Beyond the Commute: Exploring the Broader Impacts of Teleworking on Travel Demand

A Quantitative Analysis of Work-From-Home Effects on Commute and Non-Work Travel

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Abstract

This thesis examines the multidimensional impact of teleworking on travel demand, offering insights into its effect on commuting and non-work travel patterns. Policymakers and planners have long regarded teleworking as a potential solution to urban mobility challenges, such as congestion and pollution, by reducing the necessity for daily commutes. However, the potential rebound effects, including a higher willingness to commute longer distances and increases in non-work travel, are often overlooked. Using data from the Netherlands Mobility Panel, this thesis employs a random effects model to explore the effects of teleworking on travel behaviour over three years, from 2017 to 2019, focusing on the potential substitution and complementarity effects of teleworking on commute and non-work travel. The findings indicate that increased teleworking decreases commuting frequency and total commute distances, and that it leads to longer commutes and increases in the frequency and total distances of non-work travel. The net effect of teleworking on travel is found to be one of modification, thereby not reducing overall travel demand and the number of car kilometres travelled but rather changing the purpose and temporal distribution of trips, potentially leading to reduced pressure on the road and in public transportation systems during peak hours. When looking at the broader systemic and indirect effects of this reduced congestion and its associated environmental benefits, these gains could potentially be offset by induced demand as a result of improved travel conditions. Policymakers and planners should therefore not consider teleworking as a silver bullet for congestion relief, but rather see it as a part of a larger strategy.

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1. Introduction

Teleworking is an innovative and flexible working arrangement where employees can access their labour activities from locations other than the original office setting, facilitated by the use of information and communication technologies (ICT) (Pérez et al., 2004). The term teleworking can refer to working in telecentres or mobile working but is most commonly associated with working from home. In the past decades, policymakers have increasingly acknowledged teleworking as a way of solving mobility issues, such as traffic congestion and pollution, by reducing the number of commuting trips made (Ravalet & Rérat, 2019). Teleworking adds flexibility to people's lives by eliminating some or all weekly commuting trips, and this relaxation of time-space constraints is expected to lead to alterations in the travel behaviour of telecommuters and their household members (Pendyala et al., 1991). Telecommuting can therefore be considered a travel demand management (TDM) strategy and has long been hailed as an instrumental tool for reducing travel demand (Lachapelle et al., 2017). However, the effect of teleworking on travel demand is not as straightforward as it seems, as teleworking has not only been associated with changes in commute travel but also with changes in non-work travel.

While it is widely accepted that teleworking reduces the frequency of commuting, it raises questions about potential rebound effects. In line with the idea of constant time travel budgets (Ravalet & Rérat, 2019), one potential rebound effect could be that teleworkers are willing to accept longer commutes, a trend observed in several studies (Gubins et al., 2019; Mokhtarian & Chen, 2004; Ravalet & Rérat, 2019). This would mean the time gained due to a reduction in the number of commutes is reinvested in longer and less frequent ones, possibly offsetting the initial gains and contributing to urban sprawl (De Abreu E Silva & Melo, 2018). Another potential rebound effect could be the trade-off between commuting and non-work trips (Cerqueira et al., 2020), meaning that the reduction of commute travel combined with the added flexibility in scheduling could lead to the generation of additional non-work trips that telecommuters did not make before (Pendyala et al., 1991).

Teleworking can affect different types of travel in different ways. It is generally accepted that teleworking has a substitution effect on commute travel, meaning a reduction in total commute travel distances as a result of teleworking. The effect of teleworking on non-work-related travel is more ambiguous, but studies often find a complementarity effect, meaning that increases in teleworking lead to increases in travel related to non-work activities (Elldér, 2020; Salomon, 1986). If both effects exist, the magnitude of these effects is crucial in determining the overall effect of teleworking on travel demand. Does it lead to less travel demand due to a stronger commute travel effect, more travel demand due to a stronger non-work travel effect, or does it even out due to similar effect sizes?

The relationship between teleworking and travel behaviour gained new importance during the COVID-19 pandemic, as the enormous increase in teleworking practises prompted researchers to investigate how this might affect long-term travel behaviour (Faber et al., 2023). Since research suggests that the wide adoption of teleworking will outlast the policies implemented during the pandemic (Faber et al., 2023), policymakers should understand what the complex relationship between teleworking and travel behaviour looks like.

In essence, teleworking presents opportunities to reduce travel demand, peak-hour traffic, and emissions, but it also introduces complex dynamics or rebound effects that could potentially offset these benefits. For a long time, there was a general consensus that teleworking reduced total travel demand, but several new studies suggest the opposite (Elldér, 2020). Therefore, currently, there is no consensus on whether an increase in teleworking results in an increase or decrease in total travel demand (Faber et al., 2023). As teleworking adoption is expected to grow due to digitalization (Ravalet & Rérat, 2019), the purpose of this thesis is to broaden our understanding of the potential positive or negative impacts on mobility practises.

This thesis contributes to the literature in three ways. First of all, while potential rebound effects, such as the willingness to commute longer distances and increased non-work travel, are sometimes acknowledged, they are often overlooked or not thoroughly quantified. This thesis will provide a detailed analysis of these rebound effects using data from the Netherlands. Secondly, there is no academic consensus on whether teleworking reduces overall travel demand, and current research often examines either commute or non-work travel individually. This thesis will provide a more holistic approach to determining the effect of teleworking on travel demand by examining both commute and non-work travel and total travel distances as a whole. Lastly, while many studies use a binary indicator or frequency-based measures to quantify teleworking, this thesis will take a unique approach by quantifying the independent variable as the percentage of hours worked at home, allowing for a more nuanced analysis of how different levels of teleworking intensity impact travel behaviour.

2. Literature review

This literature review will thoroughly examine the complex relationship between teleworking and travel behaviour and explore how teleworking arrangements alter commuting patterns, the potential rebound effects associated with teleworking, and its overall effect on travel demand and modal choice.

2.1 Teleworking: definition, evolution and adoption

2.1.1 The definition of teleworking

Initially, teleworking was mainly associated with working from home, but the concept has evolved over the years, reflecting the changing nature of work arrangements and advancements in telecommunication technology. Defining teleworking is complex, as there are variations in work schedules, locations, frequency, and employment status (Lachapelle et al., 2017).

An early definition by Mokhtarian (1991) defines teleworking as the practice of utilising telecommunications technology to work from home or a proximate location during regular work hours. Pérez et al. (2004) broaden this definition by also including activities in telecentres and mobile working environments. Teleworking can thus be categorised into home-based teleworking, telecentre-based teleworking and mobile teleworking. Thomsin (2002) divided teleworking into three other principal forms; full- or partial-day home-based teleworking, itinerant teleworking (e.g. working in a train) and teleworking in third places such as cafes and coworking spaces. Alternatively, Schweitzer and Duxbury (2009) identify three types of home-based workers: employees who work at home instead of at the office, employees who work overtime tasks at home, and self-employed workers working from their homes. Nilles (1988), who introduced the term telecommuting in 1973, introduces a distinction between the terms teleworking and telecommuting, the difference being that telecommuting is the use of telecommunications to replace traditional home-office commuting, while he uses teleworking as a concept that entails all travel-substitutive communication technologies. Telecommuting is, therefore, a subcategory of teleworking.

The terminology around remote work differs internationally; the term ‘telecommuting’ appears more frequently in the American context, while ‘teleworking’ is more common in European and Asian countries. Other similar terms are e-work, remote work, distance work, virtual work, flexible-location work, home-working, and home-based business (Andreev et al., 2010). The definitions of teleworking vary widely due to the great diversity in arrangements that it entails, illustrating its role in the evolving landscape of work.

2.1.2 Evolution of teleworking research

The concept of teleworking first appeared in the 1970s, largely due to the oil crises that brought to light the inefficiencies and environmental costs of traditional commuting practises. Several academics, Nilles being the pioneer (He and Hu 2015), recognised teleworking's potential to relieve traffic congestion, reduce energy and oil consumption and decentralise workspaces (Pérez et al., 2004). Initially, teleworking was proposed to address transport-related issues, such as reducing overall travel demand and peak-hour congestion (Ravalet & Rérat, 2019). Subsequent research, which started in the 1970s, supported these goals, documenting positive impacts on reducing the necessity to travel to and from work and noting additional transport-related benefits (Hamer et al., 1991). By the 1990s, researchers started to acknowledge the more complex effects of teleworking on travel behaviour through the discussion and research of the potential substitutive and complementary impacts on travel patterns. This introduced more nuance into the discussion, recognising teleworking as a multifaceted phenomenon with the ability to not only affect travel dynamics but also have an influence on broader urban and environmental planning (Wang & Ozbilen, 2020).

2.1.3 Adoption trends across industries and geographies

Since the rise of ICT, teleworking has seen a gradual and uneven adoption across different industries and geographies. A closer look at the industry-specific adoption of teleworking underlines a skewness towards certain sectors and occupational groups. Research by Vilhelmson and Thulin (2016) in Sweden revealed that teleworking had higher adoption in the advanced services sector. A similar pattern emerged in studies focusing on specific occupational groups. Studies by Melo and De Abreu e Silva (2017) and S. Kim et al. (2015) showed teleworking's wider adoption among non-agricultural and white-collar workers (De Vos et al., 2019). These findings are in line with the idea that teleworking tends to be more accessible for occupations that do not require workers to be physically present or to perform direct manual labour, indicating a divide in teleworking adoption across different labour segments depending on spatial flexibility.

Pérez et al. (2004) note that in the early 2000s, around 20% of employees engaged in some type of teleworking in the U.S. Around the same time, around 6.1% of European employees participated in some form of teleworking, with noticeable differences between countries. Northern European countries like Finland and Sweden reported significantly higher rates for teleworking, 16.7% and 15.1% respectively, compared to southern European countries like Spain, where a teleworking rate of 2.8% was reported (Pérez et al., 2004). Despite high expectations of widespread adoption of teleworking in the past, before the pandemic, only 9% of the U.S. workforce and around 5% of European workers engaged in teleworking at least one day a week. Teleworking rates differed greatly between countries; Northern European countries like Denmark, the Netherlands, and Sweden showed relatively high national teleworking rates of around 30%, compared to 16% in Japan and 1.6% in Argentina. (Pulido & Martínez-Cruz, 2022). In the context of teleworking's effect on travel behaviour, it is vital to consider adoption rates, because when teleworking is restricted to a fraction of the workforce, its impacts on transportation congestion will be insignificant (Nilles, 1988).

2.2 Fundamental theories related to teleworking and travel behaviour

There are several theories, frameworks, and concepts introduced and discussed by academics that can aid in understanding the complex and multifaceted relationship between teleworking and travel behaviour.

The traditional theory of time geography suggests that an individual's patterns of activity and travel are bound by spatial and temporal limitations associated with mandatory activities, along with constraints related to their travel budget (Chapin, 1976; Hägerstrand, 1970). Related to this theory is the theory of time travel budgets, positing that people allocate a certain amount of time to travel, and this amount is relatively stable (Zahavi & Talvitie, 1980). This means that innovations in transportation technologies enabling an increase in speed or efficiency do not cause people to allocate less of their time to travel but instead allow people to travel more often and over greater distances. In the context of teleworking, this would mean a reduction in the weekly commuting frequency could lead to investments in increased commuting distances by changing one’s residential location (Ravalet & Rérat, 2019). This is referred to by Kiko et al. (2023) as the residential location effect and is related to the theory of residential self-selection, which holds that people have the tendency to choose residential locations based on their travel needs and preferences (Van Wee & Cao, 2022). Similarly, this higher tolerance for longer commute distances could influence one’s work location when seeking employment.

Kiko et al. (2023) and Zhu (2011) discuss the possibility of teleworking to trigger behavioural shifts, including its influence on the long-term decision-making of teleworkers to live further away from their workplaces, given the reduced need for daily travel, causing longer travel distances on the days they do commute. Asgari et al. (2016) and Stiles and Smart (2020) extend this idea by examining how teleworking changes temporal and spatial constraints related to work, suggesting that the flexibility of teleworkers allows them to redistribute their time savings to a variety of other activities, known as the activity-based theory. In other words, the flexibility afforded by teleworking may not only cause longer commutes but could also induce non-work-related travel as individuals invest their time savings to run errands or engage in leisure activities that they would otherwise not have time for. Kiko et al. (2023) refer to this as the non-work travel effect. The direct effect of teleworking, which is the reduction in commuting trips and is referred to as the work travel effect, might thus be offset by the non-work travel effect and the residential location effect.

When looking at the broader systemic and indirect effects of teleworking on travel behaviour, there is a third effect that Kiko et al. (2023) describe that could offset reductions in commute travel by teleworkers: induced demand. Faber et al. (2023) discuss induced demand as a consideration, meaning that a reduction in travel demand by teleworkers could be offset by increased travel demand by non-teleworkers. Induced demand is often associated with improvements in road capacity but can be applied to any decongestion effort, such as teleworking (Kiko et al., 2023).

The interaction between ICT and travel behaviour is another important field of study to understand. Salomon's (1986) ICT and Travel Behaviour Framework, elaborated on by Andreev et al. (2010), categorised the impacts of ICT on travel into substitution, complementarity, modification, and neutrality. One can speak of substitution when teleworking directly reduces the need to commute, while complementarity, related to the theory of constant time travel budgets and the concept of a rebound effect, refers to the idea that an increase in teleworking leads to an increase in other forms of travel. Modification occurs when travel is neither eliminated nor replaced by ICT but instead altered in other ways, while neutrality means that ICT does not influence personal activities and the associated travel (Andreev et al., 2010). The four classifications can help distinguish the different ways in which teleworking and advancements in ICT can alter travel patterns, ranging from the reduction of physical travel to modifying the nature and purpose of trips.

These various theoretical perspectives emphasise the complexity of the relationship between teleworking and travel behaviour and highlight the possibility of unwanted rebound effects of policies focusing on facilitating teleworking. The frameworks above provide a foundation for further exploration of the expected and unexpected ways that teleworking interacts with travel patterns.

2.3 The effect of teleworking on travel behaviour

2.3.1 Commuting behaviour

The potential of teleworking to alter commuting patterns, particularly the decrease in commuting frequency and total commuting distances, has been a topic of interest amongst policymakers for some decades since the rapid advancements in information technology made these work arrangements possible. Simplified reasoning would follow that one day of teleworking a week would reduce individual weekly commuting distances for a full-time employee by 20%. However, empirical evidence suggests that this is not the case.

Teleworking offers teleworkers flexibility in both residential and job locations. This residential flexibility, also discussed by De Vos et al. (2019), can lead to a preference for residences in more distant, desirable, or affordable locations, referred to by Kiko et al. (2023) as the residential location effect. While the authors primarily refer to the expansion of the acceptable residential living radius around the work location, this residential location effect also implies that teleworking allows people to expand their job search area, enabling them to seek positions that offer teleworking options while maintaining their total commuting times. The presence of the residential location effect would result in longer commuting distances per trip as a result, which raises important questions about the overall effectiveness of teleworking in terms of total commuting travel distances.

There is a general agreement that teleworking reduces commuting trip frequency, at least on full-day teleworking days. In their teleworking experiment in the Netherlands, Hamer et al. (1991) found that teleworking reduced the commute trip frequency by 15%. He and Hu (2015) also found a negative relationship between telecommuting and the number of commute trips in the US. These findings are supported by De Abreu E Silva and Melo (2018) who found that for British single-worker households, an increase in home teleworking frequency was paired with a reduction in commuting trips and no reduction in weekly commuting miles. The latter suggests that when commute trip frequency decreases, commute distances must increase.

