminar at U Trier for helpful comments and suggestions.

3.1 Introduction

Overweight and obesity are rapidly growing health problems that affect an increasing number of countries worldwide.[29] Nowadays more than half a billion adults are classified as obese and the worldwide occurrence of obesity has nearly doubled between 1980 and 2014. According to the World Health Organization (WHO 2014b), 39% of adults (38% of men and 40% of women) were overweight and 13% (11% of men and 15% of women) were obese in 2014. The prevalence of overweight and obesity is highest in the Americas (61% overweight, 27% obese) and lowest in South-East Asia (22% overweight, 5% obese).

The worldwide growth in overweight and obesity is a serious cause for concern because weight or more precisely, an excessive BMI is a risk factor for a number of major illnesses including cardiovascular diseases, diabetes, musculoskeletal disorders and cancer (WHO 2014b). In the European Union, 8% of all deaths are attributed to excess weight, while in the United States obesity is the second leading cause of preventable diseases and of death next to smoking (e.g., Banegas et al. 2003, Flegal et al. 2004).

Besides the direct consequences in terms of health problems, excess weight also imposes a substantial financial burden. Overweight and obesity account, inter alia, for up to 21% of national health care expenditures (Cawley and Meyerhoefer 2012). In addition to these direct medical costs, obesity also entails more indirect costs. Excessive weight is, for example, shown to lower productivity. The literature in this area includes analyses of the aggregate productivity losses originating in the labour market, including sickness absence and also presenteeism (Hammond and Levine 2010). Excess weight may also have other consequences that affect economic outcomes. Overweight or obese individuals are more likely to suffer from social stigmatisation and discrimination. Such consequences have been documented in a variety of settings, including health care and the labour market (e.g., WHO 2004, Zettel-Watson and Britton 2008). In the latter case, there is growing evidence that obese people receive lower wages and are less likely to be employed than non-obese people (e.g., Cawley 2004, Morris 2007, Lakdawalla and Philipson 2007, Wada and Tekin 2010, Majumder 2013,

[29] Overweight and obesity are defined as abnormal or excessive fat accumulation that may impair health. Overweight and obesity are normally measured in terms of body mass index (BMI), which is a simple index of weight-for-height. It is defined as a person's weight in kilograms divided by the square of height in meters (kg/m^2). The BMI range generally considered to be healthy is 20 to 25 kg/m^2. Those with a BMI below 20 kg/m^2 are underweight, those with a BMI greater than or equal to 25 kg/m^2 are overweight and those with a BMI greater than or equal to 30 kg/m^2 are obese (WHO 2014b).

Averett 2014). This multitude of detrimental effects indicates how important it is to slow the growth of overweight and obesity.

The fundamental cause of excessive weight is an energy imbalance whereby the energy intake from food and drink surpasses energy expenditure for metabolic processes and physical activity. Usually, energy balance within the body is well regulated by a range of physiological responses. However, societal and environmental factors may influence energy intake and expenditure through effects on dietary and physical activity patterns, resulting in an attenuation of the physiological control of body weight. Such factors include, but are not limited to, a changing food and activity environment, varying modes of transportation, increasing urbanisation and a modified work environment. In particular, the increased demand for more worker flexibility and mobility and, hence, longer commuting times and distances, have led to a situation which complicates planned nutrition and participation in physical activity (e.g., European Policy Brief 2008, Abramowitz 2016). Such behavioural changes may result in a higher BMI (Gill 2015).

Therefore, in recent years, the journey to work has gained attention in the study of overweight and obesity. An understanding of the relationship between the travel to work and excessive weight is important not only because the social need for a mobile workforce has led to increasing commuting times and distances in recent decades, but also because commuting to the workplace is an important dimension of labour market experience as well.[30] More fundamentally, work-related mobility helps to match people with jobs they are qualified and motivated to do, thus boosting productivity and contributing to economic output. The consequences of job-related mobility, however, are not exclusively beneficial. There is a concern among researchers that increased mobility may discourage individuals from health-producing activities, such as exercise and food preparation, and thereby deteriorate health and increase body weight (e.g., Courtemanche 2009, Abramowitz 2016). This concern is compounded by the finding that commuters are more likely to suffer from excess weight. Studies that explicitly deal with the relationship between commuting and obesity are fairly common in the US, where mobility, commuting, car dependence and suburbanisation are extensive (Lindström 2006). However, despite the relevance of commuting for so many people and for societies as a whole, there appear to be very few studies in a European setting that have focused on how it may affect body weight (for exceptions, see Lindström 2008,

[30] In the US, for example, average commuting distances increased from 8.9 miles in 1983 to 21.1 miles in 2001 (Hu and Reuscher 2004). The average distance commuted to work in the UK increased from 13.4 km in 2001 to 14 km in 2011 (Office for National Statistics 2014).

Flint et al. 2014, Martin et al. 2015, Künn-Nelen 2016). The question is whether the positive relationship identified in an American context is valid in Europe, as well.

Against this background, with this paper we aim to enrich the existing knowledge of the connection between commuting and height-adjusted weight with regard to Germany. Therefore, we use data from the German Socio-Economic Panel (SOEP) for the period 2002 – 2012. The SOEP has the advantage of including a large range of individual characteristics over many years. Due to its panel structure, fixed effect (FE) analyses are possible. We intend not only to provide evidence on the effect of commuting on BMI, but also to shed some light on the mechanisms through which commuting might affect individual's body weight.

Thereby, we add to the understanding of the effect of commuting distance on BMI on at least four frontiers: First, this relationship has not been studied in Germany before, and it is not clear whether the results found for the US are valid elsewhere. Although the prevalence of obesity is increasing in Germany, it is much less widespread than in the United States. Second, we contribute to the literature by providing a more complete analysis of the link between commuting distance and BMI. To our knowledge, this is the first paper to estimate the effect of individual-level commuting distance on height-adjusted weight using panel data to control for unobserved time-invariant heterogeneity. Third, this is the first study exploring possible explanations for the relationship between commuting distance and BMI. Fourth, it is also worth stressing that our study differs from other recent analyses since our key variable is not commuting time but commuting distance. Although commuting times and distances are correlated (e.g., Small and Song 1992, Rietveld et al. 1999) we nowadays mainly observe a rise in distances travelled, which is driven by higher speeds and more pronounced urban sprawl (e.g., Crozet and Joly 2004, Lyons and Chatterjee 2008). Since commuting distance appears to be increasing at a steady rate, it is important to see what impact longer distances have on individual's BMI.

Our results cast doubt on the idea that commuting is positively associated with excess weight. More precisely, we show that an increase in commuting distance does not affect an individual's BMI. Even after controlling for time-invariant characteristics no significant associations are observed. In addition, the non-existence of a relationship between BMI and commuting distance is consistently found across various sub-samples and prevails regardless of included control variables (e.g., physical activity and eating habits). We further demonstrate that compensating health behaviour of commuters, especially healthy eating habits, could explain the non-relationship of commuting and BMI.

The structure of this paper is as follows: The next section reviews related literature. Section 3.3 presents the data used and the econometric methodology. Section 3.4 reports results, including several robustness checks, and discusses explanations for the findings. Section 3.5 concludes the study.

3.2 Related literature

We commence our exposition of the relation between commuting and BMI with a description of the research on commuting and body weight in Europe, which is focussed on the UK and Sweden.[31] Subsequently, we summarise the extensive literature for the US, for which very detailed micro data on commuting is available.[32]

Flint et al. (2014) use cross-sectional data from the UK Household Longitudinal Study (UKHLS) and find that, compared to using public or active transport, commuting by private transport mode is significantly related to higher BMI. Although Flint et al. (2014) use objectively assessed biological markers of obesity (BMI, percentage of body fat), they cannot infer the direction of causality, since data is only available for one point in time. Martin et al. (2015) use cohort data from three consecutive waves of the British Household Panel Survey (BHPS) and show that switching from private motor transport to active travel or public transport is associated with a significant reduction in BMI compared to continued private motor vehicle use. Similarly, they suggest that substituting active travel or public transport by private motor transport is associated with a significant increase in BMI. In contrast to cross-sectional studies, the main strength of this study lies in its use of cohort data from a longitudinal examination of nationally representative households to examine associations between changes in mode of travel to work and changes in BMI over time. However, important key determinants of BMI, such as physical activity and dietary behaviour, are unobserved in this data. Künn-Nelen (2016) uses data from several different waves of the

[31] Additionally, the literature of social science, planning and transportation has documented the correlation between individual travel, urban sprawl and obesity. Individuals in more walkable, mixed-use and transit-accessible neighbourhoods tend to walk or bike more and have a lower chance of obesity compared with those in automobile-dependent neighbourhoods (e.g., Frank and Engelke 2001, Handy et al. 2002, Ewing et al. 2003, Frank et al. 2004, Badland and Schofield 2005, TRB 2005, Forsyth et al. 2009, Samimi et al. 2009, Badland et al. 2012).

[32] Furthermore, there are two studies for Australia. Using cross-sectional data from a representative sample of the 2003 New South Wales Adult Health Survey, Wen et al. (2006) find a significant association between commuting to work by car and overweight or obesity compared with active transport to work such as walking or cycling. Likewise, Sugiyama et al. (2013) examine whether commuting by car is associated with weight gain among 822 adult residents of Adelaide, Australia. The study suggests that adults who commuted by car tended to gain more weight than those who did not.

BHPS to analyse the relation between sedentary commuting times and several measures of health for full-time workers. The findings indicate that especially for car drivers commuting time is positively related to a higher BMI. This relationship is not found for commuters using public transportation. The longitudinal characteristic of the BHPS allows the estimation of fixed-effects models. Once again, key determinants of BMI are not accounted for in the main analyses.

Lindström (2008) investigates the association between means of transportation to work and overweight and obesity in southern Sweden. Based on a cross-sectional postal questionnaire study, Lindström (2008) finds that walking and bicycling to work is significantly negatively associated with overweight and, to some extent, obesity.

Turning to the US, Frank et al. (2004) use data from a cross-sectional travel survey of around 11,000 adults in the Atlanta, Georgia region, to evaluate the relationship between the built environment and self-reported travel patterns (walking and time in a car), on the one hand, and obesity (BMI $\geq$ 30) on the other for specific gender and ethnicity classifications. Frank et al. (2004) show that each additional hour spent in a car per day is associated with a 6% increase in the likelihood of obesity. Conversely, each additional kilometre walked per day is associated with a 4.8% reduction in the likelihood of obesity. Further, they suggest that an increased land-use mix (net residential density and street connectivity) is associated with a 12.2% reduction in the likelihood of obesity. Key limitations of this study are the cross-sectional research design and its limited generalisability since the findings are restricted to the city of Atlanta and its suburbs.

Lopez-Zetina et al. (2006) use data from the California Health Interview Survey 2001 (CHIS 2001), the US 2000 Census, and the California Department of Transportation to examine correlations between vehicle miles of travel, population density, commute time, and county indicators of obesity and physical inactivity. Obesity is positively associated with vehicle miles of travel at the county level. Similar patterns are observed between obesity and commute time. Likewise, drawing on US data at the national level, Jacobson et al. (2011) contribute to the understanding of the relationship between miles driven per licensed driver and adult obesity. Gordon-Larsen et al. (2009) analyse the relationship between walking or biking to work and a variety of health indicators, including obesity, using cross-sectional data acquired from the Coronary Artery Risk Development in Young Adults (CARDIA) study. They find that men with any active commuting (versus none) are less likely to be obese.

Using data from the 2006 American Time Use Survey (ATUS), Dunton et al. (2009) examine the interaction between time spent in physical activity and sedentary behaviour on the one hand and BMI on the other for US adults. The results indicate that spending less time in sedentary transport (motorised vehicles) is associated with lower BMI among those engaging in some active transportation (walking, biking). Although Dunton et al. (2009) use a wide range of leisure time- and transportation-related sedentary and active behaviours, the cross-sectional survey design prohibits causal inferences. Also utilising the ATUS for 2003 – 2008 and its Eating and Health Module for 2006 and 2007, Yang and French (2013) examine the relationship between individual travel (percentage of travel time spent in a vehicle), energy expenditure and obesity. Distinguishing between sedentary commuting and non-commuting trips, their results suggest that work-related travel has a relatively larger impact on individuals' BMI, but increased levels of general travel are not associated with BMI.

The study most relevant to our analysis is that by Hoehner et al. (2012). Using cross-sectional data from 4,297 adults living in metropolitan counties in the state of Texas, they examine the impact of commuting distance on indicators of health, including BMI. Hoehner et al. (2012) find commuting distance, measured as the shortest distance along the road network between individuals' home and work, to be positively associated with BMI. While enhancing our knowledge on the relationship between commuting distance and BMI, the study has several constraints: In particular, information about actual distance travelled was not available to the authors. Moreover, the study population is limited to predominantly white, mostly male, well-educated, healthier adults of middle-to-upper socioeconomic status typically in the Dallas-Fort Worth-Arlington Metropolitan Statistical Area, a region ranked among the top five most congested metropolitan areas in the US. While this homogeneity may improve internal validity of the study, its findings may, hence, not be generalisable at the population level. Furthermore, important key determinants of BMI, such as physical activity and dietary behaviour, are unobserved in this data.

In sum, little consensus exists with respect to the effect of commuting on BMI. On the one hand, considerable evidence suggests that individuals with lengthy commute times and distances are more prone to excess weight. On the other hand, it has consistently been shown that especially active commuting, such as commuting by bicycle or walking, translates into higher levels of overall individual physical activity resulting in lower BMI. While these findings help to understand the relationship between commuting and BMI, there are a number of limitations in the existing literature. First, many of the extant studies only examine correlations of commuting time or endogenously chosen modes of commuting and BMI; and are mainly based on cross-sectional data as well as highly selective samples. Hence, causality and generalisability is a major concern of the existing studies. Second, due to data limitations important determinants of BMI, such as physical activity und dietary patterns, can often be considered only to a limited extent. Therefore, the effect of commuting on BMI may not be adequately accounted for, if such information is ignored. Closely related to this, the relevant studies fail to investigate potential channels determining the relationship between commuting and BMI. Third, the existing analyses are predominantly based on data from the US and the UK. However, European countries have much lower rates of obesity than the United States. Moreover, attitudes towards mobility and, hence, commuting behaviour is different. Consequently, findings relating, for example, to the US cannot directly be applied to other countries, such as Germany (e.g., Giuliano and Dargay 2006, Bassett et al. 2008).

3.3 Data and method

3.3.1 Data

We employ data from the German Socio-Economic Panel (SOEP), which is representative for the entire population of Germany, aged 17 and older. The SOEP includes rich information on labour market status, wealth, incomes and standard of living, health and life satisfaction as well as on family life and socio-economic variables.[33]

We restrict our sample to the years 2002, 2004, 2006, 2008, 2010 and 2012 since these years provide information on self-reported body weight and height, which are crucial for calculation of the BMI. Further, we include only working adults aged 18 to 65, and exclude self-employed respondents, since they are more likely to work from home and generally have different commuting patterns than employees (Roberts et al. 2011). Moreover, since weight may be affected by current or recent pregnancy, we exclude women who are on maternity leave at the time they report their weight or who gave birth in the year of observation.

[33] Further information about the SOEP is provided by Wagner et al. (2007) and can also be found at: http://www.diw.de/english/soep/29012.html. We use the SOEP long v30 dataset.

Given the information on self-reported body weight and height of respondents, we calculate our dependent variable labelled ‘log (BMI)’ by dividing a respondent’s weight in kilograms by the square of its height in meters (kg/m^2) before taking the logarithm.[34]

The key explanatory variable is self-reported one-way commuting distance to work, derived from the question “How far (in kilometres) is it from where you live to where you work?”. For the years we are observing, the SOEP does not provide information about commuting mode and commuting time. Nevertheless, given the travel patterns in Germany, passive commuting modes, such as commuting by car or public transport are very likely (Federal Statistical Office 2012).

The choice of control variables is informed by the literature on the determinants of commuting and obesity or overweight (e.g., Frank et al. 2004, Wen et al. 2006, Hoehner et al. 2012, Flint et al. 2014, Abramowitz 2016). The variables can be grouped into the following categories and are described in Table B.1 of Appendix B along with definitions: demographic features, education, income- and work-related characteristics, regional and year controls, as well as indicators of health status, health behaviour and time use information.[35]

Table B.2 of Appendix B presents the sample statistics for the full sample. The mean BMI for the sample is 25.55 and the mean one-way commuting distance amounts to 21.54 kilometres. This is in line with a range of other studies employing German data (e.g., OECD 2007, Clark and Etilé 2011). Figures B.1 and B.2 of the Appendix present the distributions of commuting distance and BMI and Table 3.1 reports the association between commuting distance and BMI. The mean BMI increases by about 0.20 BMI points, as one-way commute distance increases from under ten (non-commuters) to over 50 kilometres. Those individuals who commute long distances have a BMI of 25.70 on average. In other words, with a height of e.g. 1.70 meters a long distance commuter would have on average about 0.6 kilogrammes more weight than a non-commuter. Figure B.3 of Appendix B plots the average one-way commuting distance and the average BMI per year. The figure shows a clear though small increase in both the average distance, from 21.02 km in 2002 to 22.01 km in 2012, and the

[34] Self-reported weight and height could be problematic as people commonly under- or over-report their height. However, researchers with access to both self-reported and actual height have shown that correcting for errors in the self-reported values does not substantially alter coefficient estimates in regressions of body weight (i.e., Cawley 2004, Lakdawalla and Phillipson 2009).

[35] We do not have explicit information whether a job is sedentary or active. However we include detailed information on individuals’ occupational position (18 dummy variables) indicating whether someone is, for example, an agricultural worker or a managerial employee. This is a good proxy for physically demanding tasks which might influence body weight.

average BMI, from 25.08 BMI points in 2002 to 25.97 BMI points in 2012.[36] Figure B.4 of Appendix B illustrates the basically positive association between commuting distance and BMI, differentiated by survey years.

All in all, the descriptive statistics indicate that individuals who commute longer distances have a higher BMI. However, from distance category to distance category the increase of BMI points is relatively small.

Table 3.1. Descriptive statistics for the full sample and for distance categories.

	Full sample		Distance: less than 10 km		Distance: 10 – 24 km		Distance: 25 – 49 km		Distance: 50 km and more	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
BMI	25.55	4.41	25.48	4.46	25.53	4.50	25.73	4.31	25.70	4.12
BMI (log)	3.22	0.16	3.22	0.16	3.22	0.16	3.23	0.16	3.23	0.15
CD (in km)	21.54	53.79	3.81	2.49	15.16	4.03	32.22	6.60	136.38	155.83
N	47,762		21,614		14,955		7,745		3,448	
%	100%		45.25%		31.31%		16.22%		7.22%	

Notes: Summary statistics only for commuting distance. SD = Standard deviation. Appendix B shows the detailed descriptive statistics in Table B.2.

3.3.2 Method

We employ ordinary least squares (OLS) regressions to model BMI as a function of commuting distance and other covariates. This approach is feasible since we need not get the functional form perfectly right to obtain valid estimates of the average partial effects. The OLS model can be formalised as:

$$log\,(bmi_i) = \alpha + \beta CD_i + \gamma X_i + \varepsilon_i \tag{3.1}$$

where $log\,(bmi_i)$ is the individual's logarithm of height-adjusted weight, CD_i is the commuting distance, vector X_i includes all the control variables and ε_i denotes the error term. β and γ are coefficients and our main interest lies in β. The pooled estimator identifies the effect of commuting distance on BMI based on the variation in these variables between people and for each individual over time. It is assumed that unobserved characteristics, as well as measurement errors, are captured in the error term of the estimation.

Further, the longitudinal characteristic of the SOEP allows estimating fixed-effects OLS specification in which idiosyncratic effects that are time invariant can be controlled for. The effect of commuting distance on BMI is then identified by the variation in commuting

[36] In 2003 there is a drop in average commuting distance. However, this is not a problem for our results, since 2003 is not included in our specification because BMI is not available for this year.

distance within observations for the same individual. Thus, equation (3.2) takes the following form:

$$log\ (bmi_{it}) = \alpha_i + \beta CD_{it} + \gamma X_{it} + \varepsilon_{it} \tag{3.2}$$

where $log\ (bmi_{it})$ is individual i's logarithm of height-adjusted weight in year t, α_i denotes time-invariant idiosyncratic effects. The remaining notation is comparable to that of equation (3.1). Additional analyses in Sections 3.4.2 and 3.4.3 explore issues of heterogeneity and robustness of the results.

3.4 Results

3.4.1 Estimation results

Table 3.2 presents the estimation of equation (3.1), starting with a basic model using no control variables in column (1). In column (2), demographic controls are added; these include information on sex, age, number of children and having a spouse or unmarried partner in the household as well as on migration background. Two controls for individual's level of education are added in column (3) and a variable indicating an individual's income in column (4). In column (5) results are presented, additionally controlling for job-related characteristics and in column (6), results from the full model are presented, which include all controls from the previous models as well as state and year controls.[37]

The negative coefficient of commuting distance (CD) in column (6) indicates that a ten-kilometre increase in commuting distance is associated with a 0.0002 point lower logarithm of BMI. However, this effect is not statistically significant. The estimated coefficient of interest is only of significance in column (2), when demographic controls are added. This significance disappears when levels of education are controlled for. These results suggest that, firstly, a number of socio-economic and demographic variables play important roles in determining BMI and, secondly, that the commuting variable incorporates the contributory effect of education. In the past decades, many empirical findings have documented that highly educated people travel longer while low-educated people tend to work closer to home (e.g., Lee and McDonald 2003, Vance and Hedel 2008). Moreover, education is assumed to be one of the most important determinants of health. In general, education yields better health

[37] Every single covariate was also tested one by one, but this did not alter the results.

knowledge, which is important to understand the health effects of one's actions. For instance, better educated individuals should know more about the long-term health risks of being overweight. Therefore, it can be expected that they pay more attention to their nutrition and physical activities in order to watch their weight. This is also in line with studies showing that individuals who behave 'healthily' are more likely to have a higher educational status (e.g., Contoyannis and Jones 2004).

Table 3.2. The relationship between commuting distance and log (BMI).

	Pooled OLS					
	(1) Basic model	(2) Demographic controls	(3) Education controls	(4) Income controls	(5) Job controls	(6) Regional and year controls
CD	0.00001 (1.09)	-0.00003** (-2.11)	-5.67e-06 (-0.45)	-1.94e-06 (-0.15)	-6.24e-06 (-0.49)	-0.00002 (-1.54)
Women		-0.0748*** (-52.47)	-0.0751*** (-53.04)	-0.0075*** (-49.83)	-0.0713*** (-39.98)	-0.0717*** (-40.35)
Age		0.0080*** (17.14)	0.0086*** (18.52)	0.0092*** (18.81)	0.0078*** (14.63)	0.0078*** (14.52)
Age^2		-0.00006*** (-10.44)	-0.00006*** (-11.62)	-0.00007*** (-12.20)	-0.00005*** (-8.78)	-0.00005*** (-8.95)
Number of Children		-0.0041*** (-4.72)	-0.0039*** (-4.51)	-0.0042*** (-4.85)	-0.0031*** (-3.58)	-0.0031*** (-3.58)
Married		0.0212*** (11.37)	0.0199*** (10.71)	0.0199*** (10.68)	0.0208*** (11.17)	0.0218*** (11.67)
Migration background		0.0117*** (6.51)	0.0083*** (4.63)	0.0085*** (4.57)	0.0034* (1.85)	0.0056*** (2.98)
School degree			-0.0204*** (-10.89)	-0.0196*** (-10.41)	-0.0131*** (-6.52)	-0.0141*** (-7.00)
College			-0.0224*** (-11.26)	-0.0208*** (-10.12)	-0.0154*** (-6.81)	-0.0158*** (-6.91)
Log (monthly wage)				-0.0043*** (-3.52)	-0.0068*** (-3.68)	-0.00568*** (-2.94)
Working hours					0.0007*** (5.86)	0.0006*** (4.96)
Firm size: Less than 5 employees (ref.)						
5 – 19 empl.					0.0038 (1.11)	0.0030 (0.88)
20 – 99 empl.					0.0089*** (2.60)	0.0079** (2.32)
100 – 199 empl.					0.0064* (1.72)	0.0055 (1.47)
200 – 1999 empl.					0.0083*** (2.42)	0.0072** (2.13)
2000 and more empl.					0.0180*** (3.11)	0.0104*** (3.00)
Urban area						-0.0064*** (-3.45)
Constant	3.2267*** (3955.57)	3.0225*** (332.31)	3.0202*** (331.34)	3.0421*** (273.69)	3.0183*** (215.13)	3.0015*** (208.51)
Occupational position dummies					x	x
Industry dummies					x	x
Federal state dummies						x
Year dummies						x
N	47,762	47,762	47,762	47,762	47,762	47,762

Notes: All models are estimated using robust standard errors. t statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

In sum, the pooled OLS results presented in Table 3.2 suggest that commuting distance is not associated with BMI, but uncover a negative coefficient. This finding is not in line with the cross-sectional results reported by Hoehner et al. (2012) for the United States, according to which commuting distance is positively associated with BMI.

Concentrating on the models in which we account for the potential impact of time-invariant, unobservable characteristics on BMI (Table 3.3) we may draw the same conclusion with respect to the relationship between commuting and BMI.

Table 3.3. The relationship between commuting distance and log (BMI).

	Fixed-effects OLS					
	(1) Basic model	(2) Demographic controls	(3) Education controls	(4) Income controls	(5) Job controls	(6) Regional and year controls
CD	-6.76e-06	-9.32e-06	-9.53e-06	-9.22e-06	-7.43e-06	-9.00e-06
	(-0.60)	(-0.88)	(-0.90)	(-0.87)	(-0.71)	(-0.86)
Age		0.0126***	0.1254***	0.0127***	0.0121***	0.0119***
		(18.99)	(18.49)	(18.28)	(17.35)	(17.01)
Age^2		-0.00008***	-0.00008***	-0.00008***	-0.00007***	-0.00007***
		(-11.33)	(-11.02)	(-11.08)	(-10.26)	(-0.36)
Number of Children		-0.0002	-0.0002	-0.0003	-0.0004	-0.0003
		(-0.30)	(-0.28)	(-0.37)	(-0.49)	(-0.36)
Married		0.0084***	0.0084***	0.0083***	0.0081***	0.0083***
		(4.36)	(4.34)	(4.31)	(4.20)	(4.30)
School degree			0.0103	0.0103	0.0095	0.0098
			(1.28)	(1.28)	(1.17)	(1.51)
College			0.0031	0.0040	0.0071	0.0072
			(0.71)	(0.87)	(1.49)	(0.15)
Log (monthly wage)				-0.0012	0.0003	0.0005
				(-0.86)	(0.20)	(0.34)
Working hours					-0.0003***	-0.0003
					(-3.00)	(-3.01)
Firm size: Less than 5 employees (ref.)						
5 – 19 empl.					-0.0013	-0.0013
					(-0.48)	(-0.47)
20 – 99 empl.					-0.0015	-0.0013
					(-0.49)	(-0.43)
100 – 199 empl.					-0.0036	-0.0035
					(-1.06)	(-1.04)
200 – 1999 empl.					-0.0020	-0.0018
					(-0.65)	(-0.57)
2000 and more empl.					-0.0023	-0.0020
					(-0.72)	(-0.64)
Urban area						0.0048
						(1.08)
Constant	3.2272***	2.8484***	2.8467***	2.8520***	2.8429***	2.8336***
	(1.3e+04)	(199.81)	(196.74)	(179.24)	(160.07)	(144.69)
Occupational position dummies					x	x
Industry dummies					x	x
Federal state dummies						x
Year dummies						x
N	47,762	47,762	47,762	47,762	47,762	47,762

Notes: Model (6) is the preferred model. All models are estimated using robust standard errors. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Commuting distance shows no effect on BMI, but reveals negative signs of the estimated coefficients. The non-existent relationship between commuting distance and BMI remains robust to the inclusion of control variables. Comparing columns (2) of Table 3.2 and Table 3.3 indicates that when unobserved heterogeneity of individuals is accounted for with fixed effects (such as genes or attitudes towards risks, health or mobility) commuting distance is no longer significant.

Overall, the results indicate that especially age and marital status play important roles in determining BMI. These findings are consistent with findings in previous literature (e.g., Frank et al. 2004, Wen et al. 2006).

3.4.2 Heterogeneity and robustness of results

We perform several robustness analyses to satisfy ourselves of the reliability of the results. They can be grouped into two categories. In a first set of robustness checks, we analyse the relation between commuting distance and BMI for several sub-groups. Since both commuting behaviour and BMI exhibit heterogeneity by sex, we estimate equation (3.2) with the full set of controls for women and men separately. With the next sub-sample analysis, we follow Künn-Nelen (2016) and Wheatley (2014), who argue that commutes for full-time workers have a particularly large impact on health and well-being. Further, because commuting types (active vs. passive) could have opposing effects on BMI, we estimate a model that consists of individuals who report commuting more than 5 km to work.[38] We do so since we do not have explicit information on commuting mode. But, short distances are more likely to be entirely covered on foot or by bicycle, and, including both active and passive commuting types could result in their effects being cancelled out (Künn-Nelen 2016).

Finally, one major issue in the empirical study of the effect of commuting on health outcomes is reverse causation. We assume that commuting distance (CD) is exogenous in equation (3.2), because the FE specification controls for correlated unobservable effects on both commuting distance and BMI (assuming these effects are constant though time), and there do not seem to be strong reasons for expecting simultaneity between the two variables. However, the literature dealing with health consequences of commuting suggests that commuting may be endogenous. In our case, an increased BMI may reasonably affect decisions with respect to commuting. For example, an individual with high BMI may become

[38] Results do not change when we chose other cut-off points, i.e. 10 km or 15 km.

lethargic due to obesity-induced health barriers and myopic regarding the future (Majumder 2013). As a result, such individual may be less likely to accept jobs at longer distances. Consequently, commuting habits may result from excess weight. We do not have strong instruments for commuting distance, so it is not possible for us to compare the assumption of exogeneity with an instrumental variables approach. However, we have a stronger test because we are able to estimate the model for a subset of individuals who neither change employer nor residence location throughout the time period. For these individuals any variation in commuting distance is truly exogenous, caused say by an employer-induced workplace relocation. Thus, the estimated coefficient in a FE model gives an estimate of the effect of an exogenous change in commuting distance on BMI, controlling for a wide set of covariates and unobserved individual heterogeneity (the same approach is used by e.g., Roberts et al. 2011, van Ommeren and Gutiérrez-i-Puigarnau 2011, Künn-Nelen 2016).[39]

In a second set of robustness checks, we alter the methodology. First, we estimate models in which we attempt to deal with possible measurement errors in reported commuting distance. Therefore, we have experimented with several functional forms of distance. We test a quadratic function of commuting distance and log transform commuting distance to allow for non-linear effects of commuting distance in order to see whether our results are sensitive to the chosen functional specification. Moreover, we categorise commuting distance into 'short' (10 – 24 km), 'middle' (25 – 49 km) and 'long' (50 km or more) commutes. This approach is less sensitive to minor reporting errors and allows for qualitatively different effects of, for example, shorter and longer commutes on BMI. In order to further deal with the potential endogeneity of commuting, we replace commuting distance in equation (3.2) with a two-year lagged value of commuting distance in order to avoid the influence of BMI on contemporaneous commuting distance. This strategy is based on the assumption that lagged commuting distance is uncorrelated with the current BMI residual, which assumes no serial correlation in the BMI residuals for those periods. The next robustness checks address the question of how to measure BMI. Previous studies relate commuting distances to BMI or to certain ranges of the body mass index, i.e. overweight or obesity. In our main approach, we

[39] The literature dealing with the consequences of commuting argues that analyses of individuals who neither change employer nor residence reveal the effect of exogenous changes in commuting distance on health outcomes due to employer-induced workplace relocation. Unfortunately, the SOEP does not include more explicit information on workplace relocation. However, it is plausible that if a worker changes neither employer nor residence while commuting distance increases or decreases, the worker must have changed workplace location because e.g. of a firm relocation. Such changes in workplace location due to firm relocation have been shown to be quite common (Gutiérrez-i-Puigarnau and van Ommeren 2010, Gutiérrez-i-Puigarnau and van Ommeren 2015). For example, each year about 16.5% of firms in Germany are involved in relocation decisions (Federal Statistical Office 2008).

use the logarithm of BMI, whereas we treat it as a continuous (not log-transformed), binary (dummy equals 1 if BMI ≥ 25) or ordinal variable (underweight, normal weight, overweight, obese) in the next robustness checks. Therefore, we estimate, inter alia, fixed-effects logit and random-effects probit as well as fixed-effects ordered logit models.

Tables B.3 and B.4 of Appendix B report the results of the sub-sample-related and methodology-related robustness checks. Overall, our sensitivity analyses confirm the finding that BMI is not affected by commuting distance.[40]

3.4.3 Mechanisms

Given the general perception that commuting increases weight, especially for passive commuting modes, it is striking that we do not find such an association for Germany. Our findings are all the more noteworthy because they also apply to people who travel to work more than, for example, 25 kilometres per day and way and are, hence, very unlikely to actively commute (i.e., walk or cycle). Therefore, in this subsection, we analyse possible mechanisms which could explain our findings from an energy-balance and a time-use perspective because weight gain is predominantly caused by an imbalance between calories consumed (nutritional habits) and calories expended (physical activity).

Individuals usually have to travel between home and workplace during a certain window of time every day. Commuting arrangements are more rigid than other trips and cause even more stress when individuals additionally face excessively long working hours or commuting distances (Yang and French 2013). If individuals commute longer to work, available leisure time drops, ceteris paribus. This could theoretically increase individuals’ weight via two channels: First, the individual might exercise less and, hence, decrease calories expended (Courtemanche 2009). Second, the individual might devote less time to food preparation, causing a substitution from home-prepared meals to unhealthy convenience food, such as fast food and pre-prepared processed food. This substitution could increase caloric intake, as a higher frequency of eating fast food results in greater consumption of calories and fat (Satia et al. 2004) and is also associated with excess weight (Jefferey et al. 2006). In contrast to this

[40] In order to investigate whether commuting distances influence the BMI of individuals with low or high BMI differently, we additionally performed quantile regressions at the 25th, 50th, 75th and 95th quantiles which allows the effects of commuting distance on BMI to differ with BMI. Our results suggest that the BMI of individuals with a high BMI seems not to be determined by commuting distances different from those affecting the BMI of individuals with a low BMI. In other words, the effect of commuting distance on BMI is the same for people with low (at the 25% quantile) or high (at the 95% quantile) BMI. Results of the quantile regressions are available from the authors upon request.

line of argumentation, individuals who commute to work might be aware of the potentially adverse effect of commuting and, therefore, adjust their behaviour to their situational needs, e.g. they could use income to substitute away from time-intensive to goods-intensive health investments (Abramowitz 2016). In line with this hypothesis, Künn-Nelen (2016) finds evidence for compensating health behaviour among those with relatively long commutes, using data from the UK household longitudinal study Understanding Society. Long commutes appear to lead to changes in nutrition and physical activity levels that are likely to reduce weight, e.g. increased consumption of fruit and vegetables and higher levels of physical activity. Consequently, long distance commutes and the adjusted health behaviour may rather enhance health-aware nutrition and lifestyle than deteriorate it.

Even though the SOEP does not contain detailed data on nutritional habits and physical activities, we are able to perform additional analyses in order to explore whether the above mentioned mechanisms could explain the non-existence of a relationship between commuting distance and BMI in Germany. First, we estimate equation (3.2) with additional controls for health behaviours (smoking, nutritional habits, physical activity), health (health status, physical pain, physical problems, health concerns, vitality) as well as time use (overtime, working hours mismatch, time for leisure).[41] Second, since individuals do not choose their BMI directly but indirectly through, inter alia, nutrition and physical activity, we perform fixed-effects OLS and ordered logistic regressions that include commuting distance as key explanatory variable and the extent to which the respondent cares about health-conscious nutrition and the frequency of sport or exercise as dependent variables. The findings of these additional analyses can be found in the Appendix, Table B.5 and Table B.6.

The results in Table B.5 reveal that the non-relationship between commuting and BMI remains robust if adding further controls. The coefficients of the additional variables are consistent with findings of previous literature, suggesting that, for example, those paying little attention to healthy nutrition or those participating less frequently in sport activities have a significantly higher BMI compared to individuals who are conscious about healthy eating or more physically active (e.g., Yen et al. 2009, Kasteridis and Yen 2012).

Table B.6 contains evidence that commuting distance is positively associated with health-conscious nutrition. This, in turn, might induce a reduction in body weight. This result is in line with Künn-Nelen (2016) who presents descriptive evidence for compensating health

[41] Information about frequency of sport participation relates to the previous year (t – 1) since the relevant question is asked bi-annually in odd-numbered years, whereas the question relating to body weight is contained in even years.

behaviour among those with relatively long commute times. Individuals who commute longer tend to eat more fruits and vegetables. Further, our regression results presented in Table B.6 provide no support for a relationship between commuting distance and physical activity. Consequently, and contrary to expectations, we find no evidence that commuters exercise less compared to non-commuters. Hence, our additional analyses suggest that those who commute possibly compensate for it by paying more attention to a health-conscious nutrition.

