TRAVEL CHOICES, INTERNET ACCESSIBILITY, AND EXTREME WEATHER:

TRANSLATING TRENDS IN SPACE-TIME FLEXIBILITY IN THE DIGITAL AGE

by

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ABSTRACT

Extreme weather affects not only transport infrastructure, but also travel behaviour. Climate change is causing more frequent and intense severe weather events, and thus is increasing the risks to transport infrastructure, services, and travellers. Travel behaviour trends are also in flux due to shifting working and activity patterns, as space-time flexibility and accessibility choice increases, and standard commuting journeys decline. Information and communication technologies (ICT) are one reason for these changing trends in travel behaviour, and, like climate change, create uncertainty in predicting transport operations and travel choices. However, ICT also has the potential to make mobility and accessibility more sustainable and more responsive to climate change impacts. This thesis sets out to identify the opportunities that improving ICT and increasing space-time flexibility create for commuters and other travellers to maintain accessibility, particularly to work activities, that they may better respond to severe weather, risk, and transport disruption, thereby boosting resilience. The research also concludes that through the integration of travel choices and Internet accessibility and by taking action to address spatial and temporal barriers, policy might better support both resilience and sustainability.

DEDICATION

I would like to dedicate this thesis to my supervisors, Emmanouil Tranos and Lee Chapman, who guided me through the research process and offered me from the outset the very flexibility between presence and remote interaction which I eventually concluded is so important for resilient working.

I would also like to dedicate this thesis to my husband, Guy, and children, Anita and Albert, for their love and support.

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1. INTRODUCTION

This thesis is a study of sustainable access behaviours, which focuses on the adaptation and resilience aspects of sustainability, and incorporates both the travel and Information and Communication Technologies (ICT) aspects of accessibility. It reviews the literature on the impacts of weather on both infrastructure and travel behaviour, and also brings together literature on transport, digital, and accessibility trends to explore how they might manifest in more resilient responses to future climate disruption. It contributes to this literature with four quantitative, empirical studies of some of the interactions between travel choices, internet activity and severe weather events. Two of these are case studies of particular, severe weather events in English sub-regions, and two look at trends over time at a national, spatial scale. In summary, this thesis aims to offer insights into how the integration of transport and online accessibility, improvements in space-time flexibility due to socio-economic and geographic trends, and proactive policy could help deliver a more sustainable and resilient future.

1.1 Identifying the gaps between areas of research

The transport sector is a major source of greenhouse gas emissions, accounting for almost a quarter of total global emissions, and is the largest sectoral emitter in the United Kingdom (UK) (Bell et al., 2016; Sims et al., 2014). Thus, it is not surprising that studies of and policies for sustainable travel behaviours have usually focused on ways that the carbon emissions and other environmental impacts of transport, such as air and noise pollution, might be mitigated (Banister, 2008; Cairns et al., 2010). Yet the transport sector is also subject to the environmental risks arising from climate change, such as more extreme weather events. In the UK, more frequent coastal and river flooding, storm surges and more intense storms, the latter of which result in increased wind speeds and gusts, lightening, and pluvial flooding, have been identified as presenting the greatest risks to transport, energy, and other infrastructure (Brown et al., 2014; Kovats et al., 2014; McColl et al., 2012).

There are other risks to transport infrastructure, including terrorism, deterioration and insufficient investment in maintenance (Rogers et al., 2012), as well as planned disruption due to events, roadworks, or strikes. However, the unplanned nature of severe weather events and the likelihood that their increase in frequency and intensity due to climate change will cause transport disruption more often over a wider area and affect a wider population, increases the importance of understanding the impacts of severe weather not only on transport infrastructure, but also on travel behaviour. Individuals using the transport network in severe weather are at greater risk of delay, disruption to their journeys, and a reduction in their personal safety. Therefore, adaptation to climate change impacts like severe weather is as relevant to sustainable mobility and accessibility as is the mitigation of transport impacts like carbon emissions on climate. Furthermore, just as mitigation looks at transport demand and travel behaviour, so the public response to the transport disruptions caused by severe weather cannot be ignored (Mattson and Jenelius, 2015).

In order to understand the potential to reduce risk through travel behaviour adaptation to severe weather or other disruption, this thesis focuses not on mobility and its concern with the distance and speed of travel, but on accessibility and the opportunities available to participate in activities, obtain goods, and benefit from services. Of particular interest is access to work activities, as commuting is often described in the transport literature as an ‘anchor’, a ‘mandatory’ or ‘non-discretionary’ journey within a concentrated timescale around which other daily travel is organised (Le Vine et al., 2017; Miller, 2005). Yet the number of direct commuting trips in the UK are in decline, as is their share of total trips taken, due to transport trends such as substituting online access for travel through increased telecommuting; less trip-making among groups spending more time at home; and more efficient trip-making, e.g. increased trip chaining (Chatterjee et al., 2018; Goodwin, 2012; Headicar and Stokes, 2016; Le Vine et al., 2017). Economic trends also bear substantial responsibility, as advanced economies like the UK have trended towards more part-time work, self-employment, sub-contracting, and jobs where there is no fixed workplace, all of which result in observed increases in the variability of intra-personal, daily travel, which does not fit the narrow definition of commuting (Crawford et al., 2018; Haddad et. al, 2009; Le Vine et al., 2017; Messenger and Gschwind, 2016). Thus, it is important to explore fixedness or flexibility of access to work activities within a conceptual framework that can incorporate these dynamic trends and explore their potential during disruption, such as that from extreme weather scenarios.

