Travel Behaviour and Society 33 (2023) 100629

Contents lists available at ScienceDirect

Travel Behaviour and Society

journal homepage: www.elsevier.com/locate/tbs

Are slow internet connections limiting home working opportunities?

David Philip McArthur[a,*], Jinhyun Hong[b]

[a] Univeristy of Glasgow, Glasgow G12 8QQ, Scotland, United Kingdom
[b] Department of Smart Cities, University of Seoul, Seoul, South Korea

ARTICLE INFO

Keywords:
Teleworking
Work from home
Broadband
High-speed internet
Travel demand

ABSTRACT

The outbreak of COVID-19 in early 2020 resulted in many governments imposing restrictions on people's mobility and ordering workers to work from home where possible. As the pandemic has progressed, these restrictions have eased but many hope to maintain a higher frequency of working from home than they had before the pandemic. However, home working often requires a good internet connection. Those without good connections may have limited options for home working and may therefore have to travel to the office more often. In this paper, we examine whether people living in areas with faster internet connections are more likely to have increased their frequency of telecommuting compared to those in areas with slower connections. We also examine whether home working reduces overall travel demand, or whether there is a rebound effect. We find that faster connections are associated with an increase in the frequency of home working. As expected, these workers do not travel as much for work purposes. There is no evidence of a rebound effect for these workers.

1. Introduction

Advances in Information and Communication Technologies (ICTs) over the past decades have reshaped the world. The rapid fall in the cost of communicating over vast distances led economist Frances Cairncross to declare The Death of Distance (Cairncross, 1997). Part of this was the idea that jobs would disperse from cities and workers would be able to work from a variety of different locations, a practice sometimes referred to as *teleworking* or *telecommuting*.

The term telecommuting is thought to have been introduced by Jack Nilles in 1973, who believed that taking work to the workers rather than the other way around could be a way to reduce traffic congestion. Results about the impact of telecommuting on travel demand have been mixed. Hook et al. (2020) present a systematic review of the literature on the impact of telecommuting on energy use (of which travel demand is a substantial component). Most of the studies they consider show a reduction in energy use, though a significant minority show neutral effects or even an increase in energy use.

There are, however, other potential benefits from teleworking. Fonner and Roloff (2010) found that high intensity teleworkers are more satisfied than their office-based counterparts. For instance, teleworking may help to achieve a better work-life balance. Baard and Thomas (2010) reported improved job satisfaction as well as productivity gains. In China, Bloom et al. (2015) found that working from home could increase productivity. In addition, there is the potential to improve access to employment for people with disabilities (Schur et al., 2020). Anderson et al. (2015) found that there can be substantial benefits from home working, but note that the effects may vary between different types of people. Lara-Pulido and Martinez-Cruz (2022) show that workers have a substantial willingness to pay in order to be able to work at least some of the time from home.

Measuring the prevalence of teleworking can be difficult due to a lack of agreement on the definition of the term (Mokhtarian et al., 2005). Some studies focus on workers who work mainly from home. For example, using the Sixth European Working Conditions Survey (EWCS) Ojala and Pyöriä (2018) found that only around 3% of wage/salary earners in the EU teleworked mainly from home. Anderson et al. (2015) estimated the share of workers in the US who worked at least some hours from home, and found that in 2011 around one quarter of Americans worked at least some hours from home each month. Similarly high shares were reported in Sweden and Finland.

There is renewed interest in teleworking in light of the COVID-19 pandemic. The spread of the virus in early 2020 resulted in many governments around the world imposing various restrictions on their citizens. Over 80% of the global workforce lived in countries with full or partial lockdowns (ILO, 2020). Among these restrictions was a requirement for workers to work from home where possible. This led to an unprecedented rise in working from home. Okuyan et al. (2022)

* Corresponding author.
E-mail addresses: david.mcarthur@glasgow.ac.uk (D.P. McArthur), Jinhyun.Hong@uos.ac.kr (J. Hong).

https://doi.org/10.1016/j.tbs.2023.100629
Received 16 August 2022; Received in revised form 9 June 2023; Accepted 25 June 2023
Available online 14 July 2023

noted that as of February 2020, 46% of businesses in the US had implemented teleworking policies. This creates an interesting and useful natural experiment.

Many of the requirements to work from home were subsequently relaxed. However, there is evidence that many wish to incorporate more frequent home working beyond the pandemic. In a study in Melbourne, Australia, Jain et al. (2022) found that post-pandemic working from home could increase by 75%. Currie et al. (2021) also suggested increased home working in the future. Barrero et al. (2021) suggested that 20% of workdays will be supplied from home post-pandemic compared to around 5% before. Sanchez et al. (2021) estimated that globally, around 20% of jobs could be performed from home.

However, the choice to work from home is not evenly distributed across workers. While it is estimated that 37% of US jobs could be done entirely from home (Dingel and Neiman, 2020), certain jobs are better suited to this than others (Okuyan et al., 2022; Budnitz and Tranos, 2022). Access to appropriate equipment is also important in determining whether a person works from home (Jain et al., 2022). During the pandemic, it became clear that access to a high-speed internet connection was essential for most people to be able to work effectively from home (Lai and Widmar, 2021; Ford et al., 2021).

There is already evidence that access to a high-speed internet connection increases the likelihood of people working from home (Han, 2021). However, there is no generally agreed upon definition of high-speed internet. We extend the current literature by posing two research questions: 1) Are people living in areas with faster internet connections more likely to have increased their telecommuting frequency relative to its pre-pandemic level? 2) Do people who have increased their telecommuting frequency travel less than people who have not? It is particularly important to better understand these relationships at the current juncture. Levels of home working have increased, but some people may be excluded from these benefits if they live in areas with inadequate digital infrastructure or if internet connections are not affordable.

We make use of a 2021 travel survey from the Puget Sound region of Washington state, US and a series of regression models. We find evidence that higher speed connections in a person's neighbourhood are positively associated with increases in telecommuting frequency relative to pre-pandemic telecommuting frequencies. Furthermore, we find that people who have increased their telecommuting frequency tended to travel less far for work and work-related purposes. We do not find any increase in non-work travel for this group.

The paper is structured as follows. Section 2 provides a review of studies examining impacts of access to the internet, variations in the speed of access, and impacts of telecommuting on travel demand. In Section 3 we outline the data, methods and models used in the paper. Results are presented in Section 4 with some concluding remarks made in Section 5.

2. Literature review

Athanasiadou and Theriou (2021) noted that several different terms are often used interchangeably in the literature to discuss the same phenomenon e.g., homeworking, telehomeworking, telecommuting, remote working, virtual work, electronic home working, e-work, distributed work, home-anchored work, and telework. During the pandemic it became common to refer to work from home, often abbreviated to WFH (Loo and Huang, 2022; Mehta, 2021; Galanti et al., 2021). We consider studies naming any of these topics to be potentially relevant to our study.

2.1. Impacts of access to the internet

Access to a high-speed internet connection has been shown to have many benefits. It can improve student performance (Sanchis-Guarner et al., 2021; Hampton et al., 2020), stimulate the birth of new enterprises (Conroy and Low, 2022), improve employment outcomes (Zuo, 2021; Lobo et al., 2020; Dettling, 2017; Bai, 2017), improve public health and racial justice (Early and Hernandez, 2021), and even improve fertility (Billari et al., 2019). The COVID-19 pandemic and the subsequent response to it has generated renewed interest in the relationship between internet access and telecommuting.

Telecommuting and its impacts have long been of interest to researchers. Towards the end of the 20th Century, Handy and Mokhtarian (1996) discussed the potential for telecommuting. At that time, they noted that the telephone was one of the most vital pieces of equipment. In 1992, only 30% of telecommuters made use of a modem to connect to the internet. In the time since then, access to a high-speed internet connection has become essential for home working (Lai and Widmar, 2021; Ford et al., 2021; Budnitz and Tranos, 2022; Kaushik and Guleria, 2020; Cotterill et al., 2020).

During the pandemic, Ford et al. (2021) found that slow connection speeds and unreliable connections were among the most frequently mentioned challenges reported by home workers. In an application of the theory of planned behaviour, Jain et al. (2022) found that access to relevant materials (e.g., ICT) was crucial in determining people's intention of working from home post-pandemic. Lai and Widmar (2021) noted that while inadequate access to the internet had long been considered an irritation, during the pandemic it became a crisis for many.

Inadequate internet access is not evenly distributed across space or the population. This contributes to what is often referred to as a *digital divide* (Scheerder et al., 2017). Internet access is usually subject to an urban/rural divide, with rural areas having lower quality connections and infrastructure (Phillipson et al., 2020; Ali, 2020; Salemink et al., 2017; Whitacre and Mills, 2007). Sarrasanti et al. (2020) noted that women typically have less exposure to digital technologies, thus creating a potential gender gap. This gap is found to be worse in developing countries and low-income countries (Kaushik and Guleria, 2020; Singh, 2017; Fuchs, 2009). Digital divides have also been found to exist with respect to age and education (Elena-Bucea et al., 2021; Hong et al., 2020) as well as race and income (Gao and Hayes, 2021). Sanders and Scanlon (2021) noted that the digital divide is a social justice as well as a human rights issue, and that minorities are particularly likely to be excluded from reliable high-speed internet connections.

2.2. Internet speed

Much of the literature discusses internet access, or high-speed internet access. The term is often ill defined and sometimes is used only to indicate a difference between a broadband connection and a slower dial-up connection (Dettling, 2017; Savage and Waldman, 2005). As technology has advanced, the distinction between dial-up and broadband has become less important. Martins and Wernick (2021) discussed current and future requirements for broadband connections. They noted that it is not only important to consider the download speed, but also the upload speed, latency and packet loss. The relative importance of these characteristics will vary according to the application. For home working, they suggested that an upstream and downstream speed of around 250 Mbps will be required by 2025 and that low latency and packet loss will be very important.