In summary, commuting does not encourage physical inactivity in general, but tends to coincide with healthy eating behaviour. Therefore, these effects could explain why no significant relationship is found between commuting distance and BMI. Unfortunately, we are not able to investigate to which extent employees with different commuting distances eat, for example, more vegetables or/and fruits or how much time they spend doing sports or the type of sport. This limitation may be worth addressing in future research.

3.5 Conclusion

This study investigates how commuting distance affects BMI. As previous studies have mainly examined the American situation, there is a general lack of knowledge about these matters in a European context. Therefore, this paper explores the relationship between height-adjusted weight and commuting distance in Germany by using individual micro-data for the period 2002 – 2012. In contrast to other studies relating commuting to BMI, we use FE models to control for unobserved time-invariant characteristics of individuals. Hence, we argue that our findings can be interpreted as causal effects. This is confirmed by a robustness analysis in which we exploit exogenous variations of commuting distance within individuals, when there are no changes in residence and employer.

Our results provide no evidence that longer commutes are associated with a higher BMI. This non-relationship is consistently found across various sub-samples and prevails regardless of included control variables. We perform several analyses on possible mechanisms and identify a positive relationship between commuting distance and healthy nutritional habits. This could explain why there is no relation between commuting and BMI.

All in all, the German evidence presented is not in accordance with the results reported by Hoehner et al. (2012) for the United States, according to which commuting distance is positively associated with BMI. This raises the question why, is there a different relationship between commuting distance and BMI in Germany and in the US? A specific answer to this question requires further research, which is beyond the scope of this study. Nevertheless, three explanations are suggested that may account for at least some of the dissimilarity.

Firstly, the association between commuting distance and BMI found for the US does not apply to Germany, because overweight and obesity are much more common in the United States than in Germany. According to the WHO Global Database on Body Mass Index (2017), 49.2% of German adults are overweight and of these 12.9% are categorised as obese, whereas in the United States 68% of adults are classified as overweight and of those 33.8% as obese. Thus, in the United States obesity rates are almost three times higher than in Germany.

Secondly and closely related to the preceding explanation, different attitudes towards healthy lifestyles could also serve as source for the disparate findings. For example, several studies show that about three-fourths of the US population has an eating pattern that is low in vegetables and fruits, while nutrient-poor foods that are high in calories and saturated fat are consumed in excess (US Department of Health and Human Services 2015). In Germany, however, nutritional behaviour tends to be healthier since the consumption of vegetables is for example one-third higher than that in other European countries like Belgium, France, Denmark or the UK (Heuer et al. 2015). In our study, there are also signs indicating that commuters have a greater awareness of healthy dietary habits. Hence, at least in Germany, it may be the case that individuals who commute are conscious of the potential adverse effects of commuting and, therefore, adjust their behaviour to their situational needs by paying more attention to their nutrition which could explain why we do not observe any effects of commuting distance on BMI. However, more research is needed on the causal mechanisms that drive the relation between commuting and body weight.

Finally, a third difference concerns commuting behaviour, especially the average distances travelled and the means of transport used by commuters in the two countries. Unfortunately, no information is available about how the respondents in this study travel to work, but there are comparable data on how people generally travel to and from work in Germany and the US. For example, the average commuter in the US travels about 20 miles (around 32 km) each way to work. Further it has been shown that 86% commute by car, 5% by public transportation, 0.6% by bicycle and 2.8% on foot (US Census Bureau 2014). In Germany, commuting distances tend to be shorter (around 20 km), 65% commute by car, 14% by public transport, 8.8% by bicycle and 9% on foot (Federal Statistical Office 2012).

In sum, there is more than one possible explanation for the different findings. One can only speculate about the more specific underlying mechanisms that account for the differences between the two countries. It seems clear that the relationship between commuting and body weight is an underdeveloped area of social science research.

3.6 Appendix B

Table B.1. Variable definitions.

Variable	*Definition*
Dependent variable	
Log (BMI)	Logarithm of body weight in kilograms divided by the square of height in meters (BMI = kg/m²).
Focal variable	
CD	One-way commuting distance measured in kilometres.
Demographic controls	
Women	Dummy equals 1 for women.
Age	Age in years.
Married	Dummy equals 1 if individual is living together with partner (either married or unmarried couple).
Number of children	Number of children in household.
Migration background	Dummy equals 1 if individual has a direct or indirect migration background.
Education	
School degree	Dummy equals 1 if individual has a school degree higher than intermediate.
College	Dummy equals 1 if individual has a university degree.
Income and job controls	
Log (monthly wage)	Logarithm of current gross labour income.
Working hours	Contractually agreed weekly working time.
Firm size*	Dummy variables indicating firm size: less than 5 employees, 5 – 19 employees, 20 – 99 employees, 100 – 199 employees, 200 – 1999 employees, 2000 and more employees.
Occupational position*	Dummy variables for 18 occupational positions.
Industry*	Dummy variables for 9 industries: agriculture, energy, mining, manufacturing, construction, trade, transport, bank or insurance, services.
Reginal and year controls	
Urban area	Dummy equals 1 if individual lives in an urban region.
Federal states*	Dummy variables for the 16 federal states of Germany.
Year*	Dummy variables for each year covered by the sample.
Health behaviour	
Smoking	Dummy equals 1 if individual currently smokes.
Healthy nutrition*	Dummy variables indicating whether individual eats health-consciously: very strong (ref.), strong, a little, not at all.
Taking part in sports*	Dummy variables indicating the frequency with which individual participates in sport: almost never (ref.), several times a year, at least once a month, at least once a week.
Health	
Health status	Dummy variables indicating self-assessed health status: very good (ref.), good, acceptable, less good, bad.
Invalidity level	Statutory degree of disability in %.
Physical pain*	Dummy variables indicating how often physical pain is experienced in the last 4 weeks: always (ref.), often, sometimes, almost never, never.
Physical problems*	Dummy variables indicating how often limitations due to physical problems are experienced in the last 4 weeks: always (ref.), often, sometimes, almost never, never.
Health concerns*	Dummy variables indicating whether individual is concerned about own health: very concerned (ref.), somewhat concerned, not concerned at all.
Feel balanced*	Dummy variables indicating how often the individual felt balanced in the last 4 weeks: always (ref.), often, sometimes, almost never, never.
Feel energetic*	Dummy variables indicating how often the individual felt energetic in the last 4 weeks: always (ref.), often, sometimes, almost never, never.
Working and private time use	
Actual working hours	Actually weekly working hours.
Overtime	Worked overtime hours per week.
Working hours mismatch*	Dummy variables indicating mismatch in working hours: no mismatch (ref.), preference for working fewer hours, preference for working more hours.
Hours for leisure	Time in hours spent for leisure and hobbies on an average workday.

Notes: *For each possible value, a dummy variable is included in the analyses.

Table B.2. Descriptive statistics.

	N	*Mean*	*SD*	*Min.*	*Max.*
Dependent variable					
Log (BMI)	47,762	3.2270	0.1641	2.58	4.59
BMI	47,762	25.5573	4.4147	13.2851	99.20
Focal variable					
CD	47,762	21.5440	53.7904	0	999
Demographic controls					
Women	47,762	0.4926	0.4995	0	1
Age	47,762	42.2493	11.1958	18	65
Married	47,762	0.6417	0.4794	0	1
Number of children	47,762	0.6142	0.9069	0	9
Migration background	47,762	0.1871	0.3900	0	1
Education					
School degree	47,762	0.3089	0.4620	0	1
College	47,762	0.2451	0.4301	0	1
Income and job controls*					
Log (monthly wage)	47,762	7.5762	0.7538	2.30	10.46
Working hours	47,762	34.4292	9.0971	0.6	80
Firm size					
Less than 5 employees	47,762	0.0624	0.2419	0	1
5 – 19 employees	47,762	0.1558	0.3627	0	1
20 – 99 employees	47,762	0.1998	0.3998	0	1
100 – 199 employees	47,762	0.0975	0.2967	0	1
200 – 1999 employees	47,762	0.2345	0.4237	0	1
2000 and more employees	47,762	0.2497	0.4328	0	1
Reginal and year controls*					
Urban area	47,762	0.6685	0.4707	0	1
Health behaviour					
Smoking	40,520	0.3912	0.4880	0	1
Healthy nutrition					
Very strong	37,137	0.0676	0.2511	0	1
Strong	37,137	0.3926	0.4883	0	1
A little	37,137	0.4766	0.4994	0	1
Not at all	37,137	0.0630	0.2403	0	1
Taking part in sports					
Almost never or never	46,975	0.2906	0.4564	0	1
Several times a year	46,975	0.2065	0.4048	0	1
At least once a month	46,975	0.0875	0.2826	0	1
At least once a week	46,975	0.4098	0.4918	0	1
Health					
Health status					
Very good	47,744	0.1034	0.3045	0	1
Good	47,744	0.4869	0.4998	0	1
Acceptable	47,744	0.3074	0.4614	0	1
Less good	47,744	0.0903	0.2867	0	1
Bad	47,744	0.0117	0.1077	0	1
Invalidity level	47,746	2.8149	12.1084	0	100
Physical pain					
Always	47,608	0.0086	0.0925	0	1
Often	47,608	0.0730	0.2601	0	1
Sometimes	47,608	0.1877	0.3905	0	1
Almost never	47,608	0.3066	0.4610	0	1
Never	47,608	0.4239	0.4941	0	1
Physical problems					
Always	47,458	0.0084	0.0914	0	1
Often	47,458	0.0441	0.2053	0	1
Sometimes	47,458	0.1670	0.3730	0	1
Almost never	47,458	0.2749	0.4464	0	1
Never	47,458	0.5054	0.4999	0	1
Health concerns					
Very concerned	47,625	0.1193	0.3241	0	1
Somewhat concerned	47,625	0.5232	0.4994	0	1
Not concerned at all	47,625	0.3574	0.4792	0	1
Feel balanced					
Always	47,667	0.0462	0.2099	0	1

Table B.2. cont. Descriptive statistics.

	N	*Mean*	*SD*	*Min.*	*Max.*
Often	47,667	0.4308	0.4952	0	1
Sometimes	47,667	0.3704	0.4829	0	1
Almost never	47,667	0.1350	0.3418	0	1
Never	47,667	0.0173	0.1305	0	1
Feel energetic					
Always	47,613	0.0380	0.1913	0	1
Often	47,613	0.3175	0.4655	0	1
Sometimes	47,613	0.4529	0.4977	0	1
Almost never	47,613	0.1644	0.3706	0	1
Never	47,613	0.0270	0.1622	0	1
Working and private time use					
Actual working hours	47,462	37.9847	11.1031	0.4	80
Overtime	46,802	2.2323	3.4738	0	23.1
Working hours mismatch					
No mismatch	47,762	0.2678	0.4428	0	1
Prefer to work fewer hours	47,762	0.5808	0.4934	0	1
Prefer to work more hours	47,762	0.1512	0.3583	0	1
Hours for leisure time	46,841	1.8324	1.3326	0	24

Notes: *Occupational position, industry, federal states and year dummies included but not shown in this table.

Table B.3. Sub-sample-related robustness checks.

	Fixed-effects OLS (Dep. var.: log (BMI))					
	(1) Preferred model (see Table 3.3)	(2) Women	(3) Men	(4) Full-time worker	(5) Distance > 5km	(6) No change of residence and employer
CD	-9.00e-06	-8.19e-06	-9.01e-06	-6.01e-06	-6.77e-06	-0.00002
	(-0.86)	(-0.36)	(-0.77)	(-0.56)	(-0.56)	(-0.75)
Age	0.0119***	0.0116***	0.0120***	0.0117***	0.0112***	0.0096***
	(17.01)	(11.15)	(12.82)	(15.02)	(12.91)	(7.61)
Age^2	-0.00007***	-0.00006***	-0.00008***	-0.00007***	-0.00007***	-0.00005
	(-0.36)	(-5.90)	(-8.36)	(-9.07)	(-7.59)	(-4.15)
Number of Children	-0.0003	-0.0009	0.000008	0.0008	-0.0007	-0.0002
	(-0.36)	(-0.64)	(0.08)	(0.84)	(-0.75)	(-0.18)
Married	0.0083***	0.0084***	0.0082***	0.0092***	0.0056**	0.0098***
	(4.30)	(2.77)	(3.40)	(4.46)	(2.48)	(2.58)
School degree	0.0098	0.0080	0.0103	0.0070	0.0100	0.0763**
	(1.51)	(0.48)	(1.21)	(0.79)	(1.16)	(2.05)
College	0.0072	0.0073	0.0069	0.0057	0.0070	0.0007
	(0.15)	(0.91)	(1.24)	(1.01)	(1.12)	(0.05)
Log (monthly wage)	0.0005	0.00007	0.0015	0.0037*	-0.0031	0.0010
	(0.34)	(0.04)	(0.58)	(1.62)	(-0.15)	(0.30)
Working hours	-0.0003	-0.0003***	-0.0028	-0.0039*	-0.0002**	-0.0004**
	(-3.01)	(-2.66)	(-1.59)	(-1.77)	(-0190)	(-2.27)
Firm size: Less than 5 employees (ref.)						
5 – 19 empl.	-0.0013	-0.0019	-0.0011	0.0010	0.0016	0.0041
	(-0.47)	(-0.53)	(-0.26)	(0.31)	(0.42)	(0.64)
20 – 99 empl.	-0.0013	-0.0035	0.0005	0.0010	0.0009	0.0019
	(-0.43)	(-0.84)	(0.11)	(0.28)	(0.22)	(0.27)
100 – 199 empl.	-0.0035	-0.0049	-0.0027	0.0003	0.0005	0.00003
	(-1.04)	(-1.10)	(-0.53)	(0.09)	(0.12)	(0.00)
200 – 1999 empl.	-0.0018	-0.0011	-0.0032	0.0009	0.0011	0.0045
	(-0.57)	(-0.27)	(-0.68)	(0.25)	(0.26)	(0.60)
2000 and more empl.	-0.0020	-0.0014	-0.0034	0.0009	0.0003	0.0046
	(-0.64)	(-0.32)	(-0.73)	(0.23)	(0.08)	(0.60)
Urban area	0.0048	0.0035	0.0056	0.0037	-0.0022	0.0206
	(1.08)	(0.53)	(0.92)	(0.73)	(-0.42)	(1.17)
Constant	2.8336***	2.803***	2.8678***	2.8197***	2.8495***	2.8865***
	(144.69)	(96.26)	(104.59)	(116.75)	(113.53)	(62.58)
Occupational position dummies	x	x	x	x	x	x
Industry dummies	x	x	x	x	x	x
Federal state dummies	x	x	x	x	x	x
Year dummies	x	x	x	x	x	x
N	47,762	23,530	24,232	37,962	31,935	19,584

Notes: Full-time workers are individuals who work 30 hour and more per week. All models are estimated using robust standard errors. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4. Methodology-related robustness checks.

	FE OLS (Dep. var.: log (BMI))					FE OLS	FE logit	RE probit	FE ordered logit
	(1) CD (Table 3.3)	(2) CD,CD^2	(3) Log (CD)	(4) Categories	(5) Lagged CD	(6) Dep. var.: BMI	(7) Dep. var.: BMI ≥ 25	(8) Dep. var.: BMI ≥ 25	(9) Dep. var.: underweight, normal weight, overweight, obese
CD	-9.00e-06	-7.38e-07				-0.0002	0.0002	-0.0001	-0.00005
	(-0.86)	(-0.03)				(-0.82)	(0.21)	(-0.36)	(-0.07)
CD^2		-1.45e-08							
		(-0.43)							
Log (CD)			-0.0002						
			(-0.47)						
Distance categories: 0 – 9 km (ref.)									
10 – 24 km				0.0004					
				(0.24)					
25 – 49 km				0.0009					
				(0.43)					
50 km and more				0.0003					
				(0.15)					
Lagged CD					-0.00002				
					(-0.26)				
Other controls	x	x	x	x	x	x	x	x	x
Occupational position	x	x	x	x	x	x	x	x	x
Industry dummies	x	x	x	x	x	x	x	x	x
Federal state dummies	x	x	x	x	x	x	x	x	x
Year dummies	x	x	x	x	x	x	x	x	x
N	47,762	47,762	47,762	47,762	26,569	47,762	9,464[a]	47,762	47,762

Notes: Same controls as in preferred model. In models (7) and (8) the dependent variable is a dummy equals one if BMI is equal or greater than 25 BMI-points. In model (9) the dependent variable is categorical according to the WHO (2014b) definition. All models are estimated using robust standard errors. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Detailed regression results upon request. [a]All observations without within-group variance of the dependent variable are dropped, by definition.

Table B.5. Mechanisms.

	Fixed-effects OLS (Dep. var.: log (BMI))			
	(1) Preferred model (see Table 3.3)	(2) Health behaviour controls	(3) Health controls	(4) Working and private time use controls
CD	-9.00e-06 (-0.86)	-0.00001 (-0.92)	-5.48e-06 (-0.54)	-8.31e-06 (-0.74)
Smoking		-0.0185*** (-8.14)		
Healthy nutrition: Very strong (ref.)				
Strong		0.0098*** (4.28)		
A little		0.0195*** (7.64)		
Not at all		0.0177*** (5.18)		
Taking part in sports: Almost never (ref.)				
Several times a year		-0.0001 (-0.10)		
At least once a month		-0.0033** (-1.95)		
At least once a week		-0.0031** (-2.27)		
Health status: Very good (ref.)				
Good			0.0035** (2.31)	
Acceptable			0.0064*** (3.47)	
Less good			0.0049** (2.03)	
Bad			0.0045 (0.80)	
Invalidity level			0.00008 (1.07)	
Physical pain: Always (ref.)				
Often			0.0022 (0.43)	
Sometimes			0.0005 (0.10)	
Almost never			0.0006 (0.12)	
Never			-0.0002 (-0.04)	
Physical problems: Always (ref.)				
Often			-0.0021 (-0.39)	
Sometimes			-0.0020 (-0.37)	
Almost never			-0.0043 (-0.80)	
Never			-0.0032 (-0.60)	
Health concerns: Very concerned (ref.)				
Somewhat concerned			-0.0009 (-0.63)	
Not concerned at all			-0.0013 (-0.74)	

Table B.5. cont. Mechanisms.

	Fixed-effects OLS (Dep. var.: log (BMI))			
	(1) Preferred model (see Table 3.3)	(2) Health behaviour controls	(3) Health controls	(4) Working and private time use controls
Feel balanced: Always (ref.)				
Often			0.0015 (0.80)	
Sometimes			-0.0014 (-0.72)	
Almost never			-0.0028 (-1.23)	
Never			-0.0062 (-1.60)	
Feel energetic: Always (ref.)				
Often			0.0024 (1.01)	
Sometimes			0.0063*** (2.51)	
Almost never			0.0072*** (2.65)	
Never			0.0069** (1.94)	
Actual working hours				-0.0003*** (-3.31)
Overtime				-0.0001 (-0.76)
Working hours mismatch: No (ref.)				
Prefer to work fewer hours				0.0013 (1.33)
Prefer to work more hours				0.00009 (0.07)
Hours for leisure				-0.0006 (-1.57)
Constant	2.8336*** (144.69)	2.8298*** (107.37)	2.8297*** (136.19)	2.8420*** (141.56)
Other controls	x	x	x	x
Occupational position	x	x	x	x
Industry dummies	x	x	x	x
Federal state dummies	x	x	x	x
Year dummies	x	x	x	x
N	47,762	33,900	47,064	45,720

Notes: Same controls as in preferred model (see Table 3.3). All models are estimated using robust standard errors. t statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table B.6. Results for nutritional habits, frequency of doing sports and commuting.

	Healthy nutrition (not at all, a little, strong, very strong)		**Frequency of doing sports** (never, several times a year, at least once a month, at least once a week)	
	FE OLS	FE Ordered Logit	FE OLS	FE Ordered Logit
CD	0.0002*	0.0009*	-0.00007	-0.0001
	(1.87)	(1.87)	(-0.44)	(-0.31)
N	36,417	36,417	45,522	45,522

Notes: Only the coefficients for commuting distance are reported. The following control variables are included: age, age squared, health status, # of children, married, satisfaction with leisure, school degree, college, actual working hours, preferred working hours, firm size, ln(income), spatial information, occupational position, industry, federal states and year dummies. Complete results available upon request. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.1. Distributions of BMI and log (BMI).

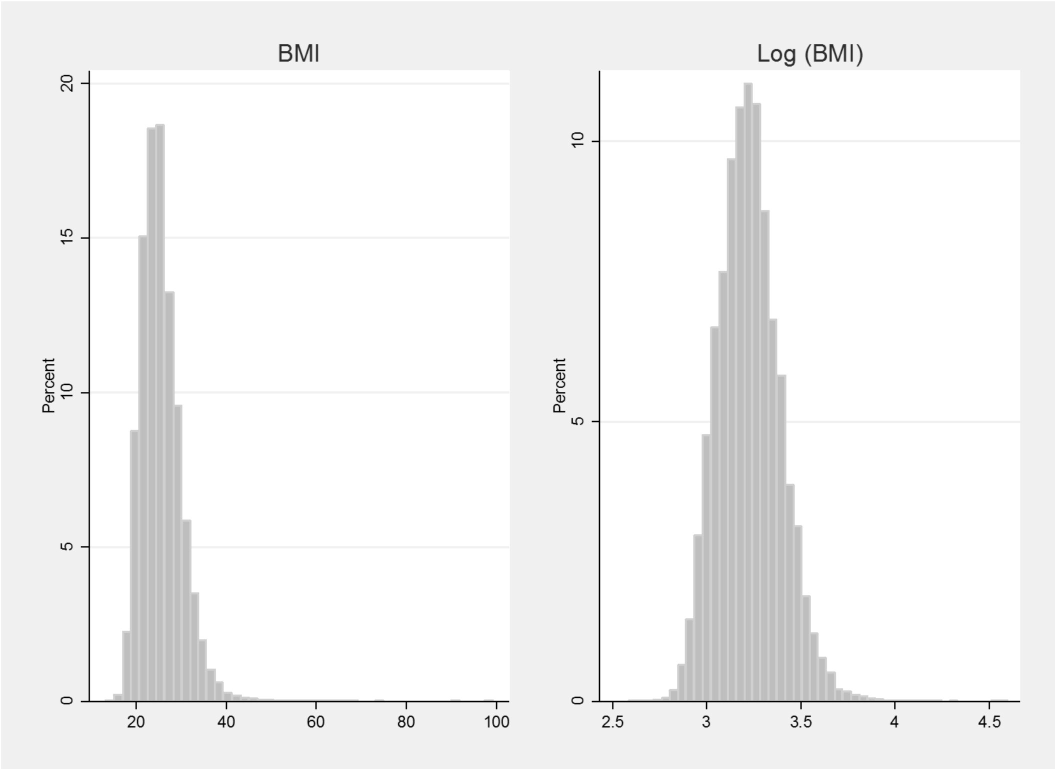


Figure B.2. Distribution of commuting distance.

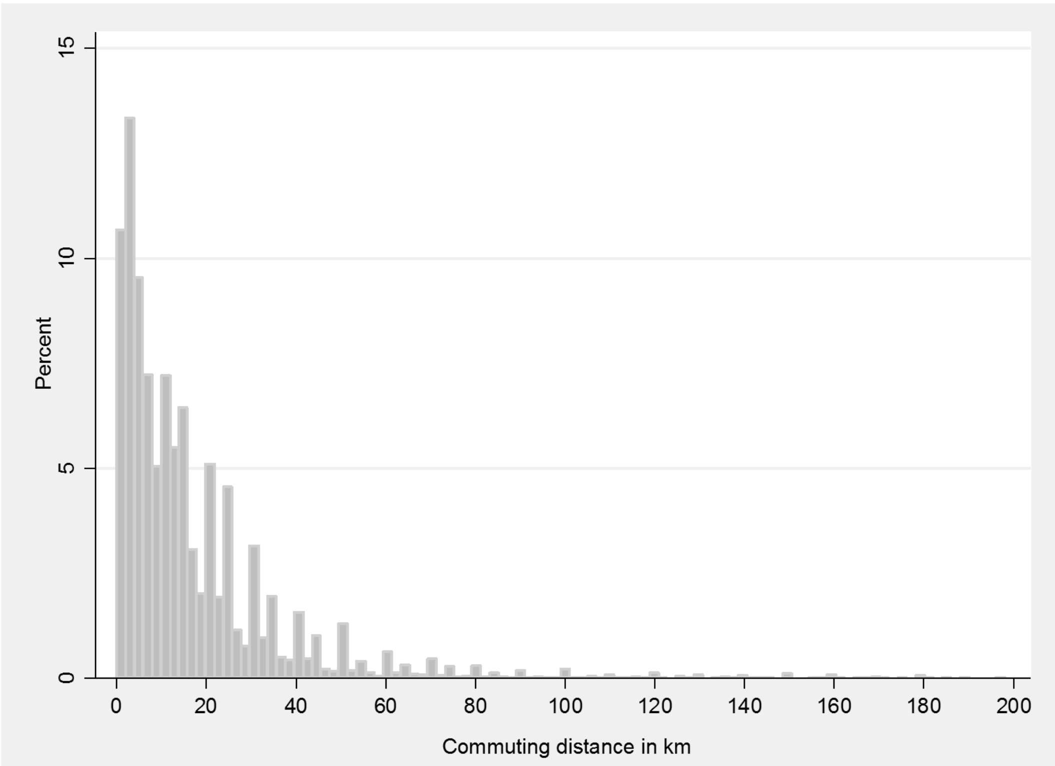


Figure B.3. Mean commuting distance (in km) and mean BMI over the years in Germany.

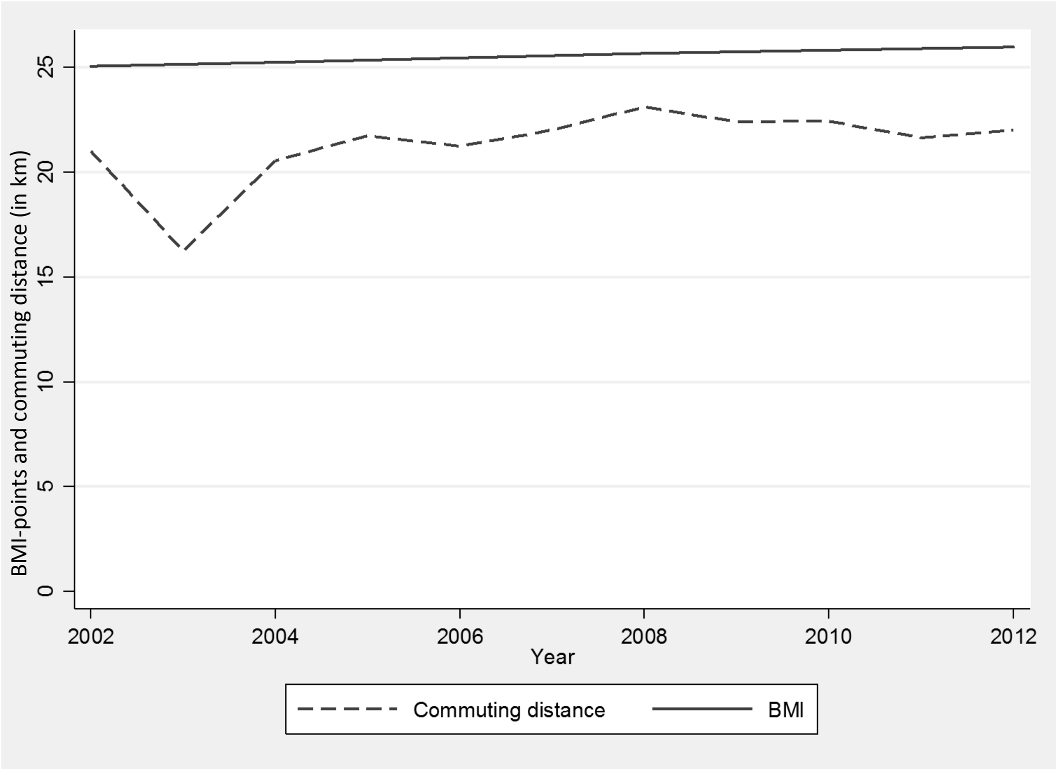
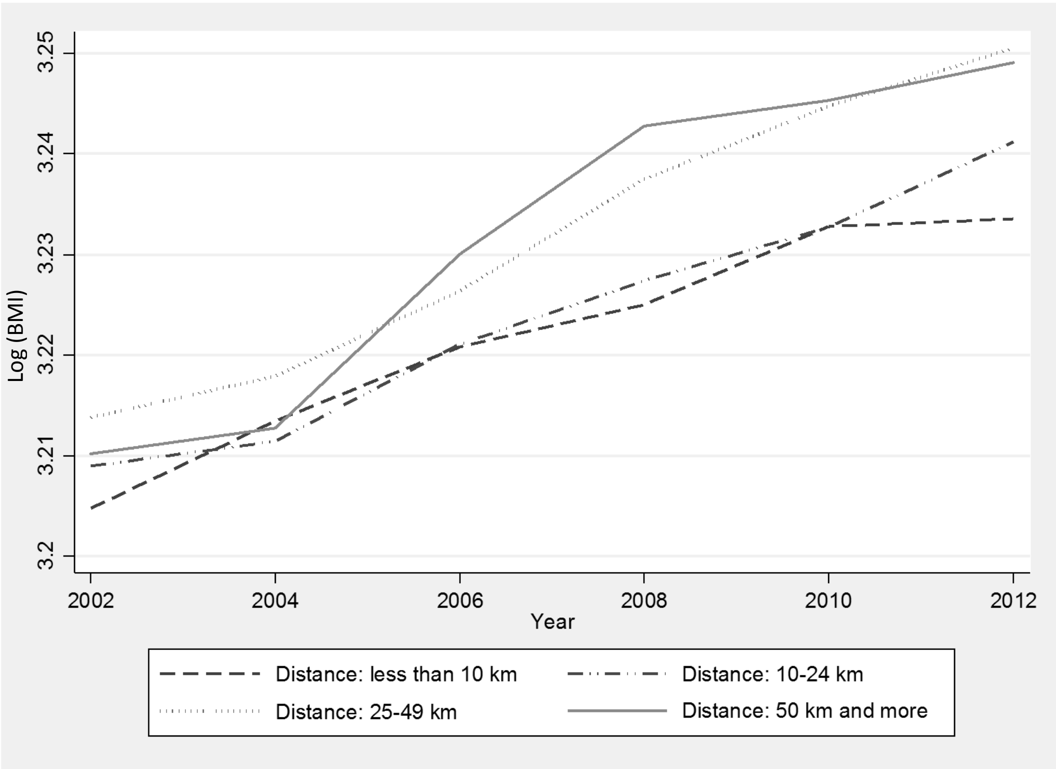


Figure B.4. Mean log of BMI by distance categories over the years in Germany.



Chapter 4

Long distance commutes and health-related lifestyles[*]

Commuting has long been recognised as risk factor for health and well-being. However, there is little knowledge of how commuting affects lifestyles like smoking, alcohol consumption, physical activity or nutritional habits which are essential input factors for health. Drawing on 2008 German Socio-Economic Panel data, a multivariate probit approach is used to estimate recursive systems of equations for commuting and lifestyle choices. Controlling for potential endogeneity of commuting by means of the multivariate probit, our results show that long distance commutes reduce the probability of a healthy lifestyle, in particular by decreasing the propensity to physical activity, healthy diet and healthy sleep patterns.

[*] I am certainly grateful to Marco de Pinto for insightful comments.

4.1 Introduction

A healthy lifestyle is a way of living that lowers the risk of being seriously ill or dying early. Accordingly, lifestyle choices are important determinants of individual health (e.g., Contoyannis and Jones 2004, Balia and Jones 2008). A famous article by J. Michael McGinnis and William H. Foege (1993) estimated that half of all deaths in the United States are due to unhealthy behaviours, most importantly tobacco use, poor diet and exercise, and excessive alcohol consumption. Besides that, insufficient sleep duration has been linked with seven of the fifteen leading causes of death, including cardiovascular disease, malignant neoplasm, cerebrovascular disease, diabetes, septicaemia and hypertension (e.g., Kochanek et al. 2014). Not all diseases are preventable, but a large proportion of deaths, particularly those from coronary heart disease and lung cancer, can be avoided (WHO 1999). Especially the co-occurrence of multiple healthy lifestyle factors has a protective effect against many diseases (e.g., Heikkilä et al. 2013). It is likely that one-third of cancers can be prevented by maintaining a healthy diet and physical activity throughout one's life (WHO 2003). Moreover, relatively moderate changes in lifestyle, particularly by increasing physical activity and improving diet, are sufficient to prevent, for example, the development of almost 60% of type II diabetes cases. Furthermore, a healthy sleep pattern, which is sleeping between seven and nine hours nightly, has been found to lower risks for all-cause mortality (e.g., Vgontzas et al. 2012).

The prevailing economic paradigm for understanding these forms of behaviour is that health behaviours are investments, where forgone pleasure leads to improvements in health (Grossman 1972).[42] Accordingly, health behaviours will differ across people, but for a given person, behaviours will be highly correlated: Those who value their health highly will have much better behaviours (e.g., not smoking, exercise, healthy eating) than those who do not (Cutler and Glaeser 2005). There is a large body of literature on the determinants of health behaviours. Especially work-related stress is seen as one factor influencing or contributing to the adoption or the maintenance of a healthy or unhealthy lifestyle. Stress due to long working hours or overtime has been shown to be associated with individual unhealthy lifestyle factors such as smoking (e.g., Kouvonen et al. 2007, Radi et al. 2007, Lallukka et al. 2008, Perdikaris

[42] For example, individuals are obese because they have calculated that the pleasure from extra food, or the pain from the forgone exercise, is sufficient to compensate for the negative consequences of obesity (Loewenstein and Haisley 2008).

et al. 2010), heavy alcohol consumption (e.g., Head et al. 2004, Kouvonen et al. 2005, Siegrist and Rodel 2006) and physical inactivity (e.g., Wemme and Rosvall 2005, Choi et al. 2010).

Another common source of work-related stress is the travel to work (e.g., Koslowsky et al. 1995, Gottholmseder et al. 2009). To date, most empirical studies tend to focus on the consequences of commuting for health, showing that especially lengthy commutes are related to increased pulse rate and blood pressure (e.g., White and Rotton 1998), musculoskeletal disorders (e.g., Koslowsky et al. 1995), fatigue symptoms (e.g., Kageyama et al. 1998), higher sickness absence (e.g., Goerke and Lorenz 2015) and lower psychological health (e.g., Roberts et al. 2011).

Since commuting has been shown to negatively influence health, commuting is also expected to affect health-related lifestyles. For instance, individuals with lengthy commutes may not find time to exercise, cook healthily and eat a healthy diet. Moreover, they may attempt to alleviate stress by smoking or drinking excessive amounts of alcohol, whereas others may choose healthy behaviours (e.g., exercise, healthy eating) as a way of coping with the commute stress (Ng and Jeffery 2003). Better awareness and information about the consequences of commuting on lifestyle choices are important for health promotion and preventative actions in public health.

However, only very few authors have associated commuting with health-related behaviours. Moreover, these studies focus almost entirely on sleep time or sleep quality. Chatzitheochari and Arber (2009) analyse UK time use data from the year 2000 and identify a negative correlation between sleep duration and the time workers spent commuting. Using cross-sectional data from Swedish health surveys, Hansson et al. (2011) find that long commutes are significantly associated with perceived poor sleep quality. Likewise, analysing cross-sectional time use data from the US, Christian (2012) demonstrates that time for longer commutes is especially drawn from sleeping time. Relatedly, based on cross-sectional data acquired from the 2015 – 2016 ‘Britain’s Healthiest Workplace’ (BHW) competition, Hafner et al. (2016) show that especially heavy commuters have shorter sleeping times. Mauss et al. (2016) analyse cross-sectional data from the Mannheim Industrial Cohort Studies (MICS) of an industrial company in Southern Germany and observe no association between commuting times and sleep quality.

Besides the analyses concentrating on sleeping, there are also some – albeit few – contributions focusing on physical activities and dietary habits. Using cross-sectional data (collected between 2000 and 2007) from adults living and working in metropolitan counties in the state of Texas, Hoehner et al. (2012) find that longer distances between work and home are correlated with less frequent participation in physical activity. Finally, using data from the UK, Künn-Nelen (2016) presents descriptive evidence for compensating health behaviour among those with relatively long commute times. Individuals who commute longer tend to eat more fruits and vegetables and tend to participate in more physical activities.

Although there is evidence that especially long commuting times or distances are correlated with some health-related behavioural patterns, the relationship between the travel to work and such lifestyle factors still remains poorly understood.[43] Therefore, the aim of the present study is to further elucidate the association between commuting long distances and health-related lifestyles. While the existing analyses on the relationship between commuting and healthy lifestyles are informative, they are of purely descriptive nature, focus on a single behaviour and report correlations only; the assessment of causality, however, requires the use of appropriate econometric techniques.