A survey by Empirica (2000) among European countries, as discussed by Pérez et al. (2004), reported that every sixth teleworker, in comparison to every 27th non-teleworking, had a commuting distance that exceeded 50 kilometres, indicating longer average commuting distances for teleworkers. Ravalet and Rérat (2019) also found longer commuting distances for Swiss teleworkers, who reported an average commuting distance of 24.6 and 16.1 kilometres for teleworkers and non-teleworkers, respectively. The average commuting distances of teleworkers seem to be higher due to a willingness to accept longer commutes. Empirical research by De Vos et al. (2018) discovered that Dutch workers are willing to accept a 5% longer commute after the adoption of teleworking and every additional 8 hours of telework in the same week is associated with 3.5% longer commuting times. Gubins et al. (2019) found that in the Netherlands, non-teleworkers in occupations that had a high adoption of teleworking had lower growth rates in commuting distances between 1996 and 2010 compared to workers in occupational groups with a low adoption of teleworking. Additionally, in the same period, teleworkers increased their commutes five to nine times more than non-teleworkers. A recent study by De Vos et al. (2019) found that on average, Dutch workers who started teleworking between 2008 and 2018 increased their commuting times by 12%. The same study reported that one day of teleworking per week increased average commuting times by 16%. A reduction in total weekly commuting times was reported for people working both five and four days a week, with a 7.2% and 13% reduction, respectively. These studies collectively indicate that teleworking tends to be associated with longer individual commuting distances and times, suggesting that the flexibility offered by teleworking enables workers to accept longer commutes when they do travel to their workplaces.

Although teleworkers tend to have longer commutes, there are varied opinions about the direction of causality; is teleworking used as a strategy to avoid the time and costs related to long commutes, or does teleworking persuade teleworkers to move further away from the workplace (De Abreu E Silva & Melo, 2018)? Empirical evidence from the U.S. showed that, despite the relaxation of spatial constraints afforded by teleworking, many individuals choose to remain in or near urban centres due to the concentration of professional opportunities and amenities these areas offer (Pérez et al., 2004). The argumentation of the author is that teleworkers are not tempted to relocate as teleworking is often done a few days a week, making commuting still necessary on some days, and teleworkers do not want to miss job opportunities in a spatially concentrated labour market. Interestingly, results from Ory and Mokhtarian (2006) showed that over a 10-year period in California, workers who engaged in teleworking practises and then decided to move generally moved closer to their workplace, while people who began teleworking after having moved tended to have relocated much further from the workplace, thus supporting the presence of sorting and the absence of residential relocation. Although residential relocation has been simulated through urban economic models, there are currently no empirical findings that convincingly establish residential relocation as a result of teleworking (Kiko et al., 2023; Pérez et al., 2004). The less discussed aspect of the residential location effect, the expansion of the radius of one's labour market, is also hard to establish empirically. The acceptable commuting distance for a job is partially determined by its associated teleworking opportunities, making it a simultaneous and bidirectional effect (Gubins et al., 2019; He & Hu 2015). Another difficulty is the possibility of reverse causality in this relationship. Longer average commutes for teleworkers could not only hint at a higher willingness for longer commutes, but it could also indicate that individuals with greater commuting distances might be more tempted to engage in teleworking practises. It is also plausible that the relationship is influenced by a self-sorting effect in which people with certain preferences or aversions, such as an aversion to commuting, may be more tempted to engage in teleworking activities to avoid their long and costly commutes (De Vos et al., 2019; Nilles, 1988).

In general, it is found that the commuting frequency is lower, and the commuting distances are higher for teleworkers. The relationship between teleworking and the average commuting distance is highly complex, with many urban economic models but little empirical evidence supporting the residential location effect. Additionally, there could be reverse causality and self-sorting, further complicating the relationship.

2.3.2 Peak-hour congestion

As teleworkers can reduce their commute trip frequency by replacing some or all former commutes to the workplace some or all days of the week, they have the potential to relieve congestion to a certain extent, as travel reductions are mainly expected during rush hour, the moment transportation networks are most stressed (Asgari et al., 2016; Nilles, 1988; Ravalet & Rérat, 2019). Locations and schedules of traditional workplaces are the anchor points of a worker's travel behaviour, and teleworking alleviates employees of these restrictions (Wang & Ozbilen, 2020). Empirically, the benefits of teleworking in reducing peak-hour congestion are reported in various studies.

To review the effect of teleworking on peak-hour traffic, it is important to make the distinction between full-day and part-day home working, as working at home for a part of the day does not remove commuting trips but rather displaces them outside peak hours (Lachapelle et al., 2017). Therefore, the effect of full-day home working is expected to be one of substitution, while part-day home working is expected to lead to commute shifting, a modification effect (Nilles, 1988). Findings by Stiles and Smart (2020) from the U.S. indeed show that working from home one day a week reduces the time spent travelling on a daily basis and increases the likelihood of avoiding peak-hour traffic for both work and non-work travel for full-day home workers, while part-day teleworkers experience no decrease in daily travel duration and avoiding peak-hour traffic is restricted to work-related trips. This is in line with Elldér's (2020) findings from Sweden, which provide evidence that full-day teleworking indeed leads to less rush-hour traffic. Hamer et al. (1991) reported a 26% decrease in the number of trips made during peak hours by a car when a person spent 20% of his working hours teleworking. Results from Stiles and Smart (2020) suggest that teleworking has a more pronounced effect on morning peak periods than on evening ones and that full-day home workers are more inclined to avoid peak-hour travel. Additionally, Pendyala et al. (1991) provide evidence that telecommuters in California distribute their home trips more evenly throughout the day on home-working days, which decreases the intensity of traditional peak periods. Stiles and Smart (2020) report that when homeworking is combined with other non-workplace locations (e.g. working in a coffee shop), there is again a high likelihood of avoiding peak-hour work travel.

While teleworking mitigates the need for peak-hour commuting and empirical evidence shows that teleworkers travel less during peak periods, it raises questions as to whether potentially improved travel conditions result in increased travel activity by non-teleworkers due to induced demand (Kiko et al., 2023). It also prompts a further assessment of overall travel behaviour, especially non-work-related travel, by teleworkers.

2.3.3 Non-work travel

It is clear that teleworking influences commuting behaviour, but its effects extend further into broader travel patterns, also influencing non-work trips. Work location and schedules are central to planning and organising daily activities, meaning that changes in these due to engagement in teleworking activities inevitably influence non-work-related travel patterns (Aguiléra et al., 2009; Cerqueira et al., 2020). Asgari et al. (2016) argue that the more relaxed work constraints afforded by teleworking could lead to the reallocation of the time budget to non-mandatory activities. Numerous studies acknowledge this rebound effect, coined the non-work travel effect by Kiko et al. (2023), where commuting time saved through teleworking is reinvested into other activities, leading to an increase in personal, non-work-related trips (He & Hu, 2015; Lachapelle et al., 2017; Ravalet & Rérat, 2019; Zhu, 2011). Similarly, He and Hu (2015) argue that working from home might also stimulate “cabin fever”, or the desire to leave home on home-working days instead of staying inside all day.

Cerqueira et al. (2020) note that many non-work trips are not conducted on their own but are planned in conjunction with work-related trips, thereby creating a network of multi-purpose trips (Hanson, 1980). The authors reason that work-related travel often plays a structural role in an individual’s travel behaviour, including non-work-related trips. Consequently, a great number of non-work trips take place in close proximity the workplace or home, or on the route between the two (Aguiléra et al., 2009). The relaxation of spatial and time-related constraints that allow teleworkers to avoid peak-hour traffic is also likely to lead to a broader distribution of non-work trips throughout the day and week. Pendyala et al. (1991) observed that teleworkers in California tend to choose non-work destinations closer to home, indicating a contraction of their action spaces. This contraction was observed on both teleworking and non-teleworking days, suggesting long-term changes in travel behaviour.

Faber et al. (2023) reported a positive effect of teleworking on leisure travel time in the Netherlands, although this effect was only found before and not during the pandemic years. Similarly, Zhu (2011) reported that in both 2001 and 2009, teleworking had a significant positive impact on American teleworkers' total daily non-work trip distance, duration, and frequency. Asgari et al. (2016) also found that teleworking increased the total daily trip frequency for both teleworkers and their household members in New York. More specifically, the relaxation in space and time constraints led to increased time spent on non-mandatory activities, leading to one extra daily trip for full-day teleworkers and one-half extra trip per day for part-day teleworkers. He and Hu (2015) looked at the purpose of trips in Chicago and found that teleworking affected the number of commute trips negatively while increasing the number of total trips, the number of pick-up and drop-off trips, and the number of maintenance/discretionary trips. Additionally, Cerqueira et al. (2020) found that teleworkers in the U.K. travel more kilometres for non-work activities on weekdays.

Conversely, findings by Glogger et al. (2008) from Germany showed that teleworking resulted in fewer trips during the day, paired with a different temporal distribution. A similar result was found by Hamer et al. (1991) in the Netherlands, where teleworking significantly reduced the total number of trips, including non-work trips, for both teleworkers and their household members. However, the majority of studies indicate the presence of the non-work travel effect.

2.3.4 Overall travel demand

Does the non-work travel effect fully offset the work travel effect? A meta-analysis conducted by Andreev et al. (2010), which examined 35 empirical studies, revealed that most studies identified a substitution relationship between teleworking and travel behaviour, indicating that teleworking decreases the need for travel (Stiles & Smart, 2020). Lachapelle et al. (2017) reported a reduction in total travel duration of 13 minutes per day on average for Canadians working from home full-day, while part-day home working increased overall travel time by almost 10 minutes, agreeing with the findings of Stiles and Smart (2020) from the U.K. that full-day telework is associated with a reduction in travel time due to a decrease in work-travel and a smaller increase in non-work travel. Additionally, Glogger et al. (2008) reported decreases in total travel distances and the number of trips during the day as a result of teleworking in Germany. Pendyala et al. (1991) reported that on teleworking days in California, the number of trips decreased, and total distance travelled decreased by 75%. Trips on telecommuting days appeared to be shorter and vehicle miles decreased by 90%.

Recent results from the study by Faber et al. (2023) indicate that the net effect of teleworking on total travel duration in the Netherlands is negative, due to the substitutive effect of teleworking on commuting time being greater than the complementarity effect on leisure travel time, in line with what Ravalet and Rérat (2020) concluded in Switzerland. Likewise, Elldér (2020) discovered that in Sweden, full-day teleworkers significantly reduce both the number and length of their trips on teleworking days. However, this overall reduction in travel demand is somewhat counterbalanced by part-day teleworkers, who tend to make more and longer trips on the days they work from home. However, as the marginal effects of full-day teleworkers were greater, the author concluded that, on the whole, teleworking can be regarded as a substitute for travel and reduced total travel demand. Kiko et al. (2023) found that in the Netherlands, at a teleworking frequency of 60%, or three days a week, vehicle hours travelled (VHT) decreased by 17.1% and vehicle kilometres travelled (VKT) decreased by 9.7%. However, when accounting for the rebound effects, gains in travel distance are reduced to 2.5% and gains in time savings are reduced by 3.2%. Consequently, they concluded a reduction in overall travel after the rebound effect cancelled 74% to 85% of gains in time savings and 62 to 68% of gains in travel distance.

Zhu's (2011) research from the U.S. disagrees and found both longer one-way commute trips, in addition to more frequent daily trips with greater distances – for both work and non-work purposes, suggesting a complementary effect between teleworking and travel. Ravalet and Rérat (2019) also found contradictory results in Switzerland as they conclude that, although the distance travelled is 67% lower on teleworking days, teleworkers travel longer distances during the week in comparison to non-teleworkers, travelling 244 kilometres and 210 kilometres, respectively. Adding to this view, De Abreu E Silva and Melo (2018) found that an increase in teleworking frequency reduced the number of commuting trips but increased the total weekly miles travelled in the U.K.

Most findings agree with the idea that teleworking impacts travel behaviour by reducing commuting needs and potentially increasing non-work trips as a rebound effect, highlighting a nuanced dynamic. Despite the increase in non-work travel, many studies find a reduction in total travel time and distance as a result of teleworking. On a nationwide scale, teleworking practises could potentially lower overall travel demand, but this is highly dependent on the share of total workers engaging in teleworking and the share of teleworkers engaging in either full-day or part-day teleworking.

2.4 The effect of teleworking on mode choice

To investigate the potential of teleworking practises to mitigate congestion and emissions, the effect on modal choice should be taken into consideration. Research has shown a notable trend toward more suburban residencies among teleworkers. Cerqueira et al. (2020) and Yen (2000) comment that teleworkers are more likely to live in suburban areas where car dependency is higher. The preference for suburban living aligns with the findings of De Abreu E Silva and Melo (2018) and S. Kim et al. (2015) who argue that teleworking does not necessarily reduce travel but rather decentralises it. As teleworkers are associated with greater commuting distances, possibly moving away from urban centres and central business districts, this could lead to increased car dependency and longer commuting distances on office days.

The built environment plays a vital role in influencing teleworkers' mode choices. Areas with compact development and robust public transport infrastructure are more likely to encourage teleworkers to opt for public transportation usage (Wang & Ozbilen, 2020), while teleworkers living in low-density areas, often having less access to public transport, are more likely to rely heavily on car access, even as their total commuting distance decreases (Pendyala et al., 1991). This is in line with De Abreu E Silva and Melo's (2018) conclusion that teleworkers are more frequent car users. Pendyala et al. (1991) highlight that changes in mode use as a result of teleworking are also probable, as the irregular commuting schedules associated with teleworking might make car-pooling a more challenging task, requiring teleworkers to drive to work on their own. Additionally, the presence of a car in the household that would normally be gone due to commuting needs might suddenly be available to household members due to engagement in teleworking, which might induce household members to switch modes too in the long term and make additional trips during the day (Pendyala et al, 1991).

Despite these concerns, other studies recognise teleworking's potential to encourage active travel modes, especially for non-work-related trips. Chakrabarti (2018) found that in the U.K., frequent telecommuting is associated with 15% more weekly walking trips and 44% higher odds of 30+ minutes of daily physical activity. Additionally, telecommuting was associated with 41% higher odds of walking or cycling more than a mile daily and 71% higher odds of 30+ minutes of daily physical activity (Chakrabarti, 2018). Elldér (2020) notes that Swedish teleworkers are more likely to engage in active travel when teleworking full days, in line with the findings that saved commuting time is being reallocated to healthier, active modes of travel (Lachapelle et al., 2017; Wang & Ozbilen, 2020). Elldér (2020) nuances these findings by stating that in a lot of studies where active travel increases as a result of teleworking, teleworkers generally make more trips for other reasons, increasing the likelihood of engaging in active travel. Although Chakrabarti (2018) observed that physical activity and non-motorised travel increased, the author also found that driving distances for telecommuters were usually longer than those of non-telecommuters. The overall impact of teleworking on sustainable travel behaviour is not surprisingly mixed and context-dependent (Wang & Ozbilen, 2020)

The relationship between teleworking and modal choice is complicated, posing both opportunities and potential rebound effects. While teleworking directly reduces the need for daily commuting, potentially stimulating active travel for shorter and more local trips, it does not seem to cause a decrease in car use and potentially encourages more of it. Especially for teleworkers, who have a higher propensity to live in low-density suburban areas with a lack of access to adequate public transportation, there is a tendency to rely on personal vehicles for non-work-related travel, possibly increasing car mode share (De Abreu E Silva & Melo, 2018). While teleworking presents opportunities to stimulate active travel and reduce commute-related pollution, greater car dependence is also a possible rebound effect.

2.5 Impact of the COVID-19 pandemic on teleworking

While teleworking has gained some adoption alongside the development of ICT throughout the years, the landscape of work underwent a significant transformation due to the COVID-19 pandemic, which caused a widespread adoption of teleworking arrangements among knowledge workers due to the necessity of social distance. Throughout the pandemic, teleworking has proven its effectiveness in ensuring community health during crises by facilitating physical distancing (Wang & Ozbilen, 2020). The mass adoption of teleworking brought a renewed interest in teleworking's potential as a tool for managing transportation issues like congestion and emissions (Stiles & Smart, 2020).

From an employee’s perspective, anecdotal evidence suggests a marked increase in the inclination of office workers towards teleworking and a sustained interest in teleworking after lockdowns (Pulido & Martínez-Cruz, 2022). During this period of mass teleworking adoption, which went hand in hand with government-imposed lockdowns, travel demand was significantly reduced (Faber et al., 2023). Although this suggests teleworking’s potential effectiveness as a travel demand management strategy, it is difficult to measure what magnitude of the effect can be attributed to teleworking arrangements and what part of the effect is caused by lockdown restrictions.