Kaushik and Guleria (2020) recommended that a reliable and fast internet connection is essential for effective home working. Good connections can be particularly important for applications such as group video calls (Amankwah-Amoah et al., 2021). Cotterill et al. (2020) noted that during the pandemic employees experienced difficulties with slow internet connections. Inadequate connections also caused problems for the academic sector as it moved many of its activities online during the pandemic (Corbera et al., 2020).

The results with respect to the role played by speed are somewhat mixed. For example, Bai (2017) studied employment impacts of broadband access at the county level. They found that access to broadband is important, but that the speed didn't seem to have an effect. Lai et al. (2020) studied the willingness to pay for internet connections in Indiana, US. They found a positive willingness to pay (WTP) for speed, though don't differentiate between upstream and downstream speed. The reliability of the connection was found to be an important attribute.

Liu et al. (2018) looked at willingness to pay for different aspects of broadband i.e., upload speed, download speed, data caps, and latency. They found a highly concave relationship for bandwidth. The WTP for different aspects depends on the usage type. For instance, people who transfer files have higher WTP for upload speeds. Gamers were more sensitive to latency than other groups.

Differentiating between different aspects of the internet connection may be important. For example, Dahiya et al. (2021) studied the performance of internet connections during the pandemic. They note that many ISPs reported the internet performed well during the pandemic despite the increase in demand. However, there was a large rise in the number of complaints. The authors suggested that part of the reason for this may be that ISPs focus on downstream speeds. These performed well during the pandemic. However, upstream speeds suffered far more. They suggested that during the pandemic, upstream speeds may have become more important and that it may be important to focus more on them.

It is worth noting that measuring the different aspects of internet connectivity can be challenging, and that even measuring speed is not entirely straightforward (Feamster and Livingood, 2020). Bronzino et al. (2021) discussed some of the limitations of different data sources for measuring speed. They noted, for instance, that survey data often gives very crude measures of access often only recording whether someone has broadband or not. Some studies adopt a different approach. For instance, Barrero et al. (2021) asked people to rate their internet connection quality based on a five-point scale detailing what percentage of the time the person can work from home without interruption caused by their connection. They found that people who rated their internet connection quality as higher indended to work from home on more days post-pandemic.

2.3. Work from home and travel demand

Our second research question asks whether people who work form home more often have reduced travel demand. Previous results on this topic are mixed, and there is substantial variability in the robustness of the methodological approaches taken (Hook et al., 2020). In a study in India, Nayak and Pandit (2021) found that work related travel decreased during the pandemic and that there was no compensatory increase in other travel.

Shabanpour et al. (2018) studied the Chicago area and found that increased home working can reduce congestion, vehicle miles travelled, and pollution. Jaff and Hamsa (2018) found that encouraging telecommuting among women in Kuala Lumpur can reduce the amount of travel they undertake.

Several other studies found that telecommuters tend to travel more. In the UK, De and Melo (2018) found that teleworking increases travel demand, and particularly travel by car. Similarly, Silva and Melo (2017) found that teleworking increases travel demand in single worker households. Several other studies also found a positive relationship between telecommuting and travel demand, sometimes caused by teleworkers having longer commute distances (Zhu et al., 2018; Zhu and Mason, 2014; Zhu, 2012).

In South Korea, Kim (2017) concluded that telecommuting can likely play only a limited role in reducing travel demand. They noted that other members of a household with a telecommuter may also have their travel patterns impacted. They did note that the departure times of telecommuters tended to be more flexible, and that telecommuting may therefore help to reduce congestion. Chakrabarti (2018) highlighted the fact that while telecommuting may help reduce travel demand, that the effect will not be automatic and that other policies may have to be implemented e.g., pedestrian infrastructure, suitable housing close to workplaces, and mixed land-use.

2.4. Summary

Previous studies have generally indicated that access to high-speed internet is an important determinant of home working. The responses to the COVID-19 pandemic saw a substantial increase in the volume of home working, and there is evidence that the level is unlikely to return to pre-pandemic levels. There is also evidence that poor internet connections posed challenges to those working or studying from home. However, there is no evidence about how the speed of available internet connections is associated with increases in telecommuting frequency.

Results about the impact of telecommuting on travel demand are mixed, with studies showing positive, negative and no effects. Given that the pandemic has increased home working so drastically, it is not clear whether the results which were relevant for pre-pandemic telecommuters are applicable to the current, expanded cohort of telecommuters.

3. Data and methods

Our first question is to establish whether there is an association between the speed of internet connections offered in an area and the likelihood of a person increasing the frequency of their telecommuting relative to pre-pandemic levels. Binomial logistic regression models will be used to test this hypothesis. For our second question, we wish to test whether travel demand is associated with changes in telecommuting frequency. This will be tested using Poisson regression models. All data processing and analysis is carried out using R [R Core Team (2022)][1].

3.1. Data sources

We make use of the 2021 travel survey conducted by the Puget Sound Regional Council[2] (PSRC). The council is a planning organisation for the metropolitan area of the city of Seattle, WA. The area has a population of around 4.3 million inhabitants. Data are collected from households across the King, Kitsap, Pierce and Snohomish counties. The survey is conducted every two years. The most recent edition, from 2021, was collected though an online survey. Respondents reported one day's travel designed to capture travel on a typical weekday. Address-based sampling was used with people being invited via mail to participate in the survey. A total of 6482 people from 2793 households were included in 2021. See RSG (2019) for more details on the survey.

Data on available internet speeds is taken from the Federal Communications Commission (FCC)[3]. The data refers to December 2020. It is derived from information filed by Internet Service Providers (ISPs) on the maximum advertised speeds (upstream and downstream) offered to different census blocks.

[1] The following packages are used: *janitor* (Firke, 2021), *purrr* (Henry and Wickham, 2020), *stringr* (Wickham, 2019), *vroom* (Hester et al., 2021), *tibble* (Müller and Wickham, 2022), *forcats* (Wickham, 2021a), *tidyverse* (Wickham, 2021b; Wickham et al., 2019), *tidyr* (Wickham and Girlich, 2022), *dplyr* (Wickham et al., 2022), and *readr* (Wickham et al., 2022) for data wrangling; *viridis* (Garnier, 2021), *ggplot* (Wickham et al., 2022; Wickham, 2016), *ggmap* (Kahle and Wickham, 2013; Kahle et al., 2019), *sf* (Pebesma, 2022; Pebesma, 2018), *hrbrthemes* (Rudis, 2020), *tigris* (Walker, 2022), *ggsflabel* (Yutani, 2022), and *ggsn* (Baquero, 2019) for data visualisation and mapping; *texreg* (Leifeld, 2013; Leifeld, 2022), *arsenal* (Heinzen et al., 2021), and *broom* (Robinson et al., 2022) for tables; and *ggeffects* (Lüdecke, 2018), *lmtest* (Hothorn et al., 2022; Zeileis and Hothorn, 2002), *sandwich* (Zeileis and Lumley, 2021; Zeileis, 2006; Zeileis et al., 2020), DescTools (Signorell, 2023), RMS (Harrell Jr, 2023),and *zoo* (Zeileis and Grothendieck, 2005; Zeileis et al., 2022) for modelling.

[2] The data are available fromhttps://www.psrc.org/household-travel-survey-program

[3] The data are available fromhttps://opendata.fcc.gov/Wireline/Fixed-Broadband-Deployment-Data-December-2020/hicn-aujz

Table 1
Summary statistics by change in telecommuting frequency.

	Increase (N = 444)	No change (N = 911)	Total (N = 1355)
Average download speed (Mbps)			
Mean (SD)	216.7 (77.3)	192.9 (94.3)	200.7 (89.7)
Range	0.0–339.5	0.0–344.2	0.0–344.2
Average upload speed (Mbps)			
Mean (SD)	76.8 (48.9)	63.9 (52.5)	68.1 (51.7)
Range	0.0–162.3	0.0–167.9	0.0–167.9
Commute distance (Miles)			
Mean (SD)	20.9 (28.3)	18.2 (19.1)	19.1 (22.6)
Range	0.0–282.5	0.0–303.7	0.0–303.7
Distance for work trips (Miles)			
Mean (SD)	7.3 (15.7)	15.4 (19.1)	12.7 (18.4)
Range	0.0–161.2	0.0–150.3	0.0–161.2
Distance for non-work trips (Miles)			
Mean (SD)	9.3 (23.1)	10.6 (72.9)	10.2 (61.2)
Range	0.0–212.0	0.0–2076.9	0.0–2076.9
Broadband			
No	30 (6.8%)	136 (14.9%)	166 (12.3%)
Yes	414 (93.2%)	775 (85.1%)	1189 (87.7%)
Age			
18–24 years	27 (6.1%)	106 (11.6%)	133 (9.8%)
25–34 years	115 (25.9%)	230 (25.2%)	345 (25.5%)
35–44 years	140 (31.5%)	209 (22.9%)	349 (25.8%)
45–54 years	82 (18.5%)	162 (17.8%)	244 (18.0%)
55–64 years	67 (15.1%)	152 (16.7%)	219 (16.2%)
65–74 years	13 (2.9%)	52 (5.7%)	65 (4.8%)
Gender			
Female	213 (48.0%)	447 (49.1%)	660 (48.7%)
Male	228 (51.4%)	457 (50.2%)	685 (50.6%)
Non-Binary	3 (0.7%)	7 (0.8%)	10 (0.7%)
Household income			
Under $25,000	16 (3.6%)	62 (6.8%)	78 (5.8%)
$25,000-$49,999	41 (9.2%)	171 (18.8%)	212 (15.6%)
$50,000-$74,999	57 (12.8%)	154 (16.9%)	211 (15.6%)
$75,000-$99,999	58 (13.1%)	141 (15.5%)	199 (14.7%)
$100,000-$199,000	175 (39.4%)	302 (33.2%)	477 (35.2%)
$200,000 or more	97 (21.8%)	81 (8.9%)	178 (13.1%)
Household includes children under 5			
No	379 (85.4%)	811 (89.0%)	1190 (87.8%)
Yes	65 (14.6%)	100 (11.0%)	165 (12.2%)
Household includes children age 5–17			
No	364 (82.0%)	719 (78.9%)	1083 (79.9%)
Yes	80 (18.0%)	192 (21.1%)	272 (20.1%)

3.2. Data processing

We begin by processing the data held in the person file. We keep only data from the 2021 survey. We include only people who are of working age and who are: 1) employed (full-time), employed (part-time), or self-employed[4]. Our analysis requires two dependent variables: one to look at whether a person has changed telecommuting frequency and the other to look at the distances travelled.

