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Whether weather causes contention: assessing the ongoing resilience opportunity of telecommuting

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Abstract The Covid-19 pandemic resulted in an unprecedented overnight explosion in telecommuting. It has highlighted a new dependence on digital infrastructures and raised new questions regarding the resilience of internet connectivity as an alternative to travel. Pre-pandemic, we considered how telecommuting could offer an opportunity for resilience when travel was disrupted by weather extremes. We analysed five years' of recorded broadband speed variation across England and Wales in order to quantify the changing demand for internet access during the working day under adverse weather conditions. Slower broadband speeds, also known as contention, are an indication of increased demand. Thus, during the working day, contention is an indication that external factors like weather can influence the choice to telecommute instead of travel. A multilevel regression model is estimated to investigate the relationship between contention during the working day and weather, whilst controlling for background spatial and demographic differences in internet services. Emergent patterns suggest that even before the pandemic, online connectivity was in greater demand when travel was disrupted or at risk of disruption. Our research provides insights into the roles that both the supply of and the demand for transport and digital technologies might play in increasing resilience and maintaining productivity during severe weather and other disruptions as experience of both types of working has become so widespread.

Keywords Broadband speeds · Telecommuting · Extreme weather · Resilience

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Introduction

This article analyses how the demand for internet access changes during the working day at times of adverse weather in order to gain insights into the ability of online applications to offer resilient accessibility to work and other activities. Transport researchers have long recognised the impact of weather parameters such as precipitation, temperature and wind-speed on travel behaviour, using surveys and transport-derived big data sources to assess whether and how people change their travel choices, including route, mode, timing, destination, or cancellation, in response to adverse weather (Böcker et al., 2013; De Palma & Rochat, 1999; Khattak & De Palma, 1997;

Koetse & Rietveld, 2009; Liu et al, 2015; Sabir et al., 2010). However, most transport research ignores the capacity of digital technologies to enable individuals to participate in social and economic activities remotely even when unplanned due to disruption, and thus to substitute some trips with online access. Gaining a better understanding of if and how digital technologies can do this could improve transport and economic policy responses to severe weather events, for example, by identifying when it might be appropriate to promote telecommuting as a resilient alternative to travel.

Although an extreme situation, the current Covid-19 pandemic has exemplified the capacity of digital technologies to enable individuals to change travel choices but still participate in productive activities, e.g. by working from home. Indeed, research demonstrates that even before the pandemic, the rate of telecommuting and periodic home-working was slowly increasing in the UK, along with other flexible working practices and intrapersonal variability in daily working and commuting patterns (Crawford, 2020; Headicar & Stokes, 2016; Le Vine et al., 2017). Yet the extent to which external factors such as weather influence the pattern of home-working and intrapersonal daily variability in work access is largely unknown, as is the extent to which digital technologies and, more specifically, internet access and applications can offer a resilient alternative to travel during periods of transport disruption. This is despite the expectation that such disruptions will cause a spike in demand for robust, quality internet services (Fu et al., 2016). Therefore, this research aimed to quantify whether the pattern of internet activity on working days is influenced by the expectation of severe weather or potential travel disruption, and what this tells us about the choice of which days people choose to telecommute.

Context of contention

In order to conduct this analysis, we utilise the records of millions of individual, geo-located and timestamped, anonymised broadband speed tests to expose experienced internet demand and quality of service changes at temporal and spatial resolutions granular enough to link these changes with changes in weather parameters and thresholds that reflect the types of adverse weather which often cause transport disruption. This data source is suitable because most online access from homes in the UK is achieved via fixed broadband networks, the availability and quality of which is time-sensitive. Residential fixed broadband access in the UK was initially provided to most dwellings over a pre-existing national network of copper telephone lines, or 'ADSL' connections. Copper lines are gradually being replaced by fibre optic, either between the telephone exchange and the street cabinet (known as 'FTTC' – Fibre to the cabinet) or direct to residential and business premises ('FTTP') either from the cabinet or from the exchange. Internet Service Providers (ISP) compete for customers, despite using the same infrastructure installed by the formerly state-owned company, BT (known as local loop unbundling). The exception is Virgin broadband, who use their own infrastructure, which was originally installed to provide cable television. Thus, maximum speeds available to a household are determined by the type of connection, e.g. ADSL or FTTC, competition between providers, and the location of the end user, with urban residents benefitting most (Nardotto et al., 2015; Philip et al., 2017; Tranos et al., 2013).

However, there is a difference between maximum available or advertised speeds and actual experienced speeds. Broadband is subject not only to outages, but also to what Ofcom, the industry regulator of Information and Communication Technologies (ICT) in the UK, defines as: "a slowdown in performance caused when multiple users share the same bandwidth within a network and the bandwidth available is less than the aggregate demand" (2018, p89). Contention, like congestion on transport networks, is not a measurement of the total capacity of a link, but rather a measure of the *relative* broadband download (and upload) speeds at different times for the same service depending on how many individuals are sharing the same bandwidth, which is often a greater number in urban areas, and how the ISP manages peaks in demand (Nardotto et al., 2015; Ofcom, 2018; Riddlesden & Singleton, 2014).

Ofcom consistently reports that the lowest average speeds on all connection types occur during the evening peak of 20.00–22.00, and this is what they measure relative to a 24-h average as an indicator of broadband performance for different ISPs. However, contention can occur at other times, such as has been observed during mass streaming of sporting

and entertainment events taking place outside of 'prime time' (Ofcom, 2014a). Therefore, we hypothesise that if severe weather conditions led to unusually high demand for internet services and data traffic because household members unexpectedly choose to stay home, the resulting contention will illustrate the temporal and geographical extent of increased internet activity, in this case in England and Wales. It will also provide insights into how broadband speed checks provide evidence of increased online interactions and activity and thus a resilient access alternative to transport during the working day to maintain productivity.

In the next section, we review the literature on the resilience of transport and broadband infrastructure to extreme weather, as well as the literature on telecommuting trends, and explore the gap between these areas of study which this article aims to address. Then we describe the data and the methods employed before the fourth and fifth sections detail the results of our multilevel model and sensitivity testing. Finally, we conclude with a discussion of the importance of our insights into how online activity varies in time and space and its relevance to resilient accessibility.

Literature review

Extreme weather, risk and resilience

Storms, floods, and other severe weather events are occurring more frequently and arguably pose the greatest hazard of climate change to transport infrastructure in the UK (Dawson, 2016; Jaroszweski et al., 2010). As Government reviews following extreme weather events detail, choosing to travel involves risking exposure to disruptions such as road closures, rail cancellations, reduced speeds and delays, as well as risks to personal safety due to the physical damage to infrastructure and property, and increased levels of road traffic accidents (Chatterton et al., 2016; Quarmby et al., 2010). Meanwhile, ICT infrastructure is more resilient than transport infrastructure during these events because components are often designed for climates more extreme than the UK; technology updates result in more frequent maintenance and replacement; and the national network has high levels of redundancy, with a density of interconnected links that can maintain service for a high proportion of end users most of the time (Dawson, 2016; Fu et al., 2016; Horrocks et al., 2010). For example, the period of well-documented storms between December 2013 and February 2014 had significant transport impacts (Chatterton et al., 2016), but minimal impacts on broadband infrastructure, as analysis conducted by Ofcom indicated that only 1% of the incidents reported to them were attributed to severe weather (2014). Therefore, whilst weather can cause technical failures in ICT infrastructure, such failures usually manifest as localised losses of connection, often to individual premises, creating issues which, in the UK, occur at a rate considered an internationally competitive benchmark, and are therefore more matters of customer service, maintenance, and standards, rather than of national resilience (Lazarus, 2013, 2014; Ofcom, 2014b; Schulman & Spring, 2011). This means that if online access is chosen over travel, it could reduce a severe weather event's associated risks, mitigate the impacts on the productivity and / or personal safety of the individual not travelling, and reduce delays and damages for those who do travel.

Surveys of commuters following Hurricane Sandy in New York and major flooding events in the UK provide evidence of increased telecommuting and related coping strategies (Allen et al., 2015; Kaufman et al., 2012; Marsden & Docherty, 2013; Marsden et al., 2016). An analysis of one of the London Internet eXchange Points or IXPs, which form the locally specific part of the wider internet service network, tracked a large increase in the volume of data traffic during consecutive extreme weather events in the UK in early March 2018, indicating that people were working remotely, checking traffic updates more, and streaming video (Stubbings & Rowe, 2019). However, whilst these case studies provide valuable insights, they focus on extreme weather events with known transport disruption, rather than the occurrence of adverse weather which only increases the risk of transport disruption. There is little evidence of a more direct relationship between increased internet activity and adverse weather parameters and thresholds over time.

The choice to telecommute

Studies of daily weather variation and travel do indicate that commuters are less likely to cancel their

trips than those travelling for other purposes (De Palma & Rochat, 1999; Khattak & De Palma, 1997; Sabir et al., 2010). Work (or education) activities are the most frequent, 'non-discretionary' interactions external to the home around which daily trip and activity patterns coalesce, even during severe weather events (Budnitz et al., 2020; Le Vine et al., 2017; Miller, 2005). However, these studies do not investigate whether cancellations of travel equate to cancellation of activities, or whether online access provides a substitute. Furthermore, Marsden et al. (2016) suggest that when faced with transport disruption, people prefer to choose an alternative means of access with which they are already familiar, such as telecommuting. Regular telecommuting is part of a growing trend in spatially and temporally flexible working patterns that include the use of digital technologies to replace all or some of the journey to and from work or to commute at different times (Felstead, 2012; Haddad et al., 2009; Siha & Monroe, 2006). Thus, even before the pandemic, it was a familiar access alternative to a growing population.

There are studies from the UK, United States and elsewhere in Europe that aim to characterise this population in terms of its preference, opportunity and frequency of choice to telecommute. Conclusions suggest that the characteristics of those who telecommute, but are not home-based workers, include the holding of professional or managerial positions, being more educated and wealthier, having longer commutes when they do travel to their main place of work, and the tendency to live in suburban/outer metropolitan neighbourhoods rather than fully rural areas (Ellen & Hempstead, 2002; Headicar & Stokes, 2016; Peters et al., 2004; Singh et al., 2013; Walls et al., 2006). Research further indicates considerable suppressed demand for the flexibility to work from home once or twice a week, particularly among women and part-time workers, fewer of whom telecommute regularly, but who are more likely to say they want to (Headicar & Stokes, 2016; Lavieri et al., 2018; Singh et al., 2013). Yet this literature barely touches the surface of what determines which days or part-days people choose to work from home, even though there is some acknowledgement that this may vary from week to week and month to month rather than be a product of fixed work schedules (Allen et al., 2015; Haddad et al., 2009). Thus, this article aims to provide insights on the question of whether the choice to telecommute on some days rather than others could be influenced by external factors such as the expectation of severe weather or potential travel disruption.

Data and methods

Modelling speed test data

In order to test the influence of weather conditions on internet activity, data were provided by *Speedchecker Ltd*,[1] a private company that allows internet users to check their own broadband upload / download speeds. The result of every speed-check is stored with a timestamp and geographical coordinates. Datasets from *Speedchecker Ltd* have been the subject of previous studies on the geographic equity of broadband speeds (Riddlesden & Singleton, 2014), and on the service quality benefits of competition and local loop unbundling (Nardotto et al., 2015). However, whilst both studies investigated spatial variation in internet access and quality of service, neither assessed the implications of daily variability, the effects of adverse weather conditions, or contention during the working day or between working days. Both mention that, even assuming fast connections to a property and proactive ISP management, contention occurs due to demand at peak times, generally in the evening, when people are likely to be streaming video content for leisure purposes (Nardotto et al., 2015; Ofcom, 2014a; Riddlesden & Singleton, 2014). This demand is specifically for download speeds, which are "by far the most important feature for household users" (Nardotto et al., 2015, p336), and are more temporally variable, so we too use download speeds as a proxy for internet activity. Only the extreme demand for internet services during the pandemic, including massive increases in video-conferencing have made contention in upload speeds visible during the working day (Budnitz & Tranos, 2021).