Space-time geography or dynamic accessibility is such a framework. It considers the spatial and temporal constraints on personal movement. These include an individual's availability to undertake activities at multiple locations within a given timeframe; where and when interactions with other people are required; and whether barriers are erected by third parties, such as the opening hours of a private space, the timetable of a transport service, or closures / cancellations due to weather (Hägerstrand, 1970; Lee and Miller, 2018; Miller, 2005; Schwanen and Kwan, 2008; Wang et al., 2018). Within this framework, the ability of travellers to respond to risk resiliently is dependent upon their spatial and temporal flexibility, which is in turn an expression of socio-economic and demographic characteristics, geographic situation, accessibility options, and information / awareness. The level of temporal flexibility is accentuated by severe weather events and the pressure extreme weather exerts upon the reliability of travel options, as well as the potential of ICT to enable more resilient access choices that offer better reliability in those circumstances.

Both transport and ICT are accessibility options that can reduce spatial and temporal constraints through additions to the networks or improved services, but transport and ICT systems can also exclude some potential users due to where they live, who they are, and what they do. Indeed, the penetration, capacity, and quality of ICT and transport access varies with density, distance, rurality, and urban form; age, skills, and affordability can affect individuals' capability to access options; and the expansion of options can also create new constraints such as increased expectations of availability (Blank et al., 2018; Clark et al., 2016; Hincks et al., 2018; Noulas et al., 2012; Philip et al., 2017; Schwanen and Kwan, 2008; Tranos et al., 2013). Just as transport accessibility is a function not only of distance, but also of time and cost or, in other words, the convenience and effort required to make a trip, so ICT accessibility requires inputs of time and effort to find information or make a transaction, affecting the attractiveness of the access available (Kwan, 2001). Therefore, it is important to consider ICT and transport modes as overlapping systems of access, as shown in Figure 1.1, recognising that numerous, similar factors influence the level of dynamic accessibility that transport and ICT networks, systems, and services offer in different places or at different times. These spatial and temporal factors, as listed in Figure 1.1, can take different forms or vary in importance depending upon the purpose and mode of access that is under analysis, but offer a starting point for defining the variables to measure or model changes in access and potential accessibility opportunities or threats during severe weather events.

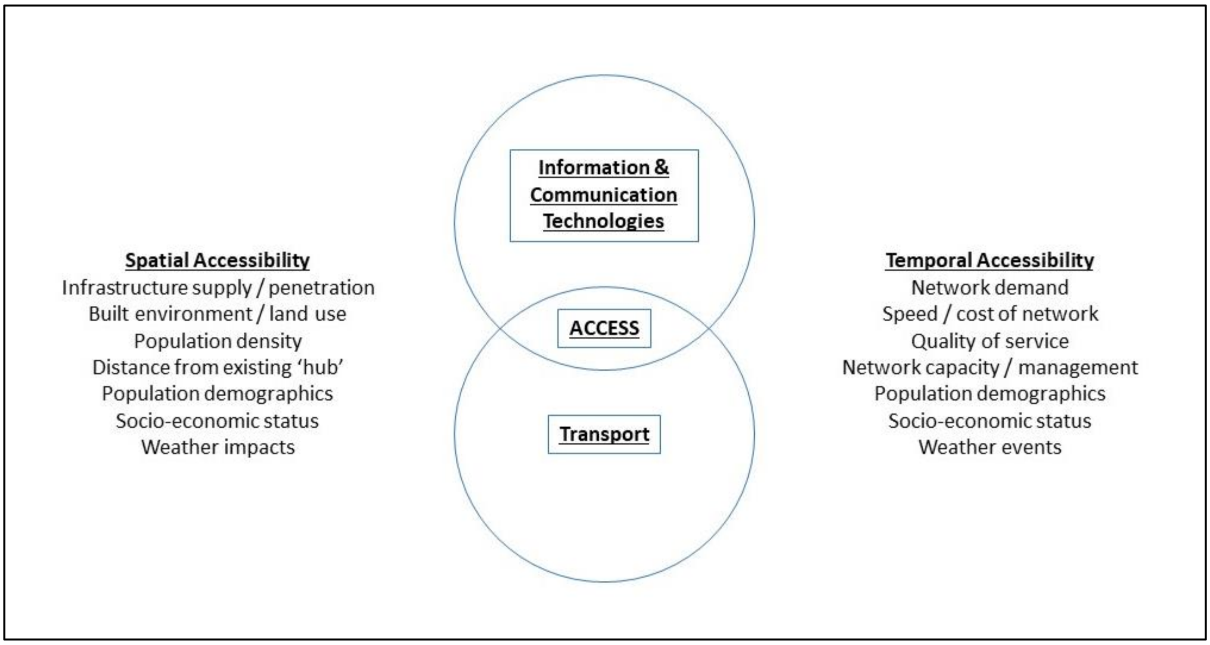

Figure 1.1: Variables influencing dynamic accessibility / level of constraints on transport / ICT networks

Severe weather affects an individual's calculations of not only the time, cost, and effort required for different access options, but also the reliability and risk affecting that option. Therefore, just as a strategy for resilient infrastructure considers whether it will be robust enough to avoid impact, provides redundancy to reduce risk, or will recover quickly after an event; resilient access behaviour choices include resisting change, replicating the norm as closely as possible via an alternative route / mode, or postponement and cancellation until access returns to normal. ICT expands these choices by enabling online access to activities from home, so that the journey may be cancelled whilst access is maintained. It can also offer immediate access to information on transport services if available, alternative destinations that might be more accessible during disruption, and local weather forecasts. Such information can inform responses such as delaying departure times or increasing / reducing the duration of an activity to avoid disruption. Recent research suggests that volumes of internet traffic and road traffic, particularly at peak commuting periods, are closely and inversely related (Stubbings and Rowe, 2019). Thus, the concept of dynamic accessibility helps put into perspective the altered access challenges faced by different groups and individuals in both time and space during severe weather and disruption to transport networks, and how ICT and transport together might overcome some of those challenges.