Our second dependent variables are extracted from the trips file. We sum the total distance travelled depending on the type of trip. If a trip's origin or destination was recorded as "work", then we class it as a work trip. Otherwise, it is classed as a non-work trip.

Next, we process the household PSRC data. We filter the data to include only the 2021 survey. The household file gives the census tract of the respondent, and a variable indicating whether the household has access to broadband. The variable records whether the household has access to broadband, whether they have the option of having broadband but don't have it, they have neither access nor the option of access, or they don't know. We recode this as a binary variable where a value of one indicates that they have access to broadband and zero indicates that they do not.

The data on broadband speeds are then processed. We extract records for the state of Washington. Next, the data is restricted to only operators offering services to consumers. The census tract's geographic identifier is exacted from the census block code. Only records relating to tracts where survey respondents live are retained. The remaining records are aggregated at the census tract level. We take the average of the maximum advertised upload and download speeds across all providers for each tract measured in Megabits per second (Mbps).

The datasets are then merged. We derive three variables. The first two are adjusted upload and download speeds. We derive these by multiplying the average speeds offered in the census tract by the dummy variable indicating whether the household has access to broadband. Therefore, if a household indicates that they have access to broadband, then they are assigned the average upload and download speeds from their census tracts. If they indicate that they do not have access to broadband, they are assigned upload and download speeds of zero.

The first dependent variable we create indicates whether someone has increased their telecommuting frequency. This is done using two variables. The first asks on how many days in the previous week the person telecommuted. The following options were available: None/never, 1–2 days, 3–4 days, 5 + days. They were also asked their telecommute frequency pre-COVID. Here, they could select: Not at all, Less than monthly, 1–3 times per month, 1–2 days a week, 3–4 days a week, 5 + days a week. Some were not asked the question, for example if they were not employed pre-COVID. If someone was not asked the question about pre-pandemic telecommuting, we counted them among the people who did not telecommute. Though their reasons for not telecommuting were different, they were nevertheless not telecommuting. Respondents were said to have increased their telecommuting frequency if they indicated that in the previous week they telecommuted more than their pre-COVID telecommuting frequency e.g., someone who telecommuted 1–2 days last week and indicated that they previously telecommuted less than weekly would be counted as having increased their telecommuting frequency.

Finally, we extract a number of control variables. We begin with the person file. Industry[5] is included as opportunities for home working vary between industries (Bartik et al., 2020; Barrero et al., 2021). Gender identity is included, with previous studies generally showing that men are less interested in home working (Barrero et al., 2021; Nguyen, 2021). Age is often included as a determinant of home working though does not always have a significant effect (Bloom et al., 2015; Barrero et al., 2021; Loo and Wang, 2018; Nguyen, 2021). We also include the distance between a person's home and workplace. This has been shown to have a broadly positive correlation with home working (De and Melo, 2018; Loo and Wang, 2018; Nguyen, 2021). From the household file we

[4] The choice of worker type included is likely to have an impact on our results. For example, someone working Monday to Friday, will have up to five days to divide between working in an office and working at home. On the other hand, part-time workers may place a greater value on flexibility and may be more likely to increase their home working frequency if possible. As a further test of robustness, we present our tables of results using only full-time workers in Appendix A.

[5] Industries are classed as: Health care, Government, Professional and business services (e.g., consulting, legal, marketing), Retail, Landscaping, Transportation and utilities, Social assistance, Financial services, Manufacturing (e.g., aerospace & defence, electrical, machinery), Public education, Technology and telecommunications, Real estate, Childcare (e.g., nanny, babysitter), Hospitality (e.g., restaurant, accommodation), Military, Sports and fitness, Private education, Arts and entertainment, Construction, Personal services (e.g., hair styling, personal assistance, pet sitting), Media, Natural resources (e.g., forestry, fishery, energy), and Other.

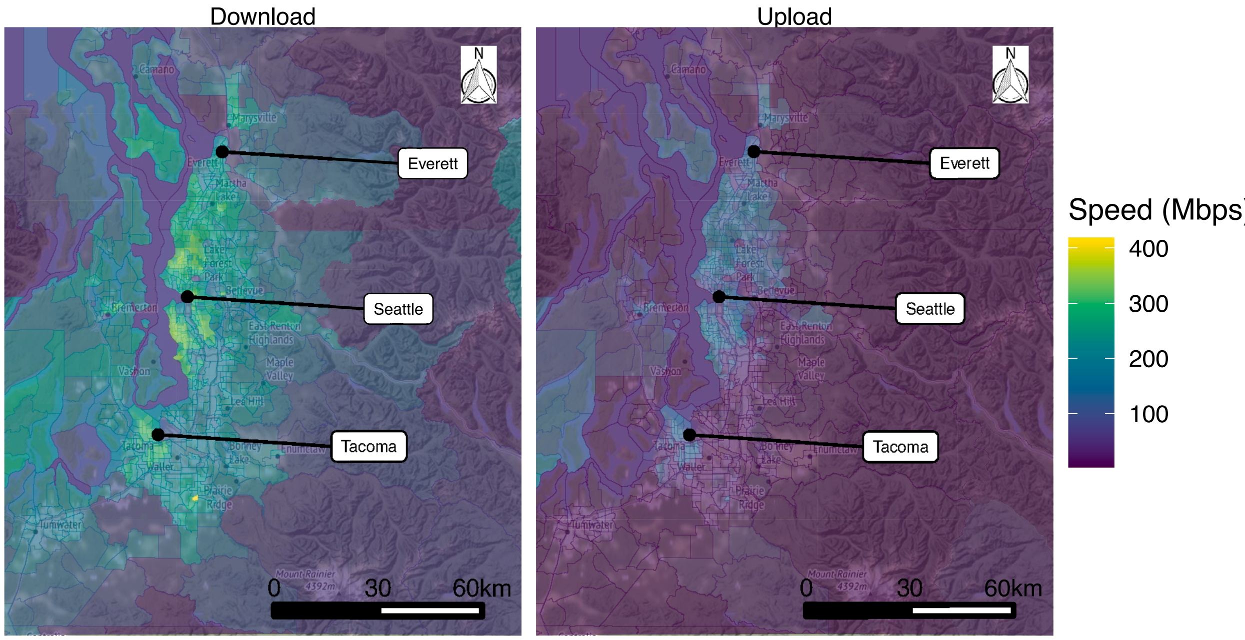

Fig. 1. Average maximum advertised speeds by census tract.

extract household income. Income has been shown to have a positive relationship with home working interest and intensity (Barrero et al., 2021; Loo and Wang, 2018; Mannering and Mokhtarian, 1995; Singh et al., 2013). We also include whether the household has children aged under 5 years or children aged 5 to 17 years. The presence of children in a household has been shown to generally have a positive relationship with the level of home working though it is not always a statistically significant effect (Barrero et al., 2021; Nguyen, 2021; Mokhtarian and Salomon, 1994; Loo and Wang, 2018; Iscan and Naktiyok, 2005; Sener and Reeder, 2012; Singh et al., 2013; Yen, 2000).

We exclude observations with data missing for these key variables. We also exclude respondents where the distance between their home and workplace is more than 1000 miles.

3.3. Summary of the data

In Table 1, we present summary statistics for our variables broken down by whether a person changed their telecommuting frequency. We see that around one third of the respondents reported an increase in telecommuting frequency compared to before the pandemic. We can also see that people who are now telecommuting more often live in areas where faster internet connections are advertised. This applies both to upload and download speeds. These people have less travel for work purposes as well as slightly less travel for non-work purposes.

One result from Table 1 is that income seems to have an important association with changes in telecommuting frequency. People living in households with the highest incomes are more likely to have increased their telecommuting frequency. This highlights the importance of controlling for income. It could be that people on higher incomes are more likely to have the kind of jobs which are amenable to home working. There are also reasons to believe that income may be correlated with internet speed and access. In our data, household income explains around 1.41% and 5.08% of the variation in upload and download speeds respectively. Recall that we multiply the connection speed by an indicator of whether the person has access to broadband. These measures thus account both for access to broadband and the available speed. If we consider only what speed is available in the area, then income is not a statistically significant predictor of either upload or download speed. For brevity, we do not include our industry variable in the summary statistics. It is worth noting, however, that industry explains around 3.55% of the variation in download speed and 3.95% of the variation in upload speed.

In Fig. 1, we consider the spatial distribution of upload and download speeds in the study area. Perhaps the most obvious pattern is that download speeds are on average higher than upload speeds. An urban/rural divide is also visible with speeds tending to be higher in the most urban areas and lower elsewhere. However, even within the urban areas there is variation in speeds between tracts.