The pandemic introduced new demographics to teleworking, potentially altering its impacts compared to pre-pandemic observations. Additionally, teleworking arrangements have outlasted the initial policies themselves and are expected to remain higher than pre-pandemic measures (Faber et al., 2023). Understanding these changes and their long-term implications is crucial for shaping future teleworking policies and practises.

2.6 Conceptual model and hypotheses

To summarise, while the introduction of teleworking was promisingly introduced as an effective strategy to reduce overall travel demand and peak-hour congestion, more recent literature acknowledged and studied the more complex effect of teleworking arrangements on overall travel behaviour, introducing more nuance in the discussion. Currently, there is a consensus on a variety of aspects, while some theories or potential rebound effects are more disputed.

Regarding consensus, it is generally accepted that teleworking reduces commuting frequency. Teleworkers working at home full-day, whether this is some or all days of the week, are likely to commute less frequently than those who do not. Additionally, teleworking’s potential to alleviate peak-hour congestion, if applied on a large scale, is widely accepted, as part-day teleworkers are tempted to plan their commutes outside of the peak hours, while full-day teleworkers avoid their commutes altogether on teleworking days. Therefore, the extent of this impact is dependent on the proportion of teleworkers and whether they work from home full-day or part-day. Also, it's well-understood that while teleworking decreases commute travel, it may lead to an increase in non-work-related travel as individuals reallocate their saved commute time to other activities.

Another area of consensus is that teleworkers are associated with greater average commuting distances. Whether this is due to residential relocation, an expansion of one's labour market, self-sorting, or whether there is a case of reverse causality is, however, disputed. While the residential location effect is often theoretically proposed, evidence is lacking, and no study has convincingly established the effect. The literature highlights several more areas of dispute or lack of consensus. The overall effect of teleworking on total travel demand remains debated. Additionally, there is considerable variation in the effect of teleworking on transportation mode choice, as it is based on many contextual factors like levels of urbanisation, public transportation availability, and individual preferences. It is still disputed whether it increases or reduces overall car travel and can therefore be considered a sustainable policy or not. Based on the literature, the following conceptual model was created:

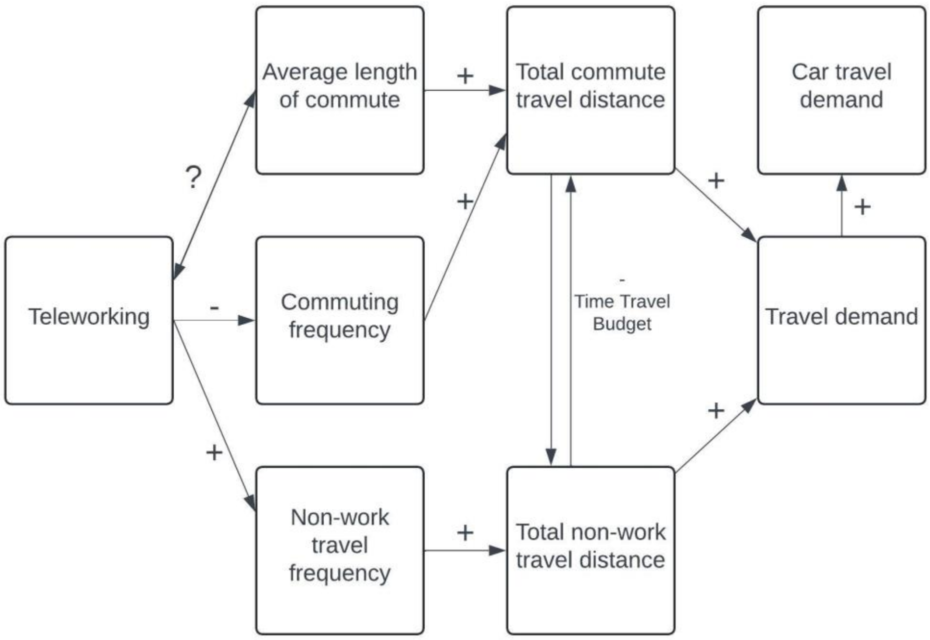


Fig. 2.1 Conceptual model of the relationship between teleworking and travel demand

The purpose of this thesis is to replicate and confirm the points of consensus and add to the existing body of literature by investigating the aspects that are still disputed. The main research question is:

What are the effects of teleworking on travel demand?

The following hypotheses will be tested:

H1: Teleworking decreases commuting frequency.
H2: Teleworking increases the acceptance of longer commutes.
H3: Teleworking decreases net commute distances.

H4: Teleworking leads to an increase in the frequency of non-work-related trips.

H5: Teleworking leads to an increase in total non-work-related travel distances.

H6: The overall effect of teleworking on travel demand is a reduction in total distances travelled.

H7: Teleworking leads to increased car kilometres travelled.

3. Data

This chapter will outline the data source and structure, the operationalization of the variables, provide summary statistics of the data, transform the variables to ensure normality, and take a first look at the potential outcomes of the hypotheses by analysing scatterplots and discussing a correlation matrix.

3.1 The panel

To test the hypotheses, data from the Netherlands Mobility Panel (MobiliteitsPanel Nederland in Dutch), MPN for short, will be used. This is a longitudinal household panel consisting of several questionnaires and a 3-day travel diary. To complement this gathered data, the dataset is augmented with information from administrative records, such as socioeconomic details of recorded postal codes, to lessen the load on respondents. The MPN aims to assess the short-term and long-term changes in travel behaviour among Dutch individuals and households and understand the relationship between changes in travel behaviour and influencing factors such as individual and household characteristics and other travel-related variables. The panel respondents are recruited based on their socio-demographic characteristics to ensure that the data is representative of the Dutch population (Hoogendoorn-Lanser et al., 2015).

The MPN has been collecting data since 2013 but started the detailed documentation of the number of hours worked at home and the workplace from 2017 onwards. Given that the data is published two years post-collection, the most recent data is 2021. However, as the COVID-19 pandemic and its corresponding lockdowns and other measures heavily influenced both travel behaviour and the adoption of teleworking, the data for 2020 and 2021 will not be used. Consequently, this study will analyse data spanning three waves from 2017 to 2019. Data collection for each of those years was conducted from September to November.

3.2 Operationalization of the variables

3.2.1 Teleworking

In order to estimate the effects of teleworking on travel demand, the relevant variables have to be defined and operationalized. Teleworking will serve as the primary independent variable across all hypotheses. Referring to the three types of teleworking described by Perez et al. (2004), which subdivide teleworking into home-based, telecentre-based, and mobile teleworking, this thesis will solely focus on home-based teleworking, which can include both full-day and partial-day home-based teleworking, as described by Thomsin (2002). This decision was made as home-based teleworking has become the predominant form of teleworking, possibly because it does not require more than a stable internet connection and a home workspace, making it very accessible for employers and employees to implement. Telecentres are not common in the Netherlands, and working while travelling does not substitute travel. Focusing on home-based teleworking allows for a more straightforward analysis of its effect on travel demand as it directly replaces the need to commute. Teleworking is operationalized as the ratio of hours worked at home to the total number of hours worked. MPN's travel diary does not report the number of hours worked (at home) on a particular day. Therefore, the ratio is based on the reported number of hours at the workplace and at home from a recent work week, which are included in the data. The ratio effectively captures the intensity of teleworking for both part-time and full-time workers, allowing the analysis to focus on the mode of work rather than the volume. Measuring the extent to which people telework is relevant, as its effects on travel demand are likely to scale with the proportion of hours worked at home. Additionally, if the model finds that a higher teleworking ratio is associated with reduced travel distances, this will inform policymakers about what a certain increase in teleworking would mean for overall travel demand.

3.2.2 Travel demand

Travel demand, the dependent variable in this study, is operationalized by several aspects of travel behaviour. The first three hypotheses focus on the substituting effect of teleworking on travel behaviour. In H1, the dependent variable is commuting frequency, which is the average daily number of commuting trips for each individual in each year. For H2, the average distance of a commute will serve as the dependent variable. H3 will look at the net effect of H1 and H2, the average daily commuting distance per individual per year, as a dependent variable.

H4 and H5 assess whether teleworking has a complementary effect on non-work travel. The frequency of non-work-related trips is the average daily number of trips for each individual in each year that were categorised as trips for services and personal care, (grocery) shopping, social and recreational activities, touring and hiking, visitations, and other purposes. Similar to H3, H5 will examine teleworking's impact on the total non-work-related travel distances, being the average daily total distances travelled for the same trips as those in H4.

For H6, all trip distances are aggregated to assess the effect the proportion of teleworking has on the average daily number of kilometres travelled during the 3-day travel diary. Ultimately, the aim of this hypothesis is to see whether teleworking reduces the total distance individuals travel. The focal point of H7 is the effect that teleworking has on the average daily distances travelled by car (as a driver).

3.2.3 Control variables

Several individual and household socio-demographic variables will be added to the base model. First of all, income and education. Income and education levels are significant determinants of teleworking adoption (De Abreu E Silva & Melo, 2018; De Graaff & Rietveld, 2004; Ravalet & Rérat, 2019). In the US, higher-income income and more educated workers were higher adopters of telework and having a college degree contributed to a higher chance of teleworking (He & Hu, 2015). This is in line with the idea that managerial and knowledge-intensive work is more easily done remotely compared to occupations that require more practical skills and education, often paired with lower incomes, which require physical presence (De Abreu E Silva & Melo, 2018; He & Hu, 2015). The opportunity for and adoption of teleworking thus varies significantly across different industry sectors. Teleworking is mainly reported in service-oriented fields, such as financial institutions and the information and communication sectors. Conversely, lower teleworking rates are observed in industries where physical presence has greater importance or is a necessity, such as agriculture, industry, and personal services (Ravalet & Rérat, 2019). As teleworking potential can greatly differ within a sector, education level is more accurate and straightforward to control for. De Abreu E Silva and Melo (2018) state that teleworking is often used by workers as a strategy to deal with long and expensive commutes. This suggests an unequal situation in which lower-income workers, who could benefit significantly from reduced commuting costs and times, often have limited or no access to telework opportunities (He & Hu, 2015). Income level can determine access to various modes of transport and the ability to live in other locations. Higher-income individuals might have more flexibility in choosing where to live and work, impacting their travel patterns. Additionally, individuals with a higher income and education level show a propensity for longer work-related travel distances, and this effect is stronger for men than for women (Aguiléra et al., 2009; Sandow & Westin, 2010). Education is grouped into three categories: basic, intermediate and higher education. Income is a categorical variable reported on the household level and is grouped into low (below the national benchmark income), medium (the national benchmark income), high (1-2x the national benchmark income) and very high income (more than 2x the national benchmark income).

Age, gender, and household composition are also added to the model, as these factors significantly influence mobility due to different social roles and responsibilities. The presence of children in the household increases the average number of non-work trips, due to escort and childcare-related travel (Aguiléra et al., 2009). Gender distinctions play an important role here, as women are more likely to undertake the previously mentioned and other kinds of non-work-related trips compared to men. The presence of children was also found to reduce the propensity to telework in the Netherlands (Peters et al., 2004). Concerning mode choice, there is a greater likelihood of men using cars compared to women (Cerqueira et al., 2020). Age affects mobility needs and choices, with younger and older populations showing different travel behaviours due to life stage and physical ability. There is less academic consensus about the effect of gender and age on teleworking adoption. Even though teleworking is often perceived as an opportunity for female employees to balance work and family life, some of the studies conclude that teleworkers are mostly men (Popuri & Bhat, 2003), often working in knowledge and managerial positions (Bailey & Kurland, 2002; Pérez et al., 2004). Conversely, Peters et al. (2004) found no disparity between male and female adoption of teleworking. Regarding age, some, including Popuri and Bhat (2003), found that older people are more likely to telework than younger people, while others, including De Graaff and Rietveld (2004, concluded the opposite. Age is included as a categorical variable, ranging from 18-29 years to 60 years and older. Gender and the presence of children in the household are included as binary variables.

In addition to the socio-demographic factors, the level of urbanisation should also be controlled for, as it affects access to employment opportunities and transportation infrastructure, which can influence teleworking practises and associated travel behaviour. Larger living spaces, often found in suburban areas, were found to increase teleworking adoption in Taiwan (Yen, 2000), hinting at a link between residential environment characteristics and the decision to telework (De Abreu E Silva & Melo, 2018). Wang and Ozbilen (2020) estimated that the built environment explains 42% to 54% of travel time spent on public transportation and engaging in active travel. The built environment and the level of urbanisation are, of course also linked to car dependency and, consequently, car usage. The residential level of urbanisation is categorised into non-urbanised areas (less than 500 inhabitants less than 500 inhabitants/km²), low urbanisation (500 to 1,000 inhabitants/km²), moderately urbanised (1,000 to 1,500 inhabitants/km²), highly urbanised (1,500 to 2,500 inhabitants/km²) and very highly urbanised (2,500 or more inhabitants/km²).

The variables described above will constitute the base model. In addition to the base model, there are some other factors that need to be controlled for. The base model will serve as the model for H2. For H1, H3, H4, H5, and H6, the total number of hours worked will be added to the model. This variable is crucial as it directly influences the need to commute, thereby affecting the commuting frequency (H1) and the total commuting distance (H3). It also impacts the remaining time that can be allocated to non-work travel – thus affecting the non-work trip frequency (H4) and the total non-work travel distance (H5). These factors together constitute the total travel distance (H6). For H7, the total travel distance, that serves as the dependent variable in H6, is added to the model as a control variable as travelling more kilometres is likely to increase car usage. Lastly, access to a car in the household is added to the model for H7, as access to a car starkly increases the chance of making car kilometres.

In summary, the base model controls for income, education, age, gender, household composition and the level of urbanisation, with additional controls for the total number of hours worked and the presence of a car in the household for certain hypotheses. Table 3.1 shows an overview of which models will be used for each hypothesis and Table 3.2 shows an overview of the variables used in this thesis.

Table 3.1 Overview of the three different models and their respective variables

Model	Hypotheses	Variables
1	H1, H3, H4, H5, H6	Base model + total hours worked
2	H2	Base model
3	H7	Base model + total travel distance + household access to a car

Table 3.2 Overview of the variables used in this thesis

Variable name	Type of variable	Definition	Coding
Teleworking %	Independent variable	The percentage of hours worked at home in a recent week	Continuous
Commuting frequency	Dependent variable	The average daily number of commuting trips	Continuous
Average commuting distance	Dependent variable	The average length of a commuting trip in kilometres	Continuous
Total commuting distance	Dependent variable	The average daily total commuting distance in kilometres	Continuous
Non-work trip frequency	Dependent variable	The average daily number of non-work-related trips	Continuous
Total non-work trip distance	Dependent variable	The average daily total non-work trip distance in kilometres	Continuous
Total travel distance**	Dependent variable	The average daily total travel distance in kilometres	Continuous
Daily car kilometres	Dependent variable	The average daily total kilometres travelled by car as a driver	Continuous
Total hours worked*	Control variable	The total number of hours worked in a recent week	Continuous
Age	Control variable	Age of individual	Categorical
Gender	Control variable	Gender of individual	Binary
Education	Control variable	Highest completed education level	Categorical
Income	Control variable	Gross aggregated household income	Categorical
Children	Control variable	Presence of children in the household	Binary
Level of urbanisation	Control variable	Urbanity at the municipal level	Categorical
Access to a car***	Control variable	The presence of a car in the household	Binary

Note. * Controlled for in H1, H3, H4, H5 and H6; ** Serves as a control variable in H7; *** Controlled for in H7.

3.3 Sample and data description

3.3.1 Summary statistics and variable transformations

The sample consists of 3,286 respondents in total, working at least 16 hours a week and aged 18 years and older. When the data is aggregated to one observation per person per year, the sample contains 6,828 observations in total. There are no missing values for all the dependent, independent, and control variables except for average commuting distance, which has 5,080 observations, as some individuals recorded no commuting trips at all during the three-day travel diary.

The average teleworking rate in the sample is 8.67%, meaning that of all hours worked by the individuals in the sample, 8.67% of hours were worked from home. As can be seen in Figure 3.1, the teleworking ratio stayed relatively constant from 2017 to 2019. The average daily commuting frequency was 1.18 commutes, with an average length of 22.36 kilometres per commute and an average daily total commuting distance of 25.62 kilometres. Regarding non-work travel, individuals in the sample made 1.85 non-work trips and travelled 15.97 kilometres for non-work-related purposes on a daily basis on average. The average daily total distance travelled is 45.63 kilometres, and the average number of kilometres travelled by car was 29.82. The summary statistics of the numeric variables are displayed in Table 3.4.