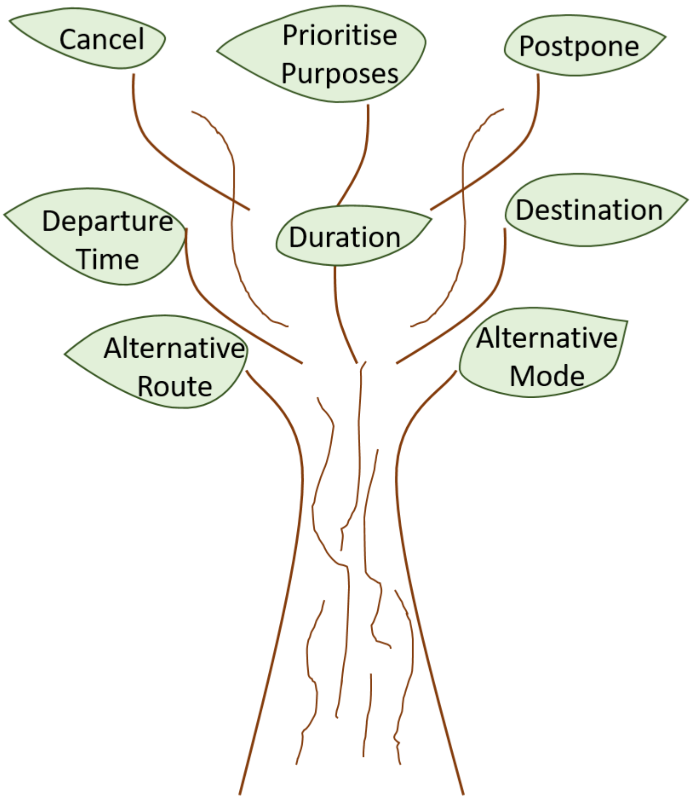

Figure 1.2: Options for responses to Transport and Access Disruption

Figure 1.2 visualises the choices / options for changing behaviour during disruption. The form and availability of these options depends upon an individual's demographic and socio-economic characteristics, and the geographic characteristics of where they live and work. Figure 1.2 is not intended to describe decision pathways, but does give some indication of a hierarchy of options. The lowest branches offer the easiest choices, where access to the proposed activity and interaction is almost fully maintained, albeit by a different route or mode. More difficult is choosing to reduce the time or spaces available for the activity, whilst at the top of the tree are the options that indicate reduced accessibility during the disruption as some activities are postponed, cancelled, or considered less essential than a priority activity that takes more time to access. Some of these options are more thoroughly explored in the literature than others, and some are explored only at a limited level of spatial and demographic detail.

1.2 Research Aim and Objectives

In summary, extreme weather affects not only transport infrastructure, but also travel behaviour. Travel behaviour trends are in flux due to shifting working and activity patterns, as space-time flexibility and accessibility choice increases, and standard commuting journeys decline. These trends influence how access choices are made during severe weather or other disruptions. Improving ICT also have the potential to make mobility and accessibility more sustainable and more responsive to weather impacts in particular, as ICT infrastructure is more robust than transport infrastructure during such events and ICT disruption more often has other causes (see section 2.2). However, like transport infrastructure and services, internet availability, quality, and usage varies geographically and socio-demographically. Therefore, the overarching aim of this thesis is to provide new evidence and answers to the following question:

> *What opportunities do improving ICT and increasing space-time flexibility create for commuters and other travellers, that they may better respond to severe weather, risk, and transport disruption, thereby boosting resilience and, with appropriate policy actions, enabling more sustainable choices?*

In order that the investigations in this thesis do more than replicate previous studies, the empirical research was designed to meet at least two of the following three objectives:

a) To focus on travel or access behaviour and how it changes during severe weather events, rather than the impact of extreme weather on infrastructure or changing travel behaviour during daily weather variation.
b) To use data sources and / or quantitative methodologies which can interrogate the influence of geographic and socio-demographic, or more particularly socio-economic, characteristics on space-time flexibility and accessibility trends in order to understand how these influences interact with the response to severe weather.
c) To seek out insights into those response options which have been subject to less research in the past, and consider their potential implications for future policy.

1.3 Thesis Structure

The literature review is split into two chapters: Chapter 2 on the documented interactions between weather and transport, and Chapter 3 on the how the interactions between ICT and transport expand the potential for greater resilience if both types of access are considered jointly. The literature presented in the first section of Chapter 2 studies the likelihood and prevalence of changes in access behaviour, including many of the choices depicted in Figure 1.2 in response to daily weather conditions or severe weather events. Case studies from around the world suggest some clear trends in the travel behavioural response to weather conditions, although there are some gaps in the evidence for certain options. Many of these studies also support the hypothesis that any response by those normally engaged in commute trips is more muted than those travelling for other purposes. The rest of Chapter 2 focuses on the supply side, and the comparative risks to transport and ICT infrastructure and services, particularly in the UK, as that is the geographical focus of the empirical studies in this thesis. Chapter 3 is divided into three sections. The first considers how ICT supports transport reliability even during disruption. The second explores how it can provide an alternative means of access, particularly through telecommuting. And the third reviews various perspectives on accessibility trends in the digital age to offer insight into how these interactions could influence both planning for and recovery from disruptive events like extreme weather.

Chapter 4 begins with a section on secondary data sources and their potential for providing evidence of the relationship between extreme weather, ICT, and travel, despite being collected for other purposes. The empirical analysis was conducted at both the national and sub-regional levels, using a variety of traditional and 'big' data sources, including the English National Travel Survey, electronic ticketing transactions, crowd-sourced broadband speed checks, origin-destination matrices derived from mobile phone network data, and a variety of open, complementary data to control for socio-economic and geographic characteristics. Next, Chapter 4 summarises the importance of a case study approach combined with a wide range of quantitative methodologies in order to extract meaningful messages from secondary data sources not designed for the research question which is the subject of this thesis. The quantitative methodologies ranged from producing summary graphs and maps to multi-level and multinomial logistic regression models in order to understand both how access behaviours change during severe weather conditions, and the potential for more resilient access behaviours in future cases or via building on existing trends.