3.4. Models

Our first research question requires us to test for an association between average internet connection speeds in an area and change in telecommuting frequency. To do this, we use a binary logistic regression model. Our dependent variable is whether someone has increased their telecommuting frequency relative to pre-pandemic levels ($y = 1$) or whether there has been no change (or a decrease) ($y = 0$). Our key independent variables are the average upload and download speeds advertised by ISPs in the respondents' census tracts. We also control for household income, age, gender identity, industry, the presence of children, and distance (by car) from a person's home to their workplace. The logistic regression model is given by:

$$Pr(y_i = 1|X) = \frac{e^{X\beta}}{1 + e^{X\beta}}$$

Where y is the probability of increasing the frequency of telecommuting, X is a matrix of explanatory variables, and β is a vector of parameters to be estimated. We are particularly interested in the parameters attached to the internet speed variables.

Our second research question asks whether an increase in telecommuting frequency is associated with changes in the distance travelled for work and non-work travel. Distance variables are highly skewed, positive, and include zero values. This makes robust estimation with ordinary least squares problematic. To deal with this skew, we use a generalised linear model (GLM) with a log link and assuming a Poisson distribution. This modelling approach is typically deployed for count data (Cameron and Trivedi (1986)). However, consistent estimates of the parameters can be obtained even when the outcome variable does

Table 2
Logistic models of whether or not the person has increased their telecommuting frequency.

	Full sample			Non-movers		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−0.1014	−0.2503	−0.1193	0.0245	−0.1804	−0.1337
	(0.7116)	(0.7115)	(0.6971)	(0.8993)	(0.9007)	(0.8871)
Internet connection speed						
Average download speed (x100 Mbps)	−0.0178	0.2466**		−0.1646	0.2248*	
	(0.1442)	(0.0841)		(0.1772)	(0.1035)	
Average upload speed (x100 Mbps)	0.5231*		0.4993***	0.7542**		0.5388***
	(0.2354)		(0.1347)	(0.2848)		(0.1624)
Commute distance						
Commute distance (x10 Miles)	0.0683*	0.0623*	0.0682*	0.0953*	0.0844*	0.0943*
	(0.0292)	(0.0289)	(0.0292)	(0.0405)	(0.0393)	(0.0402)
Household income (Ref: Under $25000)						
$25,000-$49,999	−0.1368	−0.1271	−0.1360	−0.3409	−0.3263	−0.3393
	(0.3758)	(0.3762)	(0.3758)	(0.4695)	(0.4694)	(0.4701)
$50,000-$74,999	0.2966	0.2962	0.2951	0.2400	0.2362	0.2204
	(0.3653)	(0.3651)	(0.3652)	(0.4441)	(0.4425)	(0.4436)
$75,000-$99,999	0.3345	0.3282	0.3334	0.3210	0.2930	0.3060
	(0.3649)	(0.3652)	(0.3649)	(0.4541)	(0.4533)	(0.4543)
$100,000-$199,000	0.4822	0.4571	0.4794	0.3989	0.3534	0.3688
	(0.3406)	(0.3405)	(0.3400)	(0.4115)	(0.4103)	(0.4104)
$200,000 or more	1.1315**	1.0948**	1.1275**	1.1136*	1.0616*	1.0757*
	(0.3692)	(0.3686)	(0.3678)	(0.4426)	(0.4408)	(0.4407)
Age (Ref: 18–24 years)						
25–34 years	0.2500	0.2472	0.2488	0.4043	0.3956	0.3981
	(0.2797)	(0.2794)	(0.2796)	(0.4082)	(0.4055)	(0.4080)
35–44 years	0.4381	0.4410	0.4368	0.4925	0.4917	0.4833
	(0.2804)	(0.2801)	(0.2803)	(0.3977)	(0.3952)	(0.3976)
45–54 years	0.1250	0.1100	0.1231	0.1433	0.1273	0.1312
	(0.2921)	(0.2918)	(0.2917)	(0.4026)	(0.4002)	(0.4025)
55–64 years	0.0094	−0.0155	0.0075	0.2743	0.2273	0.2578
	(0.2978)	(0.2972)	(0.2974)	(0.4074)	(0.4047)	(0.4070)
65–74 years	−0.3659	−0.4071	−0.3683	−0.0461	−0.0952	−0.0608
	(0.4135)	(0.4139)	(0.4131)	(0.5073)	(0.5059)	(0.5074)
Gender (Ref: Female)						
Male	−0.2966*	−0.3134*	−0.2982*	−0.3960*	−0.4208*	−0.4098*
	(0.1441)	(0.1437)	(0.1435)	(0.1726)	(0.1719)	(0.1719)
Non binary	−0.3506	−0.3323	−0.3509	−0.4740	−0.4704	−0.4805
	(0.7803)	(0.7817)	(0.7804)	(0.8908)	(0.8962)	(0.8923)
Children in household						
Household includes children age 5–17	−0.0321	−0.0436	−0.0325	0.0920	0.0713	0.0847
	(0.2138)	(0.2129)	(0.2138)	(0.2663)	(0.2643)	(0.2661)
Household includes children under 5	−0.2667	−0.2844	−0.2664	−0.0641	−0.0892	−0.0617
	(0.1800)	(0.1793)	(0.1800)	(0.2084)	(0.2072)	(0.2082)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
LR Test (p-value)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
McFadden pseudo-R^2	0.1826	0.1797	0.1826	0.1892	0.1833	0.1885
Nagelkerke pesudo-R^2	0.2873	0.2833	0.2873	0.2958	0.2876	0.2949
AIC	1481.1460	1484.1465	1479.1613	1057.4146	1062.5707	1056.2725
BIC	1689.6083	1687.3972	1682.4120	1252.0503	1252.3405	1246.0422
Log Likelihood	−700.5730	−703.0732	−700.5806	−488.7073	−492.2854	−489.1362
Deviance	1401.1460	1406.1465	1401.1613	977.4146	984.5707	978.2725
Num. obs.	1355	1355	1355	959	959	959

$***p < 0.001$; $**p < 0.01$; $*p < 0.05$

not follow a Poisson distribution (Gourieroux et al., 1984; Wooldridge, 2010). The assumption that the conditional variance and conditional mean are equal is unlikely to hold. While this does not affect the consistency of the parameter estimates, it does affect the standard errors. Using Eicker–Huber–White standard errors allows us to correct for this. For more on this see, for example, Motta (2019). See also Blackburn (2007) for a discussion of why quasi-maximum-likelihood methods may be more appropriate than more traditional log-transformed OLS approaches when dealing with skewed, continuous data. The distance travelled, G is given by:

$$Pr(G = g) = \frac{e^{-\lambda}\lambda^{g}}{g!}$$

where $\lambda = e^{X\gamma}$, X is our matrix of explanatory variables, and γ is a vector of parameters to be estimated. We are interested in the γ estimates attached to the telecommuting frequency variable. We estimate this model for both work and non-work travel. Goodness of fit is measured using the pseudo-R^2 recommended by Heinzl and Mittlböck (2003) for Poisson models with over- or under-dispersion.

4. Results

In this section, we present the results of our econometric models. We first examine the association between change in telecommuting frequency and average advertised internet speed. We then turn our attention to the association between distance travelled and change in telecommute frequency.

Table 3
Poisson models of total distance travelled by trip type.

	Full sample		Non-movers	
	Work	Non-work	Work	Non-work
Intercept	1.0706^{*}	−0.9456	1.5755^{**}	−2.0277
	(0.0440)	(0.3258)	(0.0052)	(0.1857)
Increase in telecommuting (Ref: No)				
Yes	-0.6979^{***}	−0.3827	-0.5054^{***}	−0.4561
	(0.0000)	(0.2845)	(0.0001)	(0.2065)
Household income (Ref: Under $25000)				
$25,000-$49,999	−0.1077	0.5363	−0.1574	0.9400^{*}
	(0.5988)	(0.0601)	(0.5292)	(0.0389)
$50,000-$74,999	0.0337	0.7320^{*}	0.0014	0.7785
	(0.8695)	(0.0190)	(0.9953)	(0.0961)
$75,000-$99,999	0.1208	0.5472	−0.0447	1.0131
	(0.5718)	(0.1014)	(0.8652)	(0.0585)
$100,000-$199,000	0.1578	0.9271^{**}	0.0780	1.3249^{**}
	(0.4325)	(0.0019)	(0.7453)	(0.0021)
$200,000 or more	−0.0452	2.0116^{*}	−0.2672	2.6713^{**}
	(0.8454)	(0.0106)	(0.3344)	(0.0060)
Age (Ref: 18–24 years)				
25–34 years	0.3160	−0.0791	0.0336	0.2113
	(0.0525)	(0.8385)	(0.8747)	(0.7480)
35–44 years	0.4201^{**}	0.5113	0.2022	0.9595
	(0.0089)	(0.4680)	(0.3117)	(0.3169)
45–54 years	0.4077^{*}	−0.0450	0.2127	0.2576
	(0.0173)	(0.9059)	(0.2974)	(0.6923)
55–64 years	0.5832^{***}	0.3213	0.4082^{*}	0.6420
	(0.0006)	(0.4294)	(0.0452)	(0.3306)
65–74 years	0.2298	0.5007	0.2149	0.7565
	(0.3266)	(0.3622)	(0.4076)	(0.2797)
Gender (Ref: Female)				
Male	0.0580	0.2681	0.0737	0.3713
	(0.4988)	(0.2336)	(0.4641)	(0.2277)
Non binary	-0.9058^{*}	0.0869	-1.2773^{**}	0.1058
	(0.0459)	(0.8646)	(0.0032)	(0.8773)
Children in household				
Household includes children under 5	−0.1229	0.0626	−0.1431	−0.0894
	(0.3319)	(0.8656)	(0.3863)	(0.8318)
Household includes children age 5–17	0.1408	−0.2272	0.1019	−0.2908
	(0.1314)	(0.4767)	(0.3537)	(0.3843)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo-R^2	0.1288	0.1518	0.1247	0.2100
LR test (p-value)	<0.0001	<0.0001	<0.0001	<0.0001
Num. obs.	1355	1355	959	959

$***p < 0.001$; $**p < 0.01$; $*p < 0.05$.