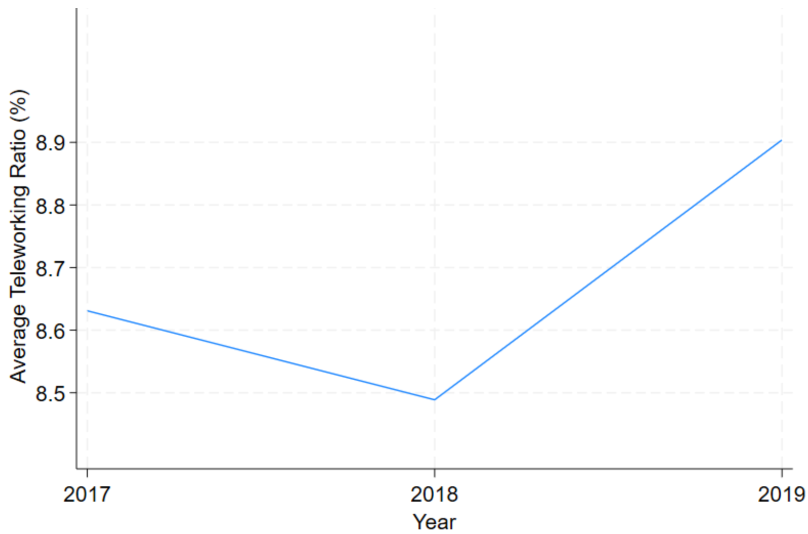


Fig. 3.1 Annual teleworking ratio in the Netherlands, 2017 - 2019

Highly skewed variables can introduce issues like heteroskedasticity, non-linearity, and an overstated influence of outliers and extreme values on the results. In order to ensure a normal univariate distribution, the skewness - a measure of the degree of asymmetry of a distribution around its mean, and kurtosis - the extent of the tail's heaviness compared to a normal distribution, of the numeric variables were examined. Dummy and categorical variables were excluded from this analysis as these variables are not able to have a normal distribution. Skewness values within the range of -2 to +2 and kurtosis values within the range of -7 to +7 are commonly considered acceptable (H. Kim, 2013). The skewness and kurtosis values of the normal and log-transformed variables are displayed in Table 3.3. In the data, zero values are meaningful and represent actual instances of no teleworking or no travel; therefore, a constant of +1 was added prior to the log transformation to ensure all values remain positive and meaningful. Of the eight numeric variables, being the independent and all dependent variables, only the commuting frequency and the non-work trip frequency follow a normal distribution. However, as the commuting frequency's and the non-work trip frequency's normality still improve after a log transformation, a log transformation is applied. After a transformation of all independent and dependent variables, all respective values for skewness and kurtosis fall within acceptable boundaries. The transformations also allow for a more straightforward interpretation, as the coefficients represent the expected percentage change in the dependent variables for a one percentage change in the teleworking ratio.

Table 3.3 Skewness and kurtosis values of the numeric variables

Variable	**Skewness**	**Kurtosis**	**Acceptable**
Teleworking %	3.071368	13.48755	No
(log) Teleworking %	.9561361	2.298657	Yes
Commuting frequency	.3968463	4.108146	Yes
(log) Commuting frequency	-.4172009	1.901365	Yes
Average commuting distance	2.423192	12.10693	No
(log) Average commuting distance	-.1743422	2.300607	Yes
Total commuting distance	3.183652	19.26127	No
(log) Total commuting distance	-.0838703	1.716096	Yes
Non-work trip frequency	1.554802	6.276225	Yes
(log) Non-work trip frequency	.1647653	2.000636	Yes
Total non-work trip distance	4.415092	32.33403	No
(log) Total non-work trip distance	.3446143	1.99867	Yes
Total travel distance	2.33371	11.30393	No
(log) Total travel distance	-.6792856	2.903628	Yes
Daily car kilometres	2.837573	15.28695	No
(log) Daily car kilometres	.0451441	1.449919	Yes

In Table 3.5 the distribution of the categorical variables is displayed. Most participants completed higher education (46.84%), with intermediate and basic education levels following at 38.97% and 14.19% respectively. For income, the biggest groups are high (39.69%) and very high income (26.54%), followed by medium (20.97%) and low income (12.80%). The age groups are skewed towards the middle-aged, with the 30-39 group being the most prevalent. The sample is nearly evenly split between males (50.59%) and females (49.41%), and more participants live with children (54%)

than without (46%). More than half of the sample live in very highly and highly urbanised areas, with lower representations from other urbanisation levels. The distribution provides a diverse socio-demographic profile of the study participants.

Table 3.4 Summary statistics of the numeric variables

Variable	***mean***	***median***	***sd***	***min***	***max***	***N***	***n***
Teleworking %	8.66524	0	18.11723	0	100	6,828	3,286
(log) Teleworking %	1.016383	0	1.474013	0	4.61512	6,828	3,286
Commuting frequency	1.175552	1.3333334	.8935693	0	8	6,828	3,286
(log) Commuting frequency	.6819505	.84729791	.454479	0	2.197225	6,828	3,286
Average commuting distance	22.35896	14.666667	24.53393	0	234	5,080	2,724
(log) Average commuting distance	2.648214	2.7515354	1.059526	0	5.459586	5,080	2,724
Total commuting distance	25.62297	10.148333	39.01306	0	468.6	6,828	3,286
(log) Total commuting distance	2.209098	2.4112899	1.640305	0	6.151881	6,828	3,286
Non-work trip frequency	1.851567	1.3333334	1.978023	0	15	6,828	3,286
(log) Non-work trip frequency	.8309655	.84729791	.6581429	0	2.772589	6,828	3,286
Total non-work trip distance	15.97211	4.2958331	31.50098	0	500	6,828	3,286
(log) Total non-work trip distance	1.726655	1.66692	1.49787	0	6.216606	6,828	3,286
Total travel distance	45.62559	28.046111	52.31306	0	500	6,828	3,286
(log) Total travel distance	3.145586	3.3688846	1.378482	0	6.216606	6,828	3,286
Daily car kilometres	29.82305	10.293667	46.29363	0	500	6,828	3,286
(log) Daily car kilometres	2.107046	2.424242	1.852242	0	6.216606	6,828	3,286
Male	.5058582	1	.5000023	0	1	6,828	3,286
Children	.5399824	1	.4984353	0	1	6,828	3,286

Table 3.5 Summary statistics of the categorical variables

Variable	**Frequency**	**%**
Education		
Higher	3,198	46.84
Intermediate	2,661	38.97
Basic	969	14.19
Income		
Very high	1,812	26.54
High	2,710	39.69
Medium	1,432	20.97
Low	874	12.80
Age		
18-29 years old	1,009	14.78
30-39 years old	1,997	29.25
40-49 years old	1,565	22.92
50-59 years old	1,717	25.15
60 years and older	540	7.91
Level of urbanisation		
Very highly urbanised	1,521	22.28
Highly urbanised	2,195	32.15
Moderately urbanised	1,212	17.75
Low urbanisation	1,367	20.02
Non-urbanised area	533	7.81

3.3.2 Teleworking ratio across different groups in the sample

When comparing the teleworking ratio between the different groups in the sample, as displayed in Figures 3.2 to 3.7, to the findings from the literature review, notable similarities and some differences can be found. Regarding income and education, the sample displays higher rates of teleworking among individuals with higher education and a higher income. While the literature disagrees on the effect of age on teleworking adoption, a clear trend can be seen in the sample, suggesting that teleworking increases with age. For age, the adoption rate is higher among women than men, suggesting that, although there is no consensus on this effect, women telework slightly more in order to balance work with trips for non-work-related purposes. This is in line with the slightly higher teleworking ratio in households with children, supporting that teleworking facilitates the juggling of work and family commitments. Finally, the data reveals the highest teleworking ratio in very highly urbanised areas, somewhat contrasting the literature that suggests a trend toward suburban living among teleworkers due to the flexibility of not commuting on a daily basis. However, this could also imply that the infrastructure and job types in highly urbanised areas are more suited to teleworking.

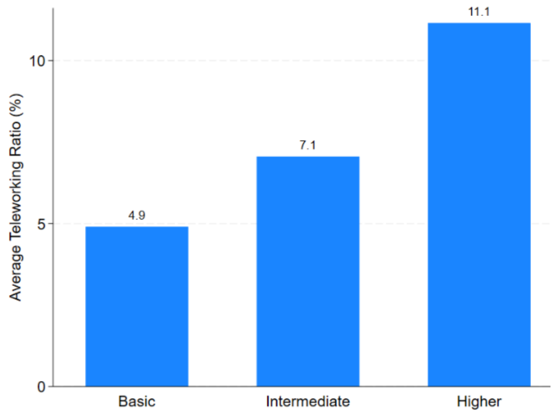


Fig. 3.2 Average teleworking ratio by level of education

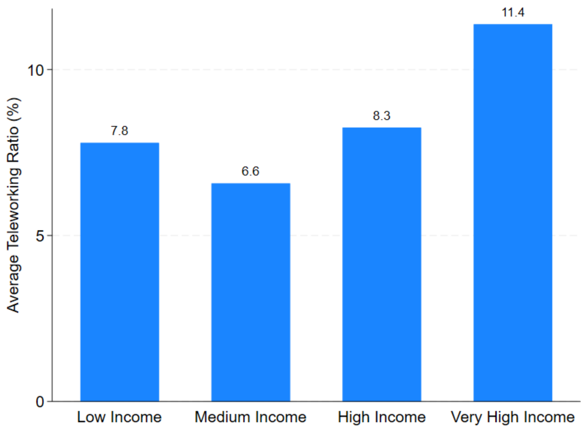


Fig. 3.3 Average teleworking ratio by income level

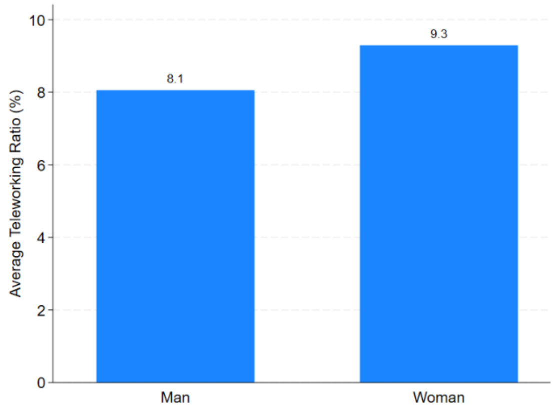


Fig. 3.4 Average teleworking ratio by gender

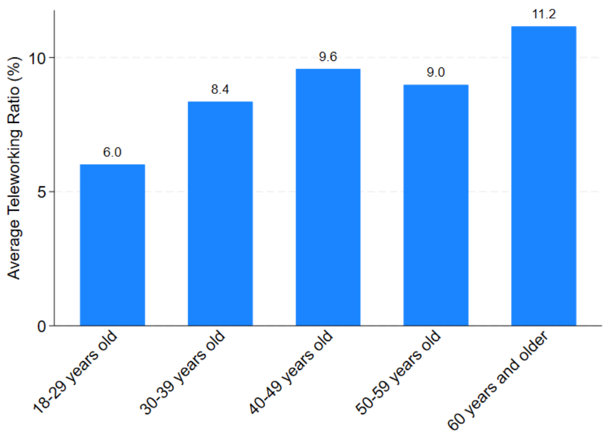


Fig. 3.5 Average teleworking ratio by age

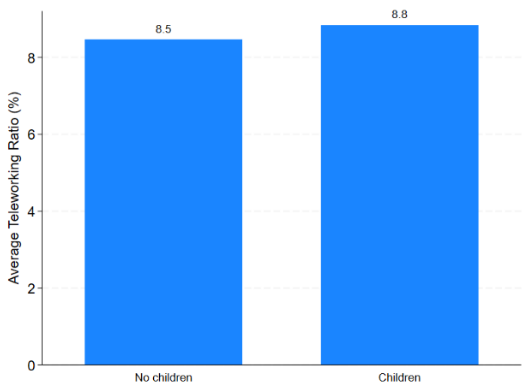


Fig. 3.6 Average teleworking ratio by household composition

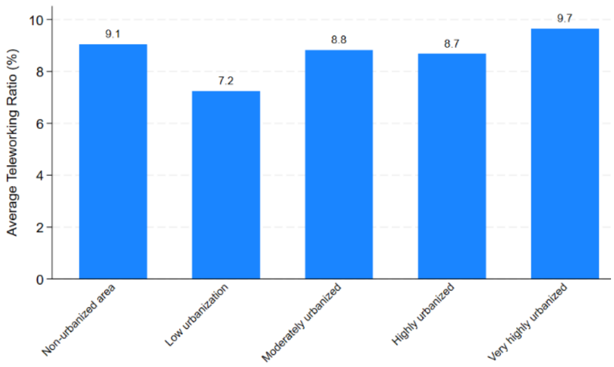


Fig. 3.7 Average teleworking ratio by level of urbanisation

3.3.3 Scatterplots

An examination of the scatter plots, as displayed in Figures 3.8 to 3.21, of the teleworking ratio in relation to the commuting frequency, average commuting distance, and total commuting distance suggests the hypothesised negative, positive and negative relationship respectively, although the effect on the total commuting distance seems weak. The scatterplot of the non-work trip frequency again shows the hypothesised positive relationship. For the scatterplot of the total non-work trip distance, the total travel distance, and the daily car kilometres, the trend line appears to be horizontal, suggesting the absence of an effect.

After the log transformations of the independent and dependent variables, the data appears to be more normally distributed. The prominent horizontal and vertical lines on the x-axis and the y-axis of all plots represent cases where either the teleworking ratio is equal to zero or the respective travel behaviour metric is equal to zero. A concentration of points along these lines indicates a significant number of observations with no telework, reflecting the relatively low share of hours worked at home and minimal travel. Again, trendlines are observed that are in favour of the hypothesised relationships for H1 to H4. Additionally, trendlines now also indicate a positive relationship between teleworking and the total non-work travel distance and the total travel distance, while the effect on daily car kilometres is still absent.