This study models a subset of the data provided by *Speedchecker Ltd*, which incorporates 2,556,025 individual speed tests run on 1239 days from 2012 to 2016 in England and Wales during the working hours of 08.00 to 18.00, Monday to Friday, excluding bank holidays and 24 December to the first of

[1] http://www.broadbandspeedchecker.co.uk

January inclusive.[2] These five years capture a period when download speeds could broadly be expected to include superfast connections of above 30Mbit/s, but prior to any substantial roll-out of ultrafast full fibre services of over 300Mbit/s. Thus, outlier tests recording download speeds of under 0.5Mbit/s or over 100Mbit/s could be removed prior to analysis following the approach taken by Riddlesden and Singleton (2014). Tests run during Storm Jude on 28 October 2013 were also excluded as outliers, as our data indicated download speeds unusually faster than surrounding working weekdays (08.00–18.00), and industry investigations revealed a record number of faults reported to BT on that day, likely due to the weather causing a widespread loss of power (Met Lazarus, 2014; Office, 2013). Indeed, when power outages are widespread, concurrent broadband outages are common and can result in increasing rather than decreasing broadband speeds where services are still available. However, the lack of consistent reporting make it difficult to pinpoint mass outages and what may have caused them except via the occasional media report. The reports Ofcom receives from ISPs, often during the later stages of an incident, are not publicly available (John, 2017). Therefore, we were unable to corroborate other dates of mass outages to exclude from our analysis.

The subset of download speeds formed the dependent variable for a multilevel regression model. We control for characteristics relevant to individual tests as well as for higher-level, socio-economic and geographic attributes, which are consistent over time and reflect some of the differences of broadband supply and demand 'between' defined areas in order to isolate any significant, time-variant or 'within' area contention effects that might be attributed to the weather (Bell & Jones, 2015). Our random intercept model is shown in Eq. (1), where the Test Speed variable represents the download speed for each individual test i which took place in the higher spatial unit j. Nardotto et al. similarly varies predictor variables by higher geographic units, in his case the telephone exchange catchment (2015). The Test Speed variable is highly skewed, so a transformation using the logarithmic function is included in the model.

$$\begin{aligned}\log\left(\text{Test Speed}_{ij}\right) = & \gamma_{00} + \gamma_{10}\text{ISP}_{ij} \\ & + \gamma_{11}\text{Distance to Nearest Exchange}_{ij} \\ & + \gamma_{12}\text{Annual Trend}_{ij} + \gamma_{13}\text{weekday}_{ij} \\ & + \gamma_{14}\text{Ratio Speed Tests to population}_{ij} \\ & + \gamma_{01}\text{Control\_Variables}_{j} \\ & + \gamma_{02}\text{Weather\_Variables}_{j} + \varepsilon_{0j} + \varepsilon_{ij}\end{aligned} \tag{1}$$

All variables in Eq. (1) are described in Table 1. The main broadband speed data also included details of the ISP, who may approach the management of contention differently. To control for this choice of broadband package by individual households, we include the variable ISP_{ij} in (1). Furthermore, only some areas have the option of Virgin's cable service, which usually offers faster top speeds but has limited bandwidth available for connections that serve multiple properties and thus suffers more from contention (Ofcom, 2018). No further data was available on supply-side characteristics of broadband provision, which was one reason to apply a multilevel model so that tests would be grouped by small enough geographic areas to control for this variation. Therefore, although data was not available on the distance from the nearest street cabinet to individual properties, which often limits achievable broadband speeds for the end user in rural areas, the spatial units j will be relatively homogeneous in terms of urban form (Nardotto et al., 2015; Philip et al., 2017). Data on Distance to the Nearest [telephone] Exchange was acquired separately and is included (Nardotto et al., 2015).

Annual average broadband speeds increased substantially over the five years. This time progression was expected, as the improvement of broadband coverage and speeds is a key government policy, although a comparison of speeds reported by Ofcom to those in this data set suggest that possible speeds are increasing faster than experienced speeds as shown in Table 2. Thus, the time trend variable, Annual Trend_{ij} in Eq. (1) controls for the annual, nation-wide improvement in broadband speeds, with 2012 coded as one, 2013 as two and so on.

In terms of other temporal variation not related to the weather, the dependent variable is a subset that includes only broadband speed tests run on working days. As work is an essential activity for those in

[2] No speed-check data were available for the weekdays 6 March 2012, 11–14 February 2014 nor 22 September 2016, presumably due to server or software failures.

Table 1 Descriptive statistics for model variables

Variable	Source	Sample size*	Mean	St. Dev	Min	Max
Mean speed (Kbps)	Speedchecker Ltd; 2012–2016	2,556,025	16,432.98	17,734.98	513	102,397
Annual trend	Derived from time stamp		3.116	1.524	1	5
Day of the week	Derived from time stamp		4.021	1.408	2	6
Distance to nearest Exchange (km)	Provided by Dr M Nardotto to authors (Nardotto et al., 2015)		0.236	0.171	0	0.68
Ratio Speed Tests to population	ONS Mid-2014 population estimates		0.074	0.162	0.007	1.689
Ratio of population working in High-tech industries	ONS 2011 Census data		0.053	0.033	0.006	0.237
Ratio of population with higher professional status			0.231	0.072	0.042	0.582
Average Commuting Distance (km)			16.31	4.419	5.9	37.5
More urban location			0.843	0.364	0	1
Ratio of population who mainly work from home			0.031	0.018	0.002	0.116
Household net weekly income (£)	ONS 2013–14 small area income estimates		514.665	112.205	230	990
Rainy day	British Atmospheric Data Centre archives 2012–2016	2,551,210	0.249	0.432	0	1
Windy day		2,552,299	0.208	0.406	0	1
Heavy rain		2,551,210	0.022	0.146	0	1
Storm		2,553,455	0.01	0.097	0	1
Freezing day		2,555,551	0.099	0.299	0	1
Snowfall		2,272,718	0.03	0.171	0	1
Hot day		2,555,551	0.004	0.06	0	1

Source *Column 2 indicates the number or sample size of speed tests that could be matched to the weather variables spatially and temporally. The other columns describe the key statistics of each variable respectively

Table 2 UK annual mean speeds (Mbit/s) reported by Ofcom (over 24 h) and the annual means of the modelled data set for working days in England and Wales

Year	Ofcom data	Modelled data
2012	12	8.9
2013	17.8	12.8
2014	22.8	16.6
2015	28.9	19.5
2016	36.2	23.9

'Average actual broadband speeds' reported in graph on page 8 of Ofcom, 2018. This graph is derived from data provided by SamKnows, who connect monitors to a representative panel of residential routers

employment, trip volumes and concentrations show less variation between working days than between work days and weekends, or between Saturdays and Sundays, making daily, intra-personal variability more visible (Crawford et al., 2017). We believe that this is also the case for contention. Furthermore, it is important to note that the working day is not normally considered the peak time for internet activity and therefore contention, which occurs in the evening. Nor does our subset include the early morning hours until 06.00, when there are unusually high speeds because activity is extremely low (Nardotto et al., 2015; Ofcom, 2014a; Riddlesden & Singleton, 2014). Since those with high speed connections are likely to consume more data of all sorts and use their connections for a variety of purposes, we expect that those who usually generate internet activity in the evening are likely to generate it during the working day if they unexpectedly choose to stay home (Hauge et al., 2010; Ofcom, 2016). However, an array of dummy variables for weekday_{ij} in Eq. (1) represent days of the week, such as Monday, Tuesday, and so on to control for some residual variation.

Multilevel modelling and weather

We have chosen Middle Layer Super Output Areas (MSOAs) for our higher-level spatial areas. These are statistical units in the UK created following each 10-year census – 2011 in this case – by grouping areas with populations of between 2000 and 6000 households by their geographic and socio-economic characteristics. Characteristics considered include predominant land use, density, affluence, and accessibility, which affect not only travel behaviour, but also the ability to telecommute. The MSOA spatial unit is expressed with the index j. A chi-square, likelihood ratio test: $\chi^2(1) = 258{,}516$, $p < 0.0001$ confirmed that a model with 'random' intercepts, in other words, constants that can vary between each of the 7201 MSOAs in England and Wales, offers a significantly better fit than one with a single, fixed intercept. Furthermore, despite the spatial granularity of individual speed tests, this is 'volunteered geographic information', so there are MSOAs with no speed tests on a given date, and others with many tests on most days. The application of a random effects model addresses some of the concerns that might otherwise arise from analysing such a data set, as these models better accommodate missing data and do not assume the independence of observations from the same spatial unit (Field et al., 2012). A variable to account for the number of tests per head of home population in each MSOA was added as γ_{14} Ratio Speed Tests to population$_{ij}$ in Eq. (1) in order to further moderate any sampling bias inherent in this crowd-sourced data. Finally, tests of the intra-class correlation (ICC) suggests that about 9% of the variation in broadband speeds recorded can be accounted for by geographic location at the MSOA level (see Fig. 3 in Sect. 5).

γ_{01} in (1) is the vector of coefficients for the fixed geographic and socio-economic attributes included in the matrix Control_Variables$_j$ for each MSOA within which the individual tests occurred. These attributes were chosen to account for how socio-demographic and geographic characteristics influence demand for broadband services, including the ability and tendency to work from home regularly or occasionally as discussed in the literature review. The presence of people who say they mainly work from home or who are in certain occupations are likely to generate some of the background demand or daily variability for online access that cannot be attributed to weather. Variables to represent these characteristics were derived mainly from census data compiled into neighbourhood statistics' tables produced by the Office for National Statistics (ONS) at MSOA level, divided by the MSOA's home population where relevant (ONS, 2014). Net weekly household income estimates were available for financial year 2013–14 (ONS, 2016a). The urban or rural character of an MSOA gives some indication of the supply available as well as demand for quality broadband services, as rural areas can still lag far behind in terms of adequate internet services (Philip et al., 2017). After some iterations of the developing model, a binary variable of the two most rural classifications (ONS, 2016b) versus the other four more urban classifications was included in the main model as offering the best improvement on model fit. The inclusion of these control variables also addressed the assumption of multilevel models that the random coefficients should be normally distributed (Field et al., 2012).

The matrix of Weather_Variables$_j$ in (1) aim to capture how certain weather conditions relate to internet speeds, and thus online activity. Weather observations are recorded by the UK Met Office, including the daily parameters relevant to this study: hourly rainfall aggregated to 24 h, daily maximum wind speeds, daily maximum gusts, daily minimum and maximum temperatures, and observations of snowfall. These weather records are kept in the British Atmospheric Data Centre (BADC) archives held at the Centre for Environmental Data Analysis and contain data from weather stations located throughout the UK (Met Office, 2006a, b, c, d). However, weather does not follow local administrative or statistical boundaries any more than does the transport infrastructure which is affected by that weather, and weather data is not collected in every MSOA.