Table 4
Summary statistics by change in telecommuting frequency for full-time workers.

	Increase (N = 385)	No change (N = 703)	Total (N = 1088)
Average download speed (Mbps)			
Mean (SD)	219.5 (73.0)	196.9 (91.9)	204.9 (86.3)
Range	0.0–339.5	0.0–343.0	0.0–343.0
Average upload speed (Mbps)			
Mean (SD)	78.1 (48.3)	65.9 (52.6)	70.2 (51.4)
Range	0.0–162.3	0.0–167.9	0.0–167.9
Commute distance (Miles)			
Mean (SD)	18.9 (17.7)	19.1 (19.6)	19.0 (19.0)
Range	0.0–134.2	0.0–303.7	0.0–303.7
Distance for work trips (Miles)			
Mean (SD)	7.4 (15.6)	17.1 (19.6)	13.7 (18.9)
Range	0.0–161.2	0.0–150.3	0.0–161.2
Distance for non-work trips (Miles)			
Mean (SD)	8.9 (20.7)	11.1 (81.3)	10.3 (66.5)
Range	0.0–212.0	0.0–2076.9	0.0–2076.9
Broadband			
No	20 (5.2%)	95 (13.5%)	115 (10.6%)
Yes	365 (94.8%)	608 (86.5%)	973 (89.4%)
Age			
18–24 years	16 (4.2%)	60 (8.5%)	76 (7.0%)
25–34 years	102 (26.5%)	190 (27.0%)	292 (26.8%)
35–44 years	124 (32.2%)	166 (23.6%)	290 (26.7%)
45–54 years	75 (19.5%)	134 (19.1%)	209 (19.2%)
55–64 years	59 (15.3%)	121 (17.2%)	180 (16.5%)
65–74 years	9 (2.3%)	32 (4.6%)	41 (3.8%)
Gender			
Female	178 (46.2%)	321 (45.7%)	499 (45.9%)
Male	205 (53.2%)	378 (53.8%)	583 (53.6%)
Non-Binary	2 (0.5%)	4 (0.6%)	6 (0.6%)
Household income			
Under $25,000	7 (1.8%)	33 (4.7%)	40 (3.7%)
$25,000-$49,999	29 (7.5%)	123 (17.5%)	152 (14.0%)
$50,000-$74,999	48 (12.5%)	129 (18.3%)	177 (16.3%)
$75,000-$99,999	52 (13.5%)	110 (15.6%)	162 (14.9%)
$100,000-$199,000	159 (41.3%)	244 (34.7%)	403 (37.0%)
$200,000 or more	90 (23.4%)	64 (9.1%)	154 (14.2%)

4.1. Telecommute frequency and broadband speed

We present six models in Table 2*****. Models 1, 2 and 3 differ in the way internet speed is included. Model 1 includes both the upload and download speeds. These variables are highly correlated ($\rho = 0.82$), so there is likely to be significant multicollinearity in this model. In Model 2 we include only download speed and in Model 3 we include only upload speed.

In Model 1, only the average upload speed is statistically significant. The average download speed is not statistically significant and is incorrectly signed. This may be due to the high correlation between them. In model two, where upload speed is excluded, the download speed variable is positive and statistically significant at the 5% level of significance. In Model 3, where download speed is excluded, the upload speed is positive and statistically significant. According to both the AIC and BIC, Model 3 fits the data best out of these three models.

As with many questions about travel behaviour, there are substantial risks of endogeneity, making causal inference difficult. For instance, while having access to a good internet connection may increase telecommuting frequency, it might also be that people who want to work from home choose to live in areas with good internet connections. This is more problematic if we look at the speed of the internet connections in a person's home. For example, someone who wants to work from home may opt to subscribe to a higher speed service. We do not work with the data at the individual level in this way. Instead, we look at the speeds being offered by different providers in the area the person lives in. Still, it could be the case that when people choose where to live, they consider the speed of the available internet connections. Higher speed connections don't seem to capitalise into house prices (Conley and Whitacre, 2020), but may still play a role in the decision making process. To eliminate this possibility, Models 4, 5, and 6 are estimated. These are the same as Models 1, 2, and 3 but are estimated using only people who have been at their current address for at least two years. This means that they have not moved since before the pandemic. If we think of the pandemic as an exogenous shock which impacted home working, then we can have more confidence that residential location choice does not fully explain the relationship between speed and change in telecommute frequency.

Among the workers in our sample, around 30% report that they have lived at their current address for 2 years of less. This is a high percentage of movers, particularly at a time when we might expect moving rates to be lower as a result of the pandemic. However, data from the US Census Bureau shows that for the Seattle-Tacoma-Bellevue metropolitan area in 2021, 16.8% of the population reported living at a different address in the previous year. Our data covers a two-year period, making a figure of

Table 5
Logistic models of whether or not the person has increased their telecommuting frequency for full-time workers.

	Full sample			Non-movers		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.8120	0.6989	0.8019	0.9836	0.7985	0.8025
	(1.2478)	(1.2492)	(1.2381)	(1.4249)	(1.4311)	(1.4125)
Internet connection speed						
Average download speed (x100 Mbps)	−0.0105	0.2284*		−0.1702	0.2121	
	(0.1629)	(0.0949)		(0.2047)	(0.1187)	
Average upload speed (x100 Mbps)	0.4602		0.4466**	0.7109*		0.4956**
	(0.2587)		(0.1482)	(0.3171)		(0.1797)
Commute distance						
Commute distance (x10 Miles)	0.0201	0.0121	0.0201	0.0505	0.0327	0.0482
	(0.0387)	(0.0386)	(0.0387)	(0.0539)	(0.0530)	(0.0537)
Household income (Ref: Under $25000)						
$25,000-$49,999	−0.2246	−0.2120	−0.2246	−0.9264	−0.9240	−0.9346
	(0.5207)	(0.5203)	(0.5208)	(0.6441)	(0.6444)	(0.6449)
$50,000-$74,999	0.3816	0.3828	0.3803	0.1166	0.0895	0.0806
	(0.5004)	(0.4994)	(0.5000)	(0.5920)	(0.5911)	(0.5910)
$75,000-$99,999	0.5321	0.5355	0.5311	0.3386	0.3116	0.3137
	(0.4997)	(0.4991)	(0.4995)	(0.6021)	(0.6022)	(0.6024)
$100,000-$199,000	0.6563	0.6404	0.6543	0.3798	0.3238	0.3374
	(0.4802)	(0.4793)	(0.4793)	(0.5654)	(0.5644)	(0.5636)
$200,000 or more	1.3689**	1.3401**	1.3662**	1.1823*	1.1170	1.1317
	(0.5019)	(0.5007)	(0.5002)	(0.5928)	(0.5912)	(0.5899)
Age (Ref: 18–24 years)						
25–34 years	0.4902	0.4784	0.4894	0.7693	0.7723	0.7826
	(0.3481)	(0.3472)	(0.3479)	(0.5670)	(0.5637)	(0.5663)
35–44 years	0.7205*	0.7156*	0.7197*	0.8452	0.8618	0.8580
	(0.3503)	(0.3493)	(0.3500)	(0.5579)	(0.5546)	(0.5573)
45–54 years	0.4397	0.4199	0.4386	0.5951	0.5938	0.6030
	(0.3594)	(0.3585)	(0.3589)	(0.5589)	(0.5557)	(0.5585)
55–64 years	0.3296	0.2984	0.3284	0.7120	0.6814	0.7149
	(0.3672)	(0.3660)	(0.3667)	(0.5642)	(0.5607)	(0.5636)
65–74 years	0.0003	−0.0204	−0.0007	0.3243	0.3086	0.3292
	(0.5104)	(0.5111)	(0.5102)	(0.6784)	(0.6769)	(0.6783)
Gender (Ref: Female)						
Male	−0.3086	−0.3310*	−0.3096	−0.4422*	−0.4713*	−0.4553*
	(0.1588)	(0.1582)	(0.1580)	(0.1920)	(0.1910)	(0.1913)
Non binary	−0.1850	−0.1816	−0.1854	−0.4804	−0.4958	−0.4919
	(1.0055)	(1.0041)	(1.0054)	(1.2648)	(1.2641)	(1.2621)
Children in household						
Household includes children age 5–17	0.0026	−0.0013	0.0025	0.0360	0.0362	0.0342
	(0.2313)	(0.2304)	(0.2313)	(0.2921)	(0.2902)	(0.2921)
Household includes children under 5	−0.1723	−0.1868	−0.1723	0.0463	0.0184	0.0431
	(0.1971)	(0.1963)	(0.1971)	(0.2320)	(0.2304)	(0.2317)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
LR Test (p-value)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
McFadden pseudo-R^2	0.1751	0.1728	0.1751	0.1841	0.1789	0.1834
Nagelkerke pesudo-R^2	0.2798	0.2766	0.2798	0.2920	0.2846	0.2910
AIC	1246.4306	1247.6243	1244.4347	877.0419	880.1543	875.7285
BIC	1446.1145	1442.3160	1439.1265	1062.1635	1060.6479	1056.2221
Log Likelihood	−583.2153	−584.8121	−583.2174	−398.5209	−401.0771	−398.8642
Deviance	1166.4306	1169.6243	1166.4347	797.0419	802.1543	797.7285
Num. obs.	1088	1088	1088	756	756	756

$***p < 0.001$; $**p < 0.01$; $*p < 0.05$

around 30% seem reasonable for the Puget Sound region.