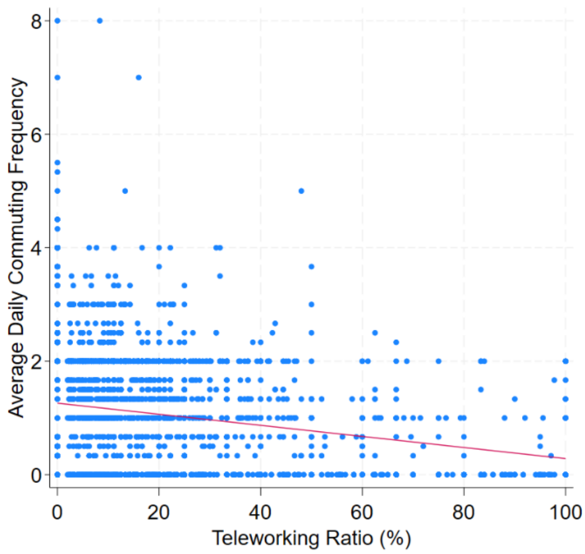


Fig. 3.8 Teleworking ratio vs. average daily commuting frequency

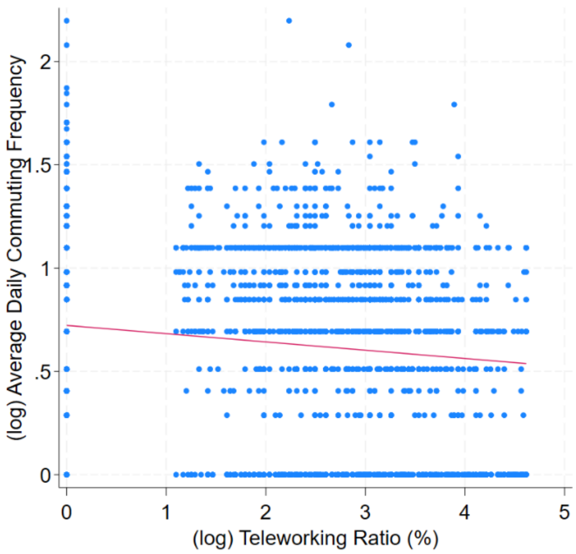


Fig. 3.9 (log) Teleworking ratio vs. (log) average daily commuting frequency

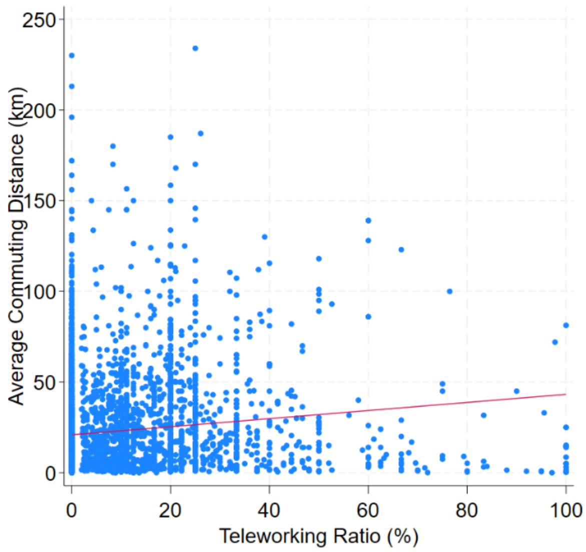


Fig. 3.10 Teleworking ratio vs. average commuting distance

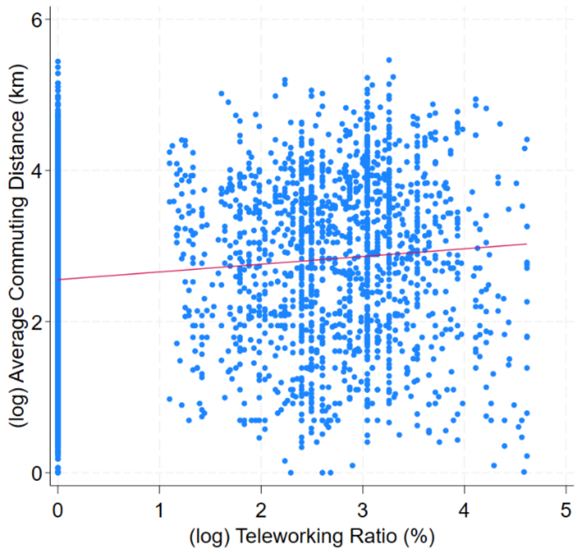


Fig. 3.11 (log) Teleworking ratio vs. (log) average commuting distance

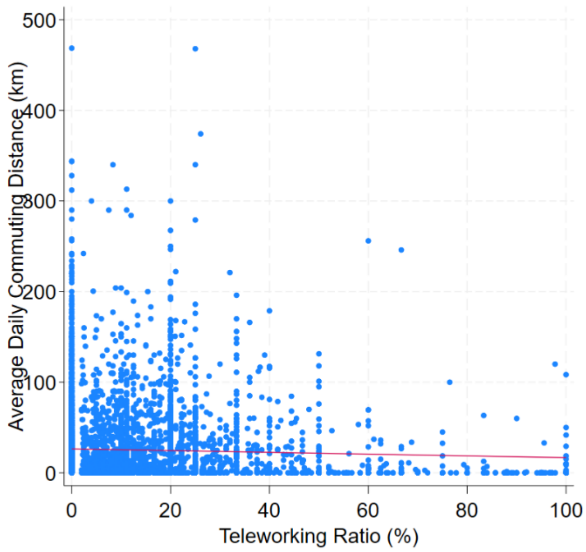


Fig. 3.12 Teleworking ratio vs. average daily commuting distance

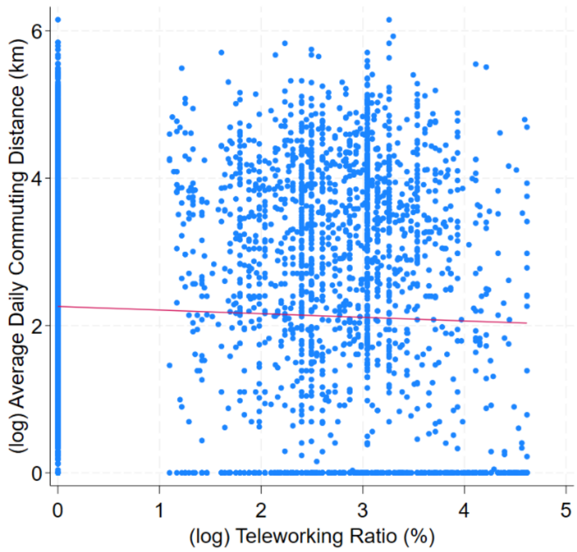
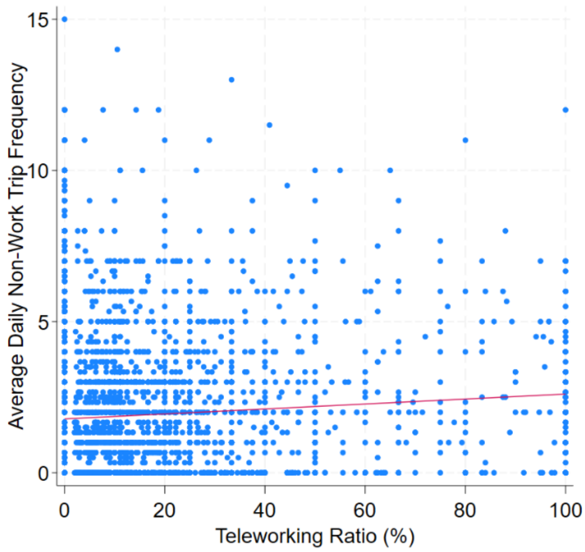


Fig. 3.13 (log) Teleworking ratio vs. (log) average daily commuting distance



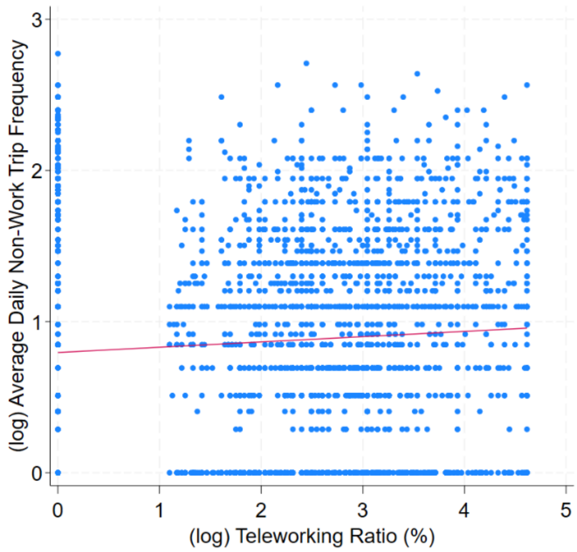
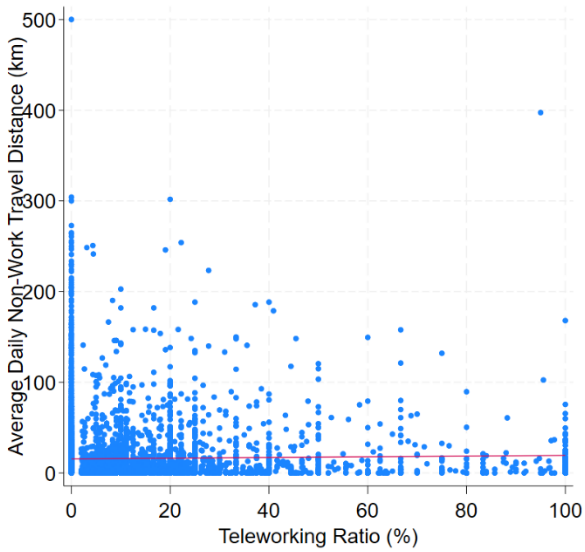


Fig. 3.14 Teleworking ratio vs. average daily non-work trip frequency

Fig. 3.15 (log) Teleworking ratio vs. (log) average daily non-work trip frequency



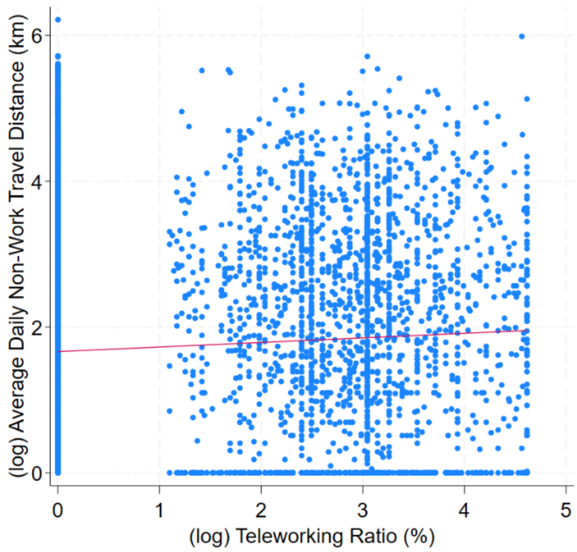


Fig. 3.16 Teleworking ratio vs. average daily non-work travel distance

Fig. 3.17 (log) Teleworking ratio vs. (log) average daily non-work travel distance

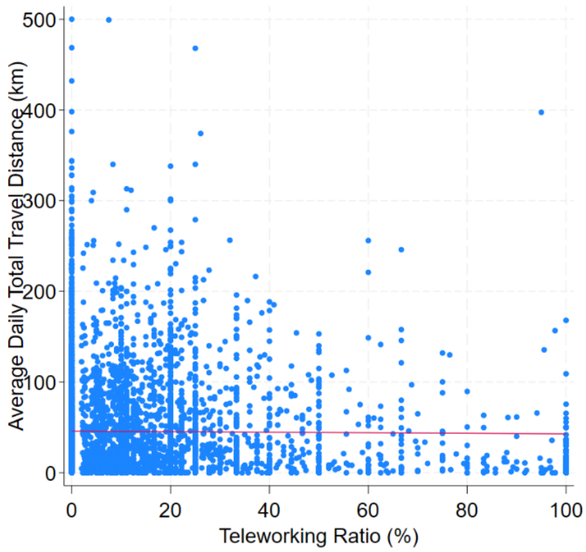


Fig. 3.18 Teleworking ratio vs. average daily total travel distance

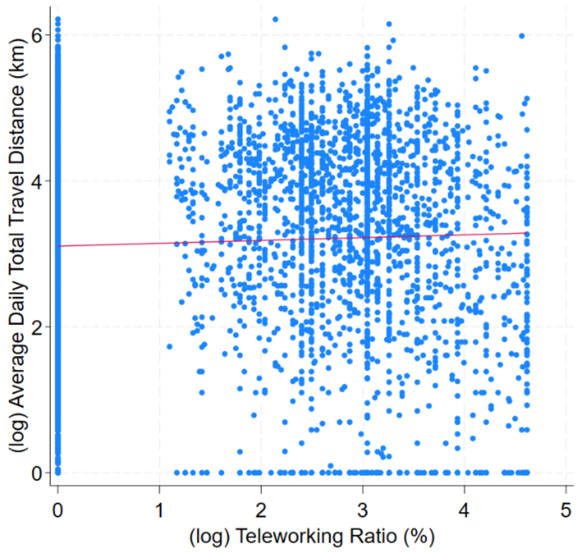


Fig. 3.19 (log) Teleworking ratio vs. (log) average daily total travel distance

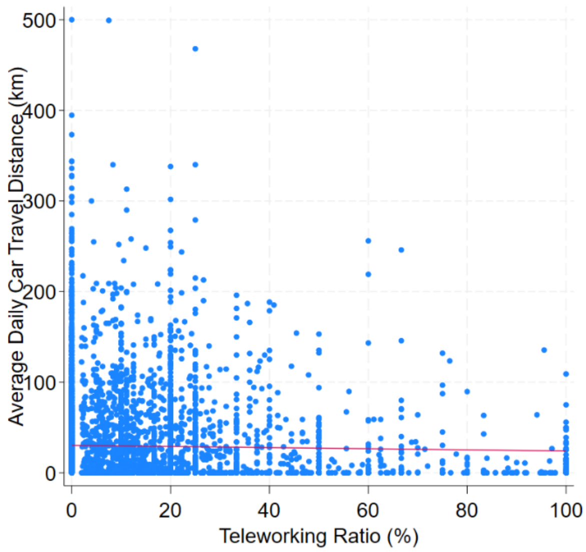


Fig. 3.20 Teleworking ratio vs. average daily car travel distance

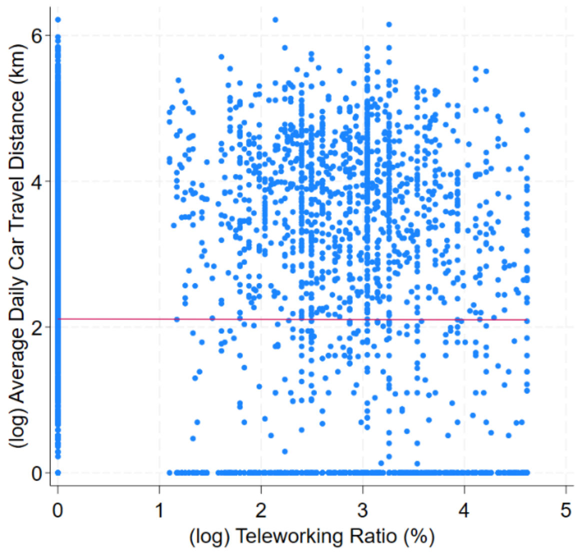


Fig. 3.21 (log) Teleworking ratio vs. (log) average daily car travel distance

3.3.4 Correlation matrix

An exploration of the relationships between the dependent and independent variables is presented in the correlation matrix in Table 3.6. Except for the correlation between the log of teleworking and the log of both the total commuting distance and the daily car kilometres and the correlation between the log of commuting frequency and the log of average commuting distance, all correlations are statistically significant at the 5% significance level. The log of teleworking ratio negatively correlates with the log of commuting frequency (-0.1138*), indicating that increased levels of teleworking reduce the need to commute, in line with H1. Conversely, positive correlations are established between the log of teleworking ratio on the one hand and the log of average commuting distance (0.1478*), the log of non-work trip frequency (0.0931*), the log of total non-work trip distance (0.0827*) and the log of total travel distance (0.0819*) on the other hand, supporting H2, H4, H5, and H6.

A further analysis of the independent variables reveals expected, and often strong, correlations, highlighting systematic relationships that align with travel behaviour theories. Specifically, there is a clear link between the frequency of trips - both work-related and non-work-related, and the total distances travelled, indicating that higher frequencies result in greater cumulative travel distances. Additionally, the negative correlations between commute travel and non-work travel-related variables underscore the substitutive relationship, in line with the theory of constant-time travel budgets (Ravalet & Rérat, 2019). It should be noted, however, that the slight positive correlation between the log of average commuting distance and the log of total non-work travel distance (0.0742*), indicates potential complexities in this straightforward application of the constant time travel budgets theory. Lastly, daily car kilometres show significant correlations with the log of average commuting distance (0.5061*) and the log of total commuting distance (0.4405*), indicating that car use is heavily influenced by commuting behaviours.

Table 3.6 Correlation matrix of the dependent and independent variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) (log) Teleworking ratio	1.000							
(2) (log) Commuting frequency	-0.114*	1.000						
(3) (log) Average commuting distance	0.148*	-0.017	1.000					
(4) (log) Total commuting distance	-0.017	0.781*	0.933*	1.000				
(5) (log) Non-work travel frequency	0.093*	-0.320*	-0.083*	-0.263*	1.000			
(6) (log) Total non-work travel distance	0.083*	-0.259*	0.074*	-0.131*	0.766*	1.000		
(7) (log) Total travel distance	0.082*	0.359*	0.823*	0.645*	0.222*	0.480*	1.000	
(8) (log) Daily car kilometres	0.026	0.208*	0.506*	0.441*	0.150*	0.325*	0.633*	1.000

Note. * $p < 0.05$.