In order to close this gap, this paper adopts a narrow definition of healthy lifestyle which focuses on a set of six health-related behaviours (i.e., smoking, nutritional habits, alcohol intake, physical activity, sleep duration and medical care utilisation) which are considered to influence health and are usually deemed to involve a substantial amount of free choice. In general, identification of the effects of commuting on health and health-related behaviour is often difficult in empirical analyses, since serious econometric problems arise: endogeneity, heterogeneity and selection-bias. These are important aspects which nonetheless have been ignored in previous studies relating commuting to healthy lifestyle choices. To address the potential biases, we rely on structural models for individual health investment decisions and commuting, where the choices to commute long distances are described by reduced-form equations and appear as potentially endogenous regressors in the lifestyle equations. Using data from the 2008 German Socio-Economic Panel (SOEP), recursive bi- and multivariate probit models are implemented to account for omitted variables bias, endogeneity and unobservable heterogeneity and, hence, to control for the simultaneous correlation existing between the unobservable determinants of commuting and health-related behaviours. These approaches thus allow us to obtain estimates of the causal effects of commuting on healthy lifestyles.

[43] In addition, further medical evidence consistently suggest that active commuting, such as commuting by bicycle or walking, translates into higher levels of overall individual physical activity (e.g., Brown et al. 2004, Dunn et al. 2005, Humphreys et al. 2013).

According to our results, long distance commutes have a negative effect on healthy lifestyle choices. Commuting long distances particularly decreases the probability of doing physical exercise, following a healthy diet, having healthy sleep patterns and drinking moderate amounts of alcohol. Further, we find significant correlations between the residuals of each equation, indicating that those with unobservable characteristics which lead them to commute are more likely to have unobservable attitudes which increase the probability of exercising and eating healthy. Consequently, the causal effect of commuting on health-related behaviours is likely to be masked when unobservable heterogeneity and endogeneity are ignored.

The structure of the paper is as follows. Section 4.2 presents the dataset. Section 4.3 describes our estimation strategy, while the empirical results are discussed in Section 4.4. Section 4.5 contains a short conclusion.

4.2 Data and variables

The current study is based on information from the German Socio-Economic Panel (SOEP). The SOEP is a longitudinal, nationally representative survey of private households in Germany. Currently around 30,000 people in approximately 15,000 households participate in the survey. The SOEP includes rich information on labour market status, wealth, income and standard of living, health and life satisfaction as well as on family life and socio-economic variables.[44] This paper focuses on the survey year 2008 as this year contains data on self-reported commuting distance and all relevant self-reported, health-related behaviours. We restrict the sample to working adults aged 18 to 65, and we exclude self-employed respondents, since they are more likely to work from home and generally have different commuting patterns than employees (Roberts et al. 2011).

The health-related lifestyle factors assessed in our study are tobacco smoking, healthy diet, alcohol intake, physical activity, sleep duration and doctors consultations.[45]

To measure smoking behaviour, we use a binary variable which equals one if an individual is currently a non-smoker and zero otherwise.

[44] Further information about the SOEP is provided by Wagner et al. (2007) and can also be found at: http://www.diw.de/english/soep/29012.html. We use the SOEP long v31 dataset.

[45] We adopt a narrow and operationalisable definition of healthy lifestyle factors which accords with the epidemiological literature (e.g., Marmot et al. 1997, Heikkilä et al. 2013). In line with epidemiologic literature, body mass index is not considered in our study since it is regarded as health outcome, which is the result of, inter alia, health-related behaviours, such as physical activity and healthy nutritional habits.

As a measure of healthy diet, we also employ a binary variable which equals one if an individual professes maintaining a healthy diet and zero otherwise.

We measure alcohol intake as binary variable which equals one if an individual moderately consumes alcohol (i.e., seldom or once in a while) and zero otherwise. Hence, moderate drinking is defined as healthy and excessive drinking or complete abstinence from alcohol as unhealthy because there is evidence that moderate alcohol consumption is associated with decreased cardiovascular disease risk (Heikkilä et al. 2013). However, this categorisation should not be interpreted as advice for individuals abstaining from alcohol to take up drinking for health reasons.

As a measure of physical activity, we use a binary variable which equals one if an individual takes part in sport or exercise at least once a week and zero otherwise.

Since sleep patterns have been recognised as important health-related behaviour, we create a binary variable which takes the value one if an individual sleeps between 7 and 9 hours per night on average, which is found to be the optimal sleeping level. A variety of epidemiologic analyses shows that both an increased (> 9 h) and reduced sleep duration (< 7 h) raise the risk of all-cause mortality, cardiovascular disease, and developing symptomatic diabetes (e.g., Alvarez and Ayas 2004, Vgontzas et al. 2012).[46]

Heath care utilisation is also recognised as a behavioural variable which is important for health and, hence, is regarded as health-related behaviour (Künn-Nelen 2016). It is reasonable to assume that as individuals use more medical inputs, health status will improve since the use of preventive health care services reduces the likelihood of developing a disease or disorder (WHO 2003). However after a certain point, more use of medical inputs will result in smaller improvements in health and could even be detrimental to health (Bernell 2016). Therefore, we employ a binary variable which equals one if an individual reports about 4 to 9 annual health care visits, which is considered to be a reasonable number (National Center for Health Statistics 2016).[47]

[46] In addition, further epidemiologic evidence suggest that an ‘unhealthy’ sleep duration may also impair cognitive abilities, leading to more traffic accidents, industrial accidents, medical errors and loss of work productivity (Nuckols et al. 2009).

[47] Reviewing epidemiological evidence suggests that individuals who go either rarely or very often to the doctor are more likely to suffer from ill-health (Australian Institute for Health and Welfare (AIHW) 2014). For example, the risk of infection increases with the number of doctor visits, long-term use of medications may have harmful side effects, and surgeries may lead to additional complications. However, using other cut-off points (e.g., 1 – 5 annual health care visits) yields almost identical bi- and multivariate estimation results. Moreover, slightly different definitions of the single health-related lifestyles (i.e., alcohol intake, sleep) do hardly change the results of the bi- and multivariate probit specifications.

Finally, we define a healthy lifestyle as having at least three healthy lifestyle factors out of the above mentioned six: being a non-smoker, eat a healthy diet, drinking moderate amounts of alcohol, being physically active, having an optimal sleep duration and using health care services regularly. We hereby follow Heikkilä et al. (2013) who operationalise overall healthy lifestyles as the co-occurrence of healthy lifestyle factors. Accordingly, we create a binary variable which takes the value one if an individual has at least three healthy lifestyle factors and zero otherwise.[48] It is useful to aggregate the single lifestyle choices into an overall measure to see whether the global impact of commuting on a healthy lifestyle is generally positive or negative (Gibson et al. 2011).

Commuting distance is derived from the question "How far (in kilometres) is it from where you live to where you work?". We have transformed the continuous indicator of commuting distance into a binary variable that takes the value one if an individual reports long distance commutes of 50 kilometres and more and zero otherwise.[49] It is reasonable to assume that most of all long commuting distances will influence health-related behaviours, in particular since detrimental health effects have also been especially found for long distance commutes (see Section 4.1).[50]

The set of control variables is informed by the literature on the determinants of commuting and lifestyle choices (e.g., Eliasson et al. 2003, Lee and McDonald 2003, Contoyannis and Jones 2004, Paci et al. 2007, Balia and Jones 2008). The variables can be grouped into the following categories and are considered in Table C.1 of Appendix C along with their definitions: physical traits, health status, marital and family information, education and work characteristics, regional and housing information.[51]

Table C.2 presents sample statistics for the full sample as well as for sub-samples of individuals who commute long distances and those who do not as well as individuals who

---

[48] This cut-off point is the median (the 50th percentile). The results are robust to different definitions of an overall healthy lifestyle, i.e. having at least four healthy behaviours.

[49] The Federal Statistical Office of Germany (2014) defines a long distance trip as a trip of 50 kilometres or more. Only 7.77% (n = 561) of individuals in our sample report to commute long distances. Of these 4.10% (n = 23) state to have no healthy lifestyle factors, 16.04% (n = 90) have 1 healthy lifestyle factor, 24.96% (n = 140) have 2 healthy lifestyle factors, 25.13% (n = 141) indicate to have 3 healthy lifestyle factors, 20.32% (n = 114) have 4 healthy lifestyle factors, 7.84% (n = 44) have 5 factors and 1.60% (n = 9) have all 6 healthy lifestyle factors.

[50] For the year we are observing, the SOEP does not provide information about commuting mode and commuting time. Given the travel patterns in Germany and the used definition of long distance commutes, passive commuting modes, such as commuting by car or public transport are very likely (Federal Statistical Office 2009). Moreover, it has been shown that commuting distance and commuting time are correlated (e.g., Small and Song 1992, Rietveld et al. 1999).

[51] To take care of reverse causality, we used two-year lagged values of health status in order to avoid the influence of commuting on contemporaneous health status.

have a healthy lifestyle and those who do not. Around 8% of the individuals interviewed report a commuting distance of 50 kilometres and more. 55% of individuals in the sample have a healthy lifestyle (as defined above). Only 32% are smokers, 44% devote time to physical activities at least once a week, 46% usually eat healthy, 67% sleep a 'healthy' number of hours and 22% are prudent in the consumption of alcohol. Individuals mostly assess their health as good or acceptable. Around 32% of the sample have an educational level higher than intermediate and 25% have a university degree.

Further examination of Table C.2 suggests that the prevalence of an overall healthy lifestyle is lower among individuals who commute long distances.[52] Figure C.1 of Appendix C illustrates the association of commuting and the single lifestyle factors. Long distance commuters are more likely to be smokers, have unhealthy sleep patterns, exercise less and pay less attention to a healthy nutrition. Moreover, those who commute long distances are more likely to be male, younger and better educated. 45% have a school degree higher than intermediate and 36% have a university degree. 88% of long distance commuters are full-time workers with an average of 43 working hours per week.

Hence, descriptive evidence suggests that individuals tend to engage less in health-promoting behaviours when commuting long distances.

4.3 Empirical strategy

The primary interest is to determine the effect of commuting long distances on the individual propensity to an overall healthy lifestyle and to particular healthy lifestyle choices. Yet, common methodological problems in the empirical estimation of health-related lifestyle choices are unobservable individual heterogeneity, endogeneity and selection bias.

Generally, the decision to commute long distances might be intrinsically correlated with health-related behaviours. We might expect the existence of observable and unobservable individual characteristics that influence both commuting long distances and the choice of lifestyles. Observable attributes such as age play an important role in shaping these correlated decisions. However, other characteristics that are unobservable to the researcher might have the same effect. For instance, it is possible that unobservable characteristics such as risk aversion might decrease the willingness to commute and reduce the motivation to engage in

[52] On average, long distance commuters have 2.71 healthy lifestyle factors and non-long distance commuters have 2.88 healthy lifestyle factors. The difference in the number of healthy lifestyles between long distance commuters and non-long distance commuters is significant at the 1% level; the F-statistic is 8.26.

harmful activities like smoking or dangerous sports. Hence, the issue is to take into account this unobservable individual-specific heterogeneity and endogeneity in the estimation procedure in order to recover consistent and causal estimates of the coefficients.

For the estimation of the described problems we use recursive systems of simultaneous equations, which are increasingly adopted in different economics fields. These models have the advantage of relying on structural equations and accounting for unobservable heterogeneity, omitted variables and endogeneity.[53] Other empirical analyses that related commuting to healthy lifestyle choices have relied on single equations as well as single behaviours and have examined the correlation between commuting and health-related behaviours (see Section 4.1) without the basis of an underlying structural model and, hence, failed to address the methodological problems mentioned above. However, endogeneity can arise with the inclusion of commuting distance as regressor in lifestyle equations, due to potential correlation between the error terms of commuting and health-related behaviours. If endogeneity is a problem, then estimates from simple univariate models will be inconsistent.

Therefore, our approach is based on recursive bi- and multivariate probit models in which the commuting decision is described by a reduced-form equation and appears as a potentially endogenous regressor in the lifestyle equations. Due to the structural method the random components of the commuting equations are allowed to be freely correlated with the random components of the lifestyle equations. If there are unobservable individual characteristics influencing both an individual's probability of commuting long distances and health-related behaviours, the models are able to take them into account. The structure of the models will be illustrated below.

4.3.1 The bivariate probit model

First, the bivariate probit model provides a convenient setting for estimating the causal effect of the endogenous binary regressor ('LDC' = Long distance commuter) on a binary outcome variable (overall healthy lifestyle or particular lifestyle choices). Formally, the structural model consists of two latent equations and builds on a first reduced form equation

---

[53] In health economics, these models are typically used to analyse the effect of supplemental insurance ownership on dichotomous health demand indicators (e.g., Holly et al. 1998) and of lifestyle choices on self-assessed health (e.g., Contoyannis and Jones 2004, Balia and Jones 2008). In labour economics, for example, Bryson et al. (2004) investigate the effect of union membership on job satisfaction. Pudney and Shields (2000) examine the promotion process for male and female nurses working in the UK.

for commuting distance and a second structural form equation for lifestyle with the inclusion of commuting distance as endogenous regressor:

$$\begin{aligned} y_{1i}^{*} &= \beta_1' x_{1i} + \varepsilon_{1i} \,, \\ y_{2i}^{*} &= \beta_2' x_{2i} + u_{2i} = \delta_1 y_{1i} + \delta_2' z_{2i} + \varepsilon_{2i} \,, \end{aligned} \tag{4.1}$$

where y_{1i}^{*} and y_{2i}^{*} are latent variables for commuting long distances and having a healthy lifestyle, y_{1i} and y_{2i} are dichotomous variables observed according the rule:

$$\begin{cases} y_{li} = 1 \; if \; y_{li}^{*} > 0 \\ y_{li} = 0 \; if \; y_{li}^{*} \leq 0 \end{cases}; l = 1{,}2;$$

x_{1i} and z_{2i} are vectors of control variables, β_1' and δ_2' are parameter vectors, δ_1 is the parameter we are interested in and β_2'= $(\delta_1 \; \delta_2')'$. We assume that z_{2i} does not include all the variables which are included in x_{1i}, otherwise equation two of model (4.1) is not identified.[54] The error terms ε_{1i} and ε_{2i} are assumed to be independently and identically distributed as bivariate normal:

$$\begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{pmatrix} \sim N, \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right]$$

The variance-covariance matrix of the cross-equation error terms has the values of one on the leading diagonal, and the off-diagonal element ρ, is to be estimated. Here the correlation coefficient ρ can be interpreted as the correlation between the unobservable explanatory variables of the two equations. When $\rho = 0$, y_{1i} is exogenous for the second equation of model (1). On the contrary, $\rho \neq 0$ implies that y_{1i} is correlated with ε_{2i} and therefore endogenous. The equations can be estimated separately as single probit models only in the case of independent error terms (ρ is not significantly different from zero) (Maddala 1983). The parameters β_1', β_2' and ρ can be estimated by maximum likelihood.

4.3.2 The multivariate probit model

Second, the multivariate probit allows us to determine the causal effect of commuting on the individual propensity to a set of health-related behaviours. Like the bivariate probit model, the multivariate probit model consists of a range of latent equations and builds on a reduced

[54] For details, see the discussion of ‘Model 6’ in Maddala (1983, pp. 122 – 123). Maddala (1983) proposes that at least one of the reduced-form exogenous variables (x_{1i}) is not included in the structural equations as explanatory variables. Our imposed exclusion restrictions are explained in Section 4.3.2.

form equation for commuting distance and six structural form equations for each lifestyle described in Section 4.2. Commuting distance is included as endogenous regressor in each lifestyle equation. The error terms of the equations are allowed to be freely correlated. The multivariate probit model can be formalised as:

$$
\begin{aligned}
y_{1i}^* &= \beta_1' x_{1i} + \varepsilon_{1i} \,, \\
y_{2i}^* &= \beta_2' x_{2i} + u_{2i} = \delta_2 y_{1i} + \delta_2' z_{2i} + \varepsilon_{2i} \,, \\
y_{3i}^* &= \beta_3' x_{3i} + u_{3i} = \delta_3 y_{1i} + \delta_3' z_{3i} + \varepsilon_{3i} \,, \\
&\vdots \\
y_{7i}^* &= \beta_7' x_{7i} + u_{7i} = \delta_7 y_{1i} + \delta_7' z_{7i} + \varepsilon_{7i} \,,
\end{aligned}
\tag{4.2}
$$

Hence, we have seven equations and the notation is comparable to that of model (4.1). For the latent dependent variables, we assume that:

$$
\begin{cases} y_{li} = 1 \; if \; y_{li}^* > 0 \\ y_{li} = 0 \; if \; y_{li}^* \leq 0 \end{cases} ; l = 1, \dots, 7;
$$

The error terms, ε_{li}, with $l = 1, \dots, 7$, are distributed as multivariate normal, each with a mean zero and a variance-covariance matrix Γ. Γ has values of one on the leading diagonal and correlations $\rho_{jk} = \rho_{kj}$ on off-diagonal elements, where ρ_{jk} is the covariance between the error terms of equations j and k and measures in how far the unobserved factors influence health-related behaviours and commuting. Again, all the equations of model (4.2) can be estimated separately as single probit models; only in the case of independent error terms i.e. all ρ are not significantly different from zero.[55]

There has been considerable argument in the literature about the identification of such models. Maddala (1983) shows that the parameters of the equations are not identified if z_{li}, with $l = 2, \dots, 7$, includes all the variables in x_{1i}. Hence, estimation of the above-described multivariate probit model requires some considerations for the identification of the model parameters. Maddala (1983) proposes that at least one of the reduced-form exogenous variables (x_{1i}) is not included in the structural equations as explanatory variables. Moreover,

[55] The estimations are carried out using Stata's *mvprobit* command which applies the method of simulated maximum likelihood (SML) that uses the Geweke-Hajivassiliour-Keane (GHK) smooth recursive conditioning simulator to evaluate the multivariate normal distribution. To further reduce the variance of the simulators, we use antithetic acceleration. The number of replications, R, used by the GHK simulator is a key choice for *mvprobit* users. Increasing the number of R increases accuracy but at the cost of lengthening run time. We set the number of random draws to R = 300, which is considered to be sufficient since it is larger than the square root of our sample size (Cappelari and Jenkins 2003). In the multivariate probit method, it is not possible to calculate the average marginal effects relating to individual coefficients. However, it is possible to comment on the sign, statistical significance and the relative size of the coefficients.

the structural equations may contain variables not included in the reduced-form equations. Hence, following Maddala's approach, identification is provided here by excluding some regional, housing and work related information, assuming that it has only an indirect effect on healthy lifestyle choices. Here, for example, the idea is that car or home ownership is more likely to affect attitudes towards commuting than attitudes towards smoking or sleeping. Moreover, for the outcome equations, health status is excluded to avoid causality problems with the dependent variables.[56]

4.4 Results

4.4.1 Results from the bivariate probit models

Table 4.1 and Table C.3 of Appendix C show the estimates from the bivariate probit for commuting, overall healthy lifestyle and additionally each single lifestyle factor.

Table 4.1. Estimates from *bi*variate probit for commuting, overall healthy lifestyle and lifestyle factors.

	(1) Healthy lifestyle	(2) Non-Smoker	(3) Healthy diet	(4) Moderate drinker	(5) Exercise	(6) Sleep	(7) Medical care
LDC	-0.4160*	0.0339	-0.2610	-0.2308	-0.8091***	-0.4386**	0.2039
	(0.2226)	(0.2139)	(0.1856)	(0.1804)	(0.2390)	(0.1884)	(0.1791)
ρ	0.1248	-0.0673	0.1509	0.1072	0.4324***	0.1225	-0.1482
	(0.1322)	(0.1271)	(0.1081)	(0.1075)	(0.1475)	(0.1110)	(0.1030)
N	7,213	7,213	7,213	7,213	7,213	7,213	7,213

Notes: Only the coefficients for the commuting variables are reported. Table C.3 shows the results for the LDC-equation and the control variables. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Colum (1) of Table 4.1 shows the coefficient for the structural overall healthy lifestyle equation estimated jointly (with the reduced commuting equation) in the full recursive model. The results indicate that commuting long distances exerts a negative effect on the propensity to having an overall healthy lifestyle. Whereas the effect is borderline significantly (at the 10% level), commuting long distances reduces the probability of a healthy lifestyle by a sizeable amount ($\beta_{LDC} = -0.4160$) compared to the other coefficients of the model. The effect is, for example, greater than the impact due to having a higher education ($\beta_{school\ degree} = 0.1788$), which is assumed to be one of the most important determinants of a healthy

[56] In general, we notice that results are not very sensitive to alternative sets of exclusion restrictions. We choose the best set of exclusion restrictions looking at the statistical fit (Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)) of different specifications.

lifestyle.[57] In general, education yields better health knowledge, which is important to understand the health effects of one's actions. For instance, better educated individuals should know more about the long-term health risks of being overweight, so it can be expected that they pay more attention to their nutrition and physical activities in order to watch their weight. This is also in line with studies showing that individuals who behave 'healthily' are more likely to have a higher educational status (e.g., Contoyannis and Jones 2004).

With respect to the other control variables, women are more likely than men to have a healthy lifestyle. The results further reveal that both more time spent on child care and care of elderly, are significantly related to a lower probability of having a healthy lifestyle, whereas having a partner and the number of household members are related to a higher probability of a healthy life. In the past decades, many empirical findings have documented potential health benefits of marriage or cohabiting: people having a partner appear to be healthier and to have a longer life expectancy than individuals without partner, since individuals in a partnered relationship engage in low-risk activities, share resources and enjoy caring from each other (e.g., Hu and Wolfe 2002, Di Novi 2010). Our findings are also consistent with previous findings that household size and composition may affect health behaviours. Takeda et al. (2004), for instance, find that an increasing number of women in households is associated with a strong presence of protective health behaviours (i.e., less smoking, less heavy drinking), but also with more sedentary behaviour, while the presence of men in household is associated with a higher probability of heavier smoking. Last, an increasing number of working hours per week reduces the probability of having a healthy lifestyle. This association has also been observed in other studies according to which working hours are associated with ill health and unhealthy behaviours such as smoking, heavy alcohol consumption, and lack of physical exercise (e.g., Siegrist and Rodel 2006, Taris et al. 2011).

Columns (2) – (7) of Table 4.1 show the bivariate probit estimates for commuting long distances and the single lifestyle factors, where each lifestyle choice is separately modelled as joint decision with commuting long distances. From these empirical models it emerges that long distance commutes are significantly and negatively related to the probability of participating in physical activities at least once a week and to the propensity of having healthy sleep patterns. This accords with the perspective of Christian (2012) who focuses on trade-offs between commuting time and time spent on health-related activities and argues that commuting times are associated with modest time reductions for those activities. The greatest

[57] The coefficients are statistically different: $\chi_1^2 = 6.90$; p-value= 0.0085.

percentage of time for commuting is taken from sleeping time (28 – 35%) followed by time for physical activity (16%). Again, we observe that the effect of commuting on these health behaviours is greater than the impact due to having a higher education.[58] These results further support the idea that commuting is a fundamental factor in determining health behaviours.

However, our results suggest that commuting does not influence either the probability of non-smoking, or the probability of health care utilisation, but displays positive coefficients on both health behaviours. Moreover, the bivariate models indicate that long distance commutes are not associated with healthy nutritional habits or moderate alcohol intake, but uncover negative coefficients.

Concerning the other estimated coefficients we find similar results to the overall healthy lifestyle model: The effect of education on the single lifestyle factors is similar across the models. Those with a higher education are observed to display a higher probability of behaving healthy. In particular, a higher education increases the probability of being a non-smoker and moderate drinker, of participating in sports, as well as of having healthy eating habits and healthy sleeping patterns. The effect of marital status, household size and time spent on caregiving are as explained above: Household size and having a partner confer benefits, while time devoted to caregiving reduces the probability of healthy lifestyles. Further, an increasing number of working hours per week reduces the probability of healthy behaviours. Last, we observe that women behave healthier than men, which is a common finding in the epidemiologic literature (e.g., Fisher et al. 1999, Cockerham et al. 2006).

As mentioned previously, we have estimated each lifestyle equation separately but each as joint decision with commuting long distances using the bivariate probit specification. The multivariate probit allows us to test for unobserved heterogeneity whose effect is captured by the correlation between the error terms. Therefore, Table 4.1 shows the correlations between the error terms from each of the single bivariate probit models. A positive significant correlation only exists between the commuting equation and the exercise equation (column (5): $\rho = 0.4324$; $p < 0.01$): some unobservables that increase the likelihood of commuting long distances increase the likelihood of physical activity. The statistically significant correlation coefficient suggests that a bivariate probit model is better than a univariate model for the

[58] In both equations the coefficients are statistically different from each other (‘exercise’ equation: $\chi_1^2 = 17.34$; p-value= 0.0000; ‘sleep’ equation: $\chi_1^2 = 2.54$; p-value= 0.1008).

observed data. A univariate probit model would incorporate this positive effect as a bias of the causal effect of commuting, reducing its negative influence on physical activity.[59]

As outlined above, we will next present the results of the multivariate probit model where we allow for correlations between the error terms of all equations since it has been shown that health-related behaviours are strongly correlated. The bivariate probit model, however, is not able to take these correlations into account.

4.4.2 Results from the multivariate probit model

Table 4.2 and Table C.5 of Appendix C show the coefficients of the multivariate probit specification. The results of the multivariate probit model can be considered qualitatively similar to the bivariate estimates, which is a good robustness indicator.

Table 4.2. Estimates from *multi*variate probit for commuting and healthy lifestyle factors.

	(1) Non-Smoker	(2) Healthy diet	(3) Moderate drinker	(4) Exercise	(5) Sleep	(6) Medical care
LDC	-0.1271 (0.1983)	-0.2964* (0.1601)	-0.2796* (0.1570)	-0.7792*** (0.2215)	-0.4304*** (0.1762)	0.1555 (0.1691)
N	7,213	7,213	7,213	7,213	7,213	7,213

Notes: Only the coefficients for the commuting variables are reported. Table C.5 shows the results for the LDC-equation and the control variables. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

According to the multivariate probit, commuting long distances decreases the probability of doing sports and of having healthy sleep patterns. Additionally, our results show that commuting long distances now has a negative effect on eating healthily as well as on drinking moderate amounts of alcohol once correlations between the single health behaviours are taken into account, suggesting that these correlations drive the changes in the results we observe. [60]

[59] As a benchmark, estimates from univariate probit models are depicted in Table C.4 of Appendix C. The univariate probit estimates indicate that commuting long distances reduces the probability of having an overall healthy lifestyle, of participating in physical activities and of having healthy sleep patterns. This is in line with the findings of the bivariate probit specifications. Further, the results suggest that the univariate probit model incorporates the positive effect of commuting on physical activities as a bias of the causal effect of commuting, reducing its negative influence on physical activity by a sizable amount.

[60] Excluding the variable 'exercise' from the overall health lifestyle measure allows us to use two survey years of the SOEP data (2008 and 2010, n = 13,889). The core finding – long distance commutes decrease the probability of having an overall healthy lifestyle – remains robust (β_{LDC} = -0.3613, p-value = 0.034). Commuting long distances especially reduces the probability of having healthy sleep patterns (β_{LDC} = -0.4498, p-value = 0.001). Furthermore, employing fixed-effects ordinary least squares (OLS) and fixed-effects logit regressions to model the single health-related behaviours as functions of commuting long distances and other covariates also allows us to use more survey years. The results of both estimation methods suggest that commuting long distances is negatively related to healthy sleep patterns ($\beta_{LDC}^{FE\ OLS}$ = -0.0228, p-value = 0.107; $\beta_{LDC}^{FE\ LOGIT}$ = -0.1813, p-value = 0.081) and physical activity ($\beta_{LDC}^{FE\ OLS}$ = -0.0226, p-value = 0.046; $\beta_{LDC}^{FE\ LOGIT}$ = -0.1990, p-value = 0.019). We find no effect of commuting on the other lifestyle measures.

Concerning the other estimated coefficients we find similar patterns, as already explained in the previous section.

Table C.6 shows the correlation matrix for the full recursive model. The null of exogeneity is rejected in nine cases. This suggests that the hypothesis of independence across the error terms of the seven latent equations can be rejected, and a multivariate probit model is a better model for the observed data. We also performed a likelihood-ratio (LR) test for the joint restriction of all the correlation coefficients equal to zero. The test is a $\chi^2_{21} = 414.87$ with a p-value < 0.00, which also confirms the rejection of the null of exogeneity. The correlation parameters indicate whether and how unobservable factors jointly affect lifestyle decisions and the decision to commute long distances. In the case of healthy nutritional habits, the correlation coefficient has a positive sign. This would suggest that unobservable factors that increase the probability of healthy eating also increase the probability of commuting and vice versa. Some evidence for this result is provided by Künn-Nelen (2016) who finds that commuting time is positively correlated to both the number of days per week commuters eat fruits and vegetables and the number of usual portions of fruit and/or vegetables they eat on such days.

Moreover, the correlation between the error terms of the commuting and physical activity equations is positive, meaning that unobserved factors that increase the probability of being a long distance commuter also increase the probability of doing physical exercise.[61] For example, it might be the case that individuals with high energy levels and a high natural need for activity (unobservable characteristic) are more likely to commute long distances and are also more likely to be physically active. Other potentially unobserved variables could be related to differences in childhood circumstances, attitudes to risk and the rate of time preference. Barsky et al. (1997) offer some evidence for the impact of risk attitudes on lifestyle choices using experimental data. They find that risk tolerance is positively related to risky behaviours such that risk tolerance is a statistically significant and quantitatively important factor in explaining whether an individual is a heavy drinker or a current smoker. Further, Nowotny (2014) shows that risk aversion has a negative effect on the willingness to commute. Weber and Milliman (1997) offer some evidence for risk preferences of commuters using experimental data. They find that commuters are more risk averse, which could be one

[61] This finding is consistent with the lower estimates in the univariate probit. From the univariate calculations we obtain that the exogeneity assumption generates biased estimates of the causal effects of commuting. Accounting for endogeneity of the LDC regressor allows us to capture a statistically significant effect of unobserved factors both on the probability of commuting and the probability of some healthy behaviour.

explanation for the positive correlation coefficients of commuting and health behaviours found in our study. The univariate probit model ignores these channels, yielding biased estimates of the effect of commuting on health behaviours.[62]

From the correlation matrix it further appears that unobserved factors that increase the probability of being a non-smoker also increase the likelihood of following a healthy diet, be physically active and having healthy sleep patterns. Further, unobservables that increase the likelihood of a healthy nutrition increase the probability of doing physical exercise and of having a 'healthy' sleep duration. This suggests some degree of complementarity between these lifestyle choices. Our results are in line with other studies looking at correlations of lifestyle choices although in different frameworks (e.g., Contoyannis and Jones 2004, Balia and Jones 2008, Stanciole 2008, Di Novi 2010).

Overall, from the results it emerges that the unobserved propensity for certain lifestyle choices seems to be explained by unobserved characteristics, which in turn determine whether an individual commutes long distances. Our results further demonstrate the importance of allowing for unobservable heterogeneity and endogeneity which both are ignored in previous analyses relating commuting to healthy lifestyle choices.[63]

4.5 Conclusion

This study investigates how commuting long distances affects overall healthy lifestyle as well as particular health-related lifestyle decisions – an issue that has received little attention in the commuting-related effect literature. The main econometric issues that arise in our analyses are unobservable individual heterogeneity and endogeneity of commuting for health-related behaviours. To tackle these problems we use data from the German Socio-Economic Panel to estimate a recursive system of equations based on bi- and multivariate probit models for commuting and overall healthy lifestyle as well as six health-related behaviours: smoking,

[62] It should be noted that the coefficient robust standard errors in the multivariate probit model are between three and five times those in the univariate probit model. This is a common characteristic and is expected as identification is provided by 'purely' exogenous commuting distance.

[63] The interpretation of our main results, namely that commuting negatively influences healthy lifestyles, does not change when we use a dummy that takes the value one if an individual reports a commuting distance of 25 kilometres and more. However, the coefficients of the '≥ 25km-dummy'-variable are much smaller compared to those of the used LDC-variable. Additionally, we observe that commuting 25 kilometres and more exerts a negative influence on a smaller number of healthy lifestyle factors (see Appendix C, Table C.7 and Table C.8). We find no effects of commutes with distances between 25 and 49 km (compared to commuting distances of 50 km and more) on a healthy lifestyle. These findings demonstrate that especially long distance commutes are detrimental to a healthy lifestyle.

nutritional habits, alcohol intake, physical activity, sleep duration and medical care utilisation. This structural approach assumes that commuting and healthy lifestyle choices are interdependent decisions. In the multivariate model, the choice to commute is described by a reduced-form equation and appears as potential endogenous regressor in the lifestyle equations. The possible endogeneity of commuting and the lifestyle variables in the recursive model is reflected in the correlation between the error terms and the covariates as well as in the correlation between disturbances of all the equations of the model. Further, the multivariate probit model allows us to test whether unobservable characteristics (e.g., biological or genetic characteristic, resilience, risk attitudes) influencing commuting also affect health-related behaviours, a point which is ignored in previous analyses.

According to our results, long distance commutes have a negative impact on healthy lifestyles. Commuting long distances particularly decreases the probability of doing physical exercise, having healthy sleep patterns, following a healthy diet and drinking moderate amounts of alcohol. Commuting is found to be statistically unimportant for smoking and medical care utilisation. We find significant correlations between the residuals of each equation, indicating that those with unobserved characteristics which induce them to commute are more likely to have unobservable characteristics which increase the probability of exercising and eating healthy. Hence, the effects we observe for the univariate probit models are severe underestimates of the true effects, since univariate probit models incorporate the positive effect of commuting on physical activities and healthy nutritional habits as a bias of the causal effect of commuting, reducing its negative influence on physical activity and nutritional habits by a sizable amount. Consequently, the effect of commuting on lifestyle choices is likely to be masked when unobservable heterogeneity is ignored.

Because commuting plays a large role in the everyday life of the working population, the adverse effects of commuting on lifestyle choices should receive more attention. Longer commutes are increasingly associated with behavioural patterns which, over time, may contribute to poor health outcomes since individuals with longer commutes are increasingly less engaged in health-related activities. Unhealthy behaviours (i.e., smoking, heavy drinking, adverse food habits, and physical inactivity) are key modifiable determinants of major preventable diseases. According to WHO estimates, up to 80% of cases of coronary heart disease, 60% of type II diabetes cases, and one-third of cancers can be avoided by increases in physical activity, a healthier diet and by quitting smoking (WHO 2003, 2010). Hence, given the impacts on health and health-related behaviours, long distance commutes should be a more salient issue in our society and should be seen as a public-health concern which may, inter alia, be addressed by changes in individual behaviour, supported by employers, public-policy measures and individuals themselves. Further research enabling us to clarify if and how commuting contributes to health behaviours which in turn contribute to ill health would provide important information to help balance policies that lead to an increase in commuting, and in the development of measures to reduce the negative effects of commuting.

4.6 Appendix C

Table C.1. Variable definitions.

Variable	Definition
Long distance commuter (LDC)	1 if distance to work is greater than or equal to 50 kilometres, 0 otherwise.
Healthy lifestyle and lifestyle factors	
Non-smoker	1 if individual does not smoke, 0 otherwise.
Healthy diet	1 if individual eats health-consciously, 0 otherwise.
Moderate drinker	1 if individual consumes alcohol prudently, 0 otherwise.
Exercise	1 if individual takes part in sport or exercise at least once a week, 0 otherwise.
Sleep	1 if individual sleeps 7 – 9 hours, 0 otherwise.
Medical care	1 if individual reports about 4 – 9 annual health care visits, 0 otherwise.
Healthy lifestyle	1 if individual has at least three healthy lifestyle factors, 0 otherwise.
Physical traits	
Female	1 if female, 0 otherwise.
Age	Age in years.
Age2	Age squared.
Health status (2-year lagged values)	
Very good (ref.)	1 if self-assessed health is very good, 0 otherwise.
Good	1 if self-assessed health is good, 0 otherwise.
Acceptable	1 if self-assessed health is acceptable, 0 otherwise.
Less good	1 if self-assessed health is less good, 0 otherwise.
Bad health	1 if self-assessed health is bad, 0 otherwise.
Marital and family information	
Partner	1 if individual is living together with partner (either as married or unmarried couple), 0 otherwise.
Number of children	Number of children in household.
Hours for child care	Time in hours spent for childcare on an average workday.
Hours for care of elderly	Time in hours spent for support for persons in need of care on an average workday.
Household size	Number of persons in household.
Education	
School degree	1 if school degree is higher than intermediate, 0 otherwise.
University degree	1 if individual has a university degree, 0 otherwise.
Work	
Tenure	Number of years in present job.
Tenure2	Tenure squared.
Full-time worker	1 if individual works full time, 0 otherwise.
Working hours	Actual weekly working time.
Unemployment experience	1 if individual has ever been unemployed, 0 otherwise.
Income (log)	Logarithm of current gross labour income.
Occupational position*	Dummy variables for 18 occupational positions.
Industry*	Dummy variables for 9 industries.
Regional and housing information	
Car	1 if car in household, 0 otherwise.
Owner	1 if owner of dwelling, 0 otherwise.
Same town	1 if individual is living and working in the same town, 0 otherwise.
Urban area	1 if urban area, 0 otherwise.
Federal state*	Dummy variables for the 16 federal states of Germany.