Reassuringly, the results from Models 4, 5, and 6 are similar to their counterparts estimated on the full sample. Out of the subsample models, the upload-speed-only model (Model 6) fits the data best. Here we can see a positive and statistically significant association between average advertised upload speed and change in telecommuting frequency.

Our preferred model is therefore Model 3. This model includes the average advertised upload speed and makes use of our full sample. According to this model, a 100 Mbps increase in upload speed is associated with 65% ($e^{0.539}$) higher odds of increasing telecommuting frequency relative to pre-pandemic levels. In line with previous findings in the literature, this model finds a positive association between commute distance and change in telecommuting frequency. The model also suggests people from higher income households are more likely to have increased their telecommuting frequency. Age does not appear to have a statistically significant effect on the increasing telecommuting frequency. Men seem to be less likely to have increased their telecommuting frequency compared to women.

4.2. *Telecommute frequency and travel demand*

We next turn our attention to the question of whether an increase in telecommuting is associated with travel demand. An important point to note here is that the dataset we use is designed to capture travel on a typical weekday. Our results, therefore, will not capture weekend travel. This may have important implications for our results on non-work travel. The results are presented in Table 3. We estimate models for work and work-related travel, as well as for non-work travel. Once again, we estimate the models for the full sample as well as for the subsample of people who have not moved in the past two years.

Table 6
Poisson models of total distance travelled by trip type for full-time workers.

	Full sample		Non-movers	
	Work	Non-work	Work	Non-work
Intercept	0.0091	−1.2395	0.2149	−3.8782*
	(0.9912)	(0.3780)	(0.8036)	(0.0408)
Increase in telecommuting (Ref: No)				
Yes	−0.7138***	−0.5103	−0.5231***	−0.6175
	(0.0000)	(0.1842)	(0.0001)	(0.0775)
Household income (Ref: Under $25000)				
$25,000-$49,999	0.1643	0.7269	0.2796	1.8846***
	(0.4762)	(0.0721)	(0.3263)	(0.0002)
$50,000-$74,999	0.2959	0.9915*	0.4577	1.8279**
	(0.1819)	(0.0248)	(0.0885)	(0.0018)
$75,000-$99,999	0.4638*	0.8039	0.5312	1.9952**
	(0.0453)	(0.0991)	(0.0712)	(0.0010)
$100,000-$199,000	0.3749	1.0837*	0.4911	2.2202***
	(0.0816)	(0.0110)	(0.0623)	(0.0000)
$200,000 or more	0.1784	2.2931*	0.0875	3.7939***
	(0.4697)	(0.0176)	(0.7740)	(0.0003)
Age (Ref: 18–24 years)				
25–34 years	0.3025	0.0323	0.0390	1.0726
	(0.0915)	(0.9532)	(0.8808)	(0.2012)
35–44 years	0.4277*	0.8317	0.2720	2.1520*
	(0.0177)	(0.3603)	(0.2749)	(0.0473)
45–54 years	0.3829*	0.0916	0.2133	1.2348
	(0.0473)	(0.8595)	(0.4093)	(0.1303)
55–64 years	0.5625**	0.5207	0.4211	1.6369
	(0.0031)	(0.3816)	(0.0960)	(0.0621)
65–74 years	0.5288*	−0.3844	0.5199	0.6543
	(0.0292)	(0.5658)	(0.0776)	(0.4653)
Gender (Ref: Female)				
Male	0.0780	0.3018	0.0856	0.4742
	(0.3837)	(0.2542)	(0.4194)	(0.1691)
Non binary	−0.8717	0.4348	−1.4197***	0.9181
	(0.0918)	(0.4488)	(0.0001)	(0.2195)
Children in household				
Household includes children under 5	−0.1034	−0.0658	−0.1662	−0.3444
	(0.4101)	(0.8642)	(0.3005)	(0.3609)
Household includes children age 5–17	0.2097*	−0.2975	0.1584	−0.3712
	(0.0350)	(0.3037)	(0.1894)	(0.1834)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo-R^2	0.1288	0.1518	0.1247	0.2100
LR test (p-value)	<0.0001	<0.0001	<0.0001	<0.0001
Num. obs.	1088	1088	756	756

$***p < 0.001$; $**p < 0.01$; $*p < 0.05$.

In both samples, there is the expected negative and statistically significant association between increasing telecommuting frequency and distance travelled for work. There are no statistically significant differences in demand for non-work travel between the people who have increased their telecommuting frequency and those who have not. People from households with a higher income tend to travel more for non-work purposes than lower income households. In general, older workers tend to travel more for work-related purposes. There are no statistically significant differences in distances travelled between men and women, though people identifying as non-binary appear to travel less for work than women. The model estimated on the full sample suggests that people who have increased their telecommuting frequency travel about 50% ($e^{0.698}$) less for work purposes. The model estimated on the subsample of non-movers suggests a reduction of around 40% ($e^{0.505}$).

5. Conclusion

Our paper set out to address two research questions. The first asks whether there was an association between the speed of internet connections in an area and a person's likelihood of increasing their telecommuting frequency relative to pre-pandemic levels. The hypothesis being tested was that people with faster connections would be more likely to have increased their frequency of telecommuting. The results supported this hypothesis. Faster connections were associated with increases in the frequency of home working. This result held even when using only respondents who had not moved since before the pandemic, thus eliminating the possibility that frequent telecommuters had chosen to live in areas with fast internet connections. In this way, the large increase in home working as a result of the pandemic can act as a natural experiment to help us better understand the complex relationships between travel demand and telecommuting.

The results also supported some discussion in the literature which suggested that for home working, it was not only the download speed which counts. Characteristics such as upload speed are identified as important for home working. Our results support this, with upload speeds being more strongly associated with increases in telecommuting frequency compared to download speeds. This may also reflect the fact that the upload speeds offered by ISPs tend to be substantially lower than download speeds. As a result, the marginal benefit from improvements in upload speed may be more important than marginal improvements in already high download speeds.

This finding has implications for ISPs as well as regulators and policy makers. For instance, in a study of willingness to pay for different aspects of an internet connection, Liu et al. (2018) suggest that the FCC punishes latency too much when issuing subsidies. The change in working and travel patterns brought about by the COVID19 pandemic may have changed the way people use internet connections and the value they place on different aspects of the connection. Our results support a hypothesis that upload speed facilitates more home working.

Our results also suggest that policy makers should be aware that the digital divide may be limiting options for home working in the post-pandemic context. Areas with slow internet connections are less suited to home working. This may leave workers with little option but to commute to the office, thus forgoing the potential benefits of home working. Poor quality infrastructure may also reduce the resilience of the economy should further restrictions need to be introduced or if there are future virus outbreaks requiring similar action.

There has been a decades long discussion about whether telecommuting can be an effective policy measure to reduce travel demand. Several studies have found that it cannot and there is a tendency for any time saved commuting to be used to increase the commute length or on non-work travel. Our results do not find evidence of this *rebound* effect. People who had increased their frequency of telecommuting tended to travel less for work. There was no association with non-work travel. However, it is worth noting that this survey took place in the Spring of 2021 when people may still have been reducing their travel to avoid COVID19. An increase in non-work travel may also occur at weekends, but our dataset focussed on weekday travel. It may also be a short run effect. Once people settle into new working patterns, they may consider changing their residential location. Still, it is important to investigate whether what we know about home working and travel demand from pre-COVID19 times still applies post-COVID. If home working becomes more widespread it is not clear whether results which applied to the pre-COVID19 telecommuters would apply to the expanded population of home workers in a post-COVID context.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank the Economic and Social Research Council (Grant: ES/S007105/1) and the Korea Ministry of Land, Infrastructure and Transport (MOLIT) as Innovative Talent Education Program for Smart City for providing funding for the research. We would also like to express our gratitude to two anonymous reviewers for taking the time to read our paper and provide comments.

Appendix A

In this section, we present descriptive statistics and model results for full-time workers only as a further robustness check. We begin by presenting the descriptive statistics in Table 4. As with the full sample, workers who have increased their telecommuting frequency have faster upload and download speeds available in their neighbourhoods.

In Table 5 we present logistic regression models looking at whether full-time workers have increased their telecommuting frequency compared to the pre-pandemic period. Once again, we find that people who increased their telecommuting frequency were more likely to live in areas with faster internet connection speeds. The point estimate of the association between internet connection speed and change in telecommuting frequency is slightly lower for full time workers than it was for the full sample. This indicates that part-time and self-employed people were more likely to have increased their telecommuting frequency and to live in areas with faster internet connections.

In Table 5, we present the results of the regression models testing for a possible rebound effect for full-time workers. As before, there is no evidence of a rebound effect in our data. Workers who increased their telecommuting frequency travelled less for work purposes but there was no statistically significant difference in travel for non-work purposes. The magnitude of the reduction in distance travelled for work is slightly larger for the full-time workers than for the full sample. Table 6.