Chapters 5 through 8 form the empirical portion of this thesis, and provide additional detail on the context, data sources, derived variables, and methodology utilised in four related, but separate studies, as well as the results of each analysis. Chapter 5 is a relatively simple case study of changes in bus travel in the small, urban area of Reading, UK during a single, impactful winter storm. A clear switch between public transport modes, namely train to bus / park and ride along a particular interurban corridor with key employment destinations, is highlighted and discussed. Chapter 6 also takes a case study approach, but analyses a much larger spectrum of movements throughout the entire metropolitan area around Birmingham, UK. Mobile phone network data is used in this case study to interrogate the accessibility of every neighbourhood in the study area as both residential origin and workplace destination for work and non-work trip purposes. The chapter interrogates the geographic and socio-economic influences on the revealed increase in direct commuting trips and decline in journeys for other purposes under storm conditions. Chapter 7 expands the study area further to the entirety of England and Wales and models how internet activity varies across time and space as measured through the proxy of broadband speed. The slower speeds revealed in regions where and when winter weather and / or storm-level winds were recorded offer an insight into how ICT provides an alternative channel of access, with speeds significantly affected when demand increases due to adverse weather conditions, even though any telecommuting within this demand cannot be quantified. The final empirical chapter is premised on the potential for telecommuting to offer a resilient alternative for those all-important work trips which were prioritised in the earlier chapters during weather risk and disruption. Thus, Chapter 8 offers an alternative translation of the potential sustainability of the non-work travel patterns of telecommuters using data from the English National Travel Survey.

Finally, Chapter 9 concludes with a discussion of the findings, policy implications and future research. This thesis provides examples of how trends in increasing space-time flexibility and ICT use *currently* manifest in travel behaviour and accessibility change during severe weather events, and adds to the literature by offering insights into some of the less evidenced responses in the options tree, such as prioritising work journeys over access to other activities or using online access from home to replace travel to other destinations. These findings are also linked back to the wider trends in the literature in order to identify the *potential* for policy, strategy, planning, and evaluation to encourage more sustainable and resilient behaviours.

2. THE RELEVANCE OF WEATHER TO TRANSPORT AND TRAVEL BEHAVIOUR[1]

This chapter reviews how weather affects travel behaviour, transport infrastructure, and activity participation. The studies summarised in the following two sections can be divided into three broad areas of research, as shown in Figure 2.1: studies of the influence of daily meteorological parameters on travel, reviews and case studies of the impacts of severe weather events on transport services and infrastructure, and forecasts of the risks presented by climate change to transport delivery. Finally, some studies assess the vulnerabilities and dependencies between transport and other infrastructures, including ICT, to identify cascading threats.