Notes: *For each possible value, a dummy variable is included in the analyses .

Table C.2. Descriptive statistics for full sample and sub-samples.

Variable	Full sample (N=7,213)				LDC (n=561)		Non-LDC (n=6,652)		Healthy lifestyle (n=3,999)		Unhealthy lifestyle (n=3,214)	
	Mean	SD	Min	Max	Mean	SD	Mean	SD	Mean	SD	Mean	SD
LDC	0.0777	0.2678	0	1					0.0725	0.2593	0.0843	0.2779
Healthy lifestyle and lifestyle factors												
Non-smoker	0.6780	0.4672	0	1	0.6720	0.4698	0.6785	0.4670	0.8712	0.3350	0.4377	0.4961
Healthy diet	0.4655	0.4988	0	1	0.4260	0.4949	0.4688	0.4990	0.6894	0.4627	0.1869	0.3899
Moderate drinker	0.2194	0.4139	0	1	0.2192	0.4141	0.2194	0.4139	0.2253	0.4178	0.2121	0.4089
Exercise	0.4418	0.4966	0	1	0.4385	0.4966	0.4421	0.4966	0.6564	0.4749	0.1748	0.3799
Sleep	0.6748	0.4684	0	1	0.5882	0.4925	0.6822	0.4656	0.8332	0.3728	0.4779	0.4995
Medical care	0.3876	0.4872	0	1	0.3707	0.4834	0.3890	0.4875	0.5293	0.4991	0.2112	0.4082
Healthy lifestyle	0.5544	0.4970	0	1	0.5490	0.5001	0.6128	0.4967				
Physical traits												
Female	0.4978	0.5000	0	1	0.3244	0.4685	0.5124	0.4998	0.5616	0.4962	0.4184	0.4933
Age	42.521	11.168	18	65	40.739	11.103	42.662	11.162	43.096	11.054	41.7871	11.2689
Health status (2-year lagged values)												
Very good (ref.)	0.1018	0.3025	0	1	0.1069	0.3093	0.1014	0.3019	0.1160	0.3202	0.0843	0.2779
Good	0.4903	0.4999	0	1	0.5098	0.5003	0.4887	0.4999	0.5178	0.4997	0.4561	0.4981
Acceptable	0.3070	0.4612	0	1	0.2905	0.4544	0.3084	0.4619	0.2860	0.4519	0.3332	0.4714
Less good	0.0908	0.2873	0	1	0.0855	0.2799	0.0912	0.2879	0.0717	0.2581	0.1144	0.3184
Bad	0.0098	0.0987	0	1	0.0071	0.0842	0.0100	0.0998	0.0082	0.0904	0.0118	0.1081
Marital and family information												
Partner	0.6373	0.4808	0	1	0.6131	0.4874	0.6393	0.4802	0.6704	0.4701	0.5961	0.4907
Number of children	0.5935	0.8944	0	8	0.5561	0.8644	0.5966	0.8969	0.6096	0.9079	0.5734	0.8771
Hours for child care	1.0740	2.6557	0	24	0.5294	1.5662	1.1199	2.7228	1.0842	2.6096	1.0612	2.7123
Hours for care of elderly	0.0930	0.6317	0	19	0.0909	0.6413	0.0932	0.6310	0.0765	0.4239	0.1135	0.8194
Household size	2.8423	1.2230	1	10	2.9090	1.1804	2.8367	1.2264	2.8699	1.2232	2.8080	1.2220
Education												
School degree	0.3263	0.4689	0	1	0.4491	0.4978	0.3159	0.4649	0.3963	0.4891	0.2392	0.4267
University degree	0.2563	0.4366	0	1	0.3654	0.4819	0.2471	0.4313	0.3215	0.4671	0.1751	0.3801
Work												
Tenure	11.3011	10.1931	0	47	9.2076	9.5690	11.4776	10.2251	11.7356	10.2258	10.7604	10.1279
Full-time worker	0.7013	0.4576	0	1	0.8859	0.3181	0.6858	0.4642	0.6691	0.4705	0.7414	0.4379
Working hours	37.9570	12.1073	1	80	43.0547	10.0962	37.5271	12.1652	36.8843	12.2209	39.2918	11.8312
Unemployment experience	0.3653	0.4815	0	1	0.3921	0.4886	0.3630	0.4809	0.3160	0.4650	0.4265	0.4946
Income (log)	7.5493	0.8122	3.912	10.365	7.8554	0.6820	7.5235	0.8171	7.5793	0.8203	7.5119	0.8005
Regional and housing information												
Car	0.9288	0.2570	0	1	0.9483	0.2216	0.9272	0.2597	0.9434	0.2309	0.9107	0.2852
Owner	0.5307	0.4990	0	1	0.5953	0.4912	0.5252	0.4993	0.5823	0.4932	0.4663	0.4989
Same town	0.4522	0.4977	0	1	0.0017	0.0422	0.4902	0.4999	0.4576	0.4982	0.4455	0.4971
Urban area	0.6718	0.4695	0	1	0.5436	0.4985	0.6826	0.4654	0.6829	0.4653	0.6580	0.4744

Table C.3. Estimates from *bi*variate probit for commuting, overall healthy lifestyle and healthy lifestyle factors.

	Overall healthy lifestyle		Healthy lifestyle factors					
	LDC	Healthy lifestyle	Non-Smoker	Healthy diet	Moderate drinker	Exercise	Sleep	Medical care
		-0.4160*	0.0339	-0.2610	-0.2308	-0.8091***	-0.4386**	0.2039
		(0.2226)	(0.2139)	(0.1856)	(0.1804)	(0.2390)	(0.1884)	(0.1791)
Physical traits								
Female	-0.1923***	0.1989***	0.1507***	0.5985***	-0.1926***	-0.0439	0.1149***	0.1223***
	(0.0665)	(0.0393)	(0.0399)	(0.0387)	(0.0417)	(0.0386)	(0.0391)	(0.0381)
Age	0.0027	-0.0379***	-0.0422***	-0.0003	-0.0358***	-0.0078	-0.0265**	-0.0114
	(0.0217)	(0.0120)	(0.0122)	(0.0119)	(0.0128)	(0.0117)	(0.0121)	(0.0117)
Age2	-0.0001	0.0004***	0.0005***	0.0001	0.0003**	-4.47e-06	0.0001	0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Health status								
Good	-0.0397							
	(0.0918)							
Acceptable	0.0122							
	(0.1055)							
Less good	0.1247							
	(0.1366)							
Bad	0.0618							
	(0.3245)							
Family information								
Partner	0.0774	0.1718***	0.2422***	0.1153***	0.0246	-0.0206	0.1030***	0.0293
	(0.0738)	(0.0412)	(0.0415)	(0.0406)	(0.0439)	(0.0399)	(0.0411)	(0.0400)
Number of children	-0.0929**	-0.0069	0.0241	0.0643**	-0.0123	-0.0924***	-0.0581**	0.0188
	(0.0487)	(0.0286)	(0.0297)	(0.0280)	(0.0307)	(0.0279)	(0.0287)	(0.0275)
Hours for child care	-0.0486**	-0.0260***	-0.0161**	0.0084	-0.0148*	-0.0200***	-0.0284***	-0.0024
	(0.0234)	(0.0070)	(0.0069)	(0.0070)	(0.0088)	(0.0075)	(0.0069)	(0.0069)
Hours for care of elderly	0.0427	-0.0906***	0.0213	0.0089	-0.0311	-0.0368	-0.0712***	-0.0636***
	(0.0356)	(0.0239)	(0.0249)	(0.0250)	(0.0263)	(0.0260)	(0.0243)	(0.0234)
Household size	0.0753**	0.0416**	0.0498***	-0.0099	-0.0246	0.0425**	0.0431**	-0.0088
	(0.0333)	(0.0193)	(0.0200)	(0.0191)	(0.0206)	(0.0188)	(0.0197)	(0.0186)
Education								
School degree	0.1913***	0.1788***	0.2428***	0.1066***	0.0920**	0.2667***	-0.0175	-0.0106
	(0.0755)	(0.0451)	(0.0466)	(0.0437)	(0.0476)	(0.0432)	(0.0456)	(0.0433)
University degree	-0.1117	0.1951***	0.2024***	0.0820*	0.0180	0.0628	0.1010**	-0.0007
	(0.0843)	(0.0518)	(0.0534)	(0.0501)	(0.0546)	(0.0493)	(0.0517)	(0.0493)
Work								
Tenure	-0.0561***							
	(0.0094)							

Table C.3. cont. Estimates from *bi*variate probit for commuting, overall healthy lifestyle and healthy lifestyle factors.

	Overall healthy lifestyle		Healthy lifestyle factors					
	LDC	Healthy lifestyle	Non-Smoker	Healthy diet	Moderate drinker	Exercise	Sleep	Medical care
Tenure2	0.0011***							
	(0.0002)							
Full-time worker	0.2355***							
	(0.0976)							
Working hours		-0.0154***	-0.0097***	-0.0041**	-0.0024	-0.0111***	-0.0163***	-0.00446***
		(0.0020)	(0.0020)	(0.0019)	(0.0021)	(0.0020)	(0.0020)	(0.0019)
Unemployment experience	-0.0164							
	(0.0650)							
Income (log)	0.2201***	0.0528	0.0558	0.0054	0.0168	0.0508	0.0694**	0.0202
	(0.7394)	(0.0350)	(0.0356)	(0.0348)	(0.0380)	(0.0350)	(0.0352)	(0.0339)
Housing information								
Owner	0.0101							
	(0.0634)							
Car	-0.3971***							
	(0.1359)							
Same town	-2.7382***							
	(0.3915)							
Urban area	-0.1391**	-0.0247	-0.0691**	0.0208	0.0795**	-0.0645*	-0.0522	-0.0174
	(0.0701)	(0.0351)	(0.0359)	(0.0344)	(0.0378)	(0.0354)	(0.0350)	(0.0338)
Occupational position	*included*	*included*	*included*	*included*	*included*	*included*	*included*	*included*
Industry	*included*	*included*	*included*	*included*	*included*	*included*	*included*	*included*
Federal state	*included*	-	-	-	-	-	-	-
_cons	-2.0499***	0.5392	0.9749*	-0.7908	-0.0902	0.5180	0.6206	-0.9622
	(0.8026)	(0.5278)	(0.5600)	(0.5402)	(0.6164)	(0.5150)	(0.5415)	(0.5776)
ρ		0.1248	-0.0673	0.1509	0.1072	0.4324***	0.1225	-0.1482
		(0.1322)	(0.1271)	(0.1081)	(0.1075)	(0.1475)	(0.1110)	(0.1030)
N	7,213	7,213	7,213	7,213	7,213	7,213	7,213	7,213

Notes: Estimates of LDC from the bivariate probit for the single healthy lifestyle factors are not reported because they are very similar to the reported estimates of LDC from the overall healthy lifestyle equation. These estimates are available upon request. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4. Estimates from *uni*variate probit for commuting, overall healthy lifestyle and lifestyle factors.

	Healthy lifestyle	Non-Smoker	Healthy diet	Moderate drinker	Exercise	Sleep	Medical care
LDC	-0.2189***	-0.0718	-0.0243	-0.0643	-0.1374***	-0.2449***	-0.0320
	(0.0581)	(0.0605)	(0.0582)	(0.0634)	(0.0574)	(0.0575)	(0.0578)
Physical traits							
Female	0.2248***	0.1475***	0.5067***	-0.1877***	-0.0241	0.1209***	0.1154***
	(0.0388)	(0.0395)	(0.0382)	(0.0414)	(0.0382)	(0.0388)	(0.0378)
Age	-0.0376***	-0.0424***	0.0007	-0.0355***	-0.0069	-0.0263**	-0.0119
	(0.0120)	(0.0122)	(0.0119)	(0.1283)	(0.0118)	(0.0121)	(0.0117)
Age2	0.0004***	0.0005***	0.0001	0.0003**	-8.46e-06	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Marital and family information							
Partner	0.1709***	0.2428***	0.1143***	0.0234	-0.0249	0.1019***	0.0307
	(0.0412)	(0.0415)	(0.0406)	(0.0439)	(0.0403)	(0.0411)	(0.0400)
Number of children	-0.0039	0.0226	0.0681***	-0.0096	-0.0832***	-0.0553**	0.0152
	(0.0284)	(0.0295)	(0.0278)	(0.0306)	(0.0279)	(0.0286)	(0.0275)
Hours for child care	-0.0255***	-0.0164***	0.0091	-0.0143*	-0.0180***	-0.0279***	-0.0032
	(0.0070)	(0.0069)	(0.0070)	(0.0088)	(0.0074)	(0.0069)	(0.0069)
Hours for care of elderly	-0.0914***	0.0218	0.0080	-0.0317	-0.0403	-0.0721***	-0.0628***
	(0.0240)	(0.0249)	(0.0248)	(0.0262)	(0.0267)	(0.0243)	(0.0233)
Household size	0.0393**	0.0511***	-0.0130	-0.0268	0.0345*	0.0409**	-0.0059
	(0.0191)	(0.0198)	(0.0190)	(0.0205)	(0.0188)	(0.0196)	(0.0185)
Education							
School degree	0.1751***	0.2450***	0.1022***	0.0889*	0.2589***	-0.0212	0.0152
	(0.0450)	(0.0464)	(0.0437)	(0.0475)	(0.0434)	(0.0455)	(0.0432)
University degree	0.1940***	0.2030***	0.0810*	0.0173	0.0600	0.0999**	0.0004
	(0.0518)	(0.0533)	(0.0500)	(0.0546)	(0.0497)	(0.0517)	(0.0494)
Work							
Working hours	-0.0156***	-0.0096***	-0.0044**	-0.0026	-0.0123***	-0.0165***	-0.0043**
	(0.0020)	(0.0020)	(0.0019)	(0.0021)	(0.0019)	(0.0020)	(0.0019)
Income (log)	0.0518	0.0567	0.0038	0.0152	0.0490	0.0683**	0.0218
	(0.0351)	(0.0356)	(0.0334)	(0.0380)	(0.0351)	(0.0352)	(0.0339)
Regional and housing information							
Urban area	-0.0147	-0.0747**	0.0333	0.0887***	-0.0288	-0.0425	-0.0294
	(0.0336)	(0.0343)	(0.0334)	(0.0365)	(0.0333)	(0.0338)	(0.0328)
Occupational position	*included*	*included*	*included*	*included*	*included*	*included*	*included*
Industry	*included*	*included*	*included*	*included*	*included*	*included*	*included*
_cons	0.9754***	1.0043***	-0.4552	0.1809	0.2303	1.1654***	-0.1882
	(0.3358)	(0.3473)	(0.3314)	(0.3605)	(0.3321)	(0.3393)	(0.3273)
N	7,213	7,213	7,213	7,213	7,213	7,213	7,213

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5. Estimates from *multi*variate probit for commuting and healthy lifestyle factors.

	LDC	Non-smoker	Healthy diet	Moderate drinker	Exercise	Sleep	Medical care
LDC		-0.1271	-0.2964*	-0.2796*	-0.7792***	-0.4304***	0.1555
		(0.1983)	(0.1601)	(0.1570)	(0.2215)	(0.1762)	(0.1691)
Physical traits							
Female	-0.2060***	0.1472***	0.4964***	-0.1933***	-0.0432	0.1169***	0.1206***
	(0.0654)	(0.0397)	(0.0384)	(0.0415)	(0.0385)	(0.0390)	(0.0381)
Age	0.0023	-0.0428***	-0.0001	-0.0355***	-0.0081	-0.0266**	-0.0116
	(0.0214)	(0.0122)	(0.0119)	(0.0128)	(0.0118)	(0.0121)	(0.0117)
Age2	-0.0001	0.0005***	0.0001	0.0003**	8.79e-06	0.0001	0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Health status (2-year lagged values)							
Very good (ref.)							
Good	0.0315						
	(0.0915)						
Acceptable	0.1320						
	(0.1067)						
Less good	0.2561						
	(0.3179)						
Bad	0.1989						
	(0.3066)						
Marital and family information							
Partner	0.0810	0.2444***	0.1137***	0.0255	-0.0192	0.1035***	0.0296
	(0.0743)	(0.0414)	(0.0406)	(0.0439)	(0.0398)	(0.0410)	(0.0400)
Number of children	-0.1030**	0.0234	0.0652**	-0.0140	-0.0924***	-0.0577**	0.0181
	(0.0476)	(0.0298)	(0.0279)	(0.0307)	(0.0279)	(0.0287)	(0.0275)
Hours for child care	-0.0462**	-0.0170***	0.0085	-0.0148	-0.0199***	-0.0283***	-0.0026
	(0.0204)	(0.007)	(0.0070)	(0.0088)*	(0.0075)	(0.0069)	(0.0069)
Hours for care of elderly	0.0406	0.0205	0.0086	-0.0304	-0.0352	-0.0713***	-0.0635***
	(0.0348)	(0.0242)	(0.0242)	(0.0263)	(0.0259)	(0.0243)	(0.0233)
Household size	0.0795***	0.0511***	-0.0102	-0.0238	0.0423**	0.0430**	-0.0082
	(0.0326)	(0.0200)	(0.0190)	(0.0205)	(0.0187)	(0.0197)	(0.0186)
Education							
School degree	0.1682**	0.2469***	0.1051***	0.0926*	0.2677**	-0.0164	0.0114
	(0.0755)	(0.0465)	(0.0436)	(0.0475)	(0.0433)	(0.0456)	(0.0433)
University degree	-0.1033	0.1996***	0.0836*	0.0176	0.0635	0.0998**	-0.0003
	(0.0830)	(0.0531)	(0.0498)	(0.0546)	(0.0492)	(0.0517)	(0.0493)
Work							
Tenure	-0.0516***						
	(0.0097)						
Tenure2	0.0009***						
	(0.0026)						
Full-time worker	0.2554***						
	(0.0983)						
Working hours		-0.0094***	-0.0040**	-0.0023	-0.0111***	-0.0162***	-0.0046***
		(0.0020)	(0.0019)	(0.0021)	(0.0020)	(0.0020)	(0.0019)
Unemployment experience	0.0212						
	(0.0651)						
Income (log)	0.1902***	0.0559	0.0042	0.0162	0.0515	0.0691**	0.0209
	(0.0744)	(0.0356)	(0.0349)	(0.0379)	(0.0350)	(0.0352)	(0.0339)
Regional and housing information							
Car	-0.0307***						
	(0.1332)						
Owner	-0.0096						
	(0.0638)						
Same town	-2.6822***						
	(0.3781)						
Urban area	-0.1530**	-0.0767**	0.0204	0.0767**	-0.0627*	-0.0522	-0.0199
	(0.0705)	(0.0356)	(0.0341)	(0.0375)	(0.0351)	(0.0348)	(0.0337)

Table C.5. cont. Estimates from *multi*variate probit for commuting and healthy lifestyle factors.

	LDC	Non-smoker	Healthy diet	Moderate drinker	Exercise	Sleep	Medical care
Occupational position	*included*	*included*	*included*	*included*	*included*	*included*	*included*
Industry	*included*	*included*	*included*	*included*	*included*	*included*	*included*
Federal state	*included*	-	-	-	-	-	-
_cons	-1.1922***	1.0334*	-0.7737	-0.0943	0.5029	0.6214	-0.9493*
	(0.7826)	(0.5633)	(0.5377)	(0.6147)	(0.5129)	(0.5418)	(0.5773)
N	7,213	7,213	7,213	7,213	7,213	7,213	7,213

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.6. Correlations from *multi*variate probit for commuting and lifestyle factors.

	LDC	Non-smoker	Healthy diet	Moderate drinker	Exercise	Sleep	Medical care
LDC	1.00						
Non-smoker	0.0355	1.00					
Healthy diet	0.1556*	0.1831***	1.00				
Moderate drinker	0.1379	-0.0174	0.0119	1.00			
Exercise	0.4136***	0.2075***	0.2678***	0.0736***	1.00		
Sleep	0.1174	0.1004***	0.0677***	-0.0124	0.0286	1.00	
Medical care	-0.1177	-0.0004	-0.0122	0.0209	-0.0073	0.0369*	1.00

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.7. Results for commuting 25 kilometres and more (CD ≥ 25 km), overall healthy lifestyle and healthy lifestyle factors.

	Bivariate Probit	Multivariate Probit					
	Healthy lifestyle	Non-Smoker	Healthy diet	Moderate drinker	Exercise	Sleep	Medical care
CD ≥ 25km	-0.1596*	0.0143	-0.1056	-0.0541	-0.2682***	-0.2539***	0.0616
	(0.0855)	(0.0859)	(0.0776)	(0.0798)	(0.0849)	(0.0834)	(0.0760)
ρ	0.0553 (0.0586)	*see Table A.8*					
N	7,213	7,213	7,213	7,213	7,213	7,213	7,213

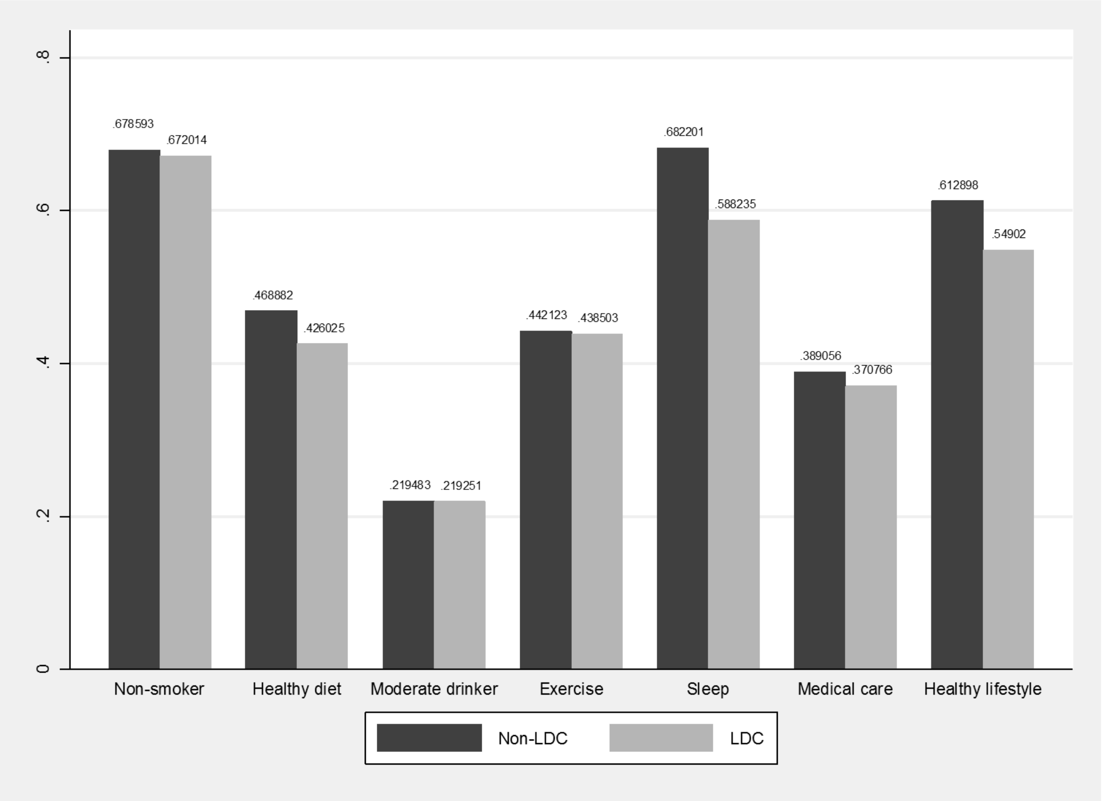
Notes: Only the coefficients for the commuting variable are reported. Table C.3 shows the results for the LDC-equation and the control variables. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.8. Correlations from *multi*variate probit for commuting 25 kilometres and more (CD ≥ 25 km) and healthy lifestyle factors.

	CD ≥ 25km	Non-smoker	Healthy diet	Moderate drinker	Exercise	Sleep	Medical care
CD ≥ 25km	1.00						
Non-smoker	-0.0293	1.00					
Healthy diet	0.0642*	0.1816***	1.00				
Moderate drinker	0.0354	-0.0177	0.0076	1.00			
Exercise	0.1050*	0.2076***	0.2622***	0.0674***	1.00		
Sleep	0.0604	0.1001***	0.0666***	-0.0110	0.0231	1.00	
Medical care	-0.0702	0.00004	-0.0095	0.0236	-0.0009	0.0365*	1.00

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.1. Probability of healthy lifestyle and lifestyle factors by commuting distance.



Chapter 5

Does commuting matter to subjective well-being?*

How and why commuting contributes to our well-being is of considerable importance for transportation policy and planning. This paper analyses the relation between commuting and subjective well-being by considering several cognitive (e.g., satisfaction with family life, leisure, income, work, health) and affective (e.g., happiness, anger, worry, sadness) components of subjective well-being. Fixed-effects models are estimated with German Socio-Economic Panel data for the period 2007 – 2013. In contrast to previous papers in the literature, according to which commuting is bad for overall life satisfaction, we find no evidence that commuting in general is associated with a lower life satisfaction. Rather, it appears that longer commutes are only related to lower satisfaction with particular life domains, especially family life and leisure time. Time spent on housework, child care as well as physical and leisure activities mediate the association between commuting and well-being.

* We thank the participants of the 2017 Colloquium on Personnel Economics (COPE) in Zürich, the 2016 Workshop on Subjective Survey Data in Labour Market Research in Trier, the 2016 Labour Economics Meeting in Trier, and a seminar at U Trier for helpful comments and suggestions.

5.1 Introduction

In the past decades, subjective well-being has become an important component of the agenda of governments and measures of subjective well-being are often used to assess the costs and benefits of policies (e.g., Blanchflower and Oswald 2004, Dolan et al. 2008, ONS 2015). According to the World Happiness Report 2015 of the United Nations, happier and more satisfied people are more likely to be healthier, productive and pro-social, resulting in benefits for the society as a whole, i.e. higher economic productivity, stronger social insurance, greater societal resilience to natural hazards, and greater mutual care (Helliwell 2015). Therefore, most governments and international organisations regard subjective well-being as the most comprehensive measure of wealth, replacing traditional measures like Gross Domestic Product (GDP) and some social indicators (OECD 2013). Partly as a result, economists are showing increasing interest in the "economics of happiness", reflected by the large body of literature that considers subjective well-being as a proxy for individual welfare.[64] Thus, it is hardly surprising that subjectively experienced well-being has, especially recently, attracted more attention in transport and mobility studies, since transport is intricately linked to the well-being of the economy as well as communities and is seen as the blood of society (e.g., Banister et al. 2011, De Vos et al. 2013). In contemporary societies, the travel to work, in particular, plays a large role in the everyday life of individuals. With increasing suburban sprawl and subsequently longer commutes, the relationship between commuting and well-being is becoming a pressing concern (e.g., Pisarski 2006, Hilbrecht et al. 2014). This is compounded by the finding that commuting to work is found to be a stress factor and the least enjoyable experience of daily life (e.g., Kahneman et al. 2004, White and Dolan 2009, Mattisson et al. 2015). Understanding the relationship between commuting and well-being may offer insight into workers' quality of life and contribute to programs and policies designed to better support population well-being. Further, understanding how commuting is related to how we feel offers insight into ways of improving existing transportation services, prioritising investments and theorising and modelling the costs and benefits of the travel to work.

Nevertheless, the relationship between travel and subjective well-being is largely "unexplored in travel behaviour research" (Ettema et al. 2010, p. 729). In the limited number

[64] Summaries and overviews of this rapidly expanding literature include: Frey and Stutzer (2000, 2002a, 2002b), Layard (2005), Kahneman and Krueger (2006), Di Tella and MacCulloch (2006), Clark et al. (2008), Dolan et al. (2008), Stutzer and Frey (2010), and MacKerron (2012).

of previous studies, subjective well-being has usually been assessed by judgements of overall life satisfaction.[65] Yet, as De Vos et al. (2013) point out, these studies are still in their infancy and many of the multifarious links between commuting and well-being are still under-examined since most studies focus mainly on life satisfaction, drawing mixed conclusions (Stutzer and Frey 2008, Dickerson et al. 2014, Hilbrecht et al. 2014, Wheatley 2014, Morris 2015). In light of travel behaviour research's strong roots in utility theory, this bias towards life satisfaction as measure of subjective well-being is no surprise. In classical urban and regional economic theory, individuals' commuting behaviour is determined by an equilibrium state of the housing and labour market, in which individuals' utility is equalised over all actual combinations of alternatives in these two markets. Accordingly, it is assumed that individuals freely optimise by changing job or residence and, hence, arbitrage away any utility differentials. If this is the case, no systematic relationship should be found between commuting behaviour and subjective well-being (respectively life satisfaction), which has been shown to be a satisfactory empirical approximation to individuals' utility (Kahneman and Krueger 2006).

However, subjective well-being covers a wider range of concepts than just life satisfaction. In fact, subjective well-being is defined as a person's cognitive and affective evaluation of his or her life, and encompasses different elements: the cognitive component consists of life satisfaction and satisfaction with specific life domains (e.g., satisfaction with family life, work satisfaction), while the affective component refers to positive emotions, moods and feelings (e.g., joy, pride) and negative ones (e.g., anger, worry) a person has (Diener 2000). In contrast to the above mentioned studies on the effect of commuting on overall life satisfaction, much less is known about the consequences of commuting on satisfaction with other life domains and emotions, although it has been shown that a distinction is important on both empirical and theoretical grounds (e.g., Kahneman et al. 1999, Kahneman and Deaton 2010, Deaton and Stone 2014). Our comprehensive investigation of this issue is intended to fill this gap and to gain further insights beyond those from the life satisfaction studies about the general consequences of commuting for well-being by adopting a more holistic view of well-being related to commuting.

Thus, this article aims to contribute to the understanding of the relationship between commuting distance and well-being by considering several components of subjective well-being, such as: cognitive evaluations of one's life and specific life domains (i.e., satisfaction

[65] A detailed review of this literature is provided by De Vos et al. (2013).

with family life, leisure time, income, work, and health), positive emotions (i.e., happiness), and negative ones (i.e., anger, worry, sadness), and potential explanatory factors in links between commuting and well-being. Since the aim of (transport) policies is to increase individuals' well-being, it is worthwhile to investigate how these different components of well-being depend on the travel to work (Ettema et al. 2010). If it is possible to establish relationships within the context of travel, subjective well-being would potentially be a powerful tool for policy appraisal.

This paper uses data from the German Socio-Economic Panel (SOEP) for the years 2007 – 2013 to analyse the relation between commuting distance and various measures of subjective well-being. We aim not only to provide evidence on the effect of commuting on well-being, but also to shed some light on the mechanisms through which commuting might affect individual's well-being. We therefore apply, firstly, linear fixed-effects models in which time-invariant idiosyncratic effects are controlled for. All the different aspects of subjective well-being are measured separately to derive a more comprehensive measure of people's quality of life and to allow a better understanding of the relationship between subjective well-being and commuting distance.[66] Second, we use a bootstrapping-based causal mediation analysis to analyse the extent to which several important daily activities (e.g., house work, caregiving, sleeping) serve as potential mediators in any association found between commuting and well-being.

We find that whereas affective well-being measures are hardly influenced by commuting, cognitive well-being measures are lower for people who commute longer. However, in contrast to previous papers in the literature, according to which commuting is bad for overall life satisfaction, we find no evidence that commuting is associated with lower levels of satisfaction with life in general. Our results suggest that longer commutes are rather related to lower satisfaction with family life and leisure time. These findings turn out to be robust against several specifications and sub-samples. Moreover, the multiple mediation analysis indicates that the relation between commuting and satisfaction with leisure and family life can largely be ascribed to changes in daily time use patterns, influenced by the work commute.

The structure of this paper is as follows: The next section reviews related literature. Section 5.3 presents the data used in the analysis. Section 5.4 describes the econometric methodology. Section 5.5 reports results, including several robustness checks, and discusses explanations for the findings. Section 5.6 concludes the study.

[66] This approach is intended to meet the recommendation of the OECD guidelines on measuring subjective well-being (2013), according to which different aspects of subjective well-being should be measured separately.

5.2 Related literature

While the literature related to commuting and well-being is diverse, it may be grouped in two streams.[67] The first stream of contributions analyses the association between commuting and cognitive measures of well-being. However, these studies focus almost entirely on life satisfaction and their findings are largely inconclusive.

Using data from the German Socio-Economic Panel (SOEP, 1985 – 2003), Stutzer and Frey (2008) show that greater commuting times lower self-reported life satisfaction (measured on a scale from 0 to 10). Further, in a robustness check, the authors also find a small negative effect of commuting distance on reported life satisfaction. Stutzer and Frey (2008) conclude that commuting is a stressful activity which does not pay off, a result which they refer to as the 'commuting paradox', as it does not correspond to the predictions from microeconomic theory according to which rational individuals would only choose to spend their time commuting if they are compensated, either in the form of improved job characteristics (including pay) or better housing prospects. Utilising cross-sectional data from the 2010 Canadian General Social Survey, Cycle 24, Hilbrecht et al. (2014) also find that commuting time is associated with lower levels of life satisfaction (measured on a scale from 1 to 10) and an increased sense of time pressure. Hilbrecht et al. (2014) argue that reduced time for physically active leisure and experiences of traffic congestion mediate the association of commute time with life satisfaction. Likewise, Nie and Sousa-Poza (2016), drawing on 2010 cross-sectional data from the China Family Studies, demonstrate that longer commuting times are associated with lower levels of life satisfaction and happiness, partially mediated through reduced sleep time. Analysing panel data from the British Household Panel Survey (BHPS, 1993 – 2009, subsumed by the Understanding Society Survey from 2009), Wheatley (2014) contributes to the understanding of the interaction between commuting time and levels of satisfaction with working hours, job, and leisure (measured on a scale from 1 to 7) among full-time working men and women in dual career households. Wheatley (2014) shows that only lengthier commutes lower satisfaction with working hours, job, and leisure for men,

[67] Besides the small body of research which directly pertains to commuting and subjective well-being, the literature dealing with this relationship is also guided by research on mental and physical health, which are both critical contributors to well-being (Hilbrecht et al. 2014). Many studies address the relation between commuting and health outcomes, showing that commuting is related to increased pulse rate and blood pressure (e.g., White and Rotton 1998), musculosketal disorders (e.g., Koslowsky et al. 1995), fatigue symptoms (e.g., Kageyama et al. 1998), self-perceived stress (e.g., Gottholmseder et al. 2009), reduced sleep time (e.g., Costa et al. 1988), higher sickness absence (e.g., Goerke and Lorenz 2015) and lower physical and psychological health (measured via GHQ score) (e.g., Roberts et al. 2011, Humphreys et al. 2013, Martin et al. 2014).

whereas short and long commuting times reduce satisfaction with leisure for women. Using cross-sectional data from the American Time Use Survey (ATUS, 2012 – 2013), Morris (2015) indicate that travel time for the purpose of work is negatively correlated with life satisfaction.

Other studies, however, find no evidence that commuting has a negative effect on cognitive measures of well-being.[68] Using data from the BHPS (1996 – 2008), Dickerson et al. (2014) revisit the debate surrounding the appropriate methodology for modelling subjective well-being data in the context of the relationship between commuting time and satisfaction with life or leisure and find no evidence that longer commutes are associated with lower levels of life satisfaction in general, but with lower satisfaction with leisure time. From a methodological point of view, the authors argue that ordered fixed-effects models are more appropriate than linear models, which are predominantly applied in the analysis of commuting and subjective well-being.

The second stream of contributions pertains to commuting and feelings and predominately focuses on experienced emotions during commutes. Morris et al. (2015), drawing on data from the American Time Use Survey's well-being module, report that commuting has basically no impact on how we feel because mood is not generally worse during travel than on average. Using cross-sectional data from the three largest urban areas of Sweden, Olsson et al. (2013) demonstrate that predominantly positive or neutral feelings (e.g., glad, active, joyful, awake, peppy, and pleased) dominate during the commute, so that work commute has a substantial influence on overall happiness, particularly due to the balance between positive and negative affect. Olsson et al. (2013) argue that, for longer work commutes, social and entertainment activities either increase positive affects or counteract stress and boredom. Jain and Lyons (2008) suggest that commuting provides transition time which allows mental shifting between different activity spheres. Thus, the way from work to home can serve as a decompression period for commuters. In several studies, Mokhtarian and colleagues (e.g., Redmond and Mokhtarian 2001, Mokhtarian et al. 2001, Ory and Mokhtarian 2005) have shown that the travel to work can also be utilised by the commuter for something positive. This could be pleasurable activities during the commute such as listening to music, enjoying the scenery or simply allowing for some coveted time alone.