Therefore, synoptic, regional weather stations as shown in Fig. 1 were chosen for both the completeness of their data and how well they represented each climatic region of England and Wales as defined by the Met Office and the World Meteorological Organization (Dobney et al., 2009; Met Office, 2016b). MSOAs were matched to the relevant regional weather station, so the weather variables are expressed with an index j in (1). Minimizing the number of weather stations from which data inputs were gathered acted as a quality control on the data, increasing its consistency. In more rural regions, such

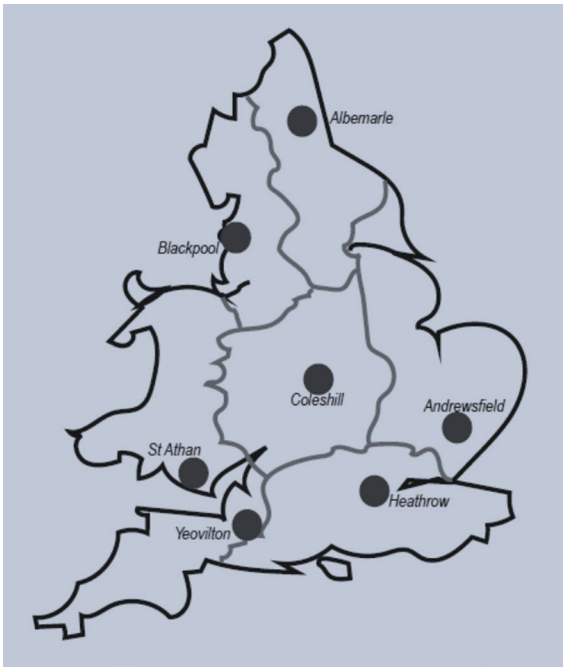


Fig. 1 Representative weather stations chosen for each Met Office 'climate region' (2016b)

as Wales and East of England, stations closer to the larger population centres were preferred, stations near military or civilian airports / airfields proved most comprehensive, and the most exposed coastal and high-altitude stations were avoided. These criteria helped ensure a more conservative identification of weather extremes, as such stations were unlikely to record the strongest wind gusts or lowest temperatures in a given region.

We also aggregated weather parameters to identify daily extremes, as this was deemed likely to capture more impacts on transport infrastructure, which can be immediate or delayed, than estimating weather effects at a more granular temporal scale. Thus, daily, regional weather parameters were matched to the broadband speed tests by date and location, then transformed into binary dummy variables to better capture the most adverse weather conditions. The most contentious dummy to set was that for Rainy Days, an issue cited in the literature, which recognises the complexity of individual response to precipitation, which may depend on season, time of day, or other factors (Hooper et al., 2014). In this study, a 'Heavy Rain' dummy was set at > = 15 mm in 24 h according to Hofman and O'Mahony (2005) who reviewed daily variability in bus travel in Ireland, whilst iterations of the developing model were used to set a simpler 'Rainy Day' dummy at accumulations of > = 2 mm and < 15 mm in 24 h. The 'Windy Day' dummy captured days with wind speeds of levels five to nine on the Beaufort Scale, whilst the Storm dummy captured any date / MSOA combinations with at least some precipitation and maximum gusts of level ten: 'Storm' and above (Met Office, 2016c). Maximum gusts, rather than maximum wind speeds, better capture extremes (McColl et al., 2012), and minimised overlap between the 'Windy Day' and 'Storm' dummies. Furthermore, the Met Office considers strong winds as the most likely to have impacts on infrastructure and property, according to their publicity on their first trial of naming storms (Eysenck, 2016; Met Office, 2016a).

An ice dummy was set where the minimum air temperature was 0 °C or below, and the snow dummy simply used the 'snowfall' record from the relevant data set. Unfortunately, records of snowfall in the Northwest region were unavailable for the chosen station, so records from another station, Hazelrigg, near Lancaster, improved the completeness of the data. The records were still more limited for that region than others, resulting in fewer days without missing data, and thus a smaller matching sample of speed tests as can be seen in Table 1. Finally, the definition of a heatwave varies by region and time of year, so a simplified heat dummy used the threshold for the Met Office heat-health watch: maximum daily temperatures of over 30 °C (2017c).

Thunderstorms or other convective storms which may cause more localised impacts, e.g. flash flooding, are unpredictable, and difficult to identify from incomplete observations of 'thunder' in the weather records, and so are not included as a separate variable in the model. Thunderstorms with their likelihood of electrical discharge are also more likely to affect ICT infrastructure and cause loss of connection than other weather systems (Schulman & Spring, 2011; Deljac et al., 2016), but again such effects could cause increased speeds, as they did in this data set during a major outage reported in the media on 20 July 2016 (Titcomb, 2016). Flooding is also not included as a variable in the model, partly because it is not a weather parameter and there are time lags between

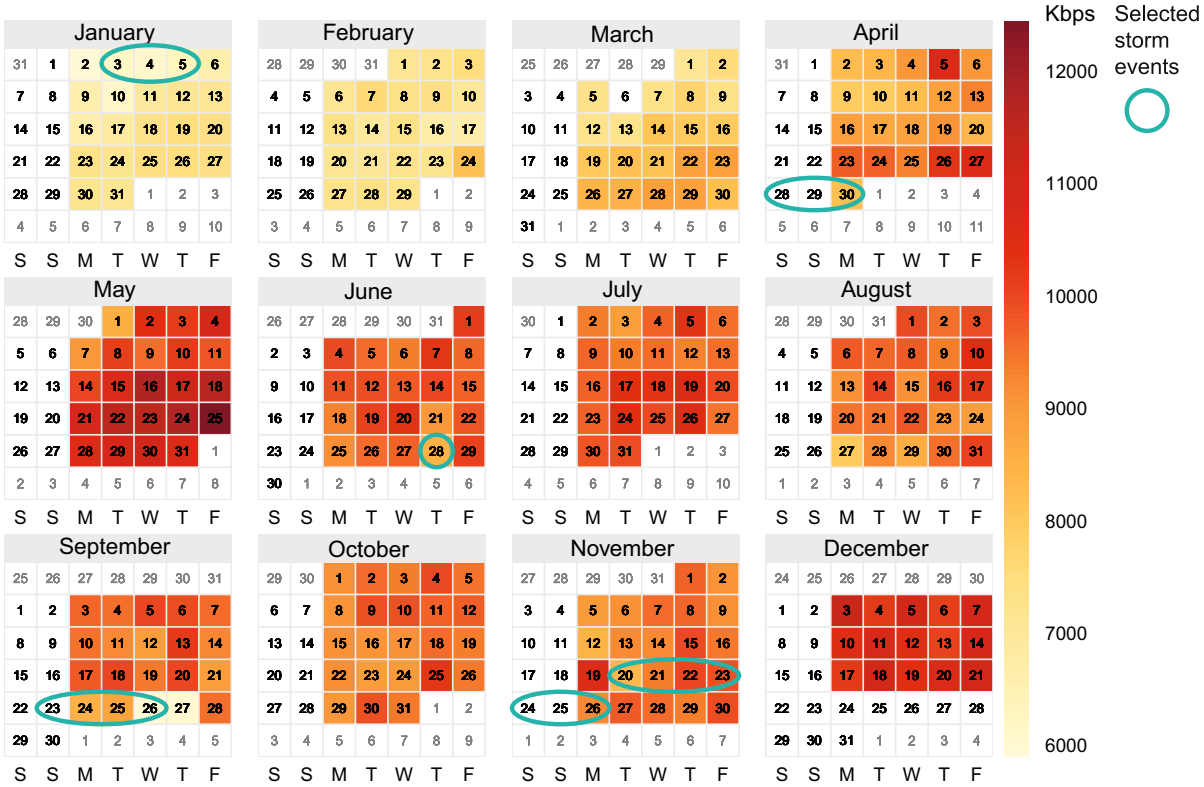


Fig. 2 Calendar plot of mean download in speeds (Kbps) for all working days (0800–1800) in 2012. A selection of storm days with known impacts are circled in blue

rainfall and fluvial (river) or groundwater flooding. Furthermore, the flooding of ICT infrastructure can also cause outages and tends to have more lasting impacts, as such faults are often more complex and take more time to fix, resulting in a potential time lag for repair (Horrocks et al., 2010; Lazarus, 2013).

The variables at test level *i* and the control variables at level *j* formed the base models (Model 1 and Model 2) of background variation. Each weather variable was inserted individually in Models 3–9 to test for effects on broadband speeds. Then they were tested jointly in Model 10, for although there are logical correlations between weather variables, e.g. Freezing Day and Snowfall, these are all under ± 0.3, a reasonably small effect (Field et al., 2012), and the changes in the coefficients for each when all weather variables are included in the estimation of (1) are of interest. Finally, sensitivity tests on subsets of data and interactions between the weather and the geographical variables were run to further explore the results.

Main results

Once all the chosen variables described above were cleaned and matched to create a single data set, we conducted an exploratory analysis to test our hypothesis that contention during extreme weather events was detectable prior to modelling. Calendar plots[3] like the one in Fig. 2 demonstrated that days of severe weather and likely increased internet activity are visible in the mean working day speeds when compared with Met Office weather event summaries (2012–2016a, 2012–2016b). Manual checks further compared storm and snow dates captured by the dummies to dates with weather impacts noted by the Met Office (2012–2016a; 2012–2016b). Many storm days were correctly picked up by the model and some others were captured by the Snow Day dummy, but a

[3] These 'calendar plots' were created using functions in R from Carslaw, D. and Ropkins, K., 2019. Package 'openair'.

few impactful storms in certain regions were missed altogether, particularly thunderstorms, which may not be accompanied by high winds, whilst for some dates with storm winds and precipitation, the Met Office did not record a notable event or impacts (2012–2016a; 2012–2016b). This analysis highlights the temporal variation that might be attributed to the presence and timing of not only weather parameters, but also weather impacts. Impacts also vary depending on what infrastructure is affected and the length of advance warning and preparation before the storm or snow – in other words, where and when adverse weather is more expected, preparation is likely to be better.

The results of the main multilevel model[4] based on Eq. (1) with intercepts that are allowed to vary by MSOA are shown in Table 3. The annual improvement in broadband speeds captured by the 'Annual Trend' coefficient is intuitive. The 26.3% average annual improvement that the coefficient represents is only slightly different from the average annual increases in *24-h* broadband speed of about 26.7% as reported by Ofcom for the UK between 2013 and 2016, although in the first year of analysis from 2012 to 2013, 24-h speeds rose much faster – see Table 2 (2016). The coefficients for ISP are also as expected, and people clearly do test their broadband more often when it is running slower than expected, as shown by the negative coefficient for tests per head of population, although any bias resulting from the fact that tests in this data set are more likely to be run "when there is other network activity ongoing" or speeds are lower than the customer expects (Riddlesden & Singleton, 2014, p. 26), may be countered by the likelihood that those who seek to test their broadband may be doing so because they are more 'tech-savvy' and / or have purchased higher speed packages that are not delivering the promised level of service.

The signs of the coefficients for the MSOA-level control variables are as expected, and the mostly high levels of significance indicate their relevance to broadband speeds. Those neighbourhoods with more residents on higher incomes or who are more tech-savvy due to the industry in which they work are more likely to purchase faster broadband connections, and such connections are more reliably available in more urban locations. Conversely, the higher the proportion of home workers, and, minimally, those with more occupational autonomy to telecommute, the more demand for broadband and the slower the speeds on the network. All the temporal trend, speed test, and control variable coefficients are broadly consistent across the different estimations of the model. The largest differences are found where the sample size used in the estimation is substantially smaller due to inclusion of the Snowfall dummy.