References

Ali, C., 2020. The politics of good enough: Rural broadband and policy failure in the united states. Int. J. Commun. 14, 23.
Amankwah-Amoah, J., Khan, Z., Wood, G., Knight, G., 2021. Covid-19 and digitalization: The great acceleration. J. Business Res. 136, 602–611.
Anderson, A.J., Kaplan, S.A., Vega, R.P., 2015. The impact of telework on emotional experience: When, and for whom, does telework improve daily affective well-being? Eur. J. Work Organizational Psychol. 24 (6), 882–897.
Athanasiadou, C., Theriou, G., 2021. Telework: systematic literature review and future research agenda. Heliyon 7 (10), e08165.
Baard, N., Thomas, A., 2010. Teleworking in south africa and challenges. SA J. Human Resour. Manage. 8 (1), 1–10.
Bai, Y., 2017. The faster, the better? the impact of internet speed on employment. Inf. Econ. Policy 40, 21–25.
Santos Baquero, O. (2019). ggsn: North Symbols and Scale Bars for Maps Created with ggplot2 or ggmap. R package version 0.5.0.
Barrero, J.M., Bloom, N., Davis, S.J., 2021. Why working from home will stick. Technical report. National Bureau of Economic Research.
Bartik, A. W., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. T. (2020). What jobs are being done at home during the COVID-19 crisis? Evidence from firm-level surveys (No. w27422). National Bureau of Economic Research.
Billari, F.C., Giuntella, O., Stella, L., 2019. Does broadband internet affect fertility? Population studies 73 (3), 297–316.
Birimoglu Okuyan, C., Begen, M.A., 2022. Working from home during the covid-19 pandemic, its effects on health, and recommendations: the pandemic and beyond. Perspectives in Psychiatric Care 58 (1), 173–179.
Blackburn, M.L., 2007. Estimating wage differentials without logarithms. Labour Economics 14 (1), 73–98.
Bloom, N., Liang, J., Roberts, J., and Ying, Z. J. (2015). Does working from home work? evidence from a chinese experiment. The Quarterly journal of economics, 130(1): 165–218.
Bronzino, F., Feamster, N., Liu, S., Saxon, J., and Schmitt, P. (2021). Mapping the digital divide: Before, during, and after covid-19. During, and After COVID-19 (February 17, 2021).
Budnitz, H., Tranos, E., 2022. Working from home and digital divides: Resilience during the pandemic. Annals of the American Association of Geographers 112 (4), 893–913.
Cairncross, F., 1997. The death of distance. Harvard Business School Press, Cambridge.
Cameron, A.C., Trivedi, P.K., 1986. Econometric models based on count data. comparisons and applications of some estimators and tests. J. Appl. Econo. 1 (1), 29–53.
Chakrabarti, S., 2018. Does telecommuting promote sustainable travel and physical activity? J. Transport Health 9, 19–33.
Conley, K.L., Whitacre, B.E., 2020. Home is where the internet is? high-speed internet's impact on rural housing values. Int. Regional Sci. Rev. 43 (5), 501–530.
Conroy, T., Low, S.A., 2022. Entrepreneurship, broadband, and gender: Evidence from establishment births in rural america. Int. Regional Sci. Rev. 45 (1), 3–35.
Corbera, E., Anguelovski, I., Honey-Rosés, J., Ruiz-Mallén, I., 2020. Academia in the time of covid-19: Towards an ethics of care. Planning Theory & Practice 21 (2), 191–199.
Cotterill, S., Bunney, S., Lawson, E., Chisholm, A., Farmani, R., Melville-Shreeve, P., 2020. Covid-19 and the water sector: understanding impact, preparedness and resilience in the uk through a sector-wide survey. Water Environ. J. 34 (4), 715–728.
Currie, G., Jain, T., Aston, L., 2021. Evidence of a post-covid change in travel behaviour–self-reported expectations of commuting in melbourne. Transp. Res. Part A: Policy Practice 153, 218–234.
Dahiya, S., Rokanas, L.N., Singh, S., Yang, M., Peha, J.M., 2021. Lessons from internet use and performance during covid-19. J. Inform. Policy 11 (1), 202–221.
De Abreu e Silva, J. and Melo, P.C. (2018). Home telework, travel behavior, and land-use patterns. Journal of Transport and Land Use, 11(1):419–441.
Dettling, L.J., 2017. Broadband in the labor market: The impact of residential high-speed internet on married women's labor force participation. ILR Review 70 (2), 451–482.
Dingel, J.I., Neiman, B., 2020. How many jobs can be done at home? J. Public Econ. 189, 104235.
Early, J., Hernandez, A., 2021. Digital disenfranchisement and covid-19: broadband internet access as a social determinant of health. Health Promotion Practice 22 (5), 605–610.
Elena-Bucea, A., Cruz-Jesus, F., Oliveira, T., Coelho, P.S., 2021. Assessing the role of age, education, gender and income on the digital divide: evidence for the european union. Inform. Systems Front. 23 (4), 1007–1021.
Feamster, N., Livingood, J., 2020. Measuring internet speed: current challenges and future recommendations. Commun. ACM 63 (12), 72–80.
Firke, S. (2021). janitor: Simple Tools for Examining and Cleaning Dirty Data. R package version 2.1.0.
Fonner, K.L., Roloff, M.E., 2010. Why teleworkers are more satisfied with their jobs than are office-based workers: When less contact is beneficial. J. Appl. Commun. Res. 38 (4), 336–361.
Ford, D., Storey, M.-A., Zimmermann, T., Bird, C., Jaffe, S., Maddila, C., Butler, J.L., Houck, B., Nagappan, N., 2021. A tale of two cities: Software developers working from home during the covid-19 pandemic. ACM Trans. Softw. Eng. Meth. (TOSEM) 31 (2), 1–37.
Fuchs, C., 2009. The role of income inequality in a multivariate cross-national analysis of the digital divide. Social Sci. Computer Rev. 27 (1), 41–58.
Galanti, T., Guidetti, G., Mazzei, E., Zappalà, S., Toscano, F., 2021. Work from home during the covid-19 outbreak: The impact on employees' remote work productivity, engagement, and stress. J. Occupational Environ. Med. 63 (7), e426.
Gao, N., Hayes, J., 2021. The digital divide in education. Public Policy Institute of California.
Garnier, S. (2021). viridis: Colorblind-Friendly Color Maps for R.R package version 0.6.2.
Garrote Sanchez, D., Gomez Parra, N., Ozden, C., Rijkers, B., Viollaz, M., Winkler, H., 2021. Who on earth can work from home? The World Bank Research Observer 36 (1), 67–100.
Gourieroux, C., Monfort, A., Trognon, A., 1984. Pseudo maximum likelihood methods: Theory. Econometrica 681–700.
Hampton, K., Fernandez, L., Robertson, C., and Bauer, J.M. (2020). Broadband and student performance gaps.
Han, L. (2021). Broadband, self-employment, and work-from-home–evidence from the american community survey. Self-Employment, and Work-from-Home–Evidence from the American Community Survey (October 4, 2021).
Handy, S.L., Mokhtarian, P.L., 1996. The future of telecommuting. Futures 28 (3), 227–240.
Harrell Jr, F.E. (2023). rms: Regression Modeling Strategies. R package version 6.7-0.
Heinzen, E., Sinnwell, J., Atkinson, E., Gunderson, T., and Dougherty, G. (2021). arsenal: An Arsenal of R Functions for Large-Scale Statistical Summaries. R package version 3.6.3.
Heinzl, H., Mittlböck, M., 2003. Pseudo r-squared measures for poisson regression models with over-or underdispersion. Comput. Stat. Data Anal. 44 (1–2), 253–271.
Henry, L. and Wickham, H. (2020). purrr: Functional Programming Tools. R package version 0.3.4.
Hester, J., Wickham, H., and Bryan, J. (2021). vroom: Read and Write Rectangular Text Data Quickly. R package version 1.5.7.
Hong, J., Thakuriah, P.V., Mason, P., Lido, C., 2020. The role of numeracy and financial literacy skills in the relationship between information and communication technology use and travel behaviour. Travel Behaviour and Society 21, 257–264.
Hook, A., Sovacool, B.K., Sorrell, S., et al., 2020. A systematic review of the energy and climate impacts of teleworking. Environ. Res. Lett. 15 (9), 093003.
Hothorn, T., Zeileis, A., Farebrother, R.W., and Cummins, C. (2022). lmtest: Testing Linear Regression Models. R package version 0.9-40.
ILO (2020). Ilo monitor: Covid-19 and the world of work. Technical report, International Labour Organization.
Iscan, O. F., and Naktiyok, A. (2005). Attitudes towards telecommuting: the Turkish case. Journal of Information Technology, 20(1), 52-63.
Jaff, M.M., Hamsa, A.A.K., 2018. Estimating commute-travel implications of telecommuting by female employees in kuala lumpur, malaysia. J. Traffic Transp. Eng. (English Edition) 5 (2), 148–155.
Jain, T., Currie, G., Aston, L., 2022. Covid and working from home: Long-term impacts and psycho-social determinants. Transp. Res. Part A: Policy Practice 156, 52–68.