[68] Sweet and Kanaroglou (2016), drawing on cross-sectional data from the 2010 General Social Survey (GSS) of Time Use in Canada, find no evidence that total daily travel times are associated with levels of life satisfaction. However, it is unclear whether commuting to work is included in the daily travel time.

Moreover, especially active commuting, such as commuting by bicycle or walking, is reported to be more relaxing and exciting than passive commuting (by car or transit) and hence, might be related to increased well-being (e.g., Gatersleben and Uzzell 2007). Accordingly, commuting creates a time out from other responsibilities and commitments and may include leisurely moments for someone, which contributes to well-being even if commuting prevents participation in other activities. Those who derive positive utility from commuting are also found to experience the commute as less stressful (e.g., Gottholmseder et al. 2009) and experience less disutility of commuting (Ory and Mokhtarian 2005). Nevertheless, when commuting distances become too long, the willingness to commute decreases (Sandow and Westin 2010). There are also studies that show that commuters would like to decrease their commuting distance, regardless of mode used (e.g., Sandow and Westin 2010, Redmond and Mokhtarian 2001).

In sum, little consensus exists regarding the effect of commuting on subjective well-being. On one hand, considerable evidence suggests that individuals with lengthy commutes are more prone to experience lower levels of life satisfaction. On the other hand, it has been shown that some individuals experience commuting (especially active commuting types) as activity that provides a time out from obligations and responsibilities, which could be beneficial to well-being.

While substantially enhancing our knowledge on the impact of commuting on well-being, there are a number of limitations in the existing literature: Many of the extant studies examine correlations of commuting time and satisfaction with life or feelings experienced during the commute, are mainly based on cross-sectional data, and do not investigate potential channels determining the relationship between commuting and well-being. Obviously, a shortcoming of measuring the well-being effects from the work commute using only life satisfaction is underestimating the effects on other areas of life. Since commuting increases the length of the total workday while simultaneously reducing time for private use, less time remains available for leisure time activities and home production, which might come at the expense of utility derived from e.g. family life or leisure time. Although often overlooked in discussions of commuting and well-being, time diaries have shown how daily behavioural patterns including the amount of time and timing of activities such as housework, leisure, caregiving and sleep may be shaped by the work commute (e.g., Kitamura et al. 1992). Lengthy commutes reduce time for leisure, family and friends and, hence, for maintaining family ties and social relationships such as going out for dinner with friends (e.g., Besser et al. 2008, van der Klis and Karsten 2009, Sandow 2014). However, such activities have been shown to be associated with greater life satisfaction, happiness as well as mental well-being and can provide opportunities for coping with supposedly stressful situations (e.g., Hutchinson and Kleiber 2005, Sweet and Kanaroglou 2016).

Moreover, from a classical urban economic perspective, commuting is just one of numerous decisions rational individuals make. If commuting has extra monetary and non-monetary costs, then travelling longer distances to and from work is only chosen if it is either compensated (in order for the commuters' well-being or utility to be equalised) by lower rents or housing prices (e.g., Renkow and Hoover 2000), desired housing or neighbourhood characteristics (e.g., Plaut 2006) or an intrinsically or financially rewarding job (e.g., So et al. 2001). Based on the aforementioned literature, we, thus, could expect that individuals who commute longer are compensated by a better job or pleasant living environment, and hence report higher satisfaction with work, dwelling or income, whereas satisfaction with family life, leisure, or health could be lower. Consequently, on average commuters' utility, respectively life satisfaction, might be the same regardless of their commuting distance.

Against this background, in this study we consider several components of subjective well-being to produce a more differentiated picture of the relation between travel to work and subjective well-being. We additionally examine whether several important daily activities – namely errands (e.g., shopping, trips to government agencies), housework and repairs (e.g., washing, cooking, cleaning, gardening), child care and support for persons in need of care, physical activities and other leisure activities (e.g., sports, fitness, gymnastic, hobbies) as well as sleeping – serve as potential mediators of the relationship between commuting and well-being. It is also worth stressing that our study differs from other recent studies since our key variable is not commuting time but commuting distance, which is a superior measure according to the transport and urban economics literatures. Although commute times and distances are correlated (e.g., Small and Song 1992, Rietveld et al. 1999), we nowadays mainly observe an increase in distances travelled, driven by higher travel speeds and improvements in transportation, in turn fostering urban sprawl (e.g., Crozet and Joly 2004, Lyons and Chatterjee 2008). Snice commuting distance appears to be increasing at a steady rate, it is important to see what impact longer distances have on individuals, when measured against a number of different proxies for subjective well-being. Further, distance is more appropriate in our context because commuting time is influenced by many other factors like the chosen transportation mode as well as the chosen timing of the commute (e.g., commuting during rush hours). Arguably, it is unclear which effect is actually captured when looking at commuting time (Koslowsky 1995). Hence, by using commuting time, the commute effect might be strongly overestimated.

5.3 Data and variables

The data used in this study is from the German Socio-Economic Panel (SOEP), which is representative for the entire population of Germany, aged 17 and older. The SOEP includes rich information on labour market status, wealth, incomes and standard of living, health and well-being as well as on family life and socio-economic variables.[69] This paper focuses on the survey years 2007 – 2013 as these years contain data on commuting as well as on cognitive and affective components of subjective well-being.

We restrict the sample to working adults aged 18 to 65, and we exclude self-employed respondents, since they are more likely to work from home and generally have different commuting patterns than employees (Roberts et al. 2011).

As our dependent variables we use data from questions, where respondents are asked to cognitively evaluate one's life and certain life domains. The questions read as follows: "How satisfied are you today with the following areas of your life?: (a) health, (b) job, (c) household income, (d) personal income, (e) dwelling, (f) leisure time, (g) family life" and "How satisfied are you with your life, all things considered?" The respondents are asked to give a response on an 11-point scale, where the lowest value (0) is labelled "completely dissatisfied" and the highest value (10) is labelled "completely satisfied".

The SOEP, furthermore, requires respondents to report on their affective well-being. The question reads: "How often have you felt (i) angry, (ii) worried, (iii) happy, (iv) sad? Please indicate for each feeling how often or rarely did you experience this feeling in the last four weeks." Each response category has a choice of five options, where the lowest value (1) is labelled "very rarely" and the highest value (5) is labelled "very often". Figures D.1 and D.2 (see Appendix D) present the distributions of the cognitive and affective well-being measures. It can be seen that the distributions of the cognitive measures are highly skewed, with the majority of the respondents at the top end of each distribution. This is a common finding in the literature on subjective well-being (Dolan et al. 2008). The distributions of the affective

[69] Further information about the SOEP is provided by Wagner et al. (2007) and can also be found at: http://www.diw.de/english/soep/29012.html. We use the SOEP long v30 dataset.

well-being measures are less skewed, but again the majority of the respondents report either relatively high or low values.

The key explanatory variable is commuting distance derived from the question "How far (in kilometres) is it from where you live to where you work?". This is one way commuting distance in kilometres and we treat it as a continuous variable.[70] Figure D.3 (see Appendix D) presents the distribution of commuting distance.

Furthermore, the SOEP requires respondents to outline the time spent on the daily activities of errands (e.g., shopping, trips to government agencies), housework and repairs on and around the house (e.g., washing, cooking, cleaning, gardening), child care and support for persons in need of care, physical activities and other leisure activities (e.g., sports, fitness, gymnastic, hobbies) and sleeping. This time use information is captured by the question, "What is a typical weekday for you? How many hours per normal workday do you spend on the following activities?".

Finally, the analyses include a number of control variables which the extant literature has shown to be relevant to subjective well-being: age, gender, number of children, marital status, health status, highest school qualification, unemployment experience, working hours, job tenure, household income, household size as well as regional and year dummies (e.g., Roberts et al. 2011, Frijters and Beatton 2012, Wheatley 2014, Dickerson et al. 2014).[71]

Table 5.1 provides summary statistics on the subjective well-being and control variables. It can be seen that the average commuting distance is about 22 km (one way). The average age in the sample is 43 years, about two thirds live in urban regions, are married or cohabiting and the average number of children in the household is 0.6. One third has been unemployed at least once. For variable definitions, see Table D.1 of Appendix D.

[70] For the years we are observing, the SOEP does not provide information about commuting mode and commuting time. Given the travel patterns in Germany, passive commuting modes, such as commuting by car (65%) or public transport (14%) are very likely (Federal Statistical Office 2012).

[71] We do not control for personality traits. Since personality traits are claimed to be time invariant, these factors would be absorbed into the fixed effect in our models and are thus irrelevant for the analysis.

Table 5.1. Summary statistics.

	Mean	Standard deviation	Min.	Max.
Satisfaction with life	7.19	1.59	0	10
Satisfaction with work	7.01	1.99	0	10
Satisfaction with household income	6.61	2.10	0	10
Satisfaction with personal income	6.32	2.21	0	10
Satisfaction with dwelling	7.84	1.80	0	10
Satisfaction with leisure	6.69	2.08	0	10
Satisfaction with family life	7.81	1.88	0	10
Satisfaction with health	6.95	1.98	0	10
Angry	2.92	0.95	1	5
Worried	1.89	0.93	1	5
Happy	3.57	0.80	1	5
Sad	2.31	0.99	1	5
Commuting distance	21.69	54.64	0	999
Age	42.90	11.37	18	65
Female	0.50	0.49	0	1
Number of children	0.64	0.93	0	8
Marital status	0.63	0.48	0	1
Health status*	2.44	0.85	1	5
Education	0.33	0.47	0	1
Unemployment experience	0.36	0.48	0	1
Working hours	37.26	12.45	0.4	80
Tenure	11.29	10.34	0	50.9
Household income (log)	7.94	0.50	5.26	12.20
Household size	2.85	1.23	1	14
Urban area	0.65	0.47	0	1
Time (h) for errands	0.90	0.64	0	8
Time (h) for housework	1.94	1.46	0	16
Time (h) for caregiving	1.30	2.93	0	24
Time (h) for leisure activities	1.64	1.37	0	15
Time (h) for sleeping	6.84	1.00	1	16

Notes: Federal states and year dummies included. *For each possible value, a dummy variable is included in the analyses.

5.4 Empirical strategy

5.4.1 Basic empirical model

The longitudinal characteristic of the SOEP allows the estimation of fixed-effects models in which idiosyncratic effects that are time-invariant can be controlled for. The effect of commuting distance on subjective well-being measures is then identified by the variation in commuting distance within observations for the same individual. In our sample, the mean (within) deviation of individual commuting experiences is 25.07 kilometres. Equation (5.1) summarises the empirical model:

$$SWB_{it} = \alpha_i + \beta CD_{it} + \gamma CD2_{it} + \lambda X_{it} + \varepsilon_{it} \tag{5.1}$$

where SWB_{it} denotes the individual's well-being,[72] α_i denotes time-invariant idiosyncratic effects, β is the coefficient of commuting distance (CD), and γ is the coefficient of its squared term ($CD2$).[73] To evaluate the effect of commuting distance on subjective well-being measures, one needs to perform a test for joint significance. The vector X includes all the control variables.[74]

5.4.2 Description of robustness checks

We perform several robustness analyses to test the sensitivity of the main results. They can be grouped into two categories.

First, we alter the methodology. We estimate a model in which we attempt to deal with possible measurement errors in reported commuting distances. Therefore, we have experimented with several functional forms of distance. We categorise commuting distance into 'short' (up to 24 km), 'middle' (25 – 49 km) and 'long' (50 km or more) commutes. This approach is less sensitive to minor reporting errors and allows for qualitatively different effects of, for example, shorter and longer commutes on well-being. We have also re-estimated models excluding observations that refer to changes in distance that are less than 3 km. In particular small distance changes will more likely refer to measurement error in the commuting distance.[75] Furthermore, we additionally log transformed commuting distance to see whether our results are sensitive to the chosen functional specification.

The next robustness check relates to the question whether different aspects of subjective well-being as measured in the SOEP can be taken to be cardinal measures or ordinal variables (Ferrer-i Carbonell and Frijters 2004). In our main approach we assume well-being to be cardinal, whereas we treat it as an ordinal variable in one robustness check. Therefore we

[72] In the main analyses, we treat the dependent variables as continuous. Thereby, the coefficients can be interpreted as marginal effects. In the robustness analyses, we apply a fixed-effect ordered logit (BUC) model as alternative specification.

[73] A quadratic specification of the effect of commuting distance on life satisfaction is chosen because we hypothesise that the marginal burden of commuting is falling.

[74] In the main analyses, we use the same set of controls. Nevertheless, in order to see how sensitive the results are to the used controls, we also alter the control variables by, for example, including more variables on job characteristics (e.g., firm size, working hours mismatch) or residential aspects (e.g., sizes of dwelling, being owner of dwelling). If the results are affected by the modified set of controls, we report on these findings in body text.

[75] As respondents in one year might, for example, report 22 km and in the next year 25 km without changing the actual commuting distance.

estimate fixed-effects ordered logit models ("Blow-up and Cluster" (BUC) estimator) as proposed by Dickerson et al. (2014).[76]

The literature dealing with the health consequences of commuting is inconsistent in terms of including potential compensating factors such as income or working hours. Hansson et al. (2011) include proxies for job strain, financial stress, and variables related to income, overtime, and unemployment history. Roberts et al. (2011) consider housing quality, job satisfaction, and net household income. By including these potential compensating factors, these two studies investigate how commuting time affects (psychological) well-being alongside those compensating variables. Roberts et al. (2011) argue that an inclusion of compensating factors is important, since the labour market is characterised by job search due to imperfections in the labour and housing markets and substantial residence relocation costs. Hence, controlling for compensating factors excludes, inter alia, on-the-job search imperfections. This (potential) compensating role is exactly the reason for Stutzer and Frey (2008) not to include household income, labour income, or working hours in their analysis on the relation between commuting and life satisfaction. They argue that the role of commuting could only be accurately predicted if all channels for compensation remain uncontrolled (Stutzer and Frey 2008). In our main analyses we follow Roberts et al. (2011) and Hansson et al. (2011). Nevertheless, in a robustness check we exclude variables with potentially compensating power (i.e., household income, working hours) to see whether those compensating factors are driving our results.

Finally, since we report results on many outcomes the probability is high to observe at least one significant result, even if it is actually not significant. One approach sometimes used to deal with multiple outcomes is to aggregate them into particular groupings to examine whether the impact of commuting on an overall outcome is different from zero. Thus, we accumulate the single dependent variables to overall well-being measures. This approach is useful to see whether the global impact of commuting distance is generally positive or negative (Gibson et al. 2011). Another way to address the issue of multiple outcomes is to consider the significance of individual coefficients when viewed as part of a family of *n*

[76] According to Dickerson et al. (2014) the BUC estimator is unbiased and the loss of efficiency relative to other methods (e.g., two step minimum distance, generalized method of moments) is very modest. In the fixed-effects ordered logit method, it is not possible to calculate the marginal effects relating to individual coefficients. However, it is possible to comment on the sign, statistical significance and the relative size of the coefficients. The BUC estimator is implemented in Stata using the *bucologit* command proposed by Dickerson et al. (2014). This approach has been used to analyse overall life satisfaction in a variety of studies, see for example Brown and Gray (2016), Mujcic and Fritjers (2015) and Dickerson et al. (2014). A more detailed description on this method can be found in Baetschmann et al. (2015).

hypotheses. For example, we consider all outcomes related to cognitive well-being as a family. The family-wise error rate is then defined as the probability of at least one type 1 error in the family. Then we can maintain the family-wise error rate at some designated level α, such as 0.05 or 0.10, by adjusting the p-values used to test each individual null hypotheses in the family (Shaffer 1995). The simplest of such methods is the Bonferroni method, which uses as critical values α/n. Several refinements to the Bonferroni method offer greater power. Ranking the n outcomes in increasing order of their p-values for testing a null effect, so that $p_1 \leq p_2 \leq \ldots \leq p_n$. Then, Holm's (1979) sequentially rejective Bonferroni method is applied as follows. In the first step, a null effect for outcome 1 is rejected if $p_1 \leq \alpha/n.$ If we cannot reject this outcome, we cannot reject null effects for all other outcomes. Otherwise, reject a null effect for outcome 2 if $p_2 \leq \alpha/(n-1)$, and at step j, reject a null effect for outcome j if and only if null effects have been rejected for all outcomes $i <$ j, and $p_j \leq \alpha/(n-j+1)$. Hochberg (1988) provides a step-up modification of this procedure, which rejects null effects for all outcomes $i \leq$ j if $p_j \leq \alpha/(n-j+1)$ for any $j = 1,2,\ldots,n$. The adjusted p-values are shown in Table D.2 of Appendix D.

In a second set of robustness checks, we analyse the relation between commuting distance and subjective well-being measures for several sub-groups. First, we estimate equation (5.1) separately for women and men, because it has been shown that commuting affects well-being for women, but not for men (Roberts et al. 2011).

With the second sub-sample, we follow Wheatley (2014), who argues that commutes for full-time workers have a particularly large impact on well-being, since a significant portion of time is devoted to work and necessary work-related activity. Moreover, for commuting full-time workers, the distribution of other elements of time-use (e.g., housework, caregiving) becomes especially relevant as time is particularly constrained.

Third, because commuting types (active vs. passive) could have opposing effects on well-being, we estimate a model that consists of individuals who report commuting more than 10 km to work. We do so since we do not have explicit information on commuting mode. But, short distances are more likely to be entirely covered on foot or by bicycle, and, including both active and passive types could result in their effects being cancelled out.

Fourth, since, by law, daily commutes of up to two and a half hours are considered to be reasonable, we restrict our sample to individuals who commute on a daily basis up to 100 km (one way), which could approximately be translated into a daily commute of two or two and a half hours. Daily commutes are expected to have a greater impact on subjective well-being than commutes on a weekly or less often basis (Ettema et al. 2010).

Fifth, we estimate the models for a subset of the sample whose employment was terminated involuntarily because of plant closure in the last year.[77] For these individuals the impact of commuting distance is triggered by an exogenous event. Therefore, individuals might be locked into a disadvantaged situation, for example, experiencing a longer commute ex post than expected ex ante from re-optimising (Stutzer and Frey 2008). By including interactions between current commuting distance and involuntary job changes in the previous year, we check whether the impact of commuting is different for those individuals who were forced to re-arrange their commuting distance due to exogenous reasons.[78]

5.4.3 Assessment of mechanisms

In order to explore whether several important daily activities serve as potential mediators of the relationship between commuting and well-being, we first include additional time-use control variables in equation (5.1): errands, housework and repairs on and around the house, child care and support for persons in need of care, physical and other leisure activities and sleeping, to see how sensitive the results are to the inclusion of these variables.

Second, we apply a causal mediation analysis to account for the pathways by which one variable affects another and hence, to identify the extent to which the mediators explain the relation between commuting distance and well-being. The test of mediation uses bootstrapping to create a reference distribution used for significance testing and 95%

[77] Only 7% of individuals in our sample experienced an occupational change. Of these changes, a significant share was attributed to voluntary changes (e.g., approximately 42% were attributed to own resignation, 18% to expiry of temporary contracts, 11% to mutual termination) and only 6.5% were attributed to involuntary changes caused by plant closure (256 observations).

[78] The literature dealing with the consequences of commuting argues that analyses of individuals who neither change employer nor residence reveal the effect of exogenous changes in commuting distance (e.g., due to workplace relocation) on health outcomes (e.g., Roberts et al. 2011, Künn-Nelen 2016). We have also investigated this sub-sample, but did not find significant results. The most plausible explanation for this is that applying this strategy in our setting might result in endogeneity from the self-selection of employees in a group of workers who do not change residence or employer because they are willing to travel long distances. Strictly speaking, people who become so dissatisfied with their commutes are more likely to relocate closer to their place of work, and/or change employer. Further, we cannot exclude the possibility that individuals with unobserved positive attitudes towards life and certain life domains are more likely to accept exogenous distance changes and are also less likely to have lower levels of well-being.

confidence interval estimation.[79] Figure D.4 of Appendix D illustrates the mediation design used in our study.

5.5 Results

5.5.1 Commuting distance and subjective well-being outcomes

Table 5.2 presents the results from the models with life satisfaction and satisfaction with specific life domains. Since commuting distance and the squared term of commuting distance are included, the table also reports the F-statistics and p-values of the joint significance. The F-statistic indicates whether there is a u-shaped relationship between commuting distance and the single subjective well-being measures.

It can be seen that people who commute longer distances report lower satisfaction with leisure time and lower satisfaction with family life. The relation between commuting distance and satisfaction with leisure is significant in a u-shaped manner, suggesting that the negative relation flattens out. However, the turning point for satisfaction with leisure time is around 470 kilometres of commuting distance. Because only 1% of the people in the sample have a commute longer than 470 kilometres, the negative linear relation between commuting distance and satisfaction with leisure holds for a substantial share of the sample. Whereas the effect is highly significant, its size is small. An increase in commuting distance of 20 kilometres with an initial commuting distance of 10 kilometres is, on average, associated with a 0.048-point lower satisfaction with leisure time (on an eleven-point scale).

Table 5.2. Estimation results on cognitive well-being outcomes.

	(1) Life	(2) Work	(3) HH-Income	(4) Income	(5) Dwelling	(6) Leisure	(7) Family life	(8) Health
Commuting distance	-0.0006	-0.0006	0.0005	0.0006	-0.0003	-0.0025***	-0.0014**	-0.0005
	(-1.40)	(-0.95)	(1.09)	(1.13)	(-0.66)	(-4.24)	(-2.45)	(-1.17)
Commuting distance squared	4.19e-07	7.08e-07	-9.23e-07	-9.61e-07	1.06e-06	2.61e-06***	7.82e-07	7.96e-07
	(0.64)	(0.72)	(-1.33)	(-1.06)	(1.44)	(2.87)	(0.92)	(1.29)
F-statistic	1.95	0.51	0.92	0.64	2.55	10.92	7.46	0.84
(p-value)	0.1427	0.5982	0.3975	0.5280	0.0784	0.0000	0.0006	0.4326
N	60,266	59,345	59,907	60,254	60,249	60,340	59,946	60,324

Notes: Fixed-effects ordinary least squares model. Only the coefficients for the commuting variables are reported. The following control variables are included: age, age squared, number of children, marital status, current health status, education, unemployment experience, actual working hours, tenure, tenure squared, household income (log), household size, urban area, federal states and year dummies. Appendix D shows the results for control variables in Table D.3. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[79] A more detailed description on this method can be found in Preacher and Hayes (2008), MacKinnon et al. (2007) and Hicks et al. (2011).

The relation between commuting distance and satisfaction with family life is significant at the 5% level, and the F-statistic indicates a u-shaped relation. Since the quadratic term of commuting distance is close to zero and not significant, this u-shaped relation is rather flat (linear). Hence, those commuting longer have lower levels of satisfaction with family life, but this negative relation flattens out with longer distances. Further, Table 5.2 indicates a jointly significant effect of commuting on satisfaction with dwelling, even though neither commuting distance nor the squared term by itself tests as statistically significant. Additional analyses show that this jointly significant relation between commuting and satisfaction with dwelling disappears when the model includes information on whether the rent is adequate or not and whether the respondent is owner or tenant of the dwelling. This indicates that commuting distance affects satisfaction with dwelling via residential amenities. This could indicate that commuting enables individuals to select places to live and, hence, to freely choose the optimal residence location.[80]

Table 5.3 reports the regression results on affective well-being outcomes. The results indicate that commuting distance has no significant impact on individuals' moods and emotions. These findings are in line with Morris et al. (2015) who analyse the relationship between emotions and the travel to work for the United States.

Table 5.3. Estimation results on affective well-being outcomes.

	(1) Angry	(2) Worried	(3) Happy	(4) Sad
Commuting distance	-0.0001	-0.0001	-0.0002	-0.0001
	(-0.32)	(-0.60)	(-1.19)	(-0.35)
Commuting distance squared	6.21e-08	4.05e-07	2.66e-07	4.44e-07
	(0.15)	(1.05)	(0.35)	(0.98)
F-statistic	0.11	0.89	0.86	1.24
(p-value)	0.8993	0.4109	0.4218	0.2892
N	57,166	57,112	57,142	57,136

Notes: Fixed-effects ordinary least squares model. Only the coefficients for the commuting variables are reported. The following control variables are included: age, age squared, number of children, marital status, current health status, education, unemployment experience, actual working hours, tenure, tenure squared, household income (log), household size, urban area, federal states and year dummies. Appendix D shows the results for control variables in Table D.4. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.5.2 Robustness checks

As described in Section 5.4.2, we perform several robustness checks to show the sensitivity of the main results. Table 5.4 and Table D.5 (see Appendix D) report the results of

[80] These results are available upon request.

the methodology-related analyses for cognitive (Table 5.4) and affective (Table D.5, Appendix D) well-being measures.

Table 5.4. Robustness checks for cognitive well-being outcomes – methodology.

	(1) Life	(2) Work	(3) HH-Income	(4) Income	(5) Dwelling	(6) Leisure	(7) Family life	(8) Health
Panel a: Categorization of commuting distances								
Short:	-0.0214	-0.0763*	0. 0152	-0. 0154	0.0497	-0.0254	-0.0470	-0.0122
10-24 km	(-0.84)	(-1.88)	(0.46)	(-0.40)	(1.50)	(-0.70)	(-1.42)	(-0.47)
Middle:	0.0182	-0.0184	0. 0585	0. 0715	0.0683	-0.1005**	0.0184	0.0207
25-49 km	(0.52)	(-0.34)	(1.32)	(1.41)	(1.51)	(-2.07)	(0.42)	(0.62)
Long:	-0.0755	-0.1341*	0.0077	0. 0344	0.0382	-0.3208***	-0.1522**	-0.0251
50 km +	(-1.60)	(-1.90)	(0.13)	(0.53)	(0.65)	(-491)	(-2.38)	(-0.56)
F-statistic	1.74	2.29	0.64	1.27	0.99	8.45	3.35	0.57
(p-value)	0.1573	0.0767	0.5870	0.2816	0.3956	0.0000	0.0181	0.6344
N	60,266	59,345	59,907	60,254	60,249	60,340	59,946	60,324
Panel b: Logarithm of commuting distance								
Log (CD)	-0.0075	-0.0410**	0.0133	0.0035	0.0251*	-0.0691***	-0.0310**	-0.0008
	(-0.69)	(-2.53)	(0.98)	(0.23)	(1.82)	(-4.68)	(-2.24)	(-0.09)
N	60,266	59,345	59,907	60,254	60,249	60,340	59,946	60,324
Panel c: Excluding small (up to 3km) distance changes								
CD	-0.0005	-0.0006	0.0006	0.0006	-0.0004	-0.0026***	-0.0014**	-0.0004
	(-1.30)	(-0.99)	(1.19)	(1.13)	(-0.79)	(-4.36)	(-2.36)	(-1.11)
CD squared	3.98e-07	7.96e-07	-1.03e-06	-1.04e-06	1.14e-06	2.77e-06***	7.14e-07	8.55e-07
	(0.59)	(0.80)	(-1.05)	(-1.16)	(1.55)	(2.98)	(0.83)	(1.34)
F-statistic	1.70	0.52	1.21	0.69	2.49	11.45	7.37	0.92
(p-value)	0.1820	0.5962	0.2978	0.5025	0.0826	0.0000	0.0006	0.3982
N	49,577	48,746	49,273	49,560	49,554	49,636	49,289	49,624
Panel d: FE ordered logit (BUC)								
CD	-0.0011	-0.0006	0.0006	0.0005	-0.0005	-0.0032***	-0.0020**	-0.0007
	(-1.40)	(-0.82)	(0.87)	(0.71)	(-0.62)	(-4.25)	(-2.48)	(-0.96)
CD squared	8.22e-07	7.63e-07	-1.11e-06	-7.89e-07	1.52e-06	3.23e-06***	1.14e-06	1.11e-06
	(0.72)	(0.67)	(-0.93)	(-0.53)	(1.40)	(2.77)	(0.96)	(1.09)
F-statistic	3.57	0.72	0.87	0.56	5.38	23.21	15.80	1.18
(p-value)	0.1679	0.6980	0.6460	0.7575	0.0679	0.0000	0.0004	0.5531
N	106,903	148,034	132,360	143,656	117,314	149,042	127,047	135,644
Panel e: Compensating factors excluded								
CD	-0.0005	-0.0005	0.0010**	0.0012**	-0.0002	-0.0030***	-0.0014***	-0.0004
	(-1.22)	(-0.89)	(1.92)	(2.09)	(-0.54)	(-4.91)	(-2.51)	(-1.06)
CD squared	3.92e-07	7.05e-07	-1.11e-06	-1.35e-06	1.03e-06	3.05e-06***	8.55e-07	7.68e-07
	(0.60)	(0.72)	(-1.53)	(-1.50)	(1.40)	(3.25)	(1.00)	(1.25)
F-statistic	1.38	0.42	2.00	2.62	1.74	15.04	7.46	0.79
(p-value)	0.2506	0.6591	0.1351	0.0729	0.1822	0.0000	0.0006	0.4539
N	60,266	59,345	59,907	60,254	60,249	60,340	59,946	60,324

Panel f: Accumulated cognitive well-being variables				
	(f1) Satisfaction with life and all life domains	(f2) Satisfaction with all life domains	(f3) Satisfaction with life and domains *without* leisure and family life	(f4) Satisfaction with domains *without* leisure and family life
CD	-0.0051**	-0.0044**	-0.0011	-0.0004
	(-2.15)	(-2.06)	(-0.58)	(-0.27)
CD squared	4.36e-06	4.00e-06	1.34e-06	9.67e-07
	(1.46)	(1.46)	(0.54)	(0.41)
F-statistic	3.28	2.87	0.17	0.11
(p-value)	0.0375	0.0569	0.8452	0.8924
N	58,402	58,471	58,753	58,824

Notes: CD = commuting distance. Only the coefficients for the commuting variables are reported. Commutes with less than 10 km are treated as the reference category in Panel a. Same controls as in Table 5.2. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Detailed regression results upon request.

Panel (a) of Table 5.4 includes a categorical measure of commuting distance. Individuals who commute less than 10 km to work are treated as the reference group. In line with the results of Table 5.2, commuting distance decreases satisfaction with leisure and family life. When commuting distance increases from under 10 km to over 50 km, satisfaction with leisure (family life) decreases by about 0.32-points (0.15-points), on average. Although shorter distances do not seem to impact satisfaction with leisure and family life, all commuting dummies are jointly significant. Further, column (2) (Panel (a), Table 5.4) indicates that all commuting distance dummies together are significantly related to satisfaction with work at the 10% level. However, this finding is not robust to the inclusion of further working time (e.g., overtime, working hours mismatch) related controls. The findings reported in Table D.5 with respect to affective well-being outcomes are similar to the ones in Table 5.3, where no significant relations between commuting distance and affective well-being measures are observed.

Panel (b) of Table 5.4 includes a log transformed measure of commuting distance. The log transformed commuting distance clearly shows a significant relation with satisfaction with leisure and family life as well.[81] Again, we observe a negative relationship between commuting distance and satisfaction with dwelling and work, which disappears when the model includes further information on residential-related variables and working time (e.g., overtime, working hours mismatch) indicating that commuting affects satisfaction with work and dwelling via residential amenities and working time-related aspects.[82] This could point, inter alia, to potential benefits of increased flexibility resulting from the implementation of the flexible working regulations for individuals who commute long distances. With respect to affective well-being measures, no or a weak relation with the log transformed commuting distance is found (see Appendix D, Table D.5).

Panel (c) of Table 5.4 reports the results for models in which small distance changes are excluded, since small distance changes will more likely refer to measurement error in reported commuting distance. This robustness check produces findings similar to those of the main model: A u-shaped relation with commuting distance is found for both satisfaction with leisure and satisfaction with family life. With respect to the other subjective well-being measures, no relation with commuting distance is found (see Table D.5).

Panel (d) of Table 5.4 presents the results from the FE ordered logit (BUC) models. In line with the findings of Table 5.2, commuting distance is significantly related to lower levels

[81] Results do not change when we include the logarithm of the squared commuting distance.
[82] Additional analyses are available upon request.

of satisfaction with leisure and family life. Whereas the sizes of the coefficients increase, the signs and significance levels remain similar, indicating that our findings are robust to this type of methodology, in which the ordinal character of the well-being measures is taken into account.

In Panel (e) of Table 5.4, potentially compensating factors are excluded from the models. The relation between commuting distance and satisfaction with leisure time and family life is comparable to the main results. Hence, variables with potentially compensating factors are not driving these results. Further, we see that commuting distance is positively associated with satisfaction with (household) income, once income and working hours are excluded. This suggests that the additional burden of commuting is compensated by a financially rewarding job so that commuters' utility is equalised. These results indicate that, on average, the positive effect of commuting on income could possibly offset the negative effect of commuting on family life and leisure so that over all life satisfaction is not affected.

Panel (f) addresses the issue of multiple hypothesis testing and reports the results for models in which the single dependent variables are added together to achieve overall well-being measures. In Panel (f) of Table 5.4 we use overall satisfaction with life and all life domains (f1), overall satisfaction with all life domains (f2), satisfaction with life and life domains but *without* leisure and family life (f3) and satisfaction with life domains but *without* leisure and family life (f4) as our dependent variables. This robustness check shows that commuting distance is significantly related to lower overall satisfaction with life and life domains and to lower overall domain satisfaction, but only in those models in which satisfaction with leisure and satisfaction with family life are taken into account (f1, f2). We observe no relationship between commuting and the aggregated well-being measures when satisfaction with family life and leisure are excluded (f3, f4). Thus we argue that the relationship between commuting and overall satisfaction with life and all life domains as well as overall domain satisfaction is driven by satisfaction with family life and leisure time. This is in line with Schwarz and Strack (1999), who argue that when people make a judgment about their general life satisfaction, particular life domains might be more salient than others. The adjusted p-values for multiple hypotheses testing (Table D.2 of Appendix D) do not reveal other results. If we were to consider all cognitive well-being measures as a family, the only outcomes that are significant are satisfaction with leisure and family life. With respect to the overall affective well-being measure (Panel (f), Table D.5), no relation with commuting distance is found.[83] Since we do not found any significant effects, p-values were not adjusted.

Tables 5.5 and D.6 (see Appendix D for Table D.6) report the results for the models with different sub-samples. Panel (a) and (b) show differentiated effects across gender for several subjective well-being measures. For both men and women, a longer commuting distance is related to lower satisfaction with leisure time. We find no statistically significant differences between men's and women's satisfaction with leisure. Further, we find a hump-shaped relation between commuting distance and satisfaction with family life for women and a u-shaped relation for men. The difference is statistically significant.[84] The results further indicate that among women, longer commuting distances are significantly related to lower health satisfaction. Commuting distance squared is positive, suggesting that the negative relation flattens out. The turning point is around 206 km and, hence, the negative relation holds for a substantial share of women in the sample. This relation is not present among men. This is consistent with the findings of Künn-Nelen (2016) and Roberts et al. (2011). Further, as shown by the F-statistics for joint significance, commuting is only weakly related to lower life satisfaction and satisfaction with dwelling for men. With respect to the other subjective well-being outcomes, no or a weak significant relation with commuting distance is found.

In Panel (c), we restrict the sample to full-time workers. It turns out that the results are robust for this sub-sample. Shown by the F-statistics for joint significance, which are significant at the 1% level, commuting is related to lower satisfaction with family life and leisure. Further, we see that commuting is weakly related to satisfaction with dwelling which is again not robust to the inclusion of residential-related controls. Affective well-being measures are not affected.

In Panel (d), we restrict the sample to individuals who commute more than 10 km to work. It turns out that there are no large differences compared to the main model: A u-shaped relation is found between commuting and satisfaction with leisure and family life. For all other variables, results similar to those from our main models are found.

[83] Since 'angry', 'worried', 'sad' can be assigned to negative emotions and 'happy' to positive ones, we first created a reverse scale of the frequency of being happy (a high value indicates a low frequency of feeling happy) before we summed up the single affective well-being variables.

[84] For women, the turning point is around 95 km and for men around 560 km. Hence, the found relationship holds for a substantial share of women and men in the sample.

Table 5.5. Robustness checks for cognitive well-being outcomes – sub-samples.