In terms of the research question, our results show that severe weather conditions have small, but highly significant effects on broadband speeds. Days recording storm-force winds, ice and snow appear to lower broadband speeds by around 3–5% individually or jointly, which could represent noticeable reductions in the level of service, depending upon the applications in use and the speeds normally available over a particular connection. Indeed, this level of contention is directly comparable to the level of daily contention during the evening peak at 2.6–5.5%, as measured by Ofcom for all connection types (2018). There are no significant effects on broadband speeds due to rain, perhaps because rainy days are so common in the UK that behaviour is unlikely to change in response, especially where the variable relates to amount of precipitation, not intensity.

As one weather parameter can affect another, such as high temperatures making intense rainfall more likely, the last estimation includes all weather variables together. Although the effects are clearly not cumulative, the negative influence of storm-force winds almost doubles to 5%. This suggests that the wind gust parameter has a stronger relationship with contention when controlling for heavy rain, snowfall, or a heatwave, which may be because there is more advance warning not to travel during major wind storms than at times of high winds during hot weather and heavy rain. The latter are more common in the afternoon or evening, when people are already out for the day, and the choice not to travel is less viable. Likewise, speeds increase on 'Hot Days' where the model controls for other weather parameters that might keep people from enjoying such days out of doors. Summer heatwaves also often occur when a substantial proportion of the working population are on holiday and, with school traffic absent, transport infrastructure is less congested and internet usage is generally lower.

[4] The model was estimated using the 'nlme' package for R.

Table 3 Main regression model results

	Dependent variable: download test speed (log)									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Annual Trend	0.263***	0.263***	0.263***	0.263***	0.263***	0.263***	0.263***	0.262***	0.263***	0.262***
	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0005	0.0004	0.0005
Distance to Nearest Exchange	− 0.017	0.040***	0.041***	0.040***	0.041***	0.040***	0.040***	0.046***	0.040***	0.047***
	0.012	0.011	0.011	0.011	0.011	0.011	0.011	0.012	0.011	0.012
Virgin Media compared to BT	0.655***	0.649***	0.649***	0.648***	0.649***	0.648***	0.649***	0.651***	0.649***	0.651***
	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Other compared to BT	− 0.394***	− 0.396***	− 0.396***	− 0.396***	− 0.396***	− 0.396***	− 0.396***	− 0.389***	− 0.396***	− 0.389***
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.002
Ratio of Speed Tests to population		− 0.645***	− 0.644***	− 0.645***	− 0.644***	− 0.645***	− 0.643***	− 0.669***	− 0.644***	− 0.667***
		0.074	0.074	0.074	0.074	0.074	0.074	0.080	0.074	0.080
Ratio of pop working in High-tech industries		1.602***	1.605***	1.595***	1.604***	1.594***	1.583***	1.832***	1.601***	1.807***
		0.174	0.174	0.174	0.174	0.174	0.174	0.188	0.174	0.188
Ratio of pop with higher professional status		− 0.185**	− 0.185**	− 0.180**	− 0.185**	− 0.180**	− 0.176**	− 0.239**	− 0.184**	− 0.225**
		0.089	0.089	0.089	0.089	0.089	0.089	0.096	0.089	0.096
Average commuting distance (log)		− 0.027*	− 0.027*	− 0.027*	− 0.027*	− 0.027*	− 0.027*	− 0.014	− 0.027*	− 0.014
		0.014	0.014	0.014	0.014	0.014	0.014	0.015	0.014	0.015
More urban location		0.343***	0.343***	0.342***	0.343***	0.342***	0.343***	0.342***	0.343***	0.342***
		0.012	0.012	0.012	0.012	0.012	0.012	0.013	0.012	0.013
Ratio of pop with home as main workplace		− 4.828***	− 4.833***	− 4.826***	− 4.833***	− 4.828***	− 4.823***	− 5.085***	− 4.829***	− 5.076***
		0.291	0.291	0.291	0.291	0.291	0.291	0.315	0.291	0.315
Household net weekly income (log)		0.171***	0.171***	0.170***	0.171***	0.170***	0.169***	0.166***	0.171***	0.163***
		0.021	0.021	0.021	0.021	0.021	0.021	0.022	0.021	0.022
Rainy Day			0.001							− 0.0004
			0.001							0.002
Windy Day				0.0004						− 0.001
				0.002						0.002
Heavy Rain					0.002					0.005
					0.004					0.005
Storm						− 0.028***				− 0.049***
						0.006				0.008
Freezing Day							− 0.036***			− 0.030***
							0.002			0.002

Table 3 (continued)

	Dependent variable: download test speed (log)									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Snowfall								− 0.057***		− 0.042***
								0.004		0.004
Hot Day									0.008	0.033***
									0.01	0.012
Constant	8.420***	7.231***	7.230***	7.239***	7.231***	7.239***	7.249***	7.230***	7.233***	7.255***
	0.005	0.112	0.112	0.112	0.112	0.112	0.112	0.122	0.112	0.122
Observations	2,556,025	2,556,025	2,551,210	2,552,299	2,551,210	2,553,455	2,555,551	2,272,718	2,555,551	2,267,476
Log Likelihood	− 3,636,473	− 3,634,705	− 3,628,047	− 3,629,246	− 3,628,047	− 3,630,936	− 3,633,861	− 3,229,738	− 3,634,009	− 3,222,000
Akaike Inf. Crit	7,272,969	7,269,446	7,256,131	7,258,530	7,256,131	7,261,911	7,267,759	6,459,514	7,268,055	6,444,051
Bayesian Inf. Crit	7,273,109	7,269,676	7,256,373	7,258,773	7,256,374	7,262,153	7,268,002	6,459,754	7,268,298	6,444,367

*p < 0.1; **p < 0.05; ***p < 0.01

Sensitivity testing

Spatial sensitivity testing

The results in Table 3 provide some clear insights into whether weather causes contention. However, we undertook sensitivity testing in order to reduce some of the statistical noise generated by a spatially and temporally heterogeneous dependent variable. As shown in Fig. 3, there is substantial variation in average speeds at MSOA level, with faster average speeds generally found in more urban areas. The results of the main model address this spatial heterogeneity by applying a multilevel model with random intercepts and including variables controlling for certain geographic and socio-economic characteristics. However, there are other methodologies, so the first sensitivity test defined repeated observations for each MSOA by date as 'panel data' using the 'within effects transformation' applied to OLS regressions.[5] This estimation produced similar results as shown in Table A1 in Appendix A.

Next, an interaction term between the weather variables and the binary urban–rural dummy was added to the original model, as there are fewer transport options in rural areas if there is disruption or reduced road access. The results, shown in Table A2 in the Appendix, indicate that rain, snow, and freezing weather all have less impact on broadband speeds in urban areas than in the 652 MSOAs classified as dispersed rural settlements. One explanation for this relationship to winter weather might be the additional vulnerability of rural roads to snow and ice, due in part to their low priority for winter road maintenance. Thus, the negative effect of snowy weather on internet speeds is greater, indicating more internet activity and a greater reliance on virtual accessibility in rural areas at such times. It is less obvious why internet activity in rural areas increases in wet weather but decreases in response to storm-level winds, although it is possible this correlation is associated not with daily travel, but with local, outdoor, rural activities, such as farming and tourism. Outdoor activities are often more difficult or less attractive in the rain, whilst storm-level winds may not be relevant if the activity is in a sheltered area or if impacts are more

[5] This regression was estimated with the 'plm' package for R.

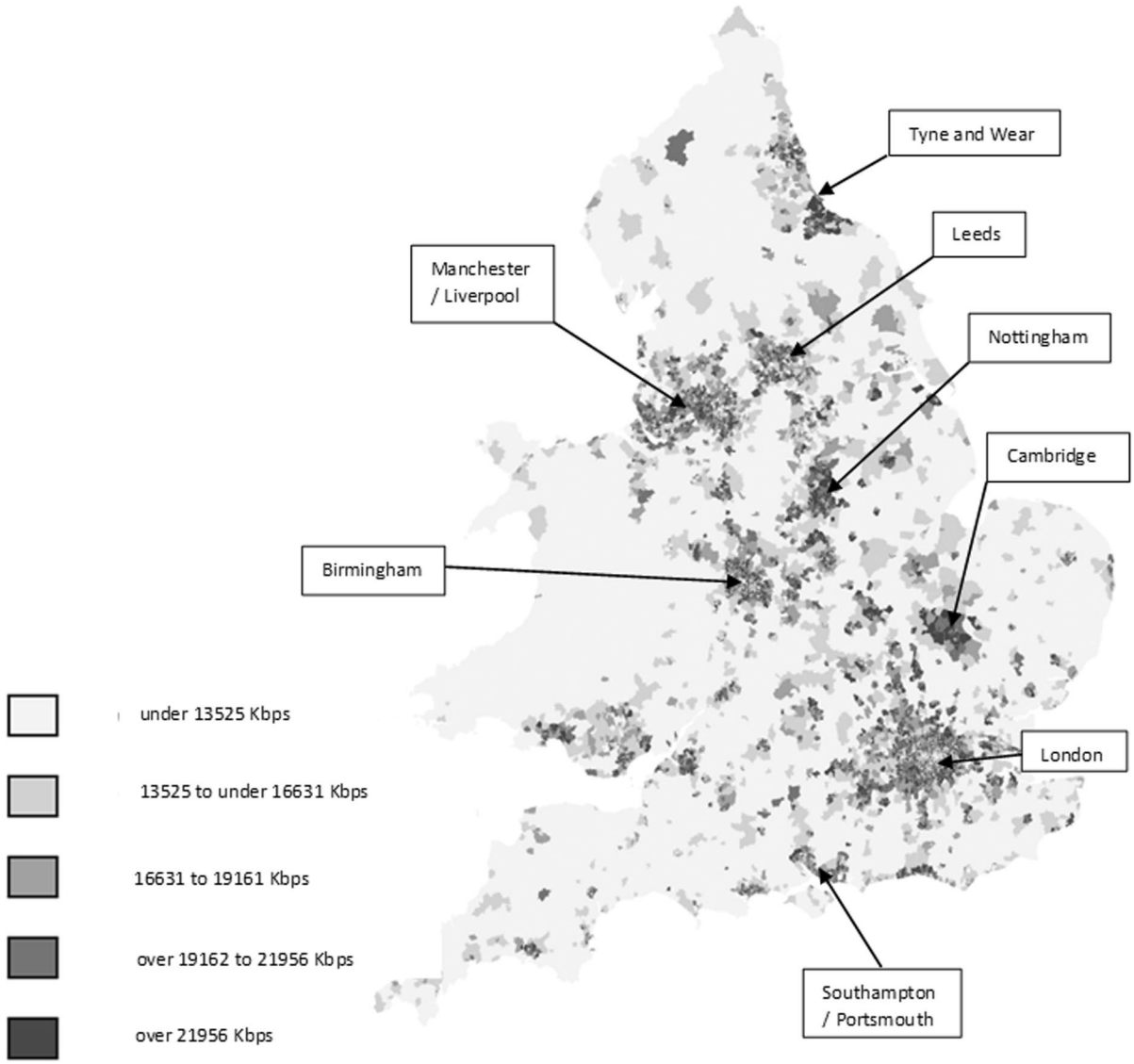
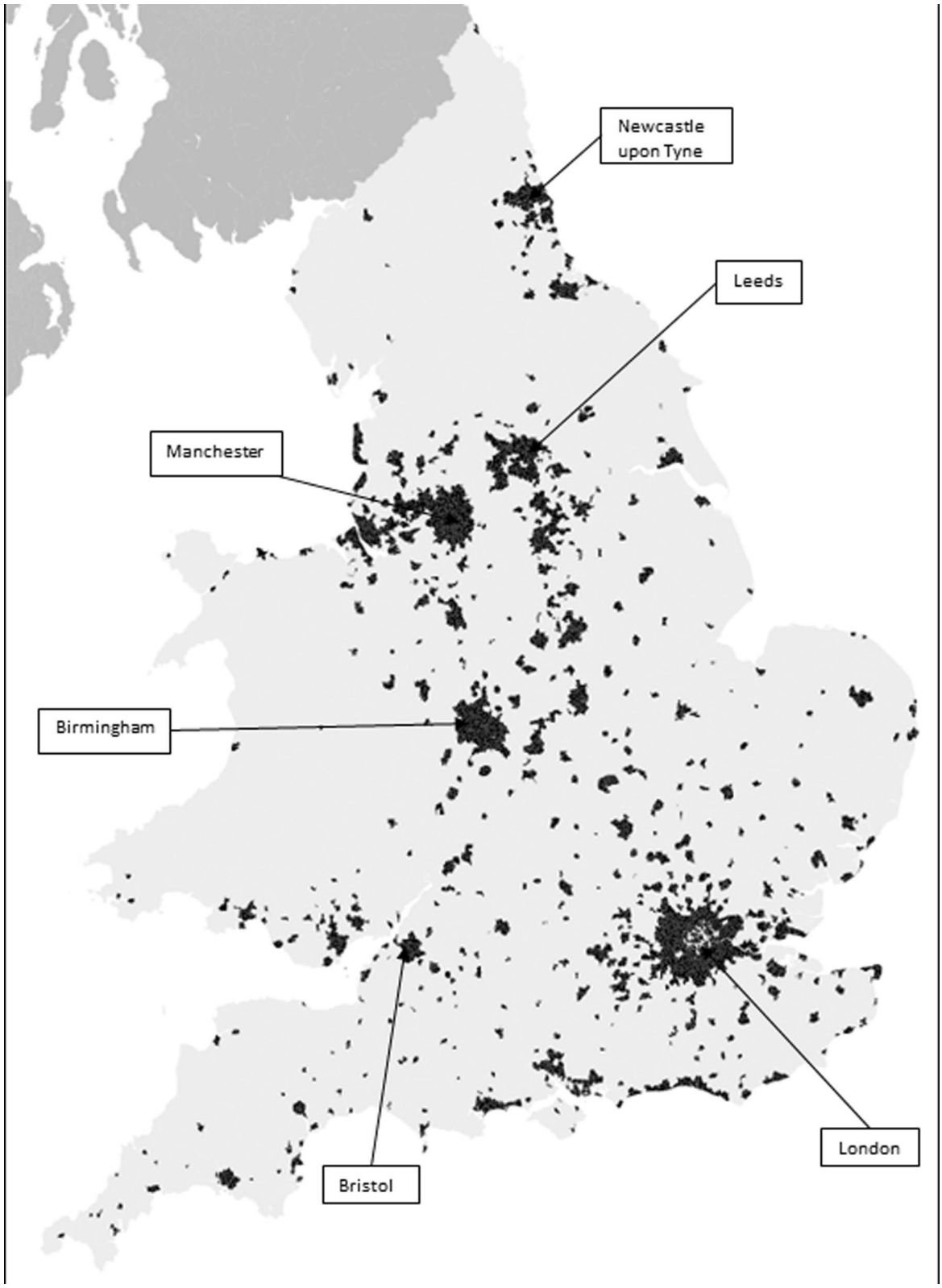