Kahle, D., Wickham, H., 2013. ggmap: Spatial visualization with ggplot2. The R Journal 5 (1), 144–161.
Kahle, D., Wickham, H., and Jackson, S. (2019). ggmap: Spatial Visualization with ggplot2. R package version 3.0.0.
Kaushik, M., Guleria, N., 2020. The impact of pandemic covid-19 in workplace. Eur. J. Business Manage. 12 (15), 1–10.
Kim, S.-N., 2017. Is telecommuting sustainable? an alternative approach to estimating the impact of home-based telecommuting on household travel. Int. J. Sustainable Transp. 11 (2), 72–85.
Lai, J., Widmar, N.O., 2021. Revisiting the digital divide in the covid-19 era. Appl. Econ. Perspectives Policy 43 (1), 458–464.
Lai, J., Widmar, N.O., Bir, C., 2020. Eliciting consumer willingness to pay for home internet service: Closing the digital divide in the state of indiana. Appl. Econ. Perspectives Policy 42 (2), 263–282.
Lara-Pulido, J.A., Martinez-Cruz, A.L., 2022. Stated benefits of teleworking in mexico city: a discrete choice experiment on office workers. Transportation 1–65.
Leifeld, P., 2013. texreg: Conversion of statistical model output in R to LaTeX and HTML tables. J. Stat. Softw. 55 (8), 1–24.
Leifeld, P. (2022). texreg: Conversion of R Regression Output to LaTeX or HTML Tables. R package version 1.38.6.
Liu, Y.-H., Prince, J., Wallsten, S., 2018. Distinguishing bandwidth and latency in households' willingness-to-pay for broadband internet speed. Inf. Econ. Policy 45, 1–15.
Lobo, B.J., Alam, M.R., Whitacre, B.E., 2020. Broadband speed and unemployment rates: Data and measurement issues. Telecommunications Policy 44 (1), 101829.
Loo, B.P., Huang, Z., 2022. Spatio-temporal variations of traffic congestion under work from home (wfh) arrangements: Lessons learned from covid-19. Cities 103610.
Loo, B. P., & Wang, B. (2018). Factors associated with home-based e-working and e-shopping in Nanjing, China. Transportation, 45(2), 365-384.
Lüdecke, D., 2018. ggeffects: Tidy data frames of marginal effects from regression models. J. Open Source Softw. 3 (26), 772.
Mannering, J. S., and Mokhtarian, P. L. (1995). Modeling the choice of telecommuting frequency in California: an exploratory analysis. Technological Forecasting and Social Change, 49(1), 49-73.
Martins, S.S., Wernick, C., 2021. Regional differences in residential demand for very high bandwidth broadband internet in 2025. Telecommunications Policy 45 (1), 102043.
Mehta, P., 2021. Work from home–work engagement amid covid-19 lockdown and employee happiness. J. Public Affairs 21 (4), e2709.
Mokhtarian, P. L., & Salomon, I. (1994). Modeling the choice of telecommuting: Setting the context. Environment and planning A, 26(5), 749-766.
Mokhtarian, P.L., Salomon, I., Choo, S., 2005. Measuring the measurable: Why can't we agree on the number of telecommuters in the us? Quality and Quantity 39 (4), 423–452.
Motta, V., 2019. Estimating poisson pseudo-maximum-likelihood rather than log-linear model of a log-transformed dependent variable. RAUSP Management Journal 54, 508–518.
Müller, K. and Wickham, H. (2022). tibble: Simple Data Frames. R package version 3.1.7.
Nayak, S., Pandit, D., 2021. Potential of telecommuting for different employees in the indian context beyond covid-19 lockdown. Transp. Policy 111, 98–110.
Nguyen, M. H. (2021). Factors influencing home-based telework in Hanoi (Vietnam) during and after the COVID-19 era. Transportation, 48(6), 3207-3238.
Ojala, S., Pyöriä, P., 2018. Mobile knowledge workers and traditional mobile workers: Assessing the prevalence of multi-locational work in europe. Acta Sociologica 61 (4), 402–418.
Pebesma, E., 2018. Simple Features for R: Standardized Support for Spatial Vector Data. The R Journal 10 (1), 439–446.
Pebesma, E. (2022). sf: Simple Features for R.R package version 1.0-7.
Phillipson, J., Gorton, M., Turner, R., Shucksmith, M., Aitken-McDermott, K., Areal, F., Cowie, P., Hubbard, C., Maioli, S., McAreavey, R., et al., 2020. The covid-19 pandemic and its implications for rural economies. Sustainability 12 (10), 3973.
R Core Team (2022). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
Robinson, D., Hayes, A., and Couch, S. (2022). broom: Convert Statistical Objects into Tidy Tibbles. R package version 0.8.0.
RSG (2019). Introductory guide to household travel survey data. Technical report.
Rudis, B. (2020). hrbrthemes: Additional Themes, Theme Components and Utilities for ggplot2. R package version 0.8.0.
Salemink, K., Strijker, D., Bosworth, G., 2017. Rural development in the digital age: A systematic literature review on unequal ict availability, adoption, and use in rural areas. J. Rural Stud. 54, 360–371.
Sanchis-Guarner, R., Montalbán, J., and Weinhardt, F. (2021). Home broadband and human capital formation. Available at SSRN 3772087.
Sanders, C.K., Scanlon, E., 2021. The digital divide is a human rights issue: Advancing social inclusion through social work advocacy. J. Human Rights Social Work 6 (2), 130–143.
Sarrasanti, N., Donkor, F.K., Santos, C., Tsagkari, M., Wannous, C., 2020. Its about time we care about an equitable world: Women's unpaid care work and covid-19. IEEE Eng. Manage. Rev. 48 (4), 37–45.
Savage, S.J., Waldman, D., 2005. Broadband internet access, awareness, and use: Analysis of united states household data. Telecommunications Policy 29 (8), 615–633.
Scheerder, A., Van Deursen, A., Van Dijk, J., 2017. Determinants of internet skills, uses and outcomes. a systematic review of the second-and third-level digital divide. Telematics Inform. 34 (8), 1607–1624.
Schur, L.A., Ameri, M., Kruse, D., 2020. Telework after covid: a "silver lining" for workers with disabilities? J. Occup. Rehab. 30 (4), 521–536.
Sener, I. N., and Reeder, P. R. (2012). An examination of behavioral linkages across ICT choice dimensions: copula modeling of telecommuting and teleshopping choice behavior. Environment and Planning A, 44(6), 1459-1478.
Shabanpour, R., Golshani, N., Tayarani, M., Auld, J., Mohammadian, A.K., 2018. Analysis of telecommuting behavior and impacts on travel demand and the environment. Transp. Res. Part D: Transp. Environ. 62, 563–576.
Signorell, A. (2023). DescTools: Tools for Descriptive Statistics. R package version 0.99.48.
e Silva, J. d. A. and Melo, P.C. (2017). The effects of home-based telework on household total travel: A path analysis approach of british households. Transportation Research Procedia, 27:832–840.
Singh, S., 2017. Bridging the gender digital divide in developing countries. J. Children Media 11 (2), 245–247.
Singh, P., Paleti, R., Jenkins, S., and Bhat, C. R. (2013). On modeling telecommuting behavior: Option, choice, and frequency. Transportation, 40, 373-396.
Walker, K. (2022). tigris: Load Census TIGER/Line Shapefiles. R package version 1.6.1.
Whitacre, B.E., Mills, B.F., 2007. Infrastructure and the rural–urban divide in high-speed residential internet access. Int. Regional Sci. Rev. 30 (3), 249–273.
Wickham, H., 2016. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag, New York.
Wickham, H. (2019). stringr: Simple, Consistent Wrappers for Common String Operations. R package version 1.4.0.
Wickham, H. (2021a). forcats: Tools for Working with Categorical Variables (Factors). R package version 0.5.1.
Wickham, H. (2021b). tidyverse: Easily Install and Load the Tidyverse. R package version 1.3.1.
Wickham, H. and Girlich, M. (2022). tidyr: Tidy Messy Data. R package version 1.2.0.
Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L.D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T.L., Miller, E., Bache, S.M., Müller, K., Ooms, J., Robinson, D., Seidel, D.P., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the tidyverse. J. Open Source Softw. 4 (43), 1686.
Wickham, H., Hester, J., and Bryan, J. (2022c). readr: Read Rectangular Text Data. R package version 2.1.2.
Wickham, H., Chang, W., Henry, L., Pedersen, T.L., Takahashi, K., Wilke, C., Woo, K., Yutani, H., and Dunnington, D. (2022a). ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics. R package version 3.3.6.
Wickham, H., Francois, R., Henry, L., and Muller, K. (2022b). dplyr: A Grammar of Data Manipulation. R package version 1.0.9.
Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. MIT press.
Yen, J. R. (2000). Interpreting employee telecommuting adoption: An economics perspective. Transportation, 27, 149-164.
Yutani, H. (2022). ggsflabel: Labels for 'sf' with''ggplot2'. R package version 0.0.1.
Zeileis, A., 2006. Object-oriented computation of sandwich estimators. J. Stat. Softw. 16 (9), 1–16.
Zeileis, A., Grothendieck, G., 2005. zoo: S3 infrastructure for regular and irregular time series. J. Stat. Softw. 14 (6), 1–27.
Zeileis, A., Hothorn, T., 2002. Diagnostic checking in regression relationships. R News 2 (3), 7–10.
Zeileis, A. and Lumley, T. (2021). sandwich: Robust Covariance Matrix Estimators. R package version 3.0-1.
Zeileis, A., Köll, S., Graham, N., 2020. Various versatile variances: An object-oriented implementation of clustered covariances in R. J. Stat. Softw. 95 (1), 1–36.
Zeileis, A., Grothendieck, G., and Ryan, J.A. (2022). zoo: S3 Infrastructure for Regular and Irregular Time Series (Z's Ordered Observations). R package version 1.8-10.
Zhu, P., 2012. Are telecommuting and personal travel complements or substitutes? Ann. Regional Sci. 48 (2), 619–639.
Zhu, P., Mason, S.G., 2014. The impact of telecommuting on personal vehicle usage and environmental sustainability. Int. J. Environ. Sci. Technol. 11 (8), 2185–2200.
Zhu, P., Wang, L., Jiang, Y., Zhou, J., 2018. Metropolitan size and the impacts of telecommuting on personal travel. Transportation 45 (2), 385–414.
Zuo, G.W., 2021. Wired and hired: Employment effects of subsidized broadband internet for low-income americans. American Economic Journal: Economic Policy 13 (3), 447–482.