	(1) Life	(2) Work	(3) HH-Income	(4) Income	(5) Dwelling	(6) Leisure	(7) Family life	(8) Health
				Panel a: Women				
CD	0.0004	-0.0013	0.0014	0.0017	0.0005	-0.0028**	0.0009	-0.0015*
	(0.52)	(-1.01)	(1.30)	(1.46)	(0.50)	(-2.40)	(0.79)	(-1.78)
CD squared	-1.62e-06	6.39e-07	-2.56e-06	-3.79e-06	-5.79e-07	2.97e-06	-4.69e-06*	3.63e-06**
	(-1.03)	(0.27)	(-1.23)	(-1.75)	(-0.28)	(1.44)	(-1.95)	(2.24)
F-statistic	0.87	1.54	0.86	1.60	0.20	3.91	4.14	2.73
(p-value)	0.4187	0.2136	0.4240	0.2019	0.8220	0.0201	0.0160	0.0653
N	30,716	30,130	30,510	30,699	30,704	30,749	30,575	30,740
				Panel b: Men				
CD	-0.0009*	-0.0001	0.0001	0.0004	-0.0007	-0.0025***	-0.0020***	-0.0003
	(-1.94)	(-0.07)	(0.28)	(0.73)	(-1.23)	(-3.56)	(-2.90)	(-0.66)
CD squared	9.31e-07	1.97e-07	-3.17-e07	-5.70e-07	1.62e-06**	2.57e-06**	1.78e-06*	4.10e-07
	(1.30)	(0.18)	(-0.41)	(-0.56)	(1.96)	(2.54)	(1.84)	(0.59)
F-statistic	2.45	0.05	0.12	0.30	3.14	7.32	6.06	0.22
(p-value)	0.0861	0.9552	0.8903	0.7445	0.0434	0.0007	0.0023	0.8043
N	29,550	29,215	29,397	29,555	29,545	29,591	29,371	29,584
				Panel c: Full-time worker				
CD	-0.0007	-0.0007	0.0003	0.0006	-0.0004	-0.0025***	-0.0015**	-0.0004
	(-1.56)	(-1.08)	(0.63)	(1.01)	(-0.83)	(-4.00)	(-2.46)	(-1.05)
CD squared	6.17e-07	1.06e-06	-5.93e-07	-8.00e-07	1.20e-06	2.70e-06***	9.69e-07	7.13e-07
	(0.91)	(1.04)	(-0.83)	(-0.87)	(1.58)	(2.86)	(1.11)	(1.13)
F-statistic	1.87	0.59	0.38	0.52	2.51	9.20	6.35	0.64
(p-value)	0.1540	0.5547	0.6848	0.5974	0.0810	0.0001	0.0017	0.5276
N	47,652	47,427	47,364	47,675	47,636	47,717	47,374	47,703
				Panel d: Leaving out distances ≤ 10 km				
CD	-0.0012	0.0001	-0.0011	0.0004	-0.0020	-0.0030*	-0.0017**	0.0002
	(-1.22)	(0.07)	(-0.85)	(0.34)	(-1.51)	(-1.82)	(-2.14)	(0.28)
CD squared	1.43e-06	-7.47e-07	4.32e-06	1.62e-06	4.86e-06	5.76e-06	1.02e-06	1.78e-06
	(0.53)	(-0.21)	(1.15)	(0.42)	(1.39)	(1.21)	(0.90)	(-0.69)
F-statistic	2.23	0.09	0.82	1.80	1.14	2.78	5.13	0.59
(p-value)	0.1079	0.9100	0.4411	0.1658	0.3198	0.0619	0.0059	0.5563
N	28,972	28,729	28,814	28,982	28,964	29,015	29,085	29,013
				Panel e: Daily commutes up to 100 km				
CD	-0.0008	-0.0014	0.0016	-0.0002	-0.0010	-0.0089*	0.0015	0.0008
	(-0.26)	(-0.25)	(0.36)	(-0.05)	(-0.23)	(-1.80)	(0.36)	(0.25)
CD squared	1.65e-06	-6.04e-06	-0.00002	0.00002	0.00001	0.00003	-0.00003	-0.00002
	(0.04)	(-0.08)	(-0.45)	(0.49)	(0.24)	(0.56)	(-0.68)	(-0.56)
F-statistic	0.18	0.36	0.11	0.77	0.03	6.14	0.47	0.40
(p-value)	0.8376	0.6979	0.8915	0.4615	0.9718	0.0022	0.6233	0.6699
N	29,489	29,313	29,324	29,504	29,481	29,532	29,353	29,529
				Panel f: 'Involuntary' terminated employment because of plant closure (last year) [+]				
CD	-0.0005	-0.0005	0.0006	0.0007	-0.0003	-0.0025***	-0.0013**	-0.0004
	(-1.26)	(-0.88)	(1.19)	(1.21)	(-0.61)	(4.14)	(-2.31)	(-1.11)
CD squared	3.47e-07	6.61e-07	-9.08e-07	-1.02e-06	1.04e-06	2.55e-06***	6.79e-07	7.74e-07
	(0.53)	(0.67)	(-1.41)	(-1.12)	(1.41)	(2.79)	(0.80)	(1.26)
PC	0.1992*	-0.2198	0.2001	0.1117	-0.0584	0.0583	0.1260	-0.0264
	(1.84)	(-1.21)	(1.33)	(0.71)	(-0.45)	(0.40)	(0.364)	(-0.21)
PC × CD	-0.0095***	-0.0053	-0.0078*	-0.0072	-0.0030	-0.0079	-0.0129***	-0.0028
	(-3.11)	(-0.75)	(-1.80)	(-1.61)	(-0.85)	(-1.59)	(-2.44)	(-0.67)
PC × CD^2	0.00001***	8.36e-06	0.00001*	0.00001	4.86e-06	0.00001*	0.00002***	3.87e-06
	(3.25)	(0.76)	(1.74)	(1.60)	(0.88)	(1.798)	(2.78)	(-0.67)
F-statistic and p-value								
all CD variables & interactions	4.16	1.53	1.05	0.79	1.57	5.41	8.03	0.86
	0.0009	0.1759	0.3854	0.5536	0.1658	0.0001	0.0000	0.4849
CD, CD^2	1.73	0.44	1.02	0.73	2.53	10.47	7.07	0.79
	0.1773	0.6436	0.3624	0.4818	0.0796	0.0000	0.0009	0.4544
N	60,266	59,345	59,907	60,254	60,249	60,340	59,946	60,324

Notes: CD = commuting distance. PC= plant closure. Only the coefficients for the commuting variables are reported. Same controls as in Table 5.2. [+]Interaction term is included since the number of observations in the cases of plant closures is very small. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Detailed regression results upon request.

In Panel (e), we restrict our sample to individuals who commute on a daily basis up to 100 km each way. For this sub-sample, the u-shaped relation between commuting and satisfaction with family life is no longer significant, perhaps reflecting that satisfaction with family life is only affected by commuting when commuting trips are linked to longer periods of absence from family, which is typical for commuting on a weekly basis (e.g., staying away from home from Mondays to Fridays).[85] Since our data has a lot of missing information in the case of frequency of commuting (i.e., daily, weekly, less often) this finding has to be interpreted with caution.

In Panel (f), we analyse whether the impact of commuting distance on subjective well-being is different for individuals whose employment was terminated involuntary in the previous year due to plant closure.[86] Since the number of employment terminations due to plant closures (n=256) is small, we include interaction terms rather doing the analyses separately. Again we see that commuting distance has a significant adverse effect on satisfaction with leisure time and family life; both the commuting distance variables and the interaction terms are jointly significant. Further, we do observe a significantly negative relation between commuting distances and satisfaction with life for those individuals whose employment was terminated involuntary one year before. The resulting F-statistic is 4.16, which has a p-value of 0.0009 and thus is significant at the 1% significance level. In sum, individuals who changed their job *involuntary* experience reduced life satisfaction if their new arrangements involve longer commuting distances.[87] Commuting distance has no impact on reported life satisfaction if the individual *voluntary* changed job or did not change job compared with one year before. With respect to the other subjective well-being outcomes no jointly significant relation with commuting distance is found.

Overall, the robustness checks confirm our general findings that whereas affective well-being measures are barely influenced by commuting distance, cognitive well-being measures are lower for individuals who commute longer distances. Particularly, our analyses uncover a robust impact of commuting longer distances on satisfaction with leisure time and family

[85] Moreover, we find no relationship between commuting and satisfaction with family life for individuals who have no children or who have no partner. These additional sub-sample analyses are available upon request.

[86] Therefore, we create a dummy variable that takes the value '1' if employment was terminated involuntary due to plant closure in the las year and '0' if individual did not change job or if the change in employment was voluntary (e.g., own resignation). Following Stock and Watson (2012) we also consider the interaction of plant closure with the cubic commuting distance.

[87] We also estimated models where we take into account that residence location is endogenously chosen. Thus, we keep residence location constant. We find that the effect of commuting distance on life satisfaction seems larger for people who do not change their residence compared with one year before ($\beta_{PC \times CD} = -0.0112, p = 0.000$; $\beta_{PC \times CD^2} = 0.00002; p = 0.000$; $\chi^2(5) = 4.79, p = 0.0002$).

life.[88] Moreover, we find no relationship between commuting distance and life satisfaction, in general. This is in line with the strong notion of equilibrium in location theory. A relation between commuting distance and satisfaction with life is only observed for individuals who were forced to re-arrange their commuting distance due to exogenous reasons.

We argue that these findings can be interpreted as causal effects because, first, FE specification controls for correlated unobservable effects on commuting distance and satisfaction with leisure time as well as family life. Second, endogenous selection, namely that (for example) only those commute who have strong family ties, can only bias the relation between commuting and satisfaction with family life downward. This is confirmed by an OLS analysis in which 'commuting distance' is estimated on lagged satisfaction with family life and a set of control variables. This analysis yields no relationship between satisfaction with family and commuting. Hence, good or bad family life does not seem to contribute to individual decision to commute. The same applies to satisfaction with leisure time.[89]

5.5.3 Mechanisms

The previous analyses have revealed robust relationships between commuting and satisfaction with leisure time and family life. This is not surprising since commuting involves much more than just covering the distance between home and work. Commuting prolongs the total workday, whilst reducing time that could be spent with family or on spare time activities.

As outlined in Section 5.2, it has been shown that commuting shapes the amount of time and timing of activities such as housework, leisure, caregiving and sleep, which in turn are linked with life satisfaction, happiness as well as mental well-being. Therefore, in this subsection, we analyse whether several important daily activities serve as potential explanatory factors in the connection between the travel to work and satisfaction with leisure and family life. We especially focus on the average daily time spent on errands (e.g., shopping, trips to government agencies), housework and repairs on and around the house (e.g., washing, cooking, cleaning, gardening), child care and support for persons in need of care, physical activities and other leisure activities (e.g., sports, fitness, gymnastic, hobbies) and sleeping. Since not all of these time use controls are available in every wave, we have to

[88] Since we use commuting distance as our key variable, any change in distance, must come from the individual either changing workplace or residence location. Both of these events could have an effect on well-being. Our results remain robust, when we additionally control for job changes (i.e., changes of employer) and changes of residence location in the main analyses.

[89] These findings are available upon request.

affirm that our results do not depend on the smaller sample size by estimating the main models based on this restricted sample. Further, in order to perform the mediation analysis properly and to be able to calculate correctly the extent to which the time use controls mediate the relationship between commuting distance and well-being, we only consider commuting distance without the quadratic term. Since the negative relation between commuting distance and satisfaction with family life and leisure holds for a substantial share of the sample and the u-shaped relation is found to be rather flat (linear) (see Table 5.2) our estimates are hardly sensitive to the exclusion of the quadratic term.

As a first step, we include the additional time-use control variables in the modified version of equation (5.1). The results in Table 5.6 reveal that more time spent on caregiving is significantly related to both lower satisfaction with leisure as well as family life, whereas more time spent on spare time activities and sleeping is related to higher satisfaction levels. The effect of commuting distance on satisfaction with leisure time and family life is still significant. Moreover, we see that the magnitudes of the estimated coefficients of the distance variables decline to some extent once potential mediators are included, at least in column (2). Therefore, commuting may reduce individual's time devoted to such activities. However, this effect does not explain the observed impact of commuting on satisfaction with leisure and family life.

Table 5.6. Contribution of time use controls to satisfaction with leisure and family life.

	(1) Leisure	(2) Leisure	(3) Family life	(4) Family life
Commuting distance	-0.0011***	-0.0010***	-0.0009***	-0.0009***
	(-3.26)	(-3.38)	(-2.97)	(-2.99)
Time (h) for errands		0.0138		-0.0067
		(0.79)		(-0.40)
Time (h) for housework		0.0017		0.0081
		(0.11)		(0.87)
Time (h) for caregiving		-0.0275***		-0.0113**
		(-4.31)		(-2.13)
Time (h) for leisure activities		0.1246***		0.0240***
		(13.88)		(2.95)
Time (h) for sleeping		0.1110***		0.0725***
		(8.31)		(5.81)
N	47,319	47,319	47,072	47,072

Notes: Fixed-effects OLS. Information on time (h) for sleeping is not available for the year 2007. Only coefficients for commuting distance and time use variables are reported. Detailed results are available upon request. The following control variables are included: age, age squared, # of children, marital status, health status, education, unemployment experience, actual working hours, tenure, tenure squared, household income (log), household size, urban area, federal states and year dummies. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As second step, mediation analysis allows an examination of the contribution of the mediators to the relationship between commuting distance and satisfaction with leisure. The results, presented in Table D.7 of Appendix D, indicate that the total indirect effect is significant ($\beta_{\text{total indirect effect}} = -0.00009, \text{p} < 0.01$), suggesting that the model was partially mediated by the addition of the respective time-use controls, which is in line with the results shown in Table 5.6. So, the multiple mediation analysis confirms that the impact of commuting distance on satisfaction with leisure is relatively robust. The mediation ratio (P_M), which denotes the proportion of the total effect of commuting on satisfaction with leisure (see Table 5.6, column (1): $\beta_{CD} = -0.0011, \text{p} < 0.01$) that is mediated by the included intervening variables, is around 91.8% ($P_M = 1 - \frac{-0.00009}{-0.0011}$). In other words, an appropriate part of the impact of commuting on satisfaction with leisure may be explained through the significant indirect effects of time spent on housework, child care and support for persons in need of care, as well as physical activities and other leisure activities.

Mediation analysis of the relationship between commuting distance and satisfaction with family life reveals a significant indirect effect of commuting (see Appendix, Table D.8: $\beta_{\text{total indirect effect}} = -0.00005, \text{p} < 0.01$), indicating that the model was also partially mediated. This supports our findings presented in Table 5.6. Again, the multiple mediation analysis confirms that the impact of commuting distance on satisfaction with family life is relatively robust. 94.4% of the total effect of commuting on satisfaction with family life (see Table 5.6, column (3): $\beta_{CD} = -0.0009, \text{p} < 0.01$) is mediated by the included intervening variables ($P_M = 1 - \frac{-0.00005}{-0.0009}$). As depicted in Table D.8 of Appendix D, we find significant indirect effects of time spent on housework as well as physical activities and other leisure activities.

5.6 Conclusion

In this paper, we analyse the relation between commuting and subjective well-being for employed workers in Germany. In contrast to most of the earlier research, our analyses focus on different affective and cognitive measures of subjective well-being. We find that whereas affective well-being is barely influenced by commuting distance, cognitive well-being is lower for people who commute longer distances. Particularly, our results suggest that commuting is related to lower levels of satisfaction with certain life domains, especially with family life and leisure time. These findings turn out to be robust against several specifications and sub-samples. Moreover, we find that the relation between commuting and satisfaction with family life and leisure can largely be explained by time scarcity. Since commuting increases the length of the total workday while simultaneously reducing time for private use, less time remains available for leisure time activities and home production, which obviously come at the expense of utility derived from family life and hobbies.

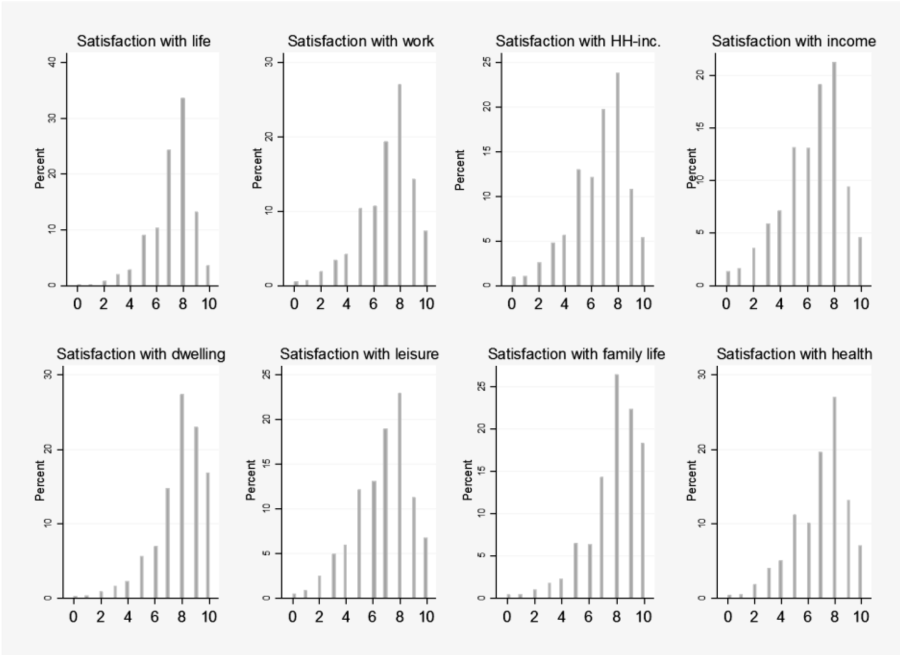
However, contrary to the common perception that commuting to work is an onerous activity which is bad for overall life satisfaction, we find no evidence that commuting distance is associated with lower levels of satisfaction with life. This finding is in line with the prediction of equilibrium location theory, according to which individuals are expected to freely optimise and, hence, maximise their utility. Consequently, travelling longer distances to and from work is only chosen if it is compensated. We find evidence that individuals are compensated for their commute by residential amnesties (e.g., sizes of dwelling, adequacy of rent) and financially rewarding jobs. We conclude that the benefits related to the labour and housing markets could potentially offset the costs related to family life and leisure, so that overall life satisfaction is not affected.

In sum, individuals' decision concerning commuting cannot be fully understood within the traditional economics framework. On the one hand, we demonstrate that individuals may generally be capable of correctly assessing the true costs of commuting for their overall well-being, whereas on the other hand, they may not be able to accurately forecast the outcome of their choices with respect to particular life domains. Our favoured interpretation is that particular life domains and experiences might be more salient than others, when people make a decision on whether to commute or not and when people make a judgement about their well-being. In particular, we do not know what people exactly include in their (life) evaluations and what they do not (see Schwarz and Strack 1999). Individuals might rely on inadequate intuitive theories when they predict how certain life domains are affected by commuting. In particular, they may make mistakes when they predict their adaptation to travel-related stress. Consequently, decision utility, inferred from choices, and experienced utility would not be identical (Ettema et al. 2010). Our results suggest that individuals tend to underestimate time constraints related to commuting and its possible consequences for family life and leisure time.

Since the aim of transport policies is to increase individuals' well-being, it is worthwhile to pay more attention to domain specific well-being. Yet, transport policies primarily tend to focus on overall life satisfaction, which might be an insufficient indicator of the effectiveness of policies. Thus, in order to develop tools that allow a complementary evaluation, the effects of policies on different domain specific requirements and aspects of life should be taken into account. Furthermore, since part of the effect of commuting arises through time scarcity caused by the commute, the relationship between the distance travelled, time-use and subjective well-being deserve more attention in transport policy and planning. Much transport policy and planning is currently fostering enlarged job regions to create more opportunities for work and strengthen the economy for both individuals and society. Thus, a more flexible and accessible labour market for companies is created by making the workforce available over larger geographical areas. For these reasons, there is the political will in many countries to expand labour market areas and transportation systems, resulting in an increase in overall commuting. Regardless, when we plan, build and manage our transport network or even the labour market, we should not lose sight of the fact that increased mobility in society is increasing the geographical spread of individuals and thereby reducing their well-being. This does not remain without consequences for social welfare.

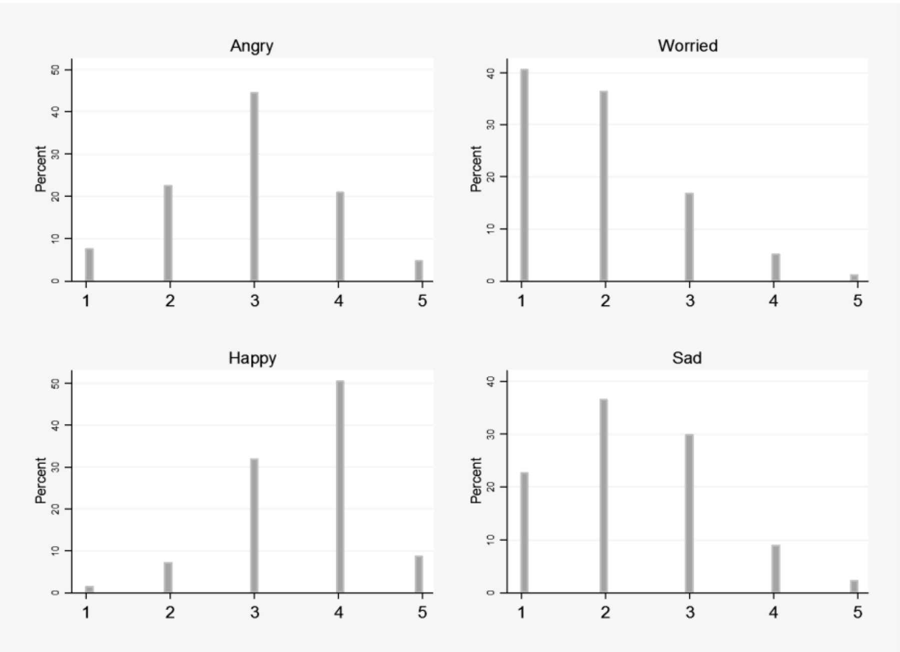
5.7 Appendix D

Figure D.1. Distributions of cognitive well-being measures.



Notes: Cognitive well-being measures on an 11-point scale, where the lowest value (0) is labelled “completely dissatisfied” and the highest value (10) is labelled “completely satisfied”.

Figure D.2. Distributions of affective well-being measures.



Notes: Affective well-being measures on a 5-point scale, where the lowest value (1) is labelled “very rarely” and the highest value (5) is labelled “very often”.

Figure D.3. Distribution of commuting distance in km.

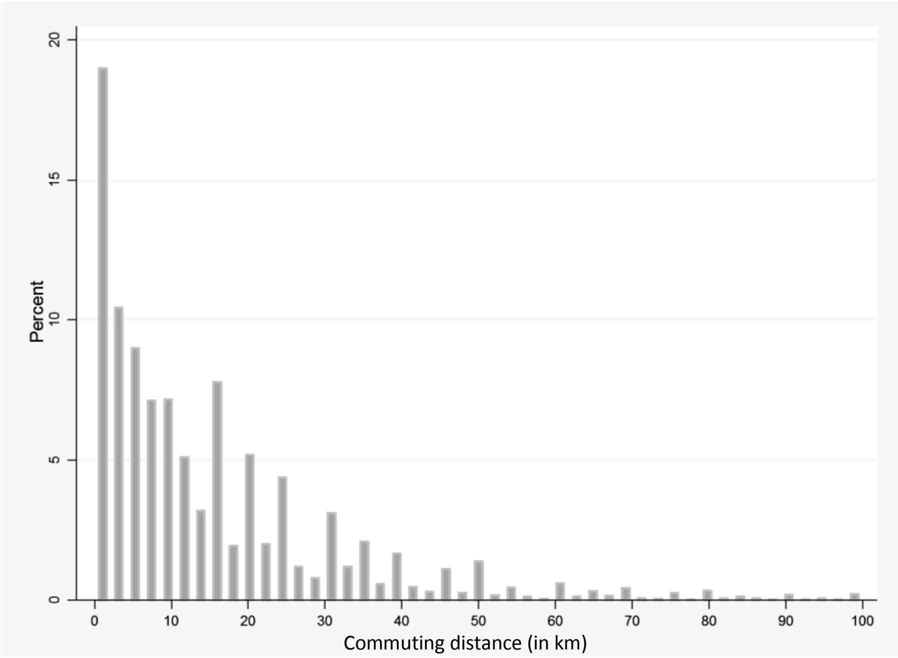
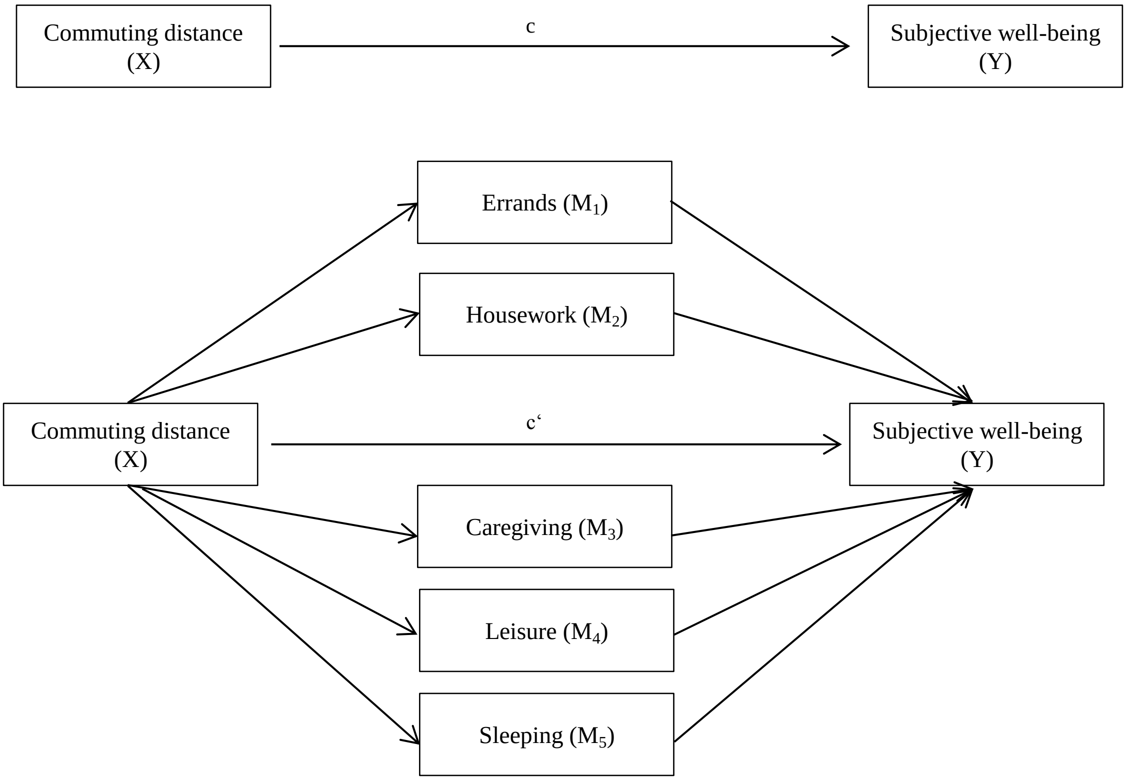


Figure D.4. Schematic of the multiple mediation model.



Notes: Figure D.4 depicts the framework for our mediation model. X represents the independent variable (commuting distance), Y the dependent variable (subjective well-being) and M the mediation variables (time-use). The top portion of the figure represents the *total effect* of X on Y, denoted by c. The bottom portion represents the introduction of the mediators. In this figure c' represents the *total indirect effect* after controlling for the proposed mediators. c' is the coefficient we are interested in. A measure that is relevant for the mediation models is the ratio of the indirect effect to the total effect, $P_M = 1 - \frac{c\prime}{c}$. P_M is also known as the validation ratio and is often interpreted as the proportion of the total effect that is mediated (Preacher and Kelley 2011). A significant c can be viewed as a necessary condition for testing mediation. If c' remains significant, one can say that the model is partially mediated. If c' is not significant, the model is fully mediated.

Table D.1. Variable definitions.

Variable	Definition
Satisfaction with life	Satisfaction with life on an 11-point scale.
Satisfaction with work	Satisfaction with work on an 11-point scale.
Satisfaction with household income	Satisfaction with household income on an 11-point scale.
Satisfaction with personal income	Satisfaction with personal income on an 11-point scale.
Satisfaction with dwelling	Satisfaction with dwelling on an 11-point scale.
Satisfaction with leisure	Satisfaction with leisure on an 11-point scale.
Satisfaction with family life	Satisfaction with family life on an 11-point scale.
Satisfaction with health	Satisfaction with health on an 11-point scale.
Angry	A five point indicator of frequency of feeling angry in the last four weeks.
Worried	A five point indicator of frequency of feeling worried in the last four weeks.
Happy	A five point indicator of frequency of feeling happy in the last four weeks.
Sad	A five point indicator of frequency of feeling sad in the last four weeks.
Commuting distance	Self-reported one-way commuting distance measured in kilometres.
Age	Age in years.
Female	Dummy equals 1 for women.
Number of children	Number of children in household.
Marital status	Dummy equals 1 if the individual is living together with partner (either married or unmarried couple).
Health status	A five point indicator of self-reported health status: 1 = "very good", 2 = "good", 3 = "acceptable", 4 = "less good", 5 = "bad".
Education	Dummy equals 1 if individual has a school degree higher than intermediate.
Unemployment experience	Dummy variable indicating whether respondent has ever been unemployed.
Working hours	Actual weekly working time.
Tenure	Number of years in present job.
Household income (log)	Logarithm of current gross labour household income.
Household size	Number of persons in household.
Urban area	Dummy equals 1 if individual lives in an urban region.
Time (h) for errands	Time in hours spent for errands on an average workday.
Time (h) for housework	Time in hours spent housework and gardening on an average workday.
Time (h) for caregiving	Time in hours spent for childcare and support for persons in need of care on an average workday.
Time (h) for leisure	Time in hours spent for leisure and hobbies on an average workday.
Time (h) for sleeping	Hours of sleep on an average workday.
Federal states	Dummy variables for the 16 federal states of Germany.
Year	Dummy variables for each year covered by the sample.

Table D.2. P-values and adjusted p-values for multiple hypothesis testing.

Dependent variables	Unadjusted p-values (Table 5.2)	Adjusted p-values		
		Bonferroni	Holm	Hochberg
Satisfaction with life	0.162	1.000	0.972	0.510
Satisfaction with work	0.340	1.000	1.000	0.510
Satisfaction with household income	0.275	1.000	1.000	0.510
Satisfaction with personal income	0.260	1.000	1.000	0.510
Satisfaction with dwelling	0.510	1.000	1.000	0.510
Satisfaction with leisure	0.000	0.000	0.000	0.000
Satisfaction with family life	0.014	0.112	0.098	0.098
Satisfaction with health	0.240	1.000	1.000	0.510

Table D.3. Complete estimation results on cognitive well-being outcomes.

	(1) Life	(2) Work	(3) HH-Inc.	(4) Income	(5) Dwelling	(6) Leisure	(7) Fam. life	(8) Health
CD	-0.0006	-0.0006	0.0005	0.0006	-0.0003	-0.0025***	-0.0014**	-0.0005
	(-1.40)	(-0.95)	(1.09)	(1.13)	(-0.66)	(-4.24)	(-2.45)	(-1.17)
CD^2	4.19e-07	7.08e-07	-9.23e-07	-9.61e-07	1.06e-06	2.61e-06***	7.82e-07	7.96e-07
	(0.64)	(0.72)	(-1.33)	(-1.06)	(1.44)	(2.87)	(0.92)	(1.29)
Age	-0.0544***	-0.0354	-0.0396*	0.0307	-0.0813***	-0.0258	-0.0401**	-0.0864***
	(-3.55)	(-1.53)	(-1.95)	(1.34)	(-4.15)	(-1.27)	(-2.06)	(5.70)
Age^2	0.0007***	0.0005**	0.0010***	0.0004*	0.0008***	0.0007***	0.0005**	0.0006***
	(4.40)	(2.17)	(4.64)	(1.83)	(4.26)	(3.29)	(2.43)	(3.92)
Number of	0.0382*	-0.0095	0.0583**	0.0652**	0.0710***	-0.1194***	0.0171	0.0037
children	(1.88)	(-0.35)	(2.36)	(2.41)	(2.94)	(-4.34)	(0.63)	(0.19)
Marital status	-0.0099	0.0637	0.0024	0.0358	-0.0078	-0.0367	0.0426	0.0210
	(-0.25)	(1.23)	(0.06)	(0.72)	(-0.16)	(-0.73)	(0.79)	(0.57)
Health status (ref.= very good)								
good	-0.2297***	-0.2273***	-0.1232***	-0.1331***	-0.1121***	-0.2522***	-0.2144***	-0.8266***
	(-10.00)	(-6.89)	(-4.12)	(-4.06)	(-3.98)	(-7.82)	(-7.39)	(-34.25)
acceptable	-0.6136***	-0.5689***	-0.3035***	-0.3272***	-0.2390	-0.5384***	-0.4407***	-1.9474***
	(-22.54)	(-14.72)	(-8.88)	(-8.71)	(-7.35)	(-14.55)	(-12.98)	(-64.07)
less good	-1.0924***	-0.9512***	-0.4765***	-0.4584***	-0.3540***	-0.7830***	-0.6396***	-3.5278***
	(-29.62)	(-18.76)	(-11.24)	(-9.95)	(-8.82)	(-16.52)	(-14.34)	(-82.80)
bad	-2.0794***	-1.3997***	-0.8462***	-0.8337***	-0.5283***	-0.9069***	-0.8648***	-5.2529***
	(-22.09)	(-11.65)	(-9.45)	(-8.59)	(-5.75)	(-8.52)	(-8.28)	(-51.32)
Education	0.1821	0.1276	0.1595	0.0106	-0.0485	-0.0546	-0.0836	0.0332
	(1.34)	(0.35)	(0.83)	(0.04)	(-0.27)	(-0.22)	(-0.41)	(0.20)
Unemployment	-0.0566	0.2181*	-0.1447	-0.1285	-0.0513	-0.1571*	-0.1534	-0.0377
experience	(-0.76)	(1.87)	(-1.52)	(-1.06)	(-0.55)	(-1.68)	(-1.55)	(-0.55)
Working hours	0.0011	-0.0006	0.0120***	0.0217***	0.0017	-0.0255***	-0.0047***	0.0014
	(1.00)	(-0.36)	(8.06)	(12.84)	(1.32)	(-15.84)	(-3.26)	(1.37)
Tenure	-0.0076	-0.1231***	-0.0156**	-0.0316***	0.0103**	0.0172***	0.0116*	-0.0113**
	(-1.57)	(-15.93)	(-2.56)	(-4.59)	(1.99)	(2.78)	(1.94)	(-2.43)
$Tenure^2$	-0.00002	0.0020***	0.00004	0.0004*	-0.0002	-0.0005***	-0.0001	0.0001
	(-0.18)	(7.93)	(0.19)	(1.84)	(-1.22)	(-2.79)	(-0.59)	(1.04)
Household	0.2722***	0.2420***	1.2553***	0.8664***	0.1676***	0.0818**	0.2578***	0.1128***
income (log)	(8.45)	(5.85)	(28.36)	(19.38)	(4.35)	(1.96)	(4.65)	(3.78)
Household size	-0.0394**	-0.0030	-0.1806***	-0.1363***	-0.0823***	-0.0596***	0.1052***	-0.0401**
	(-2.46)	(-0.13)	(-8.13)	(-5.98)	(-4.03)	(-2.65)	(4.65)	(-2.47)
Urban area	0.0175	0.2572**	0.0387	0.1127	-0.0655	-0.0281	0.2294*	0.0799
	(1.17)	(1.96)	(0.33)	(0.92)	(-0.45)	(-0.24)	(1.65)	(0.94)
_cons	6.4049***	6.5100***	-3.2258***	-2.5274***	8.5248***	7.2844***	6.5584***	10.1860***
	(15.11)	(10.56)	(-5.90)	(-4.04)	(14.98)	(12.71)	(11.41)	(25.45)
State dummies	*included*	*included*	*included*	*included*	*included*	*included*	*included*	*included*
Year dummies	*included*	*included*	*included*	*included*	*included*	*included*	*included*	*included*
F-statistic	1.95	0.51	0.92	0.64	2.55	10.92	7.46	0.84
(p-value)	0.1427	0.5982	0.3975	0.5280	0.0784	0.0000	0.0006	0.4326
N	60,266	59,345	59,907	60,254	60,249	60,340	59,946	60,324

Notes: Fixed-effects ordinary least squares model. CD = commuting distance. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.4. Complete estimation results on affective well-being outcomes.