Fig. 3 Mean speeds (Kbps) by MSOA for 2012–2016 working days

localised and thus affect a lower proportion of a dispersed population.

However, neither the binary urban–rural variable in the model, nor any of the other levels of urban–rural classification used by the ONS capture suburban areas of conurbations independently of those conurbations' central cores. These 'suburban' geographies and smaller urban areas are where telecommuters are most likely to be located, and where the relationship between adverse weather and internet accessibility is more relevant. Such areas have neither the rural economic activities and relatively slow broadband speeds under typical weather conditions of dispersed settlements, nor do they have the high densities of local employment options, other activities, and transport services of central cities, and particularly central London neighbourhoods. Therefore, residential population density by MSOA using the 2014 population estimates (ONS, 2017), was used to subset the model for further sensitivity analysis. According to Welch's *t*-tests, the subset of MSOAs with a population density of between 1000 and 15,000 residents per km^2


Newcastle upon Tyne
Leeds
Manchester
Birmingham
Bristol
London

◂**Fig. 4** The subset of MSOAs with between 1000 and 15,000 resident population / km in 2014

had mean speeds on 'Storm' days half a Mb/s less than the average for non-stormy days, which was significant at $p = 0.002$, suggesting that the null hypothesis of no difference in means could be rejected (Field et al., 2012). Furthermore, as shown in Fig. 4, this subset excluded both dispersed rural areas and those exceptional, central London neighbourhoods.

The model results in Table 4 for this subset represent over half the total data set at 1,434,642 observations. In these neighbourhoods the impact of storms on broadband speeds is a 4% decrease in speeds without controlling for other weather variables and 6.6% with controls. The effect of snowfall is also greater. In partial confirmation that rural responses to weather differ from more urban ones, the effect of home workers on broadband speeds changes from significantly negative to significantly positive. This implies that those in suburban and more urban locations who work mainly at or from home have the opportunity and are investing in higher speed services to support such work. Average commuting distance within each MSOA becomes positive and more significant, perhaps because this subset excludes outliers from rural villages with particularly long-distance commutes and slower home broadband. Overall, this sensitivity test offers additional evidence that internet activity and contention increase in adverse weather when people may prefer to stay home to avoid the risk of transport disruption or may be forced to stay home due to transport disruption. It further indicates that this effect is stronger in areas where people may be more likely and able to telecommute.

Temporal sensitivity testing

The exploratory analysis described how the weather parameters in the model capture some, but not all of the temporal variation attributable to weather. There is also non-weather-related variation in broadband activity over time, which could be due to service upgrade promotions, special events that generate weekday internet activity, or direct impacts on broadband infrastructure like power cuts or hardware failure. These could not be modelled due to lack of data. The weather dummies account for some seasonal effects, and the 'month' variable was likewise tested, but the upward trend was inconsistent at the monthly scale, and could not be compared to Ofcom's annual reports.

Figure 5 shows that whilst broadband speeds rose year on year, the trend within each year varied. The temporal profile is broadly similar for 2012 and 2013, fluctuates widely in 2014, shows a different curve in 2015 and is fairly flat in 2016. There are large fluctuations within the annual rising trend in 2014, which included missing data during the storms and flooding of February 2014. Meanwhile, the manual checks in our exploratory analysis revealed that the Storm and Snow dummies picked up more days which were not matched by known impacts in 2015 than in the other years of analysis. Mean speeds in 2015 also increased more steeply in the Autumn than the Spring, further masking any daily impact of increased internet activity during known storms in November / December 2015. Therefore, a regression was run on a subset including observations only from 2012, 2013, and 2016, in order to test whether effects might be greater if other temporal variation is more muted. The results in Table A3 in Appendix A included a Storm coefficient indicating speed reductions of 10%. This gives weight to the possibility that the patterns of significant effects on broadband speeds in Table 3, which suggest contention in response to extreme weather parameters, are likely conservative estimates.

Discussion and conclusion

This article has argued that adverse weather conditions can be seen to create contention, or lower experienced internet speeds during the working day due to increased internet use and demand. We interpret this as an indication that people are choosing 'not travelling' as a viable, resilient alternative to avoid delay and disruption. Our approach using broadband speed data to quantify temporal variation within a multilevel modelling framework has enabled us to provide evidence that winter weather and storm-level winds show significant, albeit small, effects, and thus detectable contention. Conversely, demand appears to fall during a heatwave. The temporal sensitivity test demonstrates that the model may underestimate, rather than overestimate the relationship between weather and broadband speeds, as removing 2014 and 2015, when there were known divergences between weather

Table 4 Estimation of observations for MSOAs with a population density between 1000 and 15,000 people per km^2, excluding Urban / Rural classification

	Dependent variable: download test speed (log)								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Annual Trend	0.238***	0.238***	0.238***	0.238***	0.238***	0.237***	0.235***	0.238***	0.235***
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Distance to Nearest Exchange	0.018	0.018	0.017	0.018	0.018	0.018	0.017	0.018	0.018
	0.016	0.016	0.016	0.016	0.016	0.016	0.017	0.016	0.017
Virgin Media compared to BT	0.536***	0.536***	0.536***	0.536***	0.536***	0.536***	0.538***	0.536***	0.538***
	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Other compared to BT	− 0.546***	− 0.546***	− 0.546***	− 0.546***	− 0.546***	− 0.546***	− 0.541***	− 0.546***	− 0.541***
	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Ratio of Speed Tests to population	− 0.415***	− 0.414***	− 0.414***	− 0.414***	− 0.414***	− 0.413***	− 0.436***	− 0.415***	− 0.434***
	0.072	0.072	0.072	0.072	0.072	0.072	0.079	0.072	0.079
Ratio of pop working in High-tech industries	0.652***	0.655***	0.644***	0.654***	0.646***	0.633***	0.969***	0.653***	0.946***
	0.193	0.193	0.193	0.193	0.193	0.193	0.214	0.193	0.214
Ratio of pop with higher professional status	− 0.389***	− 0.389***	− 0.384***	− 0.389***	− 0.384***	− 0.380***	− 0.519***	− 0.389***	− 0.506***
	0.096	0.096	0.096	0.096	0.096	0.096	0.107	0.096	0.107
Average Commuting Distance (log)	0.062***	0.063***	0.062***	0.063***	0.062***	0.062***	0.077***	0.062***	0.077***
	0.016	0.016	0.016	0.016	0.016	0.016	0.017	0.016	0.017
Ratio of pop with home as main workplace	2.104***	2.103***	2.111***	2.104***	2.108***	2.115***	1.832***	2.104***	1.849***
	0.439	0.439	0.439	0.439	0.439	0.439	0.493	0.439	0.493
Household net weekly income (log)	0.052**	0.052**	0.050**	0.052**	0.050**	0.049**	0.069***	0.052**	0.065***
	0.022	0.022	0.022	0.022	0.022	0.022	0.025	0.022	0.025
Rainy Day		0.003							0.002
		0.002							0.002
Windy Day			− 0.001						− 0.005*
			0.002						0.002
Heavy Rain				0.006					0.009
				0.006					0.006
Storm					− 0.039***				− 0.066***
					0.008				0.01
Freezing Day						− 0.037***			− 0.029***
						0.003			0.003
Snowfall							− 0.062***		− 0.048***
							0.005		0.005
Hot Day								− 0.006	0.018
								0.013	0.015
Constant	8.239***	8.237***	8.250***	8.238***	8.248***	8.259***	8.111***	8.239***	8.137***
	0.121	0.121	0.121	0.121	0.121	0.121	0.136	0.121	0.136
Observations	1,434,642	1,431,499	1,432,712	1,431,499	1,433,407	1,434,470	1,246,216	1,434,470	1,243,644

Table 4 (continued)

	Dependent variable: download test speed (log)								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Log Likelihood	− 2,004,639	− 2,000,369	− 2,001,845	− 2,000,370	− 2,002,875	− 2,004,293	− 1,741,277	− 2,004,384	− 1,737,522
Akaike Inf. Crit	4,009,312	4,000,774	4,003,726	4,000,776	4,005,786	4,008,622	3,482,591	4,008,803	3,475,092
Bayesian Inf. Crit	4,009,519	4,000,993	4,003,945	4,000,995	4,006,005	4,008,842	3,482,807	4,009,022	3,475,381

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

parameters and weather impacts resulted in larger effects. The spatial sensitivity tests also demonstrated the heterogeneity in response between rural, suburban and central urban areas.