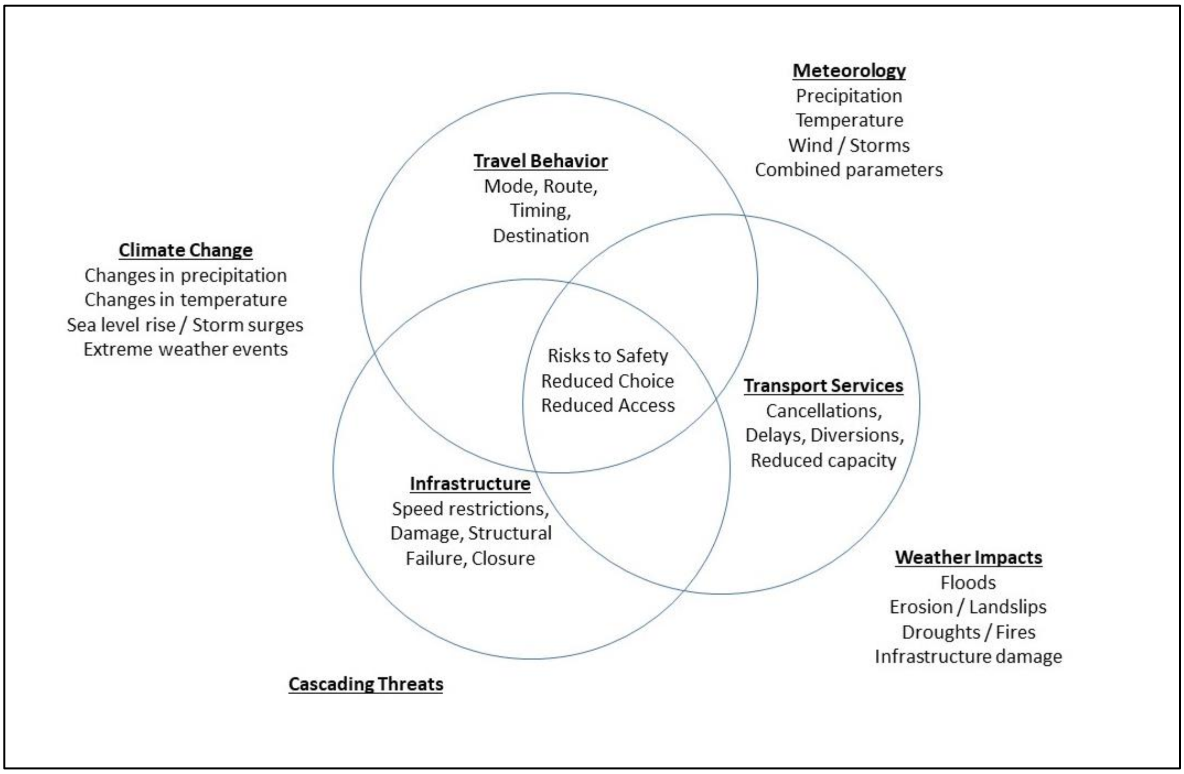

Figure 2.1: The study of Weather and Transport Interactions

[1] The majority of this chapter has been published as: Budnitz, H, Chapman, L, Tranos, E. (2019) 'Weather, travel behavior, and the influence and potential of ICT to improve resilience' in Ben-Elia, E. (ed.) ATPP: The Evolving Impact of ICT on Activities and Travel Behaviour Volume 3. https://doi.org/10.1016/bs.atpp.2019.03.001. Also, to avoid repetition, some elements from the literature reviews from the author's papers cited in Chapters 5-8 have been integrated into this Chapter.

2.1 Impact of Weather on Travel Behaviour

Among the external influences on travel behaviour and the availability and reliability of transport networks and services, the impact of weather parameters such as precipitation, temperature and wind-speed, has long been recognized by researchers. Studies have used a wide variety of statistical modelling techniques, socio-demographic and other explanatory variables, and meteorological measurements in relative or absolute terms at daily, monthly or seasonal scales, to test how weather variations empirically affect travel patterns (Böcker et al., 2013). A few studies use stated and revealed preference techniques to assess whether and how people change their travel choices, including route, mode, timing, destination, or cancellation, in response to not only the weather, but also weather forecasts (Cools and Creemers, 2013; Kilpelainen and Summala, 2007; Meng et al., 2016). Some surveys go even further, using extensive questionnaires to investigate travel behaviour more generally, focusing on how travellers respond to a combination of weather and travel information, and the influence of socio-demographic characteristics and work situation, such as flexible hours (De Palma and Rochat, 1999; Khattak and De Palma, 1997). Although these surveys might be described as traditional research methods, big data analysis techniques mean that many years of travel diaries, or records from sources covering millions of trips, such as traffic cameras, electronic ticketing transactions, mobile phones, and social media can be matched to weather observations and long-term patterns explored.

Most of the research questions from these studies are hypotheses about the impact of weather on safety, mode choice, and trip volumes, with only a few investigating the subtleties of changes to route or travel timing, e.g. leaving more time to travel or postponing travel until weather changes (Cools and Creemers, 2013; De Palma and Rochat, 1999; Khattak and De Palma, 1997; Koetse and Rietveld, 2009; Sabir et al., 2010; Sabir, 2011). Pedestrians are disproportionately impacted by the weather and various studies focus on ‘active travel’ and seasonal outdoor activities (Böcker et al., 2013; Liu et al., 2015). Researchers have used cyclist counts, travel diaries and route-side surveys to determine that rain, and to a lesser extent, temperature – both extreme heat and cold, and strong winds can reduce the amount of cycling for utility or leisure, although the size of any switch to other modes is dependent upon the share of bicycle travel in the area of study (Böcker et al., 2013; 2019; Meng et al., 2016; Sabir, 2011; Saneinejad et al., 2012). There are indications that public transport patronage decreases in bad weather and increases in good weather, and although the percentage changes are small when studying large datasets from electronic fare collection, a wide selection of tests have shown statistically significant shifts in ridership and switches from bus to rail in adverse weather, the latter of which may be related to the facilities available, such as shelter at stops and stations, although public transport can also be affected by the discomfort of the active travel leg at the start or end of a journey (Guo et al., 2007; Hofmann and O’Mahony, 2005; Kalkstein et al., 2009; Singhal et al., 2014; Stover and McCormack, 2012). On the other hand, it is less clear whether the changes in travel behaviour by public transport users result in more or less dynamic accessibility, as different public transport services have different capacities and the impacts up- or down-stream are rarely fully considered (Cats and Jenelius, 2014).

Most studies of road traffic have focused on the effects of precipitation. The influence of rain has been measured in multiple ways, with well-documented reductions in traffic speed, more frequent although less severe accidents, and increased congestion and resultant delays, particularly in denser, urban areas during already congested peak hours (Böcker et al., 2013; Cools et al., 2009; Hooper et al., 2014; Jaroszweski et al., 2014; Sabir et al., 2008, Snelder and Calvert, 2016; Tsapakis et al., 2013). Research shows that where road networks are already operating close to capacity, such as in urban areas during rush hours, the impacts of even normal weather variations are much greater than in areas with spare capacity. A study of the influence of public transport strikes supports this conclusion, demonstrating the amount of congestion relief delivered daily by public transport services even controlling for weather in urban areas where car use is relatively low (Adler and van Ommeren, 2016). Yet although congestion increases, there is evidence that rain can reduce the level of road traffic demand, dependent upon the mode shares of active or unsheltered travel that switch to private vehicles, the amount and intensity of the rain, and how weather parameters are modelled (Böcker et al., 2013; Cools et al., 2009; Snelder and Calvert, 2016; Sabir et al., 2010).

Much more obvious effects are attributed to snowfall and accumulation. Observations, simulations, and stated / revealed preference surveys, the latter of which offer a multi-modal view of travel behaviour, all indicate that trip and likely activity cancellations are most likely to occur when snow is forecast or occurring, although less so in regions where snow is most common (Böcker et al., 2013; Cools and Creemers, 2013; Kilpelainen and Summala, 2007; Kim et al., 2013; Sabir et al., 2010). This is not surprising, as snow is known to have significant negative impacts upon the resilience of physical assets and infrastructure, causing costly damage which can take some time to repair, and making it, along with flooding, a priority for transport authorities' scrutiny and review (Brown et al., 2014; Chatterton et al., 2016; Quarmby et al., 2010). Furthermore, as well as the risks snow and ice pose to the safety and availability of transport networks, the social impacts, of school closures for example, also have a major impact on travel behaviour (Marsden et al., 2016). Finally, some of the multi-modal studies provide evidence that strong winds might be one of the more significant weather parameters reducing travel demand by 2% overall and public transport demand by 22%, whilst warmer weather, at least in the temperate climates studied, may induce modal shift from vehicular to active travel (Cools et al., 2010; Sabir et al., 2010).