4. Methods

In this chapter, first the variance inflation factor (VIF) of the variables will be reviewed to check for multicollinearity, after which a Breusch-Pagan test is conducted to see whether there is evidence of heteroskedasticity. Finally, the statistical method that will be applied will be discussed.

4.1 Multicollinearity

Multicollinearity arises when two or more variables in a statistical model are highly correlated, creating a situation in which it is difficult to determine the individual impact of each covariate. This can cause inflated error terms, unreliable estimates, and overfitting. The overinflating of standard errors could ultimately lead to falsely attributing statistically insignificant results to variables that should in fact be statistically significant (Daoud, 2017). Multicollinearity can be discovered by examining the variance inflation factor (VIF). A VIF of 1 signifies that the variables are not correlated to each other, while a value between 1 and 5 indicates that the variables are moderately correlated to each other. VIF values between 5 and 10 are a sign of multicollinearity, while values above 10 indicate that the results are very heavily influenced by the presence of multicollinearity (Shrestha, 2020). The VIF values of the variables in models 1, 2 and 3 are presented in Table 4.1. With VIF values between 1 and 4 and average VIF values of around 2, there is no indication of collinearity in these models.

4.2 Heteroskedasticity

Heteroskedasticity, which refers to the circumstance where the variance of the error terms in the model is not constant across all observations, can pose several problems in regression analysis. The absence of homoskedasticity can lead to inefficient estimators, invalid standard errors, and compromised test statistics (Rigobón, 2003). Breusch and Pagan (1979) developed a method for testing heteroskedasticity, with the null hypothesis being the absence of such variance. Table 4.2 displays the results of the Breusch-Pagan test, revealing that the null hypothesis is rejected across all models, indicating the presence of heteroskedasticity in each case. In order to diminish the problems that arise due to the presence of heteroskedasticity, robust standard errors are used in all models.

Table 4.1 VIF values of variables

Variable	Model 1	Model 2	Model 3
(log) Teleworking %	1.15	1.12	1.10
Total hours worked in recent week	1.40		
(log) Total travel distance			1.06
Education			
Intermediate	2.34	2.45	2.35
Higher	2.66	2.81	2.71
Income			
Medium	2.13	2.19	2.16
High	2.67	2.76	2.77
Very high	2.63	2.71	2.74
Age			
30-39 years old	2.17	2.11	2.15
40-49 years old	2.08	2.04	2.06
50-59 years old	2.17	2.10	2.16
60 years and older	1.54	1.44	1.51
Male	1.35	1.05	1.05
Children	1.22	1.21	1.23
Level of urbanisation			
Low urbanisation	2.86	2.92	2.86
Moderately urbanised	2.71	2.79	2.71
Highly urbanised	3.51	3.60	3.52
Very highly urbanised	3.12	3.23	3.18
Presence of car in the household			1.16
Mean VIF	2.13	2.18	2.06

Note. Reference categories are Basic education for Education, Low income for Income, 18-29 years old for Age, and Non-urbanised area for Level of urbanisation.

Table 4.2 Breusch-Pagan test values

Model	X^2	p-value
1 – H1	535.26	0.0000
2 – H2	1542.72	0.0000
1 – H3	852.29	0.0000
1 – H4	721.25	0.0000
1 – H5	1018.12	0.0000
1 – H6	433.40	0.0000
3 – H7	651.48	0.0000

4.3 Statistical method

To evaluate the hypotheses and assess the impact of teleworking on travel demand, a panel data regression model will be employed, leveraging the longitudinal nature of the data. A nuanced analytical approach is required as the literature identified potential issues with self-selection in the relationship between commuting distance and the propensity to work from home (Faber et al., 2023). These nuances suggest that teleworkers have different travel preferences and patterns compared to non-teleworkers, potentially influenced by longer commuting distances for teleworkers.

While a fixed effects model is particularly suitable for addressing unobserved heterogeneity and controlling for endogeneity by focusing on within-individual changes over time, it may not be the most effective method given the characteristics of the data, as a fixed effects model eliminates any time-invariant characteristics. The vast majority of the explanatory variables in this thesis are either categorical or binary. For variables such as age, which is categorised in age brackets of 10 years, and household income, which is categorised in large income brackets, very little or no within-variations are present, especially given the three-year span of the panel. Additionally, only 38.65% of the sample participated in all three years, indicating even less within-variation. This is a significant limitation as the lack of within-variation, coupled with the short duration of the panel, reduces the effectiveness of the fixed effects model for this thesis.

Another model to consider is the random effects model. While less suitable for handling unobserved individual heterogeneity, this model utilises both within and between individual variations, thereby exploiting more of the data in the regression. Employing a random effects model not only improves the efficiency of the estimates, given the nature of the data – most covariates behave time-invariant, but also allows for the inclusion of time-invariant variables, such as gender, that contribute to the understanding of travel behaviour.

A common approach to determining which model is most suitable is to conduct the Hausman (1978) test. The results suggest opting for the fixed effects model, as the null hypothesis that the individual-specific effects are not correlated with the explanatory variables is rejected. However, as argued by

Bliese et al. (2019), a significant Hausman test does not inherently require a fixed effects model if solely between-effects are expected and between-effects are the main focus of the research. Therefore, despite the Hausman test suggesting the presence of endogeneity, the nature of the data and the research context guide the choice towards employing a random effects model.

The model is specified as follows:

$$Y_{it} = aTeleworking_{it} + \beta X_{it} + \delta T_t + \mu_i + \epsilon_{it}$$

where Y_{it} symbolizes the dependent variables capturing travel demand for individual i at time t, X_{it} represents a set of control variables, T_t captures year-specific effects, μ_i denotes the random individual-specific effect and ϵ_{it} signifies the error term.

The study estimates separate models for each dependent variable corresponding to the hypotheses: commuting frequency (H1), average commuting distance (H2), average daily commute distance (H3), frequency of non-work trips (H4), average daily non-work-related travel distance (H5), average daily total distance travelled (H6), and average daily distance travelled by car (H7). Year dummies are included to mitigate the effect of year-specific shocks, such as gas prices, on travel demand.

5. Results

In this chapter, the results of the regression analysis will be discussed to determine which hypotheses are accepted or rejected. The goodness-of-fit of the models will be examined, and robustness checks will be conducted.

5.1 Effect of teleworking on commuting behaviour (H1-H3)

The regression results are displayed in Table 5.1.[1] In support of H1, model M1-H1 reveals a statistically significant negative relationship between teleworking and commuting frequency. More specifically, the model shows that a 1% increase in the teleworking ratio reduces the commuting frequency by approximately 0.049%, suggesting that higher levels of teleworking reduce commuting frequency. Interestingly, except for the total number of hours worked (0.007, $p < 0.001$), only statistically significant effects are observed for individuals holding higher education (0.099, $p < 0.001$) and being male (0.069, $p < 0.001$), both contributing to increased commuting frequencies.

Model M2-H2 reveals a statistically significant positive relationship between the average commuting distance and teleworking, in line with H2, suggesting that a 1% increase in the teleworking ratio increases the average commuting distance by 0.047%. This relationship is influenced by income levels and education, with increased income levels and higher attained levels of education contributing to increased average commuting distances. Conversely, higher age levels are negatively associated with average commute distances. Similarly, higher levels of urbanisation are associated with shorter commutes. Being a male significantly increases commuting distances (-0.435, $p < 0.001$), while the presence of children in the household slightly decreases them (-0.093, $p < 0.001$).

Model M1-H3 supports H3 by revealing a statistically significant relationship between teleworking and the total commuting distance, showing that a 1% increase in the teleworking ratio decreases the overall net commuting distance by 0.1%, possibly due to fewer commuting trips despite longer average distances. To be expected, the total number of hours worked is also associated with greater total travel distances (0.024, $p < 0.001$). Additionally, higher education levels and very high income show a positive relationship with net commute distances, while being 50 years and older and living in very highly urbanised areas are associated with lower net commute distances. Males are associated with significantly higher net commute distances (-0.428, $p < 0.001$).

Teleworking is thus found to be associated with reduced commuting frequency and total commuting distances and increased average commuting distances, reflecting a shift towards less

[1] Reference categories are Basic education for Education, Low income for Income, 18-29 years old for Age, and Non-urbanised area for Level of urbanisation.

frequent but potentially longer commutes. The influence of gender, education, and income highlights varied commuting patterns, with males and higher-income groups exhibiting more frequent and longer commutes. Urbanisation also impacts commuting distances, signifying shorter commutes in more urban, and thus more densely populated areas.

5.2 Effect of teleworking on non-work travel behaviour (H4-H5)

Supporting H4, model M1-H4 shows that teleworking is statistically significantly associated with the frequency of non-work-related trips, suggesting that a 1% increase in the teleworking ratio increases the number of non-work-related trips by 0.032%. The total number of hours worked is negatively associated with the number of non-work-related trips (-0.011, $p < 0.001$). Similar to commute travel, individuals with higher levels of education reveal increased non-work travel frequencies. Age levels are also statistically significant, with individuals aged 60 years and older (0.197, $p < 0.001$) and individuals aged 30-39 (0.176, $p < 0.001$) travelling more often for non-work-related purposes compared to younger adults, followed by individuals aged 40-49 (0.131, $p < 0.01$) and 50-59 (0.094, $p < 0.001$). Being male is associated with making fewer non-work-related trips. (-0.152, $p < 0.001$).

Additionally, the results in M1-H5 confirm H5, indicating a statistically significant relationship between teleworking and the total non-work-related travel distance. In this model, a 1% increase in the teleworking ratio is associated with a 0.056% increase in the total non-work-related travel distance. Thus, despite reducing commuting, teleworking may encourage more frequent travel for non-work purposes, resulting in greater non-work travel distances. Similar to model M1-H4, higher education levels are associated with greater total non-work-related travel distances, and a higher number of hours worked (-0.015, $p < 0.001$) is negatively associated with non-work-related travel distances. Additionally, high (0.198, $p < 0.01$) and very high (0.207, $p < 0.01$) income levels were also associated with greater non-work-related travel distances. In contrast to model M1-H4, age reveals a less pronounced effect, with only individuals aged 30-39 showing a positive relationship with greater non-work travel distances (0.204, $p < 0.01$). Being male (-0.186, $p < 0.001$), the presence of children in the household (-0.218, $p < 0.001$) and living in highly (-0.182, $p < 0.05$) and very highly (-0.197, $p < 0.05$) urbanised areas are associated with smaller non-work-related travel distances.

Teleworking is thus associated with increased non-work travel, both in frequency and total distance. This suggests that teleworkers may indeed invest the time saved from commuting for additional non-work-related activities, in line with the theory of constant time-travel budgets. Additionally, higher education and income levels are associated with more non-work travel, while the presence of children in the household and urban living tend to reduce these travel behaviours.

5.3 Effect of teleworking on travel demand and car travel demand (H6-H7)

The results of model M1-H6 suggest that despite decreases in total commuting distances and decreases in total non-work-related distances, teleworking has no significant effect on reducing total travel distances, contrary to H6. This could be due to the increase in non-work travel offsetting the reduction in commute travel. A greater number of hours worked is associated with greater total travel distances (0.007, $p < 0.01$). Intermediate (0.289, $p < 0.001$) and higher (0.544, $p < 0.001$) education and high (0.217, $p < 0.01$) and very high (0.289, $p < 0.001$) income levels are associated with increased total travel distances. Males (0.258, $p < 0.001$) generally have greater total travel distances, while the presence of children in the household (-0.148, $p < 0.01$) is negatively associated with total travel distances. Living in moderately (-0.262, $p < 0.01$), highly (-0.251, $p < 0.01$) and very highly (-0.404, $p < 0.001$) urbanised areas reduces overall distances travelled.

Model M3-H7 examines the impact on the demand for car travel, finding no significant relationship between teleworking and total car kilometres, rejecting H7. This indicates that teleworking does not necessarily lead to an increase in car usage, despite shifts in other travel behaviours. Not surprisingly, total travel distances (0.792, $p < 0.001$) and the presence of a car in the household (1.196, $p < 0.001$) are very strongly correlated with daily car kilometres travelled. Interestingly, even though greater commute and non-work travel distances are observed for the high-income group, lower average daily car distances are associated with high-income individuals (-0.127, $p < 0.05$). Being aged 30-39 (0.122, $p < 0.05$) and being male (0.189, $p < 0.001$) are associated with increased car usage. Additionally, the higher the degree of urbanisation, the lower the number of daily car kilometres observed.

Despite alterations in commute and non-work travel patterns, teleworking was not found to significantly reduce overall travel demand or influence demand for car travel, contradicting the hypothesised relationships. Demographic factors, including education and income, were found to significantly shape travel behaviours, influencing the total travel distance and car usage, with higher degrees of urbanisation being associated with less car travel.

Table 5.1 Full sample random effects regression results

	M1-H1	M2-H2	M1-H3	M1-H4	M1-H5	M1-H6	M3-H7
(log) Teleworking %	-0.049***	0.047***	-0.100***	0.032***	0.056***	-0.010	-0.014
	(0.004)	(0.012)	(0.017)	(0.006)	(0.014)	(0.014)	(0.012)
Total hours worked in	0.007***		0.024***	-0.011***	-0.015***	0.007**	
recent week	(0.001)		(0.003)	(0.001)	(0.003)	(0.003)	
(log) Total travel distance							0.792***
							(0.014)
Education							
Intermediate	0.026	0.166**	0.208**	0.083**	0.200**	0.289***	0.108
education	(0.020)	(0.057)	(0.072)	(0.029)	(0.064)	(0.064)	(0.061)
Higher	0.099***	0.297***	0.509***	0.124***	0.249***	0.544***	0.118
education	(0.021)	(0.060)	(0.075)	(0.030)	(0.067)	(0.067)	(0.065)
Income							
Medium	0.019	0.116*	0.128	-0.009	0.105	0.120	-0.002
income	(0.022)	(0.056)	(0.079)	(0.031)	(0.070)	(0.069)	(0.065)
High income	0.000	0.160**	0.117	0.013	0.198**	0.217**	-0.127*
	(0.022)	(0.057)	(0.077)	(0.030)	(0.066)	(0.066)	(0.062)
Very high	-0.010	0.234***	0.174*	0.000	0.207**	0.289***	-0.035
income	(0.024)	(0.063)	(0.085)	(0.033)	(0.071)	(0.072)	(0.070)
Age							
30-39 years old	-0.020	-0.117*	-0.092	0.176***	0.204**	-0.039	0.122*
	(0.019)	(0.050)	(0.073)	(0.027)	(0.066)	(0.062)	(0.062)
40-49 years old	0.023	-0.176**	-0.041	0.131***	0.120	-0.030	0.128
	(0.021)	(0.056)	(0.077)	(0.030)	(0.069)	(0.067)	(0.067)
50-59 years old	0.015	-0.249***	-0.158*	0.094**	0.099	-0.110	0.047
	(0.021)	(0.058)	(0.078)	(0.029)	(0.070)	(0.067)	(0.067)
60 years and	-0.023	-0.299***	-0.363**	0.197***	0.164	-0.162	0.058
older	(0.030)	(0.080)	(0.107)	(0.040)	(0.092)	(0.088)	(0.088)
Male	0.069***	0.435***	0.428***	-0.152***	-0.186***	0.258***	0.189***
	(0.015)	(0.038)	(0.055)	(0.022)	(0.049)	(0.047)	(0.042)
Children	-0.002	-0.093*	-0.063	0.004	-0.218***	-0.148**	0.016
	(0.014)	(0.037)	(0.050)	(0.020)	(0.046)	(0.043)	(0.044)
Level of urbanisation							
Low	0.044	-0.181*	-0.005	-0.013	-0.064	-0.118	-0.168*
urbanisation	(0.027)	(0.076)	(0.101)	(0.041)	(0.091)	(0.081)	(0.076)
Moderately	0.050	-0.285***	-0.058	-0.025	-0.100	-0.262**	-0.302***
urbanised	(0.027)	(0.076)	(0.101)	(0.042)	(0.094)	(0.082)	(0.080)
Highly	0.029	-0.301***	-0.128	-0.043	-0.182*	-0.251**	-0.385***
urbanised	(0.025)	(0.073)	(0.096)	(0.039)	(0.087)	(0.077)	(0.074)
Very highly	0.025	-0.475***	-0.245*	-0.048	-0.197*	-0.404***	-0.597***
urbanised	(0.027)	(0.077)	(0.100)	(0.041)	(0.091)	(0.081)	(0.080)
Presence of car in the							1.196***
household							(0.075)

Table 5.1 (continued)

	M1-H1	M2-H2	M1-H3	M1-H4	M1-H5	M1-H6	M3-H7
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared (overall)	0.0693	0.0862	0.0773	0.0813	0.0364	0.0519	0.4771
Wald Chi2	328.06***	294.10***	364.33***	352.04***	183.16***	242.57***	4,286.96***
Number of observations	6,828	5,080	6,828	6,828	6,828	6,828	6,828
Number of individuals	3,286	2,724	3,286	3,286	3,286	3,286	3,286

Note. Robust standard errors in parentheses; dependent variables are (log) Commuting Frequency (M1-H1), (log) Average Commuting Distance (M2-H2), (log) Total Commuting Distance (M1-H3), (log) Non-work Travel Frequency (M1-H4), (log) Total Non-Work Distance (M1-H5), (log) Total Travel Distance (M1-H6) and (log) Daily Car Kilometres (M3-H7); reference categories are Basic education for Education, Low income for Income, 18-29 years old for Age, and Non-urbanised area for Level of urbanisation; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.4 Goodness of fit

The Wald Chi2 values, assessing the collective significance of the coefficients (Andrews, 1988), range significantly between models 1 and 2, having values of 183.16 to 364.33 with statistical significance at the 0.001 level. These values indicate that the independent variables collectively have a significant impact on the dependent variables from H1 to H6. The overall R-squared values across models 1 and 2 vary from 0.0364 to 0.0862, indicating that the models account for 3.64% to 8.62% of the variation of the dependent variables (Miles, 2005). Although the R-squared values could be considered low by some, similar values are not uncommon for travel behaviour models (Zhu, 2011). The effect sizes for R-squared of the models range between what is considered small (0.02) and medium (0.13) in behavioural science, as defined by Cohen (1988). For model 3, corresponding to H7, the Wald Chi2 and R-squared values are substantially higher compared to other models, with values of 4,286.96 (statistically significant at the 0.001 level) and 0.4771 respectively. This difference is likely caused by the strength of the variables representing the presence of a car in the household and the total travel distance, as the other models do not contain predictors of this magnitude.