Indeed, this very heterogeneity also reveals the limitations of our data sources and our modelling framework in detecting contention as a proxy to both quantify the demand for internet access during the working day at times of adverse weather or severe weather events and to investigate the impact of external factors like weather on the choice to telecommute. Since weather impacts have greater temporal variation than the weather parameters used in the model, it was difficult to choose thresholds that neither over-selected nor under-selected storm dates. It is also unknown whether the contention identified occurs in response to the weather parameter itself, short-term weather warnings of potential impacts that are often broadcast at the regional level, or transport disruption caused by the weather. The models could also only imperfectly capture the geographic / socio-demographic constraints on internet use and quality of service. For example, there are local initiatives to improve broadband infrastructure in some rural areas, but not others, whilst the occurrence of local faults and outages due to weather are unlikely to be evenly distributed in space or time. Nor was data available on mass outages, no matter their cause. Finally, measurements of contention cannot confirm which activities are represented in the change in demand for online access. The data is at the level of the household, not the individual, and there is no knowing how many of the household are staying home and who in the household is generating increased demand. Children at home during school closures may be watching videos or playing games that require substantial broadband capacity, whilst any adults staying at home, even if they are undertaking work tasks online, might generate a fraction of the demand.

On the other hand, a study of internet traffic found significant positive correlations between work or economic activity and the volume of data being transmitted by time of day and day of week, and a negative correlation between data flows and commuting peak hours (Stubbings & Rowe, 2019). The spatial data used in this research was nowhere near as granular as our data, but further research along these lines could usefully uncover more detailed relationships in suburban geographies where telecommuting is most likely, using additional transport data sources, different socio-economic variables, interaction terms, weather thresholds, and 'suburban' subsets. Furthermore, the substantial increase in experience of telecommuting during the pandemic may mean that future demand during adverse weather may be sufficient to detect contention in upload speeds (Budnitz & Tranos, 2021), which can be more easily linked to work activities. Finally, a case study approach building upon the understanding of contention described in this article could use broadband speeds in combination with other detailed data sources for periods of weather disruption in order to determine the extent of weather impacts, which depend on the time of day or locally-specific characteristics of infrastructure or population. One criticism of transport research is that "our approach to understanding travel is not particularly insightful in understanding reasons for not travelling" and instead participating in non-domestic activities online (Marsden et al., 2018, p50). Our research offers an alternative approach to gaining such insights by using broadband speed variation during working hours in a multilevel model to measure

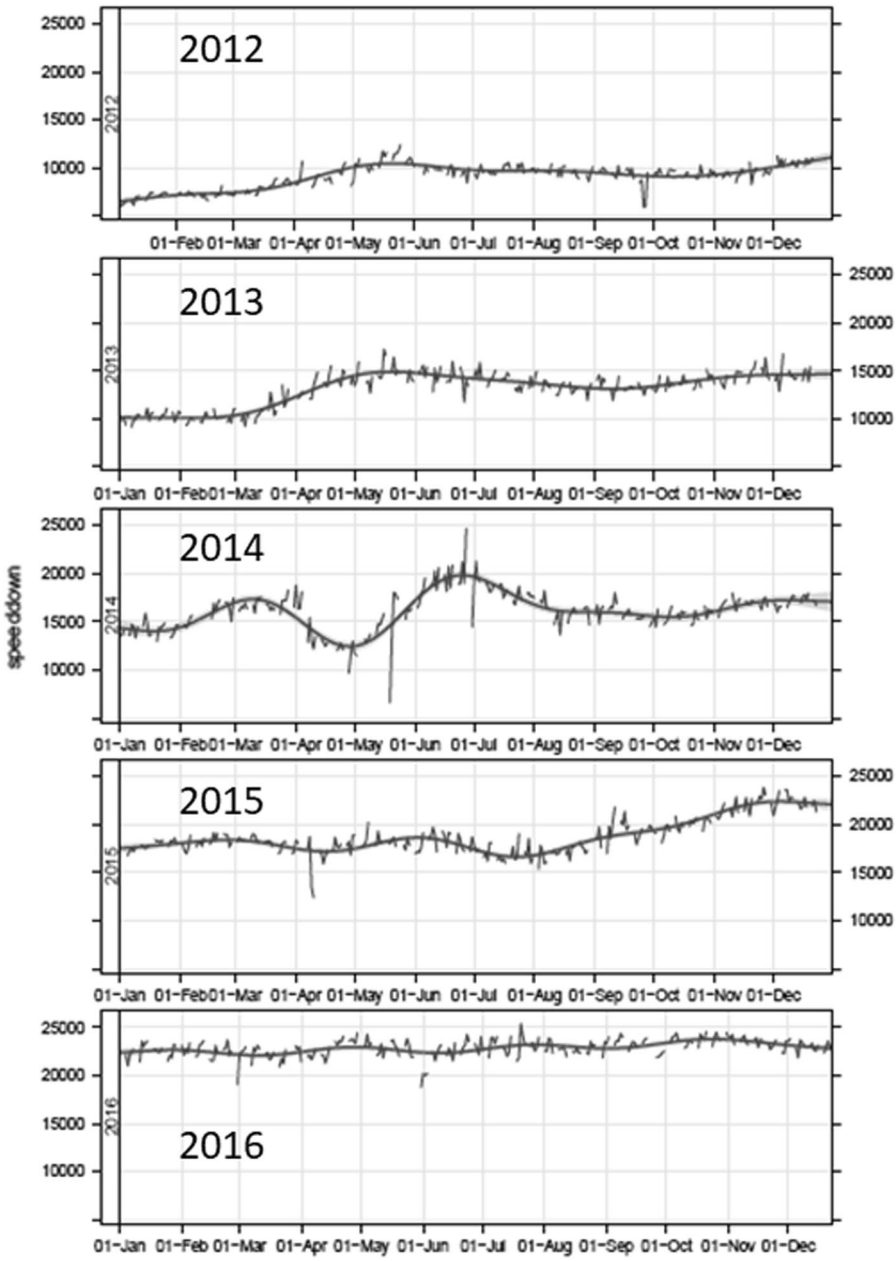


Fig. 5 Mean broadband download speeds (Kbps) by date and year for working days

internet accessibility and activity in real time with a high level of spatial granularity.

In conclusion, our study provides pre-pandemic insights into patterns of internet activity and resilient accessibility at a level of temporal granularity and geographic scale such that a small, but significant increase in contention for download speeds during severe weather like storms and snowfall is detectable. It also provides evidence of the ability of online accessibility to replace travel during adverse weather conditions, and that external factors like the risk of disruption to transport due to severe weather may well influence the choice to telecommute. Indeed, the measurable contention is not dissimilar to what is experienced during peak demand for evening entertainment, even though weather parameters rather than weather impacts are included in the modelling framework. The replacement of

travel with internet access and commuting with telecommuting is an important option to promote during extreme weather events as the most resilient and least risky choice to maintain productivity. The Covid-19 pandemic has shown just what is possible and will have created unprecedented levels of experience in this form of access, as well as resulting in a step change in both software to support telecommuting and investment in broadband infrastructure and services, a trend which will no doubt continue. Furthermore, by increasing familiarity with telecommuting, it will become an option to overcome disruptions to travel and provide resilience for a much greater share of the working population than we may have previously thought possible.

Acknowledgements The authors would like to thank Speedchecker Ltd. for its generous sharing of data and Dr M Nardotto for sharing some complementary data and his experience working on Speedchecker Ltd. Data in the past.

Author Contribution All authors contributed to the study conception and design. Material preparation, data sourcing (of secondary data rather than primary data collection) and analysis were performed by Hannah Budnitz, Emmanouil Tranos and Lee Chapman. The first draft of the manuscript was written by Hannah Budnitz and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability The datasets analysed during the current study are available in the following repositories: Office for National Statistics: https://www.nomisweb.co.uk/census/2011, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/smallareaincomeestimatesformiddlelayersuperoutputareasenglandandwales, https://ons.maps.arcgis.com/home/item.html?id=86fac76c60ed4943a8b94f64bff3e8b1, and https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareapopulationdensity; the British Atmospheric Data Centre: http://catalogue.ceda.ac.uk/uuid/1bb479d3b1e38c339adb9c82c15579d8, http://catalogue.ceda.ac.uk/uuid/a1f65a362c26c9fa667d98c431a1ad38, http://catalogue.ceda.ac.uk/uuid/954d743d1c07d1dd034c131935db54e0, and http://catalogue.ceda.ac.uk/uuid/bbd6916225e7475514e17fdbf11141c1; and similar data from the Consumer Research Data Centre https://data.cdrc.ac.uk/dataset/broadband-speed. The broadband speed data was provided directly by the private company to the researchers, and so was in a slightly different form than was deposited later with the CRDC.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

Ethical approval No ethical approval was required as all data was sourced from other data owners and is available at various repositories.

Appendix: Sensitivity Test Results

See Tables 5, 6, 7.

Table 5 Model showing the 'within effects transformation' coefficients at the individual and regional scales

	Dependent variable: download test speed (log)							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Annual Trend	0.263***	0.263***	0.263***	0.263***	0.263***	0.263***	0.263***	0.262***
	0.0004	0.0004	0.0004	0.0004	0.0004	0.0005	0.0004	0.0005
Distance to Nearest Exchange	0.029*	0.028*	0.029*	0.028*	0.028*	0.027*	0.028*	0.028*
	0.015	0.015	0.015	0.015	0.015	0.016	0.015	0.016
Virgin Media compared to BT	0.650***	0.649***	0.650***	0.649***	0.649***	0.652***	0.649***	0.652***
	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Other compared to BT	− 0.396***	− 0.396***	− 0.396***	− 0.396***	− 0.396***	− 0.390***	− 0.396***	− 0.389***
	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.002
Rainy Day	0.001							− 0.0004
	0.001							0.002
Windy Day		0.00001						− 0.001
		0.002						0.002
Heavy Rain			0.002					0.005
			0.004					0.005
Storm				− 0.028***				− 0.049***
				0.006				0.008
Freezing Day					− 0.037***			− 0.031***
					0.002			0.002
Snowfall						− 0.057***		− 0.042***
						0.004		0.004
Hot Day							0.008	0.032***
							0.01	0.012
Observations	2,551,210	2,552,299	2,551,210	2,553,455	2,555,551	2,272,718	2,555,551	2,267,476
R2	0.2	0.2	0.2	0.2	0.2	0.196	0.2	0.197
Adjusted R2	0.198	0.198	0.198	0.198	0.198	0.194	0.198	0.194
F Statistic	70,740*** (df = 9; 2,544,000)	70,858*** (df = 9; 2,545,089)	70,739*** (df = 9; 2,544,000)	70,879*** (df = 9; 2,546,245)	70,945*** (df = 9; 2,548,341)	61,471*** (df = 9; 2,265,508)	70,903*** (df = 9; 2,548,341)	36,857*** (df = 15; 2,260,260)