Yet the extent to which ICT accessibility replaces or modifies travel during severe weather events is largely unknown. Many studies focus on a single mode, there are relatively few investigations into responses such as changing destinations or cancelling trips, and although there is some indication that closer destinations are favoured for non-work trips during adverse weather, many of these studies exclude home-based activities and the use of ICT for telecommuting or other activities during severe weather events or over the longer term as experience of disruption increases (Cools and Creemers, 2013; Kaufman et al., 2012; Koetse and Rietveld, 2009; Liu et al, 2015; Marsden et al., 2013; Sabir, 2011). One reason such responses are included in so few of the studies cited in this section is that this area of literature includes many more longitudinal studies that track the relationships over time between rainfall, wind speeds, and other weather parameters and changes in trip numbers, vehicle speeds, and modal splits. Whilst longitudinal data from weather records may correlate to flooding or fallen trees, identifying quantitative thresholds of weather variables that cause sufficient transport disruption often enough in the timeline studied to be statistically significant is challenging even if issues like time of day, the "intensity of use, the availability of alternatives and the economic importance of the route or service" are considered (Brown et. al, 2014, p.9; Mitsakis et al., 2014). Thus, longitudinal studies may struggle to disentangle the response to weather from the response to weather impacts and to capture both where and when specific impacts such as road closures, rail cancellations, and other disruptions occur that may affect space-time constraints and make online access more necessary.

The alternative approach is to assess the response to a case study of an identified weather event in a particular place where known disruption occurred. This approach is commonly pursued by governments following major weather events, where estimates of the direct and indirect impacts, including the 'welfare costs' of delays, closures, cancellations, incidents, lost productivity, and any lengthy repair and recovery periods are calculated (Beiler et al., 2016; Brown et al., 2014; Chatterton et al., 2016; Quarmby et al., 2010). There are also many case studies undertaken over various geographies, such as one that calculated the total impact of the UK-wide storms on 28 June 2012 upon the national rail and road networks (Jaroszweski et al., 2015), whilst a study focused on the urban area of Newcastle-upon-Tyne on that day measured traffic flows on the network to locate critical points and possible mitigation scenarios (Pregnolato et al., 2016). Other examples track the impacts of hurricanes in the United States (Kaufman et al., 2012; Lee et al., 2009), or natural disasters around the world (Wang and Taylor, 2016). Often, such studies make assumptions about how people were affected during extreme weather using comparisons to an 'average' day or transport models built to represent 'average' daily mobility, rather than consider how people might change their behaviour (Brown et al., 2014; Chatterton et al., 2016). Thus, the engineering solutions for redundancy or recovery, the operational changes, and strategic and emergency planning coordination, ranging from the identification of diversion routes to flood defences and raising or moving infrastructure, tend to be based on similar assumptions (Beiler et al., 2016; Suarez et al., 2005).

However, many would agree that the severity of the impacts is dependent upon patterns of human behaviour such as intended activities, the time and location at which the event and disruption occurs, how they are perceived, and whether and when information about the weather event or disruption is available (Beiler et al., 2016; Dawson, 2016; Marsden et al., 2013). There is a recognition of the importance of developing a clear messaging strategy to keep the public informed and instil behavioural resilience, even within studies modelling simulated travel during severe weather without the benefit of real-life observation from either qualitative survey methodologies after known disruption or the exploration of alternative indicators and thresholds (Beiler et al., 2016; Kim et al., 2013; Snelder and Calvert, 2016; Suarez et al., 2005). Future scenario planning for resilience to severe weather and disruption must include options both for the physical re-design of infrastructure, and also for strategies addressing behavioural resilience and response, with decision-makers able to choose what will best enable adaptation or recovery in specific communities (Jaroszweski et al., 2014; Rogers et al., 2012). In either case, ICT is critical.

2.2 A Comparison of Infrastructure Resilience

The importance of ICT to resilience, both infrastructural and behavioural, is most obvious when it is not available. In Lancaster, UK, the floods caused by storms and ground saturation in December 2015 not only cut major transport links, including a motorway junction and central bridges, but also resulted in a power outage that rendered all fixed internet access as well as the base stations that enable mobile access in the area inoperable, except for a few buildings with emergency generators, like the hospital and the local radio station (Ferranti et al., 2017). This is an example of the cascading threat to the 'system of systems', where the interdependencies within and between infrastructure networks mean that failure in one area instigates failure in another, not only in relation to various transport networks, but also to electricity, water and ICT systems, which is a major risk of climate change (Chapman et al., 2013; Horrocks et al., 2010). Cascading threats can also affect behavioural resilience, even if there is a lack of consideration of traveller reactions and demand-based measures in many of the climate change risk analyses (Mattson and Jenelius, 2015). In Lancaster, the local radio, plus a few public payphones, became for many the sole source of updates and information from emergency services and others (Ferranti et al., 2017). Therefore, local residents struggled to learn what services and infrastructure were still operational, and had no ability to substitute online access if transport access was unavailable. In this case, ICT could not help coordinate the emergency response, provide information on unaffected transport links, nor enable the participation in work and other activities. The resilience of ICT in the area, and its importance in the resilience of other infrastructure networks had not been considered. Fortunately, however, systems theory also means that there are always multiple ways to improve resilience (Rogers et al., 2012), including optimizing the inherent resilience of ICT infrastructure and its lower vulnerability to cascading threats as shown in Figure 2.2.