5.5 Robustness checks

5.5.1 Time-fixed effects and temporal stability

The use of time-fixed effects allows to control for unobserved temporal influences that affect all individuals in the data, potentially reducing omitted variable bias. To assess whether time-fixed effects should be included in the model, the significance of the year dummies is displayed in Table 5.2. The coefficients for the log of commuting frequency are significantly different for both 2018 (-0.043, $p < 0.001$) and 2019 (-0.050, $p < 0.001$), indicating a trend towards less frequent commutes. Additionally, for the log of total commuting distance, the log of total non-work travel distance, and the log of total travel distance, significant drops were observed in 2019 compared to 2018. The R-squared values in Table 5.3 show that the models that include year-fixed effects lead to small but noticeable increases in the explanatory power of the models. The statistically significant coefficients and the slight increase in the R-squared values suggest that there are temporal changes that influence travel behaviour, and that the inclusion of time-fixed effects is useful.

Table 5.2 Year-fixed effects values

Variable	**Year**	**Year-fixed effect**
(log) Commuting frequency	2018	-0.043***
	2019	-0.050***
(log) Average commuting distance	2018	0.049*
	2019	0.044
(log) Total commuting distance	2018	-0.053
	2019	-0.088*
(log) Non-work travel frequency	2018	-0.011
	2019	-0.030
(log) Total non-work travel distance	2018	-0.011
	2019	-0.082*
(log) Total travel distance	2018	-0.025
	2019	-0.103**
(log) Daily car kilometres	2018	-0.018
	2019	0.028

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.3 Overall R-squared values with and without year-fixed effects

Model	**R-squared overall (with year-fixed effects)**	**R-squared overall (without year-fixed effects)**
M1-H1	0.0693	0.0670
M2-H2	0.0862	0.0856
M1-H3	0.0773	0.0769
M1-H4	0.0813	0.0809
M1-H5	0.0364	0.0358
M1-H6	0.0519	0.0511
M1-H7	0.4771	0.4770

5.5.2 Attrition bias

As displayed in Table 5.4, only 38.65% of individuals have been present in all three years. It is possible that the individuals that participated in 2018 and 2019 and the individuals that only participated in 2019 were only invited for the first time in 2018 and 2019 respectively. However, this would mean that at least 39.07% of participants dropped out of the sample at some point in time. Therefore, it is crucial to test for the possibility of attrition bias.

Table 5.4 Distribution of data presence in the sample

		Presence		
Frequency	**Percent**	**2017**	**2018**	**2019**
1270	38.65	X	X	X
478	14.55		X	X
427	12.99	X		
384	11.69	X	X	
333	10.13		X	
254	7.73			X
140	4.26	X		X

In order to test for attrition bias, two new variables are created. The first one is a binary variable that assumes a value of 1 if a person has been present for all three years. The second variable is a continuous variable that represents the number of years an individual was present in the data, thus taking values ranging from 1 to 3. If these variables are correlated with the dependent variables, it indicates that attrition might not be random, meaning that the patterns of missingness could bias the study results. The relationships between these two variables and the dependent variables are displayed in Table 5.5.

Table 5.5 Coefficients of the attrition indicators

Dependent variables	**Full presence variable**	**Years present variable**
(log) Commuting frequency	0.039** (0.013)	0.025** (0.008)
(log) Average commuting distance	-0.020 (0.038)	0.002 (0.023)
(log) Total commuting distance	0.104* (0.048)	0.080** (0.030)
(log) Non-work travel frequency	0.064** (0.020)	0.033** (0.012)
(log) Total non-work travel distance	0.067 (0.043)	0.037 (0.028)
(log) Total travel distance	0.100* (0.041)	0.077** (0.026)
(log) Daily car kilometres	0.044 (0.042)	0.042 (0.027)

Note. Robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

For the log of commuting frequency, the log of total commuting distance, the log of non-work travel frequency, and the log of total travel distance, the coefficients of both the binary full presence variable and the continuous years present variable show statistically significant results. In all cases, the relationships are positive, suggesting that the ‘stayers’ are more active travellers than the ‘dropouts’. In order to assess the possibility of attrition bias, the regression results of the pure stayer subsample, displayed in Table 5.6, will be compared to the regression results of the full sample, as presented in Table 5.1.

In the pure stayer subsample, Models 1 and 3 had 3,810 observations and 1,270 individuals, compared to 6,828 observations and 3286 individuals in the full sample. For Model 2, this was 2,906 observations and 1,157 individuals in the pure stayer subsample and 5,080 observations and 2,724 individuals in the full sample. The overall R-squared values are quite similar for both samples, while the Wald Chi2 values in the full sample are around double those in the pure stayer sample, reflecting the difference in sample size.

When looking at the coefficients for teleworking, the directions of the relationships are the same. Consequently, H1 to H5 are accepted and H6 and H7 are rejected for both the full and pure stayer samples. When looking at the differences in magnitude, the effects of teleworking on commuting (H1-H3) are slightly stronger in the full sample, while the effects of teleworking on non-work travel (H4-H5) are associated with higher coefficients in the pure stayer sample. Of the 68 statistically significant relationships observed in the full sample, 48 were also found in the pure stayer sample, and all maintained the same directional relationship. No new relationships were found in the pure stayer sample that weren't already identified in the full sample.

The consistency in the direction of relationships between teleworking and travel behaviour across both the full and pure stayer samples indicates that key findings remain robust. This consistency strengthens the validity of conclusions related to teleworking's effects on the defined travel behaviour metrics. The observed difference in magnitudes suggests that attrition bias may influence the size of the relationships identified. Additionally, the pure stayer sample reports the majority, but not all, of the relationships identified in the full sample. The absence of a share of the relationships is potentially caused by the relatively small number of observations and individuals in the pure stayer sample, as the removal of some variability makes it harder to detect subtler associations. This is reflected by the increase in standard errors in the regressions with the pure stayer sample, indicating the loss of valuable information caused by attrition. While there are signs of attrition bias, the primary concern is the impact on the magnitude of the effects. Results should be generalised with caution. However, the potential bias does not undermine the conclusions as the direction of relationships between teleworking and travel behaviour metrics remains consistent.

Table 5.6 Pure stayer subsample random effects regression results

	M1-H1	M2-H2	M1-H3	M1-H4	M1-H5	M1-H6	M3-H7
(log) Teleworking %	-0.045***	0.040**	-0.084***	0.043***	0.079***	0.017	-0.010
	(0.006)	(0.015)	(0.023)	(0.009)	(0.020)	(0.019)	(0.018)
Total hours worked in	0.008***		0.027***	-0.009***	-0.009*	0.011**	
recent week	(0.001)		(0.005)	(0.002)	(0.004)	(0.004)	
(log) Total travel distance							0.798***
							(0.021)
Education							
Intermediate	0.015	0.129	0.143	0.073	0.190	0.217*	0.094
education	(0.032)	(0.087)	(0.107)	(0.051)	(0.101)	(0.094)	(0.099)
Higher	0.101**	0.272**	0.502***	0.072	0.263*	0.481***	0.205
education	(0.032)	(0.091)	(0.114)	(0.052)	(0.105)	(0.098)	(0.105)
Income							
Medium	-0.033	-0.047	-0.132	0.002	0.058	-0.103	0.012
income	(0.034)	(0.077)	(0.119)	(0.047)	(0.106)	(0.095)	(0.102)
High income	-0.058	0.078	-0.092	0.023	0.170	0.067	-0.124
	(0.034)	(0.079)	(0.119)	(0.047)	(0.102)	(0.093)	(0.103)
Very high	-0.061	0.133	-0.029	-0.004	0.083	0.080	-0.063
income	(0.037)	(0.091)	(0.132)	(0.051)	(0.111)	(0.103)	(0.116)
Age							
30-39 years old	-0.016	-0.151*	-0.087	0.116**	0.154	-0.013	0.183
	(0.029)	(0.075)	(0.113)	(0.042)	(0.104)	(0.097)	(0.100)
40-49 years old	0.024	-0.261**	-0.103	0.094*	0.048	-0.041	0.206
	(0.031)	(0.083)	(0.120)	(0.047)	(0.110)	(0.103)	(0.109)
50-59 years old	0.004	-0.350***	-0.227	0.060	0.026	-0.190	0.202
	(0.032)	(0.088)	(0.122)	(0.047)	(0.113)	(0.105)	(0.111)
60 years and	-0.021	-0.276*	-0.351*	0.158**	0.098	-0.195	0.206
older	(0.044)	(0.114)	(0.167)	(0.060)	(0.143)	(0.137)	(0.141)
Male	0.073**	0.463***	0.448***	-0.203***	-0.309***	0.235***	0.193**
	(0.021)	(0.055)	(0.081)	(0.032)	(0.070)	(0.065)	(0.063)
Children	0.007	-0.111*	-0.042	0.004	-0.174*	-0.150*	-0.001
	(0.020)	(0.051)	(0.072)	(0.030)	(0.067)	(0.060)	(0.067)
Level of urbanisation							
Low	0.016	-0.272**	-0.137	0.018	0.012	-0.176	-0.273**
urbanisation	(0.037)	(0.098)	(0.141)	(0.063)	(0.140)	(0.111)	(0.104)
Moderately	0.023	-0.370***	-0.193	0.044	0.031	-0.317**	-0.442***
urbanised	(0.038)	(0.101)	(0.144)	(0.068)	(0.147)	(0.112)	(0.112)
Highly	0.026	-0.362***	-0.146	-0.028	-0.103	-0.247*	-0.454***
urbanised	(0.035)	(0.096)	(0.135)	(0.063)	(0.137)	(0.103)	(0.102)
Very highly	0.008	-0.515***	-0.337*	-0.054	-0.197	-0.508***	-0.710***
urbanised	(0.037)	(0.104)	(0.142)	(0.064)	(0.143)	(0.110)	(0.111)
Presence of car in the							1.218***
household							(0.106)

Table 5.6 (continued)

	M1-H1	M2-H2	M1-H3	M1-H4	M1-H5	M1-H6	M3-H7
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared (overall)	0.0725	0.0957	0.0846	0.0795	0.0399	0.0630	0.4802
Wald Chi2	167.33***	162.80***	186.77***	150.65***	91.17***	158.68***	2129.99***
Number of observations	3,810	2,906	3,810	3,810	3,810	3,810	3,810
Number of individuals	1,270	1,157	1,270	1,270	1,270	1,270	1,270

Note. Robust standard errors in parentheses; dependent variables are (log) Commuting Frequency (M1-H1), (log) Average Commuting Distance (M2-H2), (log) Total Commuting Distance (M1-H3), (log) Non-work Travel Frequency (M1-H4), (log) Total Non-Work Distance (M1-H5), (log) Total Travel Distance (M1-H6) and (log) Daily Car Kilometres (M3-H7); reference categories are Basic education for Education, Low income for Income, 18-29 years old for Age, and Non-urbanised area for Level of urbanisation; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6. Discussion

In the discussion, the findings that emerge from the results will be discussed, followed by an exploration of their implications for policymakers and planners. The end of this chapter will cover the limitations of this thesis and recommendations for further research.

6.1 Findings

6.1.1 Teleworking and commuting behaviour

The results indicate that teleworking reduces commuting frequency, increases average commuting distance, and decreases total commuting distance. More specifically, a 1% increase in the log percentage of hours worked at home is associated with a 0.049% decrease in the log of commuting frequency, a 0.047% increase in the log of average length of a commute, and a 0.100% decrease in the log of total commuting distance. As the independent and dependent variables were log-transformed, the coefficient should be interpreted as an elasticity. For instance, given that the teleworking rate in the Netherlands is approximately 8.7% (the sample mean), doubling this rate to 17.4% would represent a 100% increase. According to the analysis, this change would result in a 4.9% reduction in the number of commuting trips, a 4.7% increase in the average distance of each commute, and a 10% reduction in the total commuting distance. Consequently, H1, H2, and H3 are accepted.

The findings regarding the impact of teleworking on commuting behaviour align, for the most part, with the existing body of literature. The reduction in commuting frequency is consistent with the findings of Hamer et al. (1991), He and Hu (2015), and De Abreu E Silva and Melo (2018) from the Netherlands, the U.S., and the U.K., respectively. Additionally, the increase in the average distance of commuting trips is in line with the findings of De Vos et al. (2018) and Ravalet and Rérat (2019) from the Netherlands and Switzerland, possibly hinting at the idea of a higher willingness to accept longer commutes among teleworkers. Although no causality was established, as it was beyond the scope of this thesis, it did confirm that teleworkers are generally associated with longer average commutes than non-teleworkers. Lastly, the net result of H1 and H2, a decrease in the overall commuting distance, corresponds with findings from a recent study by De Vos et al. (2019) in the Netherlands. The results of this thesis are challenging to compare directly to other research because of the unique use of the (log of) percentage of hours worked at home as the independent variable. Most existing studies employed either binary indicators (e.g., teleworking or not) or frequency-based measures (e.g., days or hours teleworked per week). However, similar to the findings of De Vos et al. (2019), the results of this thesis suggest that the reductions in the total commuting distance are less than the naively expected decreases due to increases in commuting distances and part-time teleworking. For example, if an individual works one out of five days at home and starts working an additional day at home, reducing the number of commuting days from four to three days a week, naively, a 25% reduction in total commuting distances would be expected. However, according to the results of this research, this 100% increase in the teleworking ratio would result in a substantially smaller 10% reduction.

6.1.2 Teleworking and non-work travel behaviour

Regarding non-work travel, the results indicate that increases in the ratio of hours worked at home result in more frequent non-work-related trips and greater total daily distances travelled for non-work purposes. A 1% increase in the log of the teleworking percentage is associated with a 0.032% increase in the log of non-work trip frequency and a 0.056% increase in the log of the total non-work travel distance. More concretely, again assuming the teleworking rate in the Netherlands would double from 8.7% to 17.4%, the model suggests this would result in a 3.2% increase in the number of non-work-related trips and a 5.6% increase in the number of kilometres travelled for non-work activities. Consequently, H4 and H5 are accepted.