*p < 0.1; **p < 0.05; ***p < 0.01

Table 6 Interaction of weather variables with MSOAs' urban or rural character

	Dependent variable: download test speed (log)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Annual Trend	0.263***	0.263***	0.263***	0.263***	0.263***	0.262***	0.263***
	0.0004	0.0004	0.0004	0.0004	0.0004	0.0005	0.0004
Distance to Nearest Exchange	0.041***	0.040***	0.041***	0.040***	0.040***	0.046***	0.040***
	0.011	0.011	0.011	0.011	0.011	0.012	0.011
Virgin Media compared to BT	0.649***	0.648***	0.649***	0.648***	0.649***	0.651***	0.649***
	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Other compared to BT	− 0.396***	− 0.396***	− 0.396***	− 0.396***	− 0.396***	− 0.389***	− 0.396***
	0.001	0.001	0.001	0.001	0.001	0.002	0.001
Ratio of Speed Tests to population	− 0.645***	− 0.645***	− 0.645***	− 0.644***	− 0.643***	− 0.669***	− 0.645***
	0.074	0.074	0.074	0.074	0.074	0.08	0.074
Ratio of pop working in High-tech industries	1.606***	1.595***	1.604***	1.595***	1.584***	1.833***	1.601***
	0.174	0.174	0.174	0.174	0.174	0.188	0.174
Ratio of pop with higher professional status	− 0.186**	− 0.181**	− 0.185**	− 0.180**	− 0.176**	− 0.239**	− 0.184**
	0.089	0.089	0.089	0.089	0.089	0.096	0.089
Average Commuting Distance (log)	− 0.027*	− 0.027*	− 0.027*	− 0.027*	− 0.027*	− 0.014	− 0.027*
	0.014	0.014	0.014	0.014	0.014	0.015	0.014
More urban location	0.335***	0.341***	0.342***	0.343***	0.341***	0.341***	0.343***
	0.012	0.012	0.012	0.012	0.012	0.013	0.012
Ratio of pop with home as main workplace	− 4.826***	− 4.825***	− 4.832***	− 4.829***	− 4.823***	− 5.087***	− 4.829***
	0.291	0.291	0.291	0.291	0.291	0.315	0.291
Household net weekly income (log)	0.171***	0.170***	0.171***	0.170***	0.169***	0.167***	0.171***
	0.021	0.021	0.021	0.021	0.021	0.022	0.021
Rainy Day	− 0.025***						
	0.004						
Rainy Day x More urban	0.031***						
	0.004						
Windy Day		− 0.004					
		0.004					
Windy Day x More urban		0.005					
		0.004					
Heavy Rain			− 0.016				
			0.01				
Heavy Rain x More urban			0.021*				
			0.011				
Storm				0.004			
				0.017			
Storm x More urban				− 0.037**			
				0.019			
Freezing Day					− 0.049***		
					0.005		
Freezing Day x More urban					0.015**		
					0.006		
Snowfall						− 0.089***	
						0.01	

Table 6 (continued)

	Dependent variable: download test speed (log)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Snowfall x More urban						0.037***	
						0.011	
Hot Day							0.025
							0.03
Hot Day x More urban							− 0.019
							0.032
Constant	7.237***	7.239***	7.231***	7.239***	7.250***	7.230***	7.232***
	0.112	0.112	0.112	0.112	0.112	0.122	0.112
Observations	2,551,210	2,552,299	2,551,210	2,553,455	2,555,551	2,272,718	2,555,551
Log Likelihood	− 3,628,016	− 3,629,246	− 3,628,045	− 3,630,934	− 3,633,857	− 3,229,732	− 3,634,008
Akaike Inf. Crit	7,256,072	7,258,531	7,256,130	7,261,909	7,267,755	6,459,505	7,268,057
Bayesian Inf. Crit	7,256,327	7,258,786	7,256,385	7,262,164	7,268,010	6,459,757	7,268,312

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 7 Estimation of the subset of observations for all working day dates in 2012, 2013 and 2016

	Dependent Variable: Download Test Speed (log)									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Annual Trend	0.261***	0.260***	0.260***	0.260***	0.260***	0.260***	0.260***	0.260***	0.260***	0.260***
	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0005	0.0004	0.0005
Distance to Nearest Exchange	− 0.018	0.050***	0.051***	0.051***	0.051***	0.050***	0.051***	0.056***	0.051***	0.056***
	0.014	0.013	0.013	0.013	0.013	0.013	0.013	0.014	0.013	0.014
Virgin Media compared to BT	0.614***	0.606***	0.606***	0.606***	0.606***	0.606***	0.606***	0.609***	0.606***	0.609***
	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Other compared to BT	− 0.390***	− 0.392***	− 0.391***	− 0.392***	− 0.391***	− 0.392***	− 0.391***	− 0.385***	− 0.392***	− 0.385***
	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Ratio of Speed Tests to population		− 0.828***	− 0.827***	− 0.828***	− 0.827***	− 0.828***	− 0.828***	− 0.842***	− 0.828***	− 0.840***
		0.084	0.084	0.084	0.084	0.084	0.084	0.089	0.084	0.089
Ratio of pop working in High-tech industries		1.792***	1.786***	1.775***	1.791***	1.781***	1.772***	1.982***	1.789***	1.940***
		0.197	0.197	0.197	0.197	0.197	0.197	0.21	0.197	0.21
Ratio of pop with higher professional status		− 0.143	− 0.138	− 0.135	− 0.14	− 0.137	− 0.132	− 0.178*	− 0.141	− 0.156
		0.1	0.1	0.1	0.1	0.1	0.1	0.107	0.1	0.107
Average Commuting Distance (log)		− 0.056***	− 0.056***	− 0.056***	− 0.056***	− 0.056***	− 0.056***	− 0.047***	− 0.056***	− 0.046***
		0.016	0.016	0.016	0.016	0.016	0.016	0.017	0.016	0.017
More urban location		0.339***	0.339***	0.339***	0.339***	0.339***	0.338***	0.339***	0.338***	0.339***
		0.013	0.013	0.013	0.013	0.013	0.013	0.014	0.013	0.014
Ratio of pop with home as main workplace		− 4.877***	− 4.878***	− 4.861***	− 4.881***	− 4.873***	− 4.874***	− 5.072***	− 4.877***	− 5.045***
		0.328	0.329	0.328	0.329	0.328	0.329	0.351	0.328	0.351
Household net weekly income (log)		0.152***	0.151***	0.150***	0.151***	0.150***	0.150***	0.142***	0.151***	0.137***
		0.023	0.023	0.023	0.023	0.023	0.023	0.025	0.023	0.025
Rainy Day			− 0.005***							− 0.005**
			0.002							0.002
Windy Day				− 0.006***						− 0.004*
				0.002						0.002
Heavy Rain					0.002					0.006
					0.005					0.005
Storm						− 0.096***				− 0.114***
						0.01				0.012
Freezing Day							− 0.033***			− 0.028***
							0.002			0.003

Table 7 (continued)

	Dependent Variable: Download Test Speed (log)									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Snowfall								− 0.061***		− 0.046***
								0.005		0.005
Hot Day									0.016	0.040***
									0.011	0.012
Constant	8.430***	7.430***	7.438***	7.445***	7.434***	7.440***	7.447***	7.466***	7.434***	7.501***
	0.005	0.127	0.127	0.127	0.127	0.127	0.127	0.137	0.127	0.137
Observations	1,636,521	1,636,521	1,633,420	1,634,816	1,633,420	1,635,407	1,636,047	1,474,781	1,636,047	1,472,447
Log Likelihood	− 2,299,975	− 2,298,391	− 2,294,135	− 2,295,938	− 2,294,139	− 2,296,770	− 2,297,596	− 2,067,404	− 2,297,687	− 2,063,908
Akaike Inf. Crit	4,599,973	4,596,818	4,588,308	4,591,914	4,588,316	4,593,578	4,595,230	4,134,846	4,595,412	4,127,866
Bayesian Inf. Crit	4,600,108	4,597,039	4,588,542	4,592,148	4,588,550	4,593,812	4,595,464	4,135,078	4,595,646	4,128,171

*p < 0.1; **p < 0.05; ***p < 0.01

References

Allen, T. D., Golden, T. D. S., & KM. (2015). How effective is telecommuting? Assessing the status of our scientific findings. *Psychological Science in the Public Interest, 16*, 40–68. https://doi.org/10.1177/1529100615593273

Bell, A., & Jones, K. (2015). Explaining fixed effects: random effects modeling of time-series cross-sectional and panel data. *Political Science Research and Methods, 3*, 133–153. https://doi.org/10.1017/psrm.2014.7

Budnitz, H., & Tranos, E. (2021). Working from home and digital divides: Resilience during the pandemic'. *Annals of the American Association of Geographers, September*. https://doi.org/10.1080/24694452.2021.1939647

Budnitz, H., Tranos, E., & Chapman, L. (2020). Responding to stormy weather: Choosing which journeys to make. *Travel Behaviour and Society, 18*, 94–105. https://doi.org/10.1016/j.tbs.2019.10.008

Böcker, L., Dijst, M., & Prillwitz, J. (2013). Impact of everyday weather on individual daily travel behaviours in perspective: A literature review. *Transport Reviews, 33*, 71–91. https://doi.org/10.1080/01441647.2012.747114

Chatterton, J., Clarke, C., Daly, E., Dawks, S., et al. (2016). *The costs and impacts of the winter 2013 to 2014 floods* (pp. 1–266). Bristol: Environment Agency.

Crawford, F. (2020). Segmenting travellers based on day-to-day variability in work-related travel behaviour. *Journal of Transport Geography, 86*, 102765. https://doi.org/10.1016/j.jtrangeo.2020.102765

Crawford, F., Watling, D. P., & Connors, R. D. (2017). A statistical method for estimating predictable differences between daily traffic flow profiles. *Transportation Research Part B, 95*, 196–213. https://doi.org/10.1016/j.trb.2016.11.004

Dawson R. (2016) Chapter 4: Infrastructure. *UK Climate Change Risk Assessment 2017: Evidence Report.* Committee on Climate Change, 1–111. https://www.theccc.org.uk/uk-climate-change-risk-assessment-2017/ccra-chapters/infrastructure/.

Dobney, K., Baker, C. J., Chapman, L., & Quinn, A. D. (2009). The future cost to the United Kingdom's railway network of heat-related delays and buckles caused by the predicted increase in high summer temperatures owing to climate change. *J Proc IMechE Part f: J. Rail and Rapid Transit, 224*, 25–34. https://doi.org/10.1243/09544097JRRT292

Ellen, I., & Hempstead, K. (2002). Telecommuting and the demand for urban living: A preliminary look at white-collar workers. *Urban Studies, 39*, 749–766. https://doi.org/10.1080/00420980220119552

Felstead, A. (2012). Rapid change or slow evolution? Changing places of work and their consequences in the UK. *Journal of Transport Geography, 21*, 31–38. https://doi.org/10.1016/j.jtrangeo.2011.10.002

Field, A., Miles, J., & Field, Z. (2012). *Discovering Statistics Using R*. Sage.

Fu, G., Horrocks, L., & Winne, S. (2016). Exploring impacts of climate change on UK's ICT infrastructure. *Infrastructure Asset Management., 3*, 42–52. https://doi.org/10.1680/jinam.15.00002

Haddad, H., Lyons, G., & Chatterjee, K. (2009). An examination of determinants influencing the desire for and frequency of part-day and whole-day homeworking. *Journal of Transport Geography, 17*, 124–133. https://doi.org/10.1016/j.jtrangeo.2008.11.008

Hauge, J. A., Jamison, M. A., & Marcu, M. I. (2010). Consumer Usage of Broadband Internet Services: an analysis of the case of Portugal. In Y. K. Dwivedi (Ed.), *Adoption, Usage, and Global Impact of Broadband Technologies* (pp. 198–214). IGI Global: Pennsylvania.

Headicar P, Stokes, Gordon. (2016) On the Move 2: Making sense of travel trends in England 1995–2014: Technical Report. Independent Transport Commission. http://www.theitc.org.uk/wp-content/uploads/2016/11/OTM2-Technical-Report-FINAL.pdf.