	(1) Angry	(2) Worried	(3) Happy	(4) Sad
Commuting distance	-0.0001	-0.0001	-0.0002	-0.0001
	(-0.32)	(-0.60)	(-1.19)	(-0.35)
Commuting distance squared	6.21e-08	4.05e-07	2.66e-07	4.44e-07
	(0.15)	(1.05)	(0.35)	(0.98)
Age	-0.0328***	-0.0036	-0.0295***	-0.0240**
	(-3.28)	(-0.38)	(-3.55)	(-2.24)
Age^2	-0.00005	7.25e-07	0.0002***	0.0001
	(-0.49)	(0.01)	(2.95)	(1.19)
Number of children	0.0232*	-0.0339**	0.0096	-0.0035
	(1.69)	(-2.57)	(0.83)	(-0.24)
Marital status	0.0187	0.0086	-0.0237	-0.0229
	(0.75)	(0.36)	(-1.07)	(-0.86)
Health status (ref.= very good)				
good	0.0982***	0.0848***	-0.0931***	0.1190***
	(5.27)	(5.79)	(-7.00)	(6.98)
acceptable	0.2400***	0.2163***	-0.2220***	0.2851***
	(12.31)	(12.49)	(-14.39)	(14.38)
less good	0.3727***	0.4608***	-0.3934***	0.5297***
	(15.45)	(20.00)	(19.57)	(20.90)
bad	0.5105***	0.8838***	-0.6993***	0.8709***
	(9.85)	(15.12)	(15.40)	(16.45)
Education	-0.0332	0.1301	0.1676	-0.0268
	(-0.27)	(1.04)	(1.39)	(-0.23)
Unemployment experience	0.0194	0.0575	0.0124	0.0889*
	(0.41)	(1.26)	(0.33)	(1.82)
Working hours	0.0030***	-0.0010	-0.0002	0.0020***
	(4.21)	(-1.41)	(-0.46)	(2.66)
Tenure	0.0240***	-0.0031	0.0004	-0.0050
	(7.26)	(-1.04)	(0.18)	(-1.48)
$Tenure^2$	-0.0005***	0.0001	-0.00006	0.0002**
	(-4.89)	(1.54)	(-0.73)	(2.33)
Household income (log)	-0.0461**	-0.0849***	0.0674***	-0.0857***
	(-2.32)	(-4.42)	(3.89)	(-3.96)
Household size	0.0169	0.0059	-0.0126	-0.0440***
	(1.55)	(0.59)	(-1.34)	(-3.86)
Urban area	-0.0944	-0.1286**	0.0798	-0.1498**
	(-1.62)	(-2.46)	(1.60)	(-2.52)
_cons	4.6090***	2.7021***	3.8433***	3.6676***
	(16.58)	(10.22)	(16.12)	(12.59)
State dummies	*included*	*included*	*included*	*included*
Year dummies	*included*	*included*	*included*	*included*
F-statistic	0.11	0.89	0.86	1.24
(p-value)	0.8993	0.4109	0.4218	0.2892
N	57,166	57,112	57,142	57,136

Notes: Fixed-effects ordinary least squares model. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.5. Robustness checks for affective well-being outcomes – methodology.

	(1) Angry	(2) Worried	(3) Happy	(4) Sad
	Panel a: Categorization of commuting distances			
Short:	0.0246	-0.0004	-0.0183	-0.0099
10-24 km	(1.41)	(-0.03)	(-1.33)	(-0.55)
Middle:	0.0296	-0.0174	-0.0195	-0.0398
25-49 km	(1.25)	(-0.80)	(-1.01)	(-1.63)
Long:	-0.0214	-0.0095	-0.0281	-0.0296
50 km +	(-0.69)	(-0.35)	(-1.09)	(-0.97)
F-statistic	1.51	0.28	0.79	0.98
(p-value)	0.2090	0.8416	0.5005	0.4008
N	57,166	57,112	57,142	57,136
	Panel b: Logarithm of commuting distance			
Log (CD)	0.004	0.0016	-0.0106*	-0.0001
	(0.67)	(0.26)	(-1.84)	(-0.02)
N	57,166	57,112	57,142	57,136
	Panel c: Excluding small (up to 3km) distance changes			
Commuting distance	-0.00002	-0.0001	-0.0003	-0.00004
	(-0.08)	(-0.60)	(-1.47)	(-0.14)
Commuting distance squared	-2.86e-08	3.88e-07	3.29e-07	3.50e-07
	(-0.07)	(1.01)	(1.04)	(0.76)
F-statistic for joint significance	0.05	0.79	1.32	1.07
(p-value)	0.9487	0.4523	0.2677	0.3443
N	46,473	46,430	46,458	46,452
	Panel d: FE ordered logit (BUC)			
Commuting distance	-0.0001	-0.0005	-0.0009	-0.0002
	(-0.13)	(-0.63)	(-1.16)	(-0.35)
Commuting distance squared	1.42e-08	1.26e-06	9.81e-07	1.27e-06
	(0.01)	(1.05)	(0.94)	(0.94)
F-statistic for joint significance	0.08	1.78	1.44	2.29
(p-value)	0.9620	0.4114	0.4876	0.3182
N	76,812	66,278	56,352	78,927
	Panel e: Compensating factors excluded			
Commuting distance	-0.00003	-0.0001	-0.0001	-0.00008
	(-0.14)	(-0.74)	(-1.16)	(-0.28)
Commuting distance squared	1.07e-08	4.24e-07	2.70e-07	4.11e-07
	(0.03)	(0.10)	(0.86)	(0.91)
F-statistic for joint significance	0.04	0.79	0.77	1.19
(p-value)	0.9637	0.4544	0.4626	0.3031
N	57,166	57,112	57,142	57,136
	Panel f: Accumulated affective well-being variables			
Commuting distance	-0.00008			
	(-0.13)			
Commuting distance squared	6.71e-07			
	(0.70)			
F-statistic for joint significance	1.05			
(p-value)	0.3486			
N	57,061			

Notes: CD = commuting distance. Only the coefficients for the commuting variables are reported. Commutes with less than 10 km are treated as the reference category in Panel a. Same controls as in Table 5.3. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Detailed regression results upon request.

Table D.6. Robustness checks for affective well-being outcomes – sub-samples.

	(1) Angry	(2) Worried	(3) Happy	(4) Sad
	Panel a: Women			
Commuting distance	-0.0006	-0.0004	0.0003	-0.0004
	(-1.33)	(-0.94)	(0.67)	(-0.64)
Commuting distance squared	1.29e-06	1.18e-06	-1.25e-06*	1.32e-06
	(1.36)	(1.31)	(-1.71)	(1.03)
F-statistic for joint significance	0.94	1.00	3.75	0.74
(p-value)	0.3893	0.3683	0.0235	0.4772
N	29,242	29,213	29,231	29,231
	Panel b: Men			
Commuting distance	0.0001	-0.0001	-0.0003	-0.0001
	(0.30)	(-0.32)	(-1.38)	(-0.26)
Commuting distance squared	-2.24e-07	3.13e-07	4.92e-07	3.94e-07
	(-0.47)	(0.71)	(1.46)	(0.78)
F-statistic for joint significance	0.15	0.57	1.07	0.87
(p-value)	(0.8599)	0.5647	0.3436	0.4184
N	27,924	27,899	27,911	27,905
	Panel c: Full-time worker			
Commuting distance	-0.0001	-0.0001	-0.0002	-0.0001
	(-0.33)	(-0.67)	(-1.17)	(-0.38)
Commuting distance squared	-3.04e-08	4.01e-07	3.51e-07	4.41e-07
	(-0.07)	(1.00)	(1.10)	(0.93)
F-statistic for joint significance	0.44	0.66	0.69	1.05
(p-value)	0.6450	0.5159	0.5038	0.3508
N	45,468	45,425	45,445	45,438
	Panel d: Leaving out distances ≤ 10 km			
Commuting distance	-0.0011*	-0.0001	0.0002	-0.0001
	(-1.76)	(-0.32)	(0.54)	(-0.20)
Commuting distance squared	2.45e-06	2.26e-07	-1.19e-06	1.16e-06
	(0.46)	(0.16)	(-0.89)	(0.59)
F-statistic for joint significance	1.68	0.10	0.68	0.59
(p-value)	0.1860	0.9082	0.5086	0.5524
N	27,555	27,532	27,545	27,538
	Panel e: Daily commutes up to 100 km			
Commuting distance	-0.0034	-0.0033	-0.0017	-0.0035
	(-1.40)	(-1.51)	(-0.92)	(-1.44)
Commuting distance squared	0.00001	0.00002	0.00003	0.00001
	(0.48)	(0.94)	(0.92)	(0.66)
F-statistic for joint significance	3.24	1.88	1.66	2.77
(p-value)	0.0392	0.1526	0.1895	0.0630
N	28,030	28,000	28,017	28,012
	Panel f: 'Involuntary' terminated employment because of plant closure (last year) +			
Commuting distance	-0.00009	-0.0001	-0.0002	-0.0001
	(-0.33)	(-0.70)	(-1.11)	(-0.44)
Commuting distance squared	5.91e-08	4.38e-07	2.48e-07	4.79e-07
	(0.14)	(1.13)	(0.79)	(1.06)
Plant closure	0.0214	-0.0503	0.0393	-0.0285
	(0.26)	(0.488)	(0.62)	(-0.03)
PC × CD	-0.0002	0.0043*	-0.0024	0.0044
	(-0.09)	(1.74)	(-1.13)	(1.03)
PC × CD^2	1.17e-06	-7.01e-06*	3.64e-06	-7.63-06
	(0.26)	(-1.69)	(1.04)	(-1.10)
F-statistic (p-value)				
all CD variables & interactions	0.26	0.99	0.63	0.80
	0.9373	0.4205	0.6756	0.5507
CD, CD^2	0.12	0.93	0.77	1.26
	0.8888	0.3932	0.4651	0.2848
N	57,166	57,112	57,142	57,136

Notes: CD = commuting distance. PC = plant closure. Only the coefficients for the commuting variables are reported. Same controls as in Table 5.3. +Interaction term is included since the number of observations in the cases of plant closures is very small. All models are estimated using robust standard errors. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Detailed regression results upon request.

Table D.7. Mediation of the effect of commuting on satisfaction with leisure time.

	Observed Coefficient.	Bootstrap S.E.	95% CI		
Time (h) for errands	-3.432e-06	3.273e-06	-0.0000108	2.19e-06	(P)
			-0.0000118	1.62e-06	(BC)
			-0.0000113	1.95e-06	(BCa)
Time (h) for housework	0.00001687**	7.021e-06	4.09e-06	0.0000318	(P)
			4.33e-06	0.000032	(BC)
			4.33e-06	0.000032	(BCa)
Time (h) for caregiving	0.00001865***	5.089e-06	9.53e-06	0.0000291	(P)
			9.84e-06	0.0000294	(BC)
			9.76e-06	0.0000293	(BCa)
Time (h) for leisure activities	-0.00011709***	0.00002588	-0.000168	-0.0000665	(P)
			-0.0001681	-0.0000667	(BC)
			-0.0001668	-0.0000647	(BCa)
Time (h) for sleeping	-7.168e-06	0.00001429	-0.0000359	0.0000199	(P)
			-0.0000365	0.0000195	(BC)
			-0.0000362	0.0000198	(BCa)
Total indirect effect of commuting distance	-0.00009217***	0.00003058	-0.0001541	-0.0000337	(P)
			-0.000155	-0.0000347	(BC)
			-0.0001542	-0.0000338	(BCa)
N		47,319			
Replications		5,000			

Notes: Multiple mediation analysis. Same controls as in Table 5.2 (without CD squared). S.E. = Standard error, CI = Confidence interval, (P) = Percentile confidence interval, (BC) = Bias-corrected confidence interval, (BCa) = Bias-corrected and accelerated confidence interval. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.8. Mediation of the effect of commuting on satisfaction with family life.

	Observed Coefficient	Bootstrap S.E.	95% CI		
Time (h) for errands	2.373e-06	2.520e-06	-1.81e-06	8.17e-06	(P)
			-1.22e-06	9.32e-06	(BC)
			-1.40e-06	8.70e-06	(BCa)
Time (h) for housework	-0.0000144**	6.171e-06	-0.0000276	-3.13e06	(P)
			-0.0000279	-3.25e06	(BC)
			-0.0000278	-3.22e06	(BCa)
Time (h) for caregiving	-2.300e-06	2.283e-06	-7.23e-06	2.08e-06	(P)
			-7.40e-06	1.94e-06	(BC)
			-7.40e-06	1.95e-06	(BCa)
Time (h) for leisure activities	-0.00003659***	8.735e-06	-0.0000546	-0.0000204	(P)
			-0.0000549	-0.0000207	(BC)
			-0.0000545	-0.0000203	(BCa)
Time (h) for sleeping	-3.310e-06	7.591e-06	-0.0000184	0.0000116	(P)
			-0.0000184	0.0000116	(BC)
			-0.0000182	0.0000117	(BCa)
Total indirect effect of commuting distance	-0.00005423***	0.00001301	-0.0000805	-0.000029	(P)
			-0.0000802	-0.0000286	(BC)
			-0.0000798	-0.0000284	(BCa)
N		47,072			
Replications		5,000			

Notes: Multiple mediation analysis. Same controls as in Table 5.2 (without CD squared). S.E. = Standard error, CI = Confidence interval, (P) = Percentile confidence interval, (BC) = Bias-corrected confidence interval, (BCa) = Bias-corrected and accelerated confidence interval. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 6
Concluding remarks and outlook

Over the past decades, several forms of geographic labour mobility have intensified in Germany and most other industrialised countries. This especially refers to commuting. The commute to work has been influenced, inter alia, by changes in the organisation of production, as employers experienced increased geographic flexibility, while developing transport and communications infrastructure has made it possible for goods and services to be moved more easily to customers. The shift towards post-industrial economies and the rapid pace of change for information technologies has greatly reduced coordination costs and led to the potential for greater flexibility and dispersion in the workplace, redefining the relationship between home and work (Eurostat 2016). As a result, it has become more commonplace for individuals to travel longer distances to work. This trend appears to be continuing since the proportion of shorter work trips has declined, while the proportion of longer work trips has increased in recent years (Federal Statistical Office 2014). On the one hand, commuting may be vied positively as it increases the density of labour markets and, hence, reduces regional imbalances within the labour markets, thus boosting productivity and contributing to economic output as well as to the achievement of personal goals. On the other hand, the consequences of job-related mobility are not exclusively beneficial. There is a concern among researchers that increased mobility may be detrimental to the health and well-being of employees. Therefore, in the past decades the journey to work has gained attention in labour and health economics research. However, there are surprisingly few data from longitudinal studies exploring the well-being and health effects of commuting. Thus, this thesis contributes to a better understanding of the relationship between commuting, health and well-being.

In the first empirical chapter, Chapter 2, we show that there is a causal relationship between commuting and sickness absence from work. To account for the endogeneity in the absence-commute relationship, we focus our analysis on a subset of individuals who experience an exogenous shock to their commuting distance. Therefore, we stipulate that an employee changes neither employer nor household location during the period of observation. A variation in commuting distance will occur if a firm alters its location. Thus, the change in commuting distance will be employer driven and can be viewed as exogenous to the employee (e.g., Gutiérrez-i-Puigarnau and van Ommeren 2015). By employing fixed-effects regressions to data that meet the above criteria, we show that long distance commutes increase the numbers of days absent by about 20%. The effect of middle distance commutes is much lower, i.e. about 11%. The effect becomes zero at commuting distances of less than 25 kilometres. The results are robust across specifications and when accounting for selection effects. Furthermore, we explore potential explanations for the effect of commutes to work on absence. We find no evidence that the impact is due to poor health. The gap in sickness absence from work can also not be explained by differences in personnel characteristics, job-related aspects and factors compensating for commuting. Absence from work is much lower for those travelling shorter distances, possibly because they more frequently show up at work, despite anticipating an upcoming illness. Such behaviour could arise because short distance commuters can more easily return home if their health condition deteriorates than employees who have to travel longer distances to reach their place of residence. Consequently, we might expect individuals who commute short distances to exhibit lower levels of presenteeism. Unfortunately, we are not able to investigate to which extent individuals with different commuting distances go to work although being sick. This is the case since our data does not provide information on presenteeism days. This limitation may be worth addressing in future research since sickness presenteeism is known to have negative repercussions with regard to productivity and health (e.g., Barmby and Larguem 2009, Bergström et al. 2009).

The next chapter, Chapter 3, explores the relationship between height-adjusted weight and commuting distance and some of the driving forces behind the relationship. The results provide no evidence that longer commutes are associated with a higher BMI, at least in Germany. In contrast to other studies relating commuting to BMI, we use FE models to remove time-invariant unobserved heterogeneity. Hence, we argue that our findings can be interpreted as causal effects. This is confirmed by a sensitivity analyses in which we (i) again exploit exogenous variation of commuting distance within individuals, when there are no changes in residence and employer and (ii) replace the commuting distance variable with a lagged value in order to avoid the influence of BMI on contemporaneous commuting distance.

We further demonstrate that compensating health behaviour of commuters could explain the non-relationship of commuting and BMI.

Since the finding in Chapter 3 concerning the health behaviour of commuters should not necessarily be interpreted as a pure causal effect of commuting, Chapter 4 re-examines this finding by focusing on the relationship between a set of healthy lifestyle choices and commuting. To address the potential biases arising from endogeneity, heterogeneity and selection, we rely on a structural model for six health-related behaviours and commuting, where the choice to commute long distances is described by a reduced-form equation and appears as potential endogenous regressors in six lifestyle equations. Moreover, the structural model allows controlling for the simultaneous correlation existing between the unobservable determinants of commuting and health-related behaviours, since this approach assumes that commuting and lifestyle choices are interdependent decisions. According to the results derived from multivariate probit specifications, commuting long distances has a negative impact on health-conscious behaviour, in general. However, we also find significant correlations between the residuals of each equation, indicating that individuals with unobserved characteristics which lead them to commute long distances are more likely to have unobservable attitudes which increase the probability of exercising and eating healthy. Unfortunately, we are not able to investigate to which extent long distance commuters eat, for example, more vegetables and fruits or how much time they spend doing sports or the type of sport compared to non-commuters. This limitation may be worth addressing in future research with the aim of strengthening commuters' health consciousness, which could potentially offset some of the adverse effects of the travel to work.

Chapter 5 provides some evidence that compromised daily routines and time scarcity may at least provide a partial explanation for the low levels of subjective well-being among commuters. In particular, commuting appears to have an impact on satisfaction with family life and leisure time via changes in daily time use patterns, influenced by the work commute. Contrary to the common perception that commuting to work is an onerous activity which is bad for overall life satisfaction, we find no evidence that commuting distance is associated with lower levels of satisfaction with life in general. Since the results of Chapter 5 suggest that commuters are compensated for their commute by residential amnesties (e.g., sizes of dwelling, adequacy of rent) and financially rewarding jobs, we conclude that the benefits related to labour and housing markets could potentially counterbalance the costs related to family life and leisure, such that overall life satisfaction is not affected.

In sum, this thesis provides some evidence that commuting is an important factor for the assessment of health and well-being. Given the impacts found, additional research is needed to clarify how commuting contributes to other proxies of health and well-being. This would provide further important information to help balance policies that lead to an increase in commuting, and in the development of measures to reduce the negative effects of commuting. Chapter 3 and Chapter 4 point to the importance of fostering commuters' awareness of healthy lifestyles. This could be achieved through, for example, information and consultation as well as by offering more health programmes and support for private initiatives for improving health behaviour. Through training and education, commuters could gain necessary knowledge to improve their overall well-being and become more conscious of the dangers related to their commute. Thus, especially commuters should be a target group of company health promotion measures (Rüger and Schulze 2016).

However, Chapter 2 and Chapter 5 indicate that the adverse effect of commuting cannot only be ascribed to poorer health status *per se*. In particular, the findings suggest that commuters take more sick days off work than non-commuters although their self-assessed health status is not much worse than that of non-commuters. Moreover, levels of subjective well-being tend to be lower because commuters seem to underestimate time constraints caused by the commute and its possible consequences for private life. Thus, this points to some need for policy makers and employers to mitigate the negative effects of commuting which are not directly related to health by, for example, fostering statutory regulations and the adoption of different forms of flexible work arrangements, such as telecommuting. Telecommuting is an agreement which allows employees to work some hours of their work time or some days per week at home and, hence, may provide benefits for both employees, particularly commuters, and employers. Telecommuting might improve work-life balance of employees as it supports family life by enabling more time spent with family (e.g., Mokhtarian and Salomon 1997, Sarbu 2015). Another important benefit of telecommuting is the reduction of the number of commute trips and commute stress for employees as well as the associated reduction in road congestion and pollution (e.g., Mokhtarian 1991). In line with that, telecommuting may reduce absenteeism and sick leave usage and, thus, costs related to sickness absence while enhancing work-life balance at the same time, leading to higher employee productivity (e.g., Hill et al. 1998). Because information and communication technologies (ICT) are currently applied in nearly every company, it is now easier than ever for employers to offer these arrangements to their employees or for employees to make use of them. In Germany, however, only around 20% of firms offer their employees the possibility to telecommute, while around 40% of employees, who have hitherto never worked from home, would like to have this opportunity (e.g., German Bundestag 2016, Federal Ministry of Labour and Social Affairs 2015). This may partly be attributed to the fact that in Germany there is no explicit legal basis for telecommuting. Working from home is either agreed individually by contract or just by verbal approval between employers and employees (German Bundestag 2016). This topic, however, exceeds the scope of this thesis and needs further research. In particular, we are not yet able to address this issue as the data available does not contain sufficient information on, for example, telecommuting or ICT usage. If such data became available, the impacts of flexible work arrangements on commuter health and well-being would be interesting to investigate.

Taken together, the four research articles covered by this thesis add important findings to the previous literature on the relevance of commuting for individual health and well-being. Moreover, the thesis also improves knowledge about those factors that actually impact commuter health and well-being. This is not only relevant from a policy-maker’s perspective but also for the individual. The single chapters additionally demonstrate that there is also room for further research, since only few studies deal with the causal commute-health relationship, especially in Germany.

Bibliography

Abramowitz, J., 2016. The connection between working hours and body mass index in the US: A time use analysis. Review of Economics of the Household 14 (1), 131 – 154.

Abrantes, P.A.L., Wardman, M.R., 2011. Meta-analysis of UK values of travel time: An update. Transportation Research Part A: Policy and Practice 45 (1), 1 – 17.

Allen, S.G., 1981. An empirical model of work attendance. The Review of Economics and Statistics 63 (1), 77 – 87.

Allison, P.D., 2009. Fixed-effects regression models. Sage Publications, California.

Allison, P.D., Waterman, R.P., 2002. Fixed-effects negative binomial regression models. Social Methodology 32 (1), 247 – 265.

Alonso, W., 1964. Location and land use: Toward a general theory of land rent. Harvard University Press, Cambridge.

Alvarez, G.G., Ayas, N.T., 2004. The impact of daily sleep duration on health: A review of the literature. Progress in Cardiovascular Nursing 19 (2), 56 – 59.

Australian Institute of Health and Welfare (AIHW), 2014. Australia's health 2014. Australia's health series no. 14 (Cat. no. AUS 178), Canberra.

Averett, S.L., 2014. Obesity and labor market outcomes. The hidden private cost of obesity: Lower earnings and a lower probability of employment. IZA World of Labor 2014: 32, DOI: 10.15185/izawol.32.

Badland, H.M., Schofield, G., 2005. Transport, urban design, and physical activity: An evidence-based update. Transportation Research Part D: Transport and Environment 10 (3), 177 – 196.

Badland, H.M., Oliver, M., Kearns, R.A., Mavoa, S., Witten, K., Duncan, M.J., Batty, G.D., 2012. Association of neighbourhood residence and preferences with the built environment, work-related travel behaviours, and health implications for employed adults: Findings from the URBAN study. Social Science and Medicine 75 (8), 1469 – 1476.

Baetschmann, G., Staub, K.E., Winkelmann, R., 2015. Consistent estimation of the fixed-effects ordered logit model. Journal of the Royal Statistical Society: Series A (Statistics in Society) 178 (3), 685 – 703.

Balia, S., Jones, A.M., 2008. Mortality, lifestyle and socio-economic status. Journal of Health Economics 27 (1), 1 – 26.

Banegas, J.R., López-García, E., Gutiérrez-Fisac, J.L., Guallar-Castillón, P., Rodríguez-Artalejo, F., 2003. A simple estimate of mortality attributable to excess weight in the European Union. European Journal of Clinical Nutrition 57 (7), 201 – 208.

Banister, D., Anderton, K., Bonilla, D., Givoni, M., Schwanen, T., 2011. Transportation and the environment. Annual Review of Environment and Resources 36, 247 – 270.

Barmby, T., Larguem, M., 2009. Coughs and sneezes spread diseases: An empirical study of absenteeism and infectious disease. Journal of Health Economics 28 (5), 1012 – 1017.

Barro, R., 2013. Health and economic growth. Annals of Economics and Finance 14 (2), 329 – 366.

Barsky, R., Juster, F., Kimball, M., Shapiro, M., 1997. Preference parameters and behavioural heterogeneity: An experimental approach in the health and retirement study. Quarterly Journal of Economics 112 (2), 537 – 579.

Bassett, D.R., Pucher, J., Buehler, R., Thompson, D., Crouter, S.E., 2008. Walking, cycling and obesity rates in Europe, North America, and Australia. Journal of Physical Activity and Health 5 (6), 795 – 814.

Becker, G., 1965. A theory of the allocation of time. Economic Journal 75 (299), 493 – 517.

Bergstöm, G., Bodin, L., Hagberg, J., Lindh, T., Aronsson, G., Josephson, M., 2009. Does sickness presenteeism have an impact on future general health?. International Archives of Occupational and Environmental Health 82 (10), 1179 – 1190.

Bernell, S., 2016. Health economics: Core concepts and essential tools. Health Administration Press, Chicago.

Besser, L.M., Marcus, M., Frumkin, H., 2008. Commute time and social capital in the US. American Journal of Preventive Medicine 34 (3), 207 – 211.

Blanchflower, D.G., Oswald, A.J., 2004. Well-being over time in Britain and the USA. Journal of Public Economics 88 (7 – 8), 1359 – 1386.

Block, J., Goerke, L., Millán, J.M., Román, C., 2014. Family employees and absenteeism. Economics Letters 123 (1), 94 – 99.

Bonin, H., Eichhorst, W., Florman, C., Hansen, M., Skiöld, L., Stuhler, J., Tatsiramos, K., Thomasen, H., Zimmermann, K.F., 2008. Geographic mobility in the European Union: Optimising its social costs and benefits. IZA Research Report No. 19, Bonn.

Bratberg, E., Monstadt, K., 2015. Worried sick? Worker responses to a financial shock. Labour Economics 33, 111 – 120.

Brown, D.W., Brown, D.R., Heath, G.W., Balluz, L., Giles, W.H., Ford, E.S., Mokdad, A.H., 2004. Associations between physical activity dose and health-related quality of life. Medicine and Science in Sports and Exercise 36 (5), 890 – 896.

Brown, S., Gray, D., 2016. Household finances and well-being in Australia: An empirical analysis of comparison effects. Journal of Economic Psychology 53 (5), 17 – 36.

Brueckner, J.K., 2000. Urban sprawl: Diagnosis and remedies. International Regional Science Review 23 (2), 160 – 171.

Bryson, A., Cappellari, L., Lucifora, C., 2004. Does union membership really reduce job satisfaction? British Journal of Industrial Relations 42 (3), 439 – 459.

Cameron, C., Trivedi, P., 2008. Regression analysis of count data. Cambridge University Press, Cambridge.

Cappelari, L., Jenkins, S.P., 2003. Multivariate probit regression using simulated maximum likelihood. The Stata Journal 3 (3), 278 – 294.

Carta, F., De Philippis, M., 2015. You’ve come a long way, baby. Effects of commuting times on couples’ labour supply. Bank of Italy Temi di Discussione (Working Paper) No. 1003.

Cassidy, T., 1992. Commuting-related stress: Consequences and implications. Employee Counseling Today 4 (2), 15 – 21.

Cawley, J., 2004. The impact of obesity on wages. Journal of Human Resources 39 (2), 451 – 474.

Cawley, J., Meyerhoefer, C., 2012. The medical care costs of obesity: An instrumental variable approach. Journal of Health Economics 31 (1), 219 – 30.

Chatzitheochari, S., Arber, S., 2009. Lack of sleep, work and the long hours culture: Evidence from the UK Time Use Survey. Work, employment and society 23 (1), 30 – 48.

Chernew, M.E., Newhouse, J.P., 2012. Health care spending growth. In: Pauly, M.V., Mcguire, T.G., Barros, P.P., (Eds.): Handbook of Health Economics, 1 – 43, Elsevier, Amsterdam.

Choi, B., Schnall, P.L., Yang, H., Baker, D., Dobson, M., Israel, L., Karasek, R., Choi, B., 2010. Psychosocial working conditions and active leisure-time physical activity in middle-aged US workers. International Journal of Occupational Medicine and Environmental Health 23 (3), 239 – 253.

Christian, T.J., 2012. Trade-offs between commuting time and health-related activities. Journal of Urban Health: Bulletin of the New York Academy of Medicine 89 (5), 746 – 756.

Clark, A., Frijters, P., Shields, M., 2008. Relative income, happiness and utility: An explanation for the Easterlin paradox and other puzzles. Journal of Economic Literature 46 (1), 95 – 144.

Clark, A.E., Etilé, F., 2011. Happy house: Spousal weight and individual well-being. Journal of Health Economics 30 (5), 1124 – 1136.

Clark, X., Hatton, T., Williamson, J., 2007. Explaining U.S. immigration 1971 – 1998. Review of Economics and Statistics 89 (2), 359 – 373.

Cockerham, W.C., Hinote, B.P., Abbott, P., 2006. Psychological distress, gender, and health lifestyles in Belarus, Kazakhstan, Russia, and Ukraine. Social Science and Medicine 63 (9), 2381 – 2394.

Commissariat général au Développement durable, 2015. La mobilité à longue distance des Français en 2014, Chiffres et statistiques No. 963. Retrieved from: http://www.statistiques.developpement-durable.gouv.fr/fileadmin/documents/Produits_editoriaux/Publications/Chiffres_et_statistiques/2015/chiffres-stats693-mobilite-longue-distance-des-francais-en-2014-novembre2015.pdf (as consulted online on 24 April 2017).

Contoyannis, P., Jones, A.M., 2004. Socio-economic status, health and lifestyle. Journal of Health Economics 23 (5), 965 – 995.

Costa, G., Pickup, L., Martino, V., 1988. Commuting – a further stress factor for working people: Evidence from the European community. International Achieves of Occupational and Environmental Health 60 (5), 377 – 385.

Courtemanche, C., 2009. Longer hours and larger waistlines? The relationship between work hours and obesity. Forum for Health Economics and Policy 12 (2), 1 – 31.

Crozet, Y., Joly, I., 2004. Budget temps de transport. Les sociétés tertiaires confrontées à la gestion paradoxale du bien le plus rare. Les Cahiers scientifiques du transport 45, 27 – 48.

Cutler, D.M., Glaeser, E., 2005. What explains differences in smoking, drinking, and other health-related behaviors?. American Economic Review 95 (2), 238 – 242.

De Paola, M., 2010. Absenteeism and peer interaction effects: Evidence from an Italian public institute. The Journal of Socio-Economics 39 (3), 420 – 428.

De Vos, J., Schwanen, T., van Acker, V., Witlox, F., 2013. Travel and subjective well-being: A focus on findings, methods and future research needs. Transport Reviews 33 (4), 421 – 442.

Deaton, A., Stone, A.A., 2014. Evaluative and hedonic wellbeing among those with and without children at home. Proceedings of the National Academy of Sciences 111 (4), 1328 – 1333.

Department for Transport (DfT), 2013. National Travel Survey: 2012. Retrieved from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/243957/nts2012-01.pdf (as consulted online on 24 April 2017).

Department for Transport (DfT), 2016. National Travel Survey: England 2015. Retrieved from:https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/551437/national-travel-survey-2015.pdf (as consulted online on 24 April 2017).

Di Novi, C., 2010. The influence of traffic-related pollution on individuals' life-style: Results from the BRFSS. Health Economics 19 (11), 1318 – 1344.

Di Tella, R., MacCulloch, R., 2006. Some uses of happiness data in economics. Journal of Economic Perspectives 20 (1), 25 – 46.

Dickerson, A., Hole, A.R., Munford, L.A., 2014. The relationship between well-being and commuting revisited: Does the choice of methodology matter?. Regional Science and Urban Economics 49, 321 – 329.

Diener, E., 2000. Subjective well-being: The science of happiness and a proposal for a national index. American Psychologist 55 (1), 34 – 43.

Dionne, G., Dostie, B., 2007. New evidence on the determinants of absenteeism using linked employer-employee data. Industrial and Labor Relations Review 61 (1), 108 – 120.

Dolan, P., Peasgood, T., White, M., 2008. Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. Journal of Economic Psychology 29 (1), 94 – 122.

Drago, R., Wooden, M., 1992. The determinants of labor absence: Economic factors and workgroupnorms across countries. ILR Review 45 (4), 764 – 778.

Dunn, A.L., Trivedi, M.H., Kampert, J.B., Clark, C.G., Chambliss, H.O., 2005. Exercise treatment for depression: Efficacy and dose response. American Journal of Preventive Medicine 28 (1), 1 – 8.

Dunton, G.F., Berrigan, D., Ballard-Barbash, R., Graubard, B., Atienza, A.A., 2009. Joint associations of physical activity and sedentary behaviors with body mass index: Results from a time use survey of US adults. International Journal of Obesity 33 (12), 1427 – 1436.

Eibich, P., Ziebarth, N.R., 2014. Examining the structure of spatial health effects in Germany using Hierarchical Bayes Models. Regional Science and Urban Economics 49, 305 – 320.

Eichengreen, B., 1993. Labor markets and European monetary unification. In: Masson, P.R., Taylor, M.P., (Eds.): Policy issues in the operation of currency unions, 130 – 162, Cambridge University Press, Cambridge.

Eichhorst, W., 2013. The European labour market – Success through flexibility and mobility. Konrad-Adenauer-Stiftung, Berlin.

Eliasson, K., Lindgren, U., Westerlund, O., 2003. Geographical labour mobility: Migration or commuting?. Regional Studies 37 (8), 827 – 837.

Ettema, D., Gärling, T., Olsson. L.E., Friman, M., 2010. Out-of-home activities, daily travel, and subjective well-being. Transportation Research Part A: Policy and Practice 44 (9), 723 – 732.

European Policy Brief, 2008. Chasing work: The mobility dilemma. Retrieved from: https://cordis.europa.eu/citizens/docs/ssh_jobmob_famlives_en.pdf (as consulted online on 24 April 2017).

Eurostat 2016. Eurostat regional yearbook 2016. Publications office of the European Union, Luxembourg.

Ewing, R., Schmid, T., Killingsworth, R., Zlot, A., Raubenbush, S., 2003. Relationship between urban sprawl and physical activity, obesity, and morbidity. American Journal of Health Promotion 18 (1), 47 – 57.

Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR), 2012. Spatial Development Report 2011(Raumordnungsbericht 2011). Bonn. Retrieved from:http://www.bbsr.bund.de/BBSR/DE/Veroeffentlichungen/Sonderveroeffentlichungen/2012/DL_ROB2011.pdf?__blob=publicationFile&v=2 (as consulted online on 24 April 2017).

Federal Ministry of Labour and Social Affairs, 2015. Mobiles und entgrenztes Arbeiten. Forschungsbericht 460. Retrieved from: http://www.bmas.de/SharedDocs/Downloads/DE/PDF-Publikationen/Forschungsberichte/f460-mobiles-und-entgrenztes-arbeiten.pdf?__blob=publicationFile&v=1 (as consulted online on 24 April 2017).

Federal Statistical Office, 2008. Relocation of economic activities. Wiesbaden. Retrieved from:https://www.destatis.de/DE/Publikationen/Thematisch/UnternehmenHandwerk/VerlagerungAktivitaeten5529301069004.pdf?__blob=publicationFile (as consulted online on 24 April 2017).

Federal Statistical Office, 2009. Pendlerbefragung im Mikrozensus. Wiesbaden. Retrieved from:https://www.destatis.de/DE/Publikationen/STATmagazin/Arbeitsmarkt/2009_10/2009_10PDF.pdf?__blob=publicationFile (as consulted online on 24 April 2017).

Federal Statistical Office, 2012. Employment statistics. Wiesbaden. Retrieved from: https://www.destatis.de/DE/ZahlenFakten/GesamtwirtschaftUmwelt/Arbeitsmarkt/Erwerbstaetigkeit/TabellenArbeitskraefteerhebung/Berufspendler.html (as consulted online on 24 April 2017).

Federal Statistical Office, 2013. Verkehr auf einen Blick. Wiesbaden. Retrieved from: https://www.destatis.de/DE/Publikationen/Thematisch/TransportVerkehr/Querschnitt/BroschuereVerkehrBlick0080006139004.pdf?__blob=publicationFile (as consulted online on 24 April 2017).

Federal Statistical Office, 2014. Berufspendler: Infrastruktur wichtiger als Benzinpreis. Wiesbaden. Retrieved from: https://www.destatis.de/DE/Publikationen/STATmagazin/Arbeitsmarkt/2014_05/2014_05PDF.pdf?__blob=publicationFile (as consulted online on 24 April 2017).

Ferrer-i Carbonell, A., Frijters, P., 2004. How important is methodology for the estimates of the determinants of happiness?. Economic Journal 114 (497), 641 – 659.