The acceptance of H4, concerning the frequency of non-work trips, is in line with research from Zhu (2011), Asgari et al. (2016), He and Hu (2015). Additionally, the acceptance of H5, posing that teleworking results in increased non-work travel distances, aligns with the findings of Faber et al. (2023), Zhu (2011), Cerqueira et al. (2020). However, the results differ from those of Glogger et al. (2008) and Hamer et al. (1991), who both found that teleworking leads to a decrease in the total number of trips, including non-work trips. It should be noted, however, that both studies involved around 60 participants each, which may have impacted the generalizability of their findings. Differences could also be explained in the way non-work travel was defined. For example, Glogger et al. (2008), focus on leisure travel, excluding non-work travel-related aspects that were included in this research, such as picking up and dropping off people. Generally, it can be concluded that the results of H4 and H5 agree with the existing body of literature.

6.1.3 Teleworking and total travel demand and car travel demand

Regarding H6, no significant relationships were found between the teleworking ratio and the average total distance travelled on a daily basis. The lack of evidence that teleworking decreases overall travel distance, despite increases in commute travel and decreases in commute travel, was also found by De Abreu E Silva and Melo (2018). These findings are contrasted by those of Lachapelle et al. (2017), who found that teleworking generally reduces overall travel, aligning with findings from Elldér (2020) and Stiles and Smart (2020) who observed that full-day telework is associated with reduced travel time due to a decrease in work travel and a smaller increase in non-work travel. Similarly, Glogger et al. (2008), Kiko et al. (2023) and Pendyala et al. (1991) report significant reductions in overall travel distances as a result of teleworking, thus suggesting a substitutive relationship between teleworking and travel. Zhu (2011), instead, found a complimentary relationship between the two in the US, caused by longer one-way commute trips in addition to longer and more frequent daily work and non-work trips. In Zhu's (2011) study, the decrease in commuting frequency was thus offset by longer commuting distances, resulting in greater total commuting distances for teleworkers, resulting in greater overall travel distances. The contrast in findings could be attributed to regional differences, variations in teleworking implementation, and differing travel and urban infrastructures. This reasoning does not follow for the alternative findings by Faber et al. (2023), who used the MPN data and reported reductions in overall mobility caused by teleworking. These differences are possibly explained by quantifying mobility as time spent travelling as opposed to distances travelled, as changes in travel time do not necessarily translate into changes in travel distance. Moreover, Faber et al. (2023) did not assess the impact of teleworking on total travel time; instead, they compared its separate effects on commute travel and non-work travel, the sum of which did not add up to the total travel time.

In addition to a lack of evidence that teleworking reduces overall travel distance, this research found no evidence that teleworking positively or negatively impacts vehicle kilometres travelled by car. In the literate review, a complex relationship arose between teleworking and modal choice, suggesting that teleworking is not likely to decrease car use but could potentially encourage more of it, caused by the propensity to live in low-density suburban areas with a higher reliance on car use. This argumentation was also followed by De Abreu E Silva and Melo (2018), who found that teleworkers in the U.K. are more frequent car users with higher weekly miles travelled by car compared to non-teleworkers due to higher car dependency in their respective residential areas. The difference in this result could be attributed to the differences in car reliance in the U.K. and the Netherlands, where the latter's robust cycling infrastructure and comprehensive public transport network may provide alternative ways of travel that reduce car dependency typically associated with suburban living. Research by Pendyala et al. (1991) found that teleworking reduced the number of car trips on teleworking days but did not take into account the total vehicle kilometres travelled by including non-teleworking days. There is little consensus about the effect of teleworking on car-usage, but it is evident that the occurrence and magnitude of this effect are highly context dependent. In the Dutch context, this thesis concludes that teleworking does not encourage or discourage car use as a whole.

6.2 Implications

The findings of this study provide valuable insights into how teleworking impacts travel behaviour. Since the results suggest that teleworking decreases commute travel and increases non-work travel, while not affecting overall travel demand, the main takeaway is that teleworking has a modification effect on travel (Salomon, 1986) by modifying the purposes of travel and the distribution of trips throughout the day. This finding has several implications for policymakers.

First of all, the significant reduction in commuting frequency and overall commuting distance suggests that teleworking could be an effective tool to relieve peak-hour congestion on highways and urban areas. Although no evidence was found that teleworking decreases travel demand as a whole, the reduction in the number of commuting trips, encouraged by flexible teleworking policies, frees workers from the constraints of rigid daily schedules. The increase in non-work travel frequency and distances indicates that teleworking might shift travel demand toward non-work-related activities, thereby potentially spreading out traffic loads across the day and week. Teleworking thus has the potential to reduce pressure on existing transportation infrastructures, thereby not reducing travel demand but rather balancing it.

Secondly, as a result of reduced peak-hour traffic, teleworking can benefit the environment in three ways. First of all, the reduction of road congestion can effectively aid in mitigating air pollution by reducing the duration of car travel and dispersing traffic away from heavily congested areas, which would facilitate a reduction in the accumulation of polluted air in heavily trafficked urban areas, where harmful emissions tend to linger (Zhang & Batterman, 2013). Next, fewer cars during rush hour can contribute to a more consistent traffic flow, which is associated with lower fuel consumption and emissions per vehicle compared to the stop-and-go traffic experienced in traffic (Li & Shimamoto, 2012). Also, reduced pressure on public transportation systems can make them operate more efficiently and reliably, making public transit a more attractive option for commuters (Daraio et al., 2016).

It should be noted, when looking at the broader systemic and indirect effects of reduced congestion and its associated environmental benefits, that these gains could be offset by induced demand (Faber et al., 2023). As roads, in conjunction with public transportation systems, become less congested as a result of a wide adoption of teleworking and consequently become more attractive, non-teleworkers might be encouraged to travel more, either by taking additional trips or moving further from the workplace, knowing that the commute will be smoother. Although challenging to quantify, Kiko et al. (2023) estimated induced demand to be a significant rebound effect, being of a greater magnitude than increased commute distances and more non-work travel. Policymakers and planners should not consider teleworking as a silver bullet for congestion relief, but rather see it as a part of a larger strategy, combined with measures such as congestion pricing, in which the related rebound effects are addressed. Additionally, the effectiveness of teleworking as part of a strategy is of course highly dependent on its nationwide adoption rate, with full-day teleworking having much more effect compared to partial-day teleworking.

Thirdly, the findings established that higher levels of teleworking are associated with higher average commuting distances. Although this association was found, the existence of the residential location effect was not causally established as it was beyond the scope of this thesis. Additionally, there is the possibility of reverse causality and self-sorting influencing the results. If reverse causality is at play, teleworking could be a response to long commutes rather than a cause of longer commuting distances, and this is likely to lead to overestimates (Gubins et al., 2019; He & Hu 2015). Self-sorting might also influence the results, where individuals who have certain travel preferences are more inclined to telework. If reverse causality and self-sorting are significant factors, promoting teleworking could still be an effective strategy to support those with long commutes, reducing their travel burdens. If teleworking does in fact increase the tolerance to commute greater distances, indicating the presence of the residential location effect, this means that teleworking relaxes people's constraint to live close to their workplace. This gives workers greater freedom to apply for jobs that were previously regarded as to far away to commute to on a daily basis, while also expanding the geographical area in which companies can recruit talent. Similarly, higher levels of teleworking would allow employees to look beyond urban centres for housing, possibly making suburban and rural areas more attractive. This shift would decrease demand pressure in cities, potentially stabilise urban housing prices, and increase demand in previously less popular areas. However, in order to draw any real conclusions based on this result and design effective policies, the causality between teleworking and the average commuting distance and the possibility of self-sorting and a bidirectional relationship influencing the relationship should be thoroughly examined.

Lastly, although teleworking has been hailed as a promising sustainable TDM strategy (Lachapelle et al., 2017) with the potential to reduce transportation-related pollution (Wang & Ozbilen, 2020) by reducing overall travel demand, this research found that teleworking does not influence total travel demand, or the number of car kilometres travelled. As it is expected that teleworking adoption will rise in the future, policymakers should focus on shifting car travel demand to more sustainable modes. As the increase in non-work travel distances suggests a shift in travel demand towards non-work-related activities, policymakers should explore ways to encourage sustainable modes of transportation for leisure and personal trips. This could be done by improving infrastructure for cycling and walking, expanding public transit options, and encouraging urban development in the spirit of '15-minute-cities', where residents can access most daily non-work necessities within a 15-minute walk or bike ride from their homes (Moreno et al., 2021). These strategies can help mitigate the environmental impact of increased non-work travel.

6.3 Limitations

There are several methodological challenges in examining the relationship between teleworking and travel behaviour, some of which were not addressed in this research.

In teleworking research, it is important to recognise the possibility of self-selection bias, sorting issues and reverse causality. Individuals opting for teleworking may inherently possess different travel preferences, introducing self-selection bias. He and Hu (2015) and Mokhtarian and Chen (2004) indicate that without accounting for this bias, studies might inaccurately attribute changes in travel behaviour to teleworking. Moreover, preferences for residential locations or work-life balance can influence both teleworking decisions and travel behaviours, contributing to sorting issues. Although many relevant covariates were added to the model, complete elimination of self-selection bias and sorting issues remains challenging. Bidirectional causality further complicates matters, as longer average commutes for teleworkers can not only hint at a higher willingness for long commutes but could also suggest that people with longer commutes might be more tempted to engage in teleworking practises (De Vos et al., 2019; Nilles, 1988). Neglecting this bidirectionality may introduce bias in simple analytical models, most likely leading to overestimates (Gubins et al., 2019; He & Hu, 2015). Including lagged variables as a robustness check was considered but was not suitable as a substantial portion of the sample was only observed for one year, making it impossible to create lagged variables without reducing the sample size. This reduction would limit the statistical power of the model and potentially introduce bias as a specific subset of individuals would be excluded. Furthermore, using lagged variables would prevent a fair comparison across models with and without lagged variables as the results would be based on different subsets of data. Therefore, the presence of reverse causality in this research can not be ruled out, and the results might be overestimated. These intertwined challenges necessitate thorough analytical approaches, such as panel data with fixed effects models, to control for individual-level effects and bidirectional relationships (De Vos et al., 2018). However, due to a lack of within-individual-level variation in the data, employing a fixed effects model was not suitable for this particular thesis.

Additionally, the choice to employ a random effects model while facing a significant Hausman-test introduces another limitation in this research. While the random effects model aligns with the research objectives and the nature of the data, using a random effects model could potentially introduce endogeneity issues that were not fully addressed. By not using a fixed effects model, the analysis retained the individual-specific random effects, which might be correlated with the explanatory variables, possibly introducing bias in the estimates. This limitation highlights the trade-off between thoroughly addressing endogeneity and capturing between-effects efficiently, a common challenge in choosing the appropriate econometric model for panel analysis, especially when confronted with imperfect data structures, as in this thesis.

Lastly, it is important to acknowledge the complexity of residential location choices and the decision to engage in teleworking. Regarding residential location choices, households often make these decisions based on numerous factors that go beyond commute considerations. In the case of two-earner households, dual-career scenarios make this decision-making process even more complicated and more difficult to establish a causal link (Deding et al., 2009). Attributing changes in commuting patterns solely to teleworking overlooks these multifaceted decision-making processes. Similarly, as Kiko et al. (2023) point out, viewing teleworking as an exogenous choice overlooks the complex evaluative process that workers undertake when deciding to telework or not. This research did not focus on the complexity of and motivations behind these decisions, and this should therefore be mentioned as a limitation.

6.4 Suggestions for further research

Following this research and the complexity of the relationship between teleworking and travel behaviour, there are several directions to consider for future research.

First of all, it would be interesting to differentiate between the different types of non-work travel. In this thesis, non-work travel was defined as trips for services and personal care, (grocery) shopping, social and recreational activities, touring and hiking, visitations, and other purposes. It would be relevant to distinguish between these different types of non-work travel, possibly differentiating between essential and less vital travel to better understand the nature of teleworking's impact on daily life.

Additionally, it would be valuable to further investigate the effect of teleworking on modal choice. This aspect of travel behaviour has not been thoroughly explored yet and there is little consensus about the effects of teleworking on private vehicles, public transport, and active mode use. This research concluded that the teleworking ratio had no significant influence on car travel demand, but it would be beneficial to know its effect on active modes and public transport in order to assess teleworking's potential to reduce traffic emissions.

While the COVID-19 pandemic prompted the mass adoption of teleworking arrangements, this particular research excluded the pandemic years from its scope, as its impact on travel behaviour and teleworking adoption would be nearly impossible to discern. However, as teleworking arrangements have outlasted the initial policies themselves and are expected to remain higher than pre-pandemic measures (Faber et al., 2023), it would be worthwhile investigating whether the substantial changes in travel behaviour moved back to pre-pandemic levels or if a lasting impact was made.

Lastly, little research has examined non-linearities in the relationship between the frequency of teleworking and travel behaviour. Investigating these dynamics is a challenge as there is often a lack of very frequent teleworkers in existing datasets, highlighting the need for larger and more diverse sample populations. (De Abreu E Silva & Melo, 2018). A deeper understanding of how varying degrees of teleworking frequency affect different aspects of travel behaviour, taking non-linearities into account, could inform policymakers about tipping points where teleworking shifts from having marginal to significant effects on travel patterns, enabling more effective transportation and urban planning strategies.

7. Conclusion

In the past decades, policymakers have increasingly acknowledged teleworking as a way of solving mobility issues, such as traffic congestion and pollution, by decreasing the frequency of commuting trips. Teleworking, which adds flexibility to people's lives by eliminating some or all weekly commuting trips, enables a relaxation of time-space constraints and is expected to lead to alterations in the travel behaviour of telecommuters and their household members. However, while it is widely accepted that teleworking reduces the frequency of commuting, there is a risk of potential rebound effects. In line with the idea of constant-time travel budgets, potential rebound includes the acceptance of longer commutes on office days, an increased frequency of non-work trips, and increased car dependence. Ultimately, there is no academic consensus on whether teleworking affects overall travel demand or whether its impact is one of substitution, complementarity, modification, or neutrality.

This thesis examined the relationship between teleworking and travel demand. More specifically, this thesis aimed to establish the relationships between teleworking on the one hand and commuting frequency, the average commuting distance, the total commuting distance, the non-work trip frequency, the total non-work travel distance, the total travel distance, and the number of car kilometres travelled. Teleworking was operationalized as the percentage of hours worked at home, which allowed for an examination of the relationship between the intensity of teleworking and its associated impact on travel behaviour.

Employing random effects models with data from the Netherlands Mobility Panel (MPN), this research confirmed the following hypothesised relationships: teleworking negatively correlates with both commuting frequency and total commuting distance, while positively affecting average commuting distance, non-work trip frequency, and total non-work trip distance. Teleworking was not found to have an effect on the total travel distance or the demand for car travel. This thesis concludes that in the Netherlands, teleworking modifies travel patterns by shifting travel demand from commuting to non-work purposes without reducing the overall travel demand. This shift in travel patterns, from commute to non-work activities, implies that teleworking has the potential to alleviate peak-hour congestion on roads and in public transportation systems and reduce its associated congestion emissions. Additionally, it suggests that teleworking could promote more flexible living and working situations, allowing individuals to live further away from their work, potentially making suburban and rural areas more desirable and alleviating pressure on housing markets in urban centres. When considering the broader systemic and indirect effects of reduced congestion and its associated environmental benefits, it's crucial to recognise that these gains could be offset by induced demand, where non-teleworkers might increase their travel due to smoother commutes. This rebound effect suggests that teleworking should be part of a larger strategy, including measures like congestion pricing, to effectively address congestion relief.

These findings are in line with the more recent body of literature that, contrary to the previously widely assumed net substitution effect, finds a modification effect of teleworking on net travel demand (Faber et al., 2023). It is essential for policymakers and urban planners to consider these nuanced impacts of teleworking on travel behaviour to design and implement more effective and sustainable urban transportation policies that reflect the dynamic developments in work arrangements in the digital age.

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