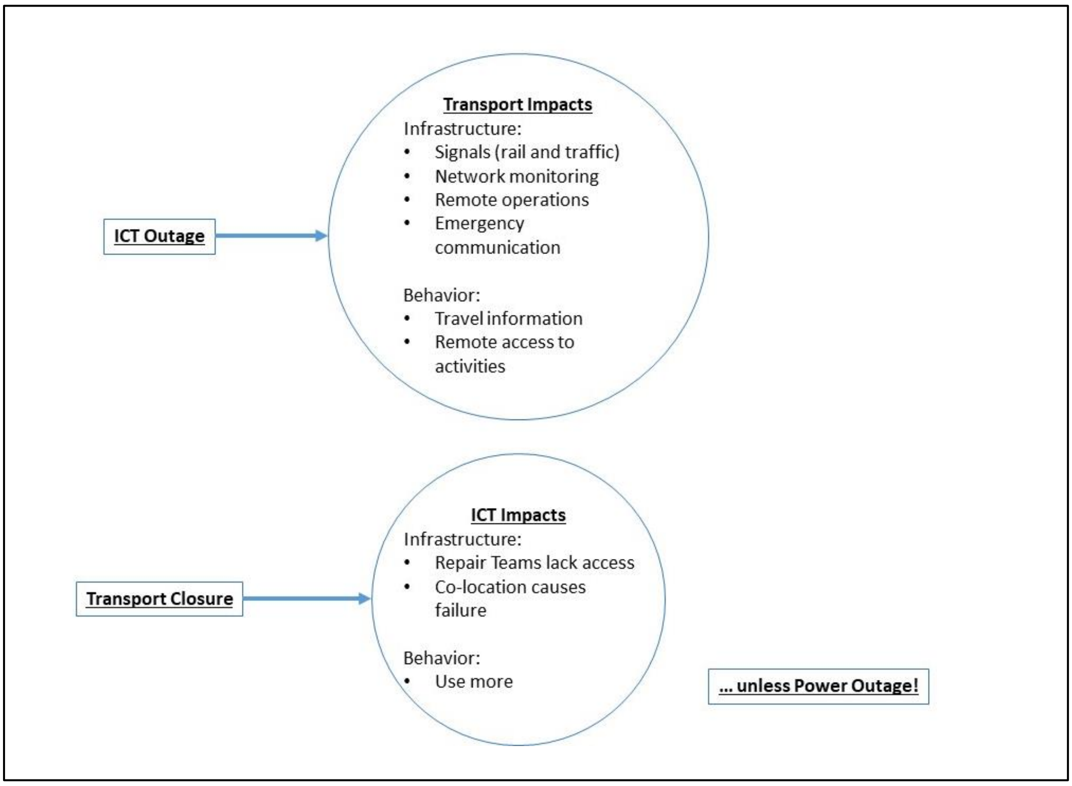

Figure 2.2: A simplified comparison of cascading threats from ICT or Transport failure

Although dependent upon energy infrastructure for uninterrupted operation as in the case described above, ICT infrastructure and topology is generally more robust, at least at a strategic level, than transport infrastructure to both weather events and a changing climate (Chapman et al., 2013). Some reasons are the international design of many components built for weather extremes rarely seen in temperate climates, the frequent asset replacement as a result of the speed of technological development, and the often built-in redundancy between fixed and mobile services and competing providers (Fu et al., 2016; Horrocks et al., 2010; OfCom, 2014). If ISPs planned and prepared for weather events more proactively, using ‘risk-aware’ routing, spare capacity, or other optimisations, ICT could be even more robust (Mukherjee et al., 2014). Yet, as the majority of faults for telephone and broadband infrastructure tend to be local and residential due to built-in redundancy at the strategic level, risk assessments by Internet Service Providers (ISPs) focus more on customer service, maintenance and standards, rather than resilience and the potential for a national emergency (Lazarus, 2013; 2014; Schulman and Spring, 2011).

In comparison, transport infrastructure systems are often older, public or publically subsidized, with national railways and local bridges in particular lacking redundancy, all of which make transport less resilient to severe weather events, especially where there has been a lack of investment and maintenance back-logs (Brown et al., 2014). Railways, for example, are particularly at risk in high temperatures due to inadequately stressed rails and electrical failure or sagging overhead lines, whereas ICT lines are often designed to withstand temperature extremes (Dawson, 2016; Dobney et al., 2009; Ferranti et al., 2016). Transport networks are also dependent upon the availability of energy and ICT infrastructure for key elements of operation, whilst ICT infrastructure is only dependent upon transport where repairs are needed, and engineers struggle to access the relevant points in the network (Horrocks et al., 2010).

Various studies have reviewed the robustness of transport networks, from road and rail to air and inland waterways by using empirical data from past severe weather events to speculate on the likely impacts of extreme weather conditions which will be more prevalent as the global climate continues to change: storms, fluvial, pluvial and coastal flooding, heatwaves, heavy rain and high winds (Dawson, 2016; Jaroszweski et al., 2014; Koetse and Rietveld, 2009; Snelder and Calvert, 2016). Such events appear likely to replicate the risks of snow to ‘normal’ dynamic accessibility by likely causing road closures, rail cancellations, and school closures, and thus similarly affecting travel behaviour, even if snow events and freezing temperatures themselves occur less often under future climate change scenarios. Research and risk analysis suggests that transport infrastructure is more vulnerable to these severe weather events due to impacts such as storm surges in coastal areas, depth of floodwaters, landslips, sinkholes, coastal erosion, and trees falling in the heavy winds, than to the more gradual climate changes in temperature or precipitation (Brown et al., 2014; Dawson, 2016; Jaroszweski et al., 2010; Koetse and Rietveld, 2009). Energy and ICT infrastructure are also more vulnerable to severe weather events than to other climate changes, but in their case, high winds, gales, and particularly lightning cause many more faults than flooding or snow, and the speed of technology upgrades make it easier to augment the robust nature of ICT infrastructure by designing in resilience (Dawson, 2016; Deljac et al., 2016; Horrocks et al., 2010; McColl et al., 2012).