Fisher, K.J., Stanton, W.R., Lowe, J.B., 1999. Healthy behaviors, lifestyle, and reasons for quitting smoking among out-of-school youth. Journal of Adolescent Health 25 (4), 290 – 297.

Fisher, P.A., Malmberg, G., 2001. Settled people don't move: On life course and (im)mobility in Sweden. International Journal of Population Geography 7 (5), 357 – 371.

Flegal, K.M., Williamson, D.F., Pamuk, E.R., Rosenberg, H.M., 2004. Estimating deaths attributable to obesity in the United States. American Journal of Public Health 94 (9), 1486 – 1489.

Flint, E., Cummins, S., Sacker, A., 2014. Associations between active commuting, body fat, and body mass index: Population based, cross sectional study in the United Kingdom. BMJ 349:g4887.

Forsyth, A., Oakes, M., Lee, B., Schmitz, K.H., 2009. The built environment, walking, and physical activity: Is the environment more important to some people than others?. Transportation Research Part D: Transport and Environment 14 (1), 42 – 49.

Frank, L.D., Andersen, M.A., Schmid, T., 2004. Obesity relationships with community design, physical activity, and time spent in cars. American Journal of Preventive Medicine 27 (2), 87 – 96.

Frank, L.D., Engelke, P.O., 2001. The built environment and human activity patterns: Exploring the impacts of urban form on public health. Journal of Planning Literature 16 (2), 202 – 218.

Frey, B.S., Stutzer, A., 2000. Happiness, economy and institutions. Economic Journal 110 (466), 918 – 938.

Frey, B.S., Stutzer, A., 2002a. Happiness and economics: How the economy and institutions affect well-being. Princeton University Press, Princeton.

Frey, B.S., Stutzer, A., 2002b. What can economists learn from happiness research?. Journal of Economic Literature 40 (2), 402 – 435.

Frick, B., Malo, M.A., 2008. Labor market institutions an individual absenteeism in the European Union: The relative importance of sickness benefit systems and employment protection legislation. Industrial Relations 47 (4), 505 – 529.

Frijters, P., Beatton, T., 2012. The mystery of the u-shaped relationship between happiness and age. Journal of Economic Behavior and Organization 82 (2), 525 – 542.

Gatersleben, B., Uzzell, D., 2007. Active appraisals of the daily commute. Environment and Behavior 39 (3), 416 – 431.

German Bundestag, 2016. Alternierende Telearbeit: Rechtliche Regelungen und europäischer Forschungsstand in den EU-Mitgliedsstaaten. Sachstandsbericht WD 6 – 3000 – 112/16. Retrieved from: https://www.bundestag.de/blob/480130/cbdb34af5f55cada9843a22027d28b27/wd-6-112-16-pdf-data.pdf (as consulted online on 24 April 2017).

Gibson, J., McKenzie, D., Stillman, S., 2011. The impacts of international migration on remaining household members: Omnibus results from a migration lottery program. The Review of Economics and Statistics 93 (4), 1297 – 1318.

Gill, T., 2015. Managing and preventing obesity: Behavioural factors and dietary interventions. Woodhead Publishing Limited, Cambridge.

Giuliano, G., Dargay, J., 2006. Car ownership, travel and land use: A comparison of the US and Great Britain. Transportation Research Part A: Policy and Practice 40 (2), 106 – 124.

Goerke, L., Lorenz, O., 2015. Commuting and sickness absence. Working Paper presented at the Annual Conference 2015 of the German Economic Association, Münster.

Goerke, L., Pannenberg, M., 2015. Trade union membership and sickness absence: Evidence from a sick pay reform. Labour Economics 33, 13 – 25.

Gordon-Larsen, P., Boone-Heinonen, J., Sidney, S., Sternfeld, B., Jacobs, D.R. Jr., Lewis, C.E., 2009. Active commuting and cardiovascular disease risk: The CARDIA study. Archives of Internal Medicine 169 (13), 1216 – 1223.

Gottholmseder, G., Nowotny, K., Puckner, G., Theurl, E., 2009. Stress perception and commuting. Health Economics 18 (5), 559 – 576.

Green, A.E., Hogarth, T., Shackleton, R.E., 1999. Longer distance commuting as a substitute for migration in Britain: A review of trends issues and implications. International Journal of Population Geography 5 (1), 49 – 67.

Grossman, M., 1972. On the concept of health capital and the demand for health. The Journal of Political Economy 80 (2), 223 – 255.

Gruber, S., 2010. To migrate or to commute?. Review of Economic Analysis 2 (1), 110 – 134.

Gulian, E., Matthews, G., Glendon, A.I., Davies, D.R., Debney, L.M., 1989. Dimensions of driver stress. Ergonomics 32 (6), 585 – 602.

Gutiérrez-i-Puigarnau, E., Mulalic, I., van Ommeren, J.N., 2016. Do rich households live farther away from their workplaces?. Journal of Economic Geography 16 (1), 177 – 201.

Gutiérrez-i-Puigarnau, E., van Ommeren, J.N., 2010. Labour supply and commuting. Journal of Urban Economics 68 (1), 82 – 89.

Gutiérrez-i-Puigarnau, E., van Ommeren, J.N., 2015. Commuting and labour supply revisited. Urban Studies 52 (14), 2551 – 2563.

Hafner, M., Stepanek, M., Taylor, J., Troxel, W.M., van Stolk, C., 2016. Why sleep matters – the economic costs of insufficient sleep: A cross-country comparative analysis. RAND Europe, Cambridge.

Hammond, R.A., Levine, R., 2010. The economic impact of obesity in the United States. Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy 3 (1), 285 – 295.

Handy, S.L., Boarnet, M.G., Ewing, R., Killingsworth, R.E., 2002. How the built environment affects physical activity: Views from urban planning. American Journal of Preventive Medicine 23 (2S), 64 – 73.

Hansson E., Mattisson, K., Bjork, J., Ostergren, P., Jakobsson, K., 2011. Relationship between commuting and health outcomes in a cross-sectional population survey in southern Sweden. BMC Public Health 11 (1), 834 – 847.

Head, J., Stansfeld, S.A., Siegrist, J., 2004. The psychosocial work environment and alcohol dependence: A prospective study. Occupational and Environmental Medicine 61 (3), 219 – 224.

Heikkilä, K., Fransson, E.I., Nyberg, S., et al., 2013. Job strain and health-related lifestyle: Findings from an individual-participant meta-analysis of 118000 working adults. American Journal of Public Health 103 (11), 2090 – 2097.

Helliwell, J.F., Richard, L., Sachs, J., 2015. World happiness report 2015. Sustainable Development Solutions Network, New York.

Hennessy, D.A., 2008. The impact of commuter stress on workplace aggression. Journal of Applied Social Psychology 38 (9), 2315 – 2355.

Hennessy, D.A., Wiesenthal, D.L., 1997. The relationship between traffic congestion, driver stress and direct versus indirect coping behaviours. Ergonomics 40 (3), 348 – 361.

Heuer, T., Krems, C., Moon, K., Brombach, C., Hoffmann, I., 2015. Food consumption of adults in Germany: Results of the German National Nutrition Survey II based on diet history interviews. British Journal of Nutrition 113 (10), 1603 – 1614.

Hicks, R., Tingley, D., 2011. Causal mediation analysis. The Stata Journal 11 (4), 1 – 15.

Hilbe, J.M., 2007. Negative binomial regression. Cambridge University Press, Cambridge.

Hilbrecht, M., Smale, B., Mock, S.E., 2014. Highway to health? Commute time and well-being among Canadian adults. World Leisure Journal 56 (2), 151 – 163.

Hill, J.E., Miller, B.C., Weiner, S.P., Colihan, J., 1998. Influences of the virtual office on aspects of work and work-life balance. Personnel Psychology 51 (3), 667 – 683.

Hochberg, Y., 1988. A sharper Bonferroni procedure for multiple tests of significance. Biometrika 75 (4), 800 – 803.

Hoehner, C.M., Barlow, C.E., Allen, P., Schootman, M., 2012. Commuting distance, cardiorespiratory fitness, and metabolic risk. American Journal of Preventive Medicine 42 (6), 571 – 578.

Holly, A., Gardiol, L., Domenighetti, G., Bisig, B., 1998. An econometric model of health care utilization and health insurance in Switzerland. European Economic Review 42 (3 – 5), 513 – 522.

Holm, S., 1979. A simple sequentially rejective multiple test procedure. Scandinavian Journal of Statistics 6 (2), 65 – 70.

Hu, P.S., Reuscher, T.R., 2004. Summary of travel trends. 2001 National Household Travel Survey. US Department of Transportation, Washington D.C.

Hu, Y.W., Wolfe, B., 2002. Health inequality between black and white women. Discussion Paper no 1251-02, Institute for Research on Poverty.

Huber, P., Nowotny, K., 2013. Moving across borders: Who is willing to migrate or to commute?. Regional Studies 47 (9), 1462 – 1481.

Humphreys, D.K., Goodman, A., Ogilive, D., 2013. Associations between active commuting and physical and mental wellbeing. Preventive Medicine 57 (2), 135 – 139.

Hutchinson, S.L., Kleiber, D.A., 2005. Gifts of the ordinary: Casual leisure's contributions to health and well-being. World Leisure Journal 47 (3), 2 – 16.

Ichino, A., Riphahn, R.T., 2005. The effect of employment protection on worker effort: Absenteeism during and after probation. Journal of the European Economic Association 3 (1), 120 – 143.

Jacobson, S.H., King, D.M., Yuan, R., 2011. A note on the relationship between obesity and driving. Transport Policy 18 (5), 772 – 776.

Jain, J., Lyons, G., 2008. The gift of travel time. The Journal of Transport Geography 16 (2), 81 – 89.

Jefferey, R., Baxter, J., McGuire, M., Linde, J., 2006. Are fast food restaurants an environmental risk factor for obesity?. International Journal of Behavioral Nutrition and Physical Activity 3 (2), 1 – 6.

Kageyama, T., Nishikido, N., Kobayashi, T., Kurkowa, Y., Kaneko, T., Kabuko, M., 1998. Long commuting time, extensive overtime, and sympathodominant state assed in terms of short-term heart rat variability among male white-collar workers in Tokyo megalopolis. Industrial Health 36 (3), 209 – 217.

Kahneman, D., Deaton, A., 2010. High income improves evaluation of life but not emotional well-being. Proceedings of the National Academy of Sciences 107 (38), 16489 – 16493.

Kahneman, D., Diener, E., Schwarz, N., 1999. Well-being: The foundations of hedonic psychology. Russell Sage Foundation, New York.

Kahneman, D., Krueger, A.B., 2006. Developments in the measurement of subjective well-being. Journal of Economic Perspectives 20 (1), 3 – 24.

Kahneman, D., Krueger, A.B., Schkade, D.A., Schwarz, N., Stone, A.A., 2004. A survey method for characterizing daily life experience: The day reconstruction method. Science 306 (5702), 1776 – 1780.

Kasteridis, P., Yen, S.T., 2012. Smoking cessation and body weight: Evidence from the behavioural risk factor surveillance survey. HSR: Health Services research 47 (4), 1580 – 1602.

Kim, S., 1989. Labor specialization and the extent of the market. Journal of Political Economy 97 (3), 692 – 705.

Kirby, D.K., LeSage, J.P., 2009. Changes in commuting to work times over the 1990 to 2000 period. Regional Science and Urban Economics 39 (4), 460 – 471.

Kitamura, R., Robinson, J., Golob, T., Bradley, M., Leonard, J., van der Horn, T., 1992. A comparative analysis of time use data in the Netherlands and California. Retrieved from: http://escholarship.org/uc/item/8dv965f6 (as consulted online on 24 April 2017).

Kluger, A.N., 1998. Commute variability and strain. Journal of Organizational Behavior 19 (2), 147 – 165.

Kochanek, K.D., Murphy, S.L., Xu, J., Arias, E., 2014. Mortality in the United States, 2013. NCHS data brief 178 (178), 1 – 8.

Koslowsky, M., Kluger, A., Reich, M., 1995. Commuting stress: Causes, effects, and methods of coping. Springer, New York.

Kouvonen A., Kivimäki, M., Vaananen, A., Heponiemi, T., Elovainio, M., Ala-Mursula, L., Virtanen, M., Pentti, J., Linna, A., Vahtera, J., 2007. Job strain and adverse health behaviors: The Finnish public sector study. Journal of Occupational and Environmental Medicine 49 (1), 68 – 74.

Kouvonen, A., Kivimäki, M., Cox, S.J., Poikolainen, K., Cox, T., Vahtera, J., 2005. Job strain, effort-reward imbalance, and heavy drinking: A study in 40,851 employees. Journal of Occupational and Environmental Medicine 47 (5), 503 – 513.

Krantz, G., Lundberg, U., 2006. Workload, work stress, and sickness absence in Swedish male and female white-collar employees. Scandinavian Journal of Public Health 34 (3), 238 – 246.

Krieger, M., Fernandez, E., 2006. Too much or too little long-distance mobility in Europe? EU policies to promote and restrict mobility. Working Paper, Foundation Seminar on Worker Mobility. European Foundation for the Improvement of Living and Working Conditions, Dublin.

Künn-Nelen, A., 2016. Does commuting affect health?. Health Economics 25, 984 – 1004.

Lakdawalla, D., Philipson, T., 2007. Labor supply and weight. The Journal of Human Resources 42 (1), 85 – 116.

Lakdawalla, D., Philipson, T., 2009. The growth of obesity and technological change. Economics and Human Biology 7 (3), 283 – 293.

Lallukka, T., Lahelma, E., Rahkonen, O., Roos, E., Laaksonen, E., Martikainen, P., Head, J., Brunner, E., Mosdol, A., Marmot, M., Sekine, M., Nasermoaddeli, A., Kagamimori, S., 2008. Associations of job strain and working overtime with adverse health behaviors and obesity: Evidence from the Whitehall II Study, Helsinki Health Study, and the Japanese Civil Servants Study. Social Science and Medicine 66 (8), 1681 – 1698.

Layard, R., 2005. Happiness: Lessons from a new science. Penguin, New York.

Lee, B.S., McDonald, J.F., 2003. Determinants of commuting time and distance for Seoul residents: The impact of family status on the commuting of woman. Urban Studies 40 (7), 1283 – 1302.

Leigh, J.P., 1983. Sex differences in absenteeism. Industrial Relations 22 (3), 349 – 361.

Li, J., Pollmann-Schult, M., 2016. Fathers' commute to work and children's social and emotional well-being in Germany. Journal of Family and Economic Issues 37 (3), 488 – 501.

Lindström, A., 2006. Commuting and citizen participation in Swedish city-regions. Political Studies 54 (4), 865 – 888.

Lindström, M., 2004. Social capital, the miniaturisation of community and self-reported global and psychological health. Social Science and Medicine 59 (3), 595 – 607.

Lindström, M., 2008. Means of transportation to work and overweight and obesity: A population-based study in southern Sweden. Preventive Medicine 46 (1), 22 – 28.

Livanos, I., Zangelides, A., 2013. Unemployment, labor market flexibility and absenteeism: A pan-European study. Industrial Relations 52 (2), 492 – 515.

Loewenstein, G., Haisley, E., 2008. The economist as therapist: Methodological ramifications of "light" paternalism. In: Caplin, A., Schotter, A., (Eds.): The foundations of positive and normative economics: A hand book, 210 – 245, Oxford University Press, New York.

Lopez-Zetina, J., Leeb, H., Friisa, R., 2006. The link between obesity and the built environment. Evidence from an ecological analysis of obesity and vehicle miles of travel in California. Health and Place 12 (4), 656 – 664.

Lucas, R., Rossi-Hansberg, E., 2002. On the internal structure of cities. Econometrica 70 (4), 1445 – 1476.

Lyons, G., Chatterjee, K., 2008. A human perspective on the daily commute: Costs, benefits and trade-offs. Transport Reviews 28 (2), 181 – 198.

MacKerron, G., 2012. Happiness economics from 35,000 feet. Journal of Economic Surveys 26 (4), 705 – 735.

MacKinnon, D.P., Fairchild, A.J., Fritz, M.S., 2007. Mediation analysis. Annual Review of Psychology 58 (1), 593 – 614.

Maddala, G.S., 1983. Limited-dependent and qualitative variables in econometrics. Cambridge University Press, New York.

Magee, C., Stefanic, N., Caputi, P., Iverson, D., 2011. Occupational factors and sick leave in Australian employees. Journal of Occupational and Environmental Medicine 53 (6), 627 – 632.

Majumder, A., 2013. Does obesity matter for wages? Evidence from the United States. Economic Papers 32 (2), 200 – 217.

Marmot, M., Ryff, C.D, Bunipass, L.L., Shipley, M., Marks, N.F., 1997. Social inequalities in health: Next questions and converging evidence. Social Science and Medicine 44 (6), 901 – 910.

Martin, A., Goryakin, Y., Suhrcke, M., 2014. Does active commuting improve psychological wellbeing? Longitudinal evidence from eighteen waves of the British Household Panel Survey. Preventive Medicine 69, 296 – 303.

Martin, A., Panter, J., Suhrcke, M., Ogilvie, D., 2015. Impact of changes in mode of travel to work on changes in body mass index: Evidence from the British Household Panel Survey. Journal of Epidemiology and Community Health 69 (8), 753 – 761.

Matthews, G., Dorn, L., Glendon, A.I., 1991. Personality correlates of driver stress. Personality and Individual Differences 12 (6), 535 – 549.

Mattisson, K., Hakansson, C., Jakobsson, K., 2015. Relationships between commuting and social capital among men and women in southern Sweden. Environment and Behavior 47 (7), 734 – 753.

Mauss, D., Jarczok, M.N., Fischer, J.E., 2016. Daily commuting to work is not associated with variables of health. Journal of Occupational Medicine and Toxicology 11 (12), 1 – 5.

McArthur, D.P., Kleppe, G., Thorsen, I., Uboe, J., 2013. The impact of monetary costs on commuting flows. Regional Science 92 (1), 69 – 86.

McGinnis, J.M., Foege, W.H., 1993. Actual causes of death in the United States. Journal of the American Medical Association 270 (18), 2207 – 2212.

Mills, B., Hazarika, G., 2001. The migration of young adults from non-metropolitan counties. American Journal of Agricultural Economics 89 (2), 329 – 340.

Mokhtarian, P.L., 1991. Telecommuting and travel: State of the practice, state of the art. Transportation 18 (4), 319 – 342.

Mokhtarian, P.L., Salomon, I., 1997. Modeling the desire to telecommute: The importance of the attitudinal factors in behavioral models. Transportation Research A: Policy and Practice 31 (1), 35 – 50.

Mokhtarian, P.L., Salomon, I., Redmond, L.S., 2001. Understanding the demand for travel: It's not purely 'derived'. Innovation 14 (4), 355 – 380.

Morris, E.A., 2015. Should we all just stay home? Travel, out-of-home activities, and life satisfaction. Transportation Research Part A: Policy and Practice 78 (C), 519 – 536.

Morris, E.A., Guerra, E., 2015. Mood and mode: Does how we travel affect how we feel?. Transportation 42 (1), 25 – 43.

Morris, S., 2007. The impact of obesity on employment. Labour Economics 14 (3), 413 – 433.

Mujcic, R., Frijters, P., 2015. Conspicuous consumption, conspicuous health, and optimal taxation. Journal of Economic Behavior and Organization, 111 (C), 59 – 70.

National Center for Health Statistics, 2016. Health, United States, 2015: With special feature on racial and ethnic health disparities. Hyattsville.

Ng, D.M., Jeffery, R.W., 2003. Relationships between perceived stress and health behaviors in a sample of working adults. Health Psychology 22 (6), 638 – 642.

Nie, P., Sousa-Poza, A., 2016. Commute time and subjective well-being in urban China. China Economic Review (forthcoming, DOI: http://dx.doi.org/10.1016/j.chieco.2016.03.002).

Novaco, R.W., Stokols, D., Campbell, J., Stokols, J., 1979. Transportation, stress, and community psychology. American Journal of Community Psychology 7 (4), 361 – 380.

Nowotny, K., 2014. Cross-border commuting and migration intentions: The role of risk aversion and time preference. Contemporary Economics 8 (2), 137 – 156.

Nuckols, T.K, Bhattacharya, J., Wolman, D., Ulmer, C., Escarce, J.J., 2009. Cost implications of reduced work hours and workloads for resident physicians. New England Journal of Medicine 360 (21), 2202 – 2215.

OECD, 2007. OECD rural policy review: Germany 2007. OECD Publishing, Paris.

OECD, 2013. OECD guidelines on measuring subjective well-being. OECD Publishing, Paris. Retrieved from: https://www.oecd.org/statistics/Guidelines%20on%20Measuring%20Subjective%20Well-being.pdf (as consulted online on 24 April 2017).

Office Fédéral de la Statistique (OFS), 2014. La pendularité en Suisse 2012. Retrieved from: https://www.bfs.admin.ch/bfs/fr/home/statistiques/mobilite-transports/transport-personnes/pendlermobilitaet.html (as consulted online on 24 April 2017).

Office for National Statistics (ONS), 2014. 2011 Census Analysis: Distance travelled to work. Retrieved from: http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/dcp171776_357812.pdf (as consulted online on 24 April 2017).

Office for National Statistics (ONS), 2015. Measuring national well-being: Life in the UK, 2015. Office for National Statistics, London.

Olsson, L., Gärling, T., Ettema, D., Friman, M., Fujii, S., 2013. Happiness and satisfaction with work commute. Social Indicators Research 111 (1), 255 – 263.

Ory, D., Mokhtarian, P., 2005. When is getting there half the fun? Modeling the liking for travel. Transportation Research Part A: Policy and Practice 39 (2/3), 97 – 123.

Oswald, A.J., Wu, S., 2010. Objective confirmation of subjective measures of human well-being: Evidence from the USA. Science 327 (5965), 576 – 579.

Paci, P., Tiongson, E.R., Walewski, M., Liwinski, J., Stoilkova, M.M., 2007. Internal labor mobility in Central Europe and the Baltic Region. World Bank Working Paper No. 105.

Patuelli, R., Reggiani, A., Gorman, S.P., Nijkamp, P., Bade, F., 2007. Network analysis of commuting flows: A comparative static approach to German data. Networks and Spatial Economics 7 (4), 315 – 331.

Perdikaris, P., Kletsiou, E., Gymnopoulou, E., Matziou, V., 2010. The relationship between workplace, job stress and nurses' tobacco use: A review of the literature. International Journal of Environmental Research and Public Health 7 (5), 2362 – 2375.

Pierrard, O., 2008. Commuters, residents and job competition. Regional Science and Urban Economics 38 (6), 565 – 577.

Piha, K., Laaksonen, M., Martikainen, P., Rahkonen, O., Lahelma, E., 2009. Interrelationships between education, occupational class, income and sickness absence. The European Journal of Public Health 20 (3), 276 – 280.

Pisarski, A.E., 2006. Commuting in America: The third national report on commuting patterns and trends. Transportation Research Board, Washington DC.

Plaut, P., 2006. The intra-household choices regarding commuting and housing. Transportation Research Part A: Policy and Practice 40 (7), 561 – 571.

Pocock, B., 2003. The work/life collision. The Federation Press, Sydney.

Preacher, K.J., Hayes, A.F., 2008. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods 40 (3), 879 – 891.

Preacher, K.J., Kelley, K., 2011. Effect size measures for mediation models: Quantitative strategies for communicating indirect effects. Psychological Methods 16 (2), 93 – 115.

Pudney, S., Shields, M., 2000. Gender, race, pay and promotion in the British nursing profession: Estimation of a generalized ordered probit model. Journal of Applied Econometrics 15 (4), 367 – 399.

Puga, D., 1999. The rise and fall of regional inequalities. European Economic Review 43 (2), 303 – 334.

Puhani, P.A., Sonderhoff, K., 2010. The effects of a sick pay reform on absence and on health-related outcomes. Journal of Health Economics 29 (2), 285 – 302.

Putnam, R.D., 2000. Bowling alone: The collapse and revival of American community. Touchstone, New York.

Radi, S., Ostry, A., Lamontagne, A.D., 2007. Job stress and other working conditions: Relationships with smoking behaviors in a representative sample of working Australians. American Journal of Industrial Medicine 50 (8), 584 – 596.

Redmond, L.S., Mokhtarian, P.L., 2001. The positive utility of the commute: Modelling ideal commuting time and relative desired commute amount. Transportation 28 (2), 179 – 205.

Renkow, M., Hower, D., 2000. Commuting, migration, and rural-urban population dynamics. Journal of Regional Science 40 (2), 261 – 287.

Rietveld, P., Zwart, B., van Wee, B., van den Hoorn, T., 1999. On the relationship between travel time and travel distance of commuters. The Annals of Regional Science 33 (3), 269 – 287.

Roberts, J., Hodgson, R., Dolan, P., 2011. 'It's driving her mad': Gender differences in the effects of commuting on psychological health. Journal of Health Economics 30 (5), 1064 – 1076.

Ross, S.L., Zenou, Y., 2008. Are shirking and leisure substitutable? An empirical test of efficiency wages based on urban economic theory. Regional Science and Urban Economics 38 (5), 498 – 517.

Rüger, H., Schulze, A., 2016. Association between commuting and stress and health: Do sociodemographic differences exist?. Prävention und Gesundheitsförderung 11 (1), 27 – 33.

Russo, G., Reggiani, A., Nijkamp, P., 2007. Spatial activity and labour market patterns: A connectivity analysis of commuting flows in Germany. The Annals of Regional Science 41 (4), 789 – 811.

Samimi, A., Mohammadian, A., Madanizadeh, S., 2009. Effects of transportation and built environment on general health and obesity. Transportation Research Part D: Transport and Environment 14 (1), 67 – 71.

Sandow, E., 2014. Till work do us part: The social fallacy of long-distance commuting. Urban Studies 51 (3), 526 – 543.

Sandow, E., Westerlund, O., Lindgren, U., 2014. Is your commute killing you? On the mortality risk of long-distance commuting. Environment and Planning A 46 (6), 1496 – 1516.

Sandow, E., Westin, K., 2010. The persevering commuter: Duration of long-distance commuting. Transport Research Part A: Policy and Practice 44 (6), 433 – 445.

Sarbu, M., 2015. Determinants of work-at-home arrangements for German employees. Labour: Review of Labour Economics and Industrial Relations 29 (4), 444 – 469.

Satia, J.A., Galanko, J.A., Siega-Riz, A.M., 2004. Eating at fast-food restaurants is associated with dietary intake, demographic, psychological and behavioural factors among African Americans in North Carolina. Public Health Nutrition 7 (8), 1089 – 1096.

Schaeffer, M.H., Street, S.W., Singer, J.E., Baum, A., 1988. Effects of control on the stress reactions of commuters. Journal of Applied Social Psychology 18 (11), 944 – 957.

Schulze, S., 2009. Einige Beobachtungen zum Pendlerverhalten in Deutschland. Hamburg Institute of International Economics (HWWI) Policy Paper, No. 1-19.

Schwarz, N., Strack, F., 1999. Reports of subjective well-being: Judgmental processes and their methodological implications. In: Kahneman, D., Diener, E., Schwarz, N., (Eds.): Well-being: The foundations of hedonic psychology, 60 – 84, Russell Sage Foundation, New York.

Shaffer, J.P., 1995. Multiple hypothesis testing. Annual Review of Psychology 46, 561 – 584.

Shuai, X., 2012. Does commuting lead to migration?. Regional Studies 42 (3), 237 – 250.

Siegrist, J., Rodel, A., 2006. Work stress and health risk behavior. Scandinavian Journal of Work Environment and Health 32 (6), 473 – 481.

Small, K.A., Song, S., 1992. Wasteful commuting: A resolution. Journal of Political Economy 100 (4), 888 – 898.

So, K.S., Orazem, P.F., Otto, D.M., 2001. The effects of housing prices, wages and commuting time on joint residential and job location choices. American Journal of Agricultural Economics 83 (4), 1036 – 1048.

Stanciole, A.E., 2008. Health insurance and lifestyle choices: Identifying ex ante moral hazard in the US market. The Geneva Papers 33 (4), 627 – 644.

Staufenbiel, T., König, C., 2010. A model for the effects of job insecurity on performance, turnover intention and absenteeism. Journal of Occupational and Organizational Psychology 83 (1), 101 – 117.

Stiglitz, J.E., Sen, A., Fitoussi, J.P., 2009. Report by the Commission on the measurement of economic performance and social progress. Technical report.

Stock, J.H., Watson, M.M., 2012. Introduction to econometrics. Pearson, Boston.

Stutzer, A., Frey, B.S., 2008. Stress that doesn’t pay: The commuting paradox. Scandinavian Journal of Economics 110 (2), 339 – 366.

Stutzer, A., Frey, B.S., 2010. Recent advances in the economics of individual subjective well-being. Social Research 77 (2), 679 – 714.

Sugiyama, T., Ding, D., Owen, N., 2013. Commuting by car. American Journal of Preventive Medicine 44 (2), 169 – 173.

Sweet, M., Kanaroglou, P., 2016. Gender differences: The role of travel and time use in subjective well-being. Transportation Research Part F: Traffic Psychology and Behaviour 40, 23 – 34.

Takeda, A., Kawachi, I., Yamagata, Z., Hashimoto, S., Matsumura, Y., Oguri, S., Okayama, A., 2004. Multigenerational family structure in Japanese society: Impacts on stress and health behaviors among women and men. Social Science and Medicine 59 (1), 69 – 81.

Taris, T.W., Ybema, J.F., Beckers, D.G., Verheijden, M.W., Geurts, S.A., Kompier, M.A., 2011. Investigating the associations among overtime work, health behaviors, and health: A longitudinal study among full-time employees. International Journal of Behavioral Medicine 18 (4), 352 – 360.

Tolley, R., 1996. Green campuses: cutting the environmental costs of commuting. Journal of Transport Geography 4 (3), 213 – 217.

Travisi, C.M., Camagni, R., Nijkamp, P., 2010. Impacts of urban sprawl and commuting: A modelling study of Italy. Journal of Transport Geography 18 (3), 382 – 392.

TRB, 2005. Does built environment influence physical activity? Examining the evidence. Transportation Research Board, Washington DC.

US Census Bureau, 2014. Modes less traveled – Bicycling and walking to work in the United States: 2008 – 2012. American Community Survey Reports, ACS-26, Washington DC.

US Department of Health and Human Services, 2015. 2015 – 2020 dietary guidelines for Americans. Retrieved from: http://health.gov/dietaryguidelines/2015/guidelines/ (as consulted online on 24 April 2017).

US Department of Transportation, 2016. Transportation statistics annual report 2016. Bureau of Transportation Statistics, Washington DC.

van der Klis, M., Karsten, L., 2009. The commuter family as a geographical adaptive strategy for the work-family balance. Community, Work and Family 12 (3), 339 – 354.

van der Klis, M., Mulder, C.H., 2008. Beyond the trailing spouse: The commuter partnership as an alternative to family migration. Journal of Housing and the Built Environment 23 (1), 1 – 19.

van Ommeren, J.N., Fosgerau, M., 2009. Workers' marginal costs of commuting. Journal of Urnan Economics 65 (1), 38 – 47.

van Ommeren, J.N., Gutiérrez-i-Puigarnau, E., 2011. Are workers with a long commute less productive? An empirical analysis of absenteeism. Regional Science and Urban Economics 41 (1), 1 – 8.

van Ommeren, J.N., van den Berg, G.J., Gorter, C., 2000. Estimating the marginal willingness to pay for commuting. Journal of Regional Science 40 (3), 541 – 563.

Vance, C., Hedel, R., 2008. On the link between urban form and automobile use: Evidence from German survey data. Land Economics 84 (1), 51 – 65.

Vgontzas, A.N., Fernandez-Mendoza, J., Bixler, E.O., Singareddy, R., Shaffer, M.L., Calhoun, S.L., Liao, D., Basta, M., Chrousos, G.P., 2012. Persistent insomnia: The role of objective short sleep duration and mental health. Sleep 35 (1), 61 – 68.

Viry, G., Kaufmann, V., 2015. High mobility in Europe – Work and personal life. Palgrave Macmillan, Edinburgh.

Vistnes, J.P., 1997. Gender differences in days lost from work due to illness. Industrial and Labor Relations Review 50 (2), 304 – 323.

Wada, R., Tekin, E., 2010. Body composition and wages. Economics and Human Biology 8 (2), 242 – 254.

Wagner, G.G., Frick, J.R., Schupp, J., 2007. The German Socio-Economic Panel study (SOEP) – Evolution, scope and enhancements. Journal of Applied Social Science (Schmollers Jahrbuch) 127 (1), 139 – 169.

Walsleben, J.A., Norman, R.G., Novak, R.D., O'Malley, E.B., Rapoport, D.M., Strohl, K.D., 1999. Sleep habits of Long Island rail road commuters. Sleep 22 (6), 728 – 734.

Weber, E.U., Milliman, R.A., 1997. Perceived risk attitudes: Relating risk perception to risky choice. Management Science 43 (2), 123 – 144.

Wemme, K.M., Rosvall, M., 2005. Work related and non-work related stress in relation to low leisure time physical activity in a Swedish population. Journal of Epidemiology and Community Health 59 (5), 377 – 379.

Wen, L.M., Orr, N., Millett, C., Rissel, C., 2006. Driving to work and obesity: Findings from the 2003 New South Wales Health Survey, Australia. International Journal of Obesity 30 (5), 782 – 786.

Wener, R., Evans, G., Phillips, D., Nadler, N., 2003. Running for the 7:45: The effects of public transit improvements on commuter stress. Transportation 30 (2), 203 – 220.

Wheatley, D., 2014. Travel-to-work and subjective well-being: A study of UK dual career households. Journal of Transport Geography 39, 187 – 196.

White, M.P., Dolan, P., 2009. Accounting for the richness of daily activities. Psychological Science 20 (8), 1000 – 1008.

White, S.M., Rotton, J., 1998. Type of commute, behavioral aftereffects, and cardiovascular activity. A field experiment. Environment and Behavior 30 (6), 763 – 780.

WHO Global Database on Body Mass Index, 2017. Global database on body mass index: An interactive surveillance tool for monitoring nutrition transition. Retrieved from: http://apps.who.int/bmi/index.jsp (as consulted online on 24 April 2017).

Winkelmann, R., 1999. Wages, firm size and absenteeism. Applied Economics Letters 6 (6), 337 – 341.

Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. MIT Press, Cambridge.

World Health Organization (WHO), 1999. Healthy Living: What is a healthy lifestyle? World Health Organization, Regional Office for Europe, Copenhagen.

World Health Organization (WHO), 2003. Health and development through physical activity and sport, noncommunicable diseases and mental health – Noncommunicable disease prevention and health promotion. WHO Press, Geneva.

World Health Organization (WHO), 2004. Obesity: preventing and managing the global epidemic. WHO Technical Report Series 894, Geneva.

World Health Organization (WHO), 2010. Global recommendations on physical activity for health. WHO Press, Geneva.

World Health Organization (WHO) 2014. Global health expenditure database. Retrieved from: http://apps.who.int/nha/database/ViewData/Indicators/en (as consulted online on 24 April 2017).

World Health Organization (WHO), 2014b. Global status report on noncommunicable diseases 2014. WHO Press, Geneva.

Yang, J., French, S., 2013. The travel-obesity connection: Discerning the impacts of commuting trips with the perspective of individual energy expenditure and time use. Environment and Planning B: Planning and Design 40 (4), 617 – 629.

Yen, S.T., Chen, Z., Eastwood, D.B., 2009. Lifestyles, demographics, dietary behaviour, and obesity: A switching regression analysis. HSR: Health Services Research 44 (4), 1345 – 1369.

Zax, J.S., 1991. The substitution between moves and quits. The Economic Journal 101 (409), 1510 – 1521.

Zax, J.S., Kain, J.F., 1996. Moving to the suburbs: Do relocating companies leave their black employees behind?. Journal of Labor Economics 14 (3), 472 – 504.

Zeng, D., You, W., Mills, B., Alwang, J., Royster, M., Anson-Dwamena, R., 2015. A closer look at the rural health disparities: Insights from four major diseases in the Commonwealth of Virginia. Social Science and Medicine 140, 62 – 68.

Zenou, Y., 2002. How do firms redline workers?. Journal of Urban Economics 52 (3), 391 – 408.

Zettel-Watson, L., Britton, M., 2008. The impact of obesity on the social participation of older adults. The Journal of General Psychology 135 (4), 409 – 423.

Ziebarth, N.R., Karlsson, M., 2010. A natural experiment on sick pay cuts, sickness absence, and labor costs. Journal of Public Economics 94 (11 – 12), 1108 – 1122.

Ziersch, A., Baum, F., Darmawan, I.G., Kavanagh, A.M., Bentley, R.J., 2009. Social capital and health in rural and urban communities in South Australia. Australian and New Zealand Journal of Public Health 33 (1), 7 – 16.

Zweifel, P., Breyer, F., Kifmann, M., 2009. Health economics. Springer, Berlin.