Hooper, E., Chapman, L., & Quinn, A. (2014). Investigating the impact of precipitation on vehicle speeds on UK motorways. *Meteorological Applications, 21*, 194–201. https://doi.org/10.1002/met.1348

Horrocks L, Beckford, J, Hodgson, N, Downing, C, *et al*. (2010) *Adapting the ICT Sector to the Impacts of Climate Change - Final Report*. Issue 5 ed.: Defra. AEA/ED49926/Issue 5. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/183486/infrastructure-aea-full.pdf.

Jaroszweski, D., Chapman, L., & Petts, J. (2010). Assessing the potential impact of climate change on transportation: The need for an interdisciplinary approach. *Journal of Transport Geography, 18*, 331–335. https://doi.org/10.1016/j.jtrangeo.2009.07.005

John J., Ofcom Corporate Services. (4 December 2017) Broadband resilience FOI. In personal communication with the author.

Kaufman S, Qing, C., Levenson, N., Hanson, M. (2012) *Transportation During and After Hurricane Sandy*. Rudin Center for Transportation, NYU Wagner Graduate School of Public Service. https://wagner.nyu.edu/files/faculty/publications/sandytransportation.pdf.

Khattak, A. J., & De Palma, A. (1997). The impact of adverse weather conditions on the propensity to change travel decisions: A survey of Brussels commuters. *Transportation Research Part a: Policy and Practice, 31*, 181–203. https://doi.org/10.1016/S0965-8564(96)00025-0

Koetse, M. J., & Rietveld, P. (2009). The impact of climate change and weather on transport: An overview of empirical findings. *Transportation Research Part D: Transport and Environment, 14*, 205–221. https://doi.org/10.1016/j.trd.2008.12.004

Lavieri, P., Dai, Q., & Bhat, C. R. (2018). Using virtual accessibility and physical accessibility as joint predictors of activity-travel behavior. *Transportation Research Part A Policy and Practice, 118*, 527–544. https://doi.org/10.1016/j.tra.2018.08.042

Lazarus A. (2013) *Openreach response to service-related questions in Ofcom's consultation documents*. Openreach. https://www.ofcom.org.uk/__data/assets/pdf_file/0026/81557/openreach_-_quality_of_service.pdf.

Lazarus A. (2014) *Openreach response to Ofcom's Fixed access market reviews: Openreach quality of service and approach to setting LLU and WLR*. Charge Controls – non-confidential version. Openreach. https://www.ofcom.org.uk/__data/assets/pdf_file/0029/80939/openreach.pdf.

Le Vine S, Polak, J, Humphrey, A. (2017) *Commuting Trends in England 1988–2015*. Department for Transport. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/877039/commuting-in-england-1988-2015.pdf.

Liu, C., Susilo, Y. O., & Karlström, A. (2015). Investigating the impacts of weather variability on individual's daily activity–travel patterns: A comparison between commuters and non-commuters in Sweden. *Transportation Research Part A Policy and Practice, 82*, 47–64. https://doi.org/10.1016/j.tra.2015.09.005

Marsden, G., & Docherty, I. (2013). Insights on disruptions as opportunities for transport policy change. *Transportation Research Part a: Policy and Practice, 51*, 46–55. https://doi.org/10.1016/j.tra.2013.03.004

Marsden G, Anable, J, Shires, J, Docherty, I. (2016) Travel Behaviour Response to Major Transport System Disruptions: Implications for Smarter Resilience Planning. Ed: Forum IT. *Preparing for Major Disruptions to Transport Systems*. Leipzig: OECD, 5–27. https://www.itf-oecd.org/sites/default/files/docs/travel-resilience-planning.pdf.

Marsden G, Dales, J, Jones, P, Seagriff, E, Spurling, N. (2018) All Change? The future of travel demand and the implications for policy and planning. *The First Report of the Commission on Travel Demand*. ISBN: 978–1–899650–83–5.

McColl, L., Pali, E. J., Thornton, H. E., et al. (2012). Assessing the potential impact of climate change on the UK's electricity network. *Climatic Change, 115*, 821–835. https://doi.org/10.1007/s10584-012-0469-6

Met Office. (2006c) *MIDAS: UK Daily Weather Observation Data*. NCAS British Atmospheric Data Centre, July 2017. http://catalogue.ceda.ac.uk/uuid/954d743d1c07d1dd034c131935db54e0.

Met Office. (2006b) *MIDAS: UK Mean Wind Data*. NCAS British Atmospheric Data Centre, July 2017. http://catalogue.ceda.ac.uk/uuid/a1f65a362c26c9fa667d98c431a1ad38.

Met Office. (2006d) *MIDAS: UK Hourly Rainfall Data*. NCAS British Atmospheric Data Centre, July 2017. http://catalogue.ceda.ac.uk/uuid/bbd6916225e7475514e17fdbf11141c1.

Met Office. (2006a) *MIDAS: UK Daily Temperature Data*. NCAS British Atmospheric Data Centre, July 2017. http://catalogue.ceda.ac.uk/uuid/1bb479d3b1e38c339adb9c82c15579d8.

Met Office. (2013) *'St Jude's Day' storm - October 2013*. Available at: www.metoffice.gov.uk/about-us/who/how/case-studies/st-judes-day-storm-oct-2013.

Met Office. (2016b) *Past weather events*. www.metoffice.gov.uk/climate/uk/interesting.

Met Office. (2016a) *Climate summaries*. https://www.metoffice.gov.uk/climate/uk/summaries.

Met Office. (2016c) *UK regional climates*. www.metoffice.gov.uk/climate/uk/regional-climates/.

Met Office, (2016e) *Name Our Storms 2016e. The UK's storms will be named again this coming Autumn and Winter.*

www.metoffice.gov.uk/news/releases/2016e/nameoursterms2016e .

Met Office. (2016d) *Beaufort wind force scale*. www.metoffice.gov.uk/guide/weather/marine/beaufort-scale.

Met Office. (2017) *Heat-health watch.* www.metoffice.gov.uk/public/weather/heat-health/.

Miller, H. J. (2005). A measurement theory for time geography. *Geographical Analysis, 37*, 17–45. https://doi.org/10.1111/j.1538-4632.2005.00575.x

Nardotto, M., Valletti, T., & Verboven, F. (2015). Unbundling the incumbent: Evidence from UK broadband. *Journal of the European Economic Association, 13*, 330–362. https://doi.org/10.1111/jeea.12127

Ofcom. (2014b) *Fixed access market reviews: wholesale local access, wholesale fixed analogue exchange lines, ISDN2 and ISDN30*. https://webarchive.nationalarchives.gov.uk/ukgwa/20200701124437/https://www.ofcom.org.uk/phones-telecoms-and-internet/information-for-industry/telecoms-competition-regulation/narrowband-broadband-fixed/fixed-access-market-reviews-2014b/statement.

Ofcom. (2014a) *Infrastructure Report 2014a*. 1–192. https://webarchive.nationalarchives.gov.uk/ukgwa/20200701124642/https://www.ofcom.org.uk/research-and-data/multi-sector-research/infrastructure-research/infrastructure-2014a.

Ofcom. (2016) *Connected Nations Report 2016*. 1–88. https://webarchive.nationalarchives.gov.uk/ukgwa/20200701124514/https://www.ofcom.org.uk/research-and-data/multi-sector-research/infrastructure-research/connected-nations-2016.

Ofcom. (2018) *UK Home Broadband Performance: The performance of fixed-line broadband delivered to UK residential consumers.* Research Report. 1–94. https://www.ofcom.org.uk/__data/assets/pdf_file/0027/113796/home-broadband-2017.pdf.

Office for National Statistics (ONS). (2014) *2011 Census data on Nomis*. https://www.nomisweb.co.uk/census/2011. Contains National Statistics data © Crown copyright and database right [2011]

Office for National Statistics (ONS). (2016b) *Rural Urban Classification (2011) of Middle Layer Super Output Areas in England and Wales.* https://ons.maps.arcgis.com/home/item.html?id=86fac76c60ed4943a8b94f64bff3e8b1. Contains National Statistics data © Crown copyright and database right [2011]

Office for National Statistics (ONS). (2016a) *Small area income estimates for middle layer super output areas, England and Wales.* https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/smallareaincomeestimatesformiddlelayersuperoutputareasenglandandwales. Contains National Statistics data © Crown copyright and database right [2013–14]

Office for National Statistics (ONS). (2017). *Lower Super Output Area Population Density (National Statistics).* https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareapopulationdensity. Contains National Statistics data © Crown copyright and database right [2014]

De Palma, A., & Rochat, D. (1999). Understanding individual travel decisions: Results from a commuters survey in Geneva. *Transportation, 26*, 263–281. https://doi.org/10.1023/A:1005121605832

Peters, P., Tijdens, K. G., & Wetzels, C. (2004). Employees' opportunities, preferences, and practices in telecommuting adoption. *Information & Management, 41*, 469–482. https://doi.org/10.1016/S0378-7206(03)00085-5

Philip, L., Cottrill, C., Farrington, J., Williams, F., & Ashmore, F. (2017). The digital divide: Patterns, policy and scenarios for connecting the 'final few' in rural communities across Great Britain. *Journal of Rural Studies, 54*, 386–398. https://doi.org/10.1016/j.jrurstud.2016.12.002

Quarmby D, Smith, B, Green, C. (2010) *The Resilience of England's Transport Systems in Winter: An Independent Review*. Final Report ed. London: Department for Transport. http://data.parliament.uk/DepositedPapers/Files/DEP2010-1862/DEP2010-1862.pdf.

Riddlesden, D., & Singleton, A. D. (2014). Broadband speed equity: A new digital divide? *Applied Geography., 52*, 25–33. https://doi.org/10.1016/j.apgeog.2014.04.008

Sabir M, van Ommeren, J., Koetse, M.J., Rietveld, P. (2010) Impact of weather on daily travel demand. *Proceedings of the Tinbergen Institute discussion paper.* Amsterdam: VU University.

Schulman A, Spring, N. (2011) Pingin' in the Rain. *Internet measurement conference 2011*. Berlin: Association for Computing Machinery, 19–28. DOI: https://doi.org/10.1145/2068816.2068819

Siha, S., & Monroe, R. W. (2006). Telecommuting's past and future: A literature review and research agenda. *Business Process Management Journal, 12*, 27. https://doi.org/10.1108/14637150610678078

Singh, P., Paleti, R., Jenkins, S., & Bhat, C. R. (2013). On modeling telecommuting behavior: Option, choice, and frequency. *Transportation, 40*, 23. https://doi.org/10.1007/s11116-012-9429-2

Stubbings P, Rowe, J. (2019) What can Internet use tell us about our society and the economy?: Extracting social-economic signals from Internet traffic data. https://datasciencecampus.ons.gov.uk/projects/what-can-Internet-use-tell-us-about-our-society-and-the-economy/ (Accessed 30/09/2019).

Titcomb J. (2016) BT Down: Broadband service suffers major outage across the UK. *The Telegraph.* https://www.telegraph.co.uk/technology/2016/07/20/bt-down-broadband-service-suffers-major-outage-across-the-uk/

Tranos, E., Reggiani, A., & Nijkamp, P. (2013). Accessibility of cities in the digital economy. *Cities, 30*, 59–67. https://doi.org/10.1016/j.cities.2012.03.001

Walls, M., Safirova, E., & Jiang, Y. (2006). *What Drives Telecommuting? The Relative Impact of Worker Demographics, Employer Characteristics, and Job Types*. Washington DC: Resources for the Future.