For example, where ICT connections use historic copper wires originally installed for voice telephony, they may be unsuitable for high bandwidth applications and face reduced asset life and additional maintenance, compounded by increased temperatures and humidity (Lazarus, 2013; 2014; OfCom, 2014; Schulman and Spring, 2011). Fibre-copper hybrid networks are also vulnerable to extreme weather events such as the one described above in Lancaster, UK, whereas a network of robust optical fibres not only from hubs to street cabinets, but also between a hub and individual residences is much more resilient as was seen during the same weather event in nearby rural areas, which maintained their ICT connections (Brunnen, 2016). ICT infrastructure is also sometimes housed in historic industrial buildings located on floodplains, and is known to become inaccessible to repair teams if transport routes are blocked, especially if there are no clear lines of responsibility within the sector for emergency response or incorporating strategic planning for resilience as the technology is refreshed (Horrocks et al., 2010; Lazarus, 2014; UKCIP, 2013; Schulman and Spring, 2011). Therefore, the challenge becomes one of governance and policies to reinforce the robust nature of ICT infrastructure, which is why it is important that ICT is not viewed as a 'critical' infrastructure in isolation, but one upon which many other infrastructures and behaviours are dependent (Horrocks et al., 2010).

In summary, section 2.1 reviewed the breadth of literature investigating the impact of weather variation on travel behaviour as well as the post-event government reports and academic studies on the impact of severe weather events on transport infrastructure. The research reviewed in section 2.1 offers insights into the prominence of some of the behavioural changes depicted in Figure 1.2, but few studies include the substitution of online access, changes to the choice of destination, or the implications of prioritising certain journey purposes. Most do not analyse the changes to travel behaviour during disruptions caused by more extreme weather events either, and those that do are too narrow in scope to allow insights into how any response may have been shaped by geography, socio-demographic trends, or improving ICT. Section 2.2 describes how and why ICT infrastructure is more resilient to weather disruption than transport infrastructure, with OfCom estimating that a mere 1% of incidents reported to them between September 2013 and August 2014 were caused by severe weather, a period that included extreme rain and flooding events (2014). Although there is not a comparable figure for transport infrastructure, this is an indication of the importance and potential of ICT to improve access behavioural resilience which, as explored in the following sections, could augment the case for better governance and integration of ICT into adaptation and emergency planning.

3. THE RESILIENCE POTENTIAL OF CHANGES IN SPACE-TIME FLEXIBILITY AND ICT[2]

Various studies have investigated the resilience of transport systems in terms of how reliable or vulnerable infrastructure is and whether, instead of simple repair, proactive redesign might aim for robustness or resistance to damage, redundancy, or quick recovery and stabilization (Mattson and Jenelius, 2015; Rogers et al., 2012; Wang, 2015). Yet the interaction of transport infrastructure and services with patterns of human behaviour, mobility, and ICT use means that physical adaptation of transport systems is only part of the solution, whilst mitigation, coordination, and communication could offer more flexible, immediate ways to respond to disruption caused by weather or other events (Cox et al., 2011; Jaroszweski et al., 2014; Rogers et al., 2012). ICT and transport are both 'general purpose technologies' that are integral to many sectors of the economy, catalyse innovation in those sectors, and change the geography of activities people want to access (Karlsson et al., 2010). Both are industries of 'derived demand', providing access to satisfy desires for goods, services, employment, leisure, and information, whilst minimizing the costs in terms of time and distance and balancing preferences and attitudes, ignoring any 'undirected' travel (Banister, 2008; Mokhtarian and Salomon, 2001; Van Acker et al., 2010). The ongoing digital revolution means that transport and the internet can be seen as ever more interchangeable, flexible, and seamless options for increasing accessibility (Lyons, 2015).

[2] The majority of this chapter has been published as: Budnitz, H, Chapman, L, Tranos, E. (2019) 'Weather, travel behavior, and the influence and potential of ICT to improve resilience' in Ben-Elia, E. (ed.) ATPP: The Evolving Impact of ICT on Activities and Travel Behaviour Volume 3. https://doi.org/10.1016/bs.atpp.2019.03.001. Also, to avoid repetition, some elements from the literature reviews from the author's papers cited in Chapters 5-8 have been integrated into this Chapter.

Thus, if resilience hinges upon the ability or capacity to avoid or minimize delay, disruption, and risk to personal safety and property, ideally maintaining an acceptable level of accessibility to intended activities, then ICT has a number of roles to play, as shown in Figure 3.1. ICT has enabled a step-change in the provision of travel information, making it an essential part of coordination and communication between the public and those with responsibility for transport services and for contingency / emergency planning during disruption from severe weather. ICT has changed how, when, and where people access activities, which can mitigate the risks and enable some to avoid disruption through online access or other temporal and spatial flexibility. Finally, ICT trends have resulted in the delivery of new transport services, facilities, and interactions, which could speed and enhance recovery following disruption. The influences and impacts of ICT on information, flexibility, productivity, lifestyles, transport services, and travel behaviour are growing areas of research, but the value of this in terms of resilience has been explored in much less detail. Thus, this chapter considers not only the research directly addressing resilience benefits from ICT, but also that related to the influence of ICT on accessibility which underlies the potential for enabling more resilient access behaviours in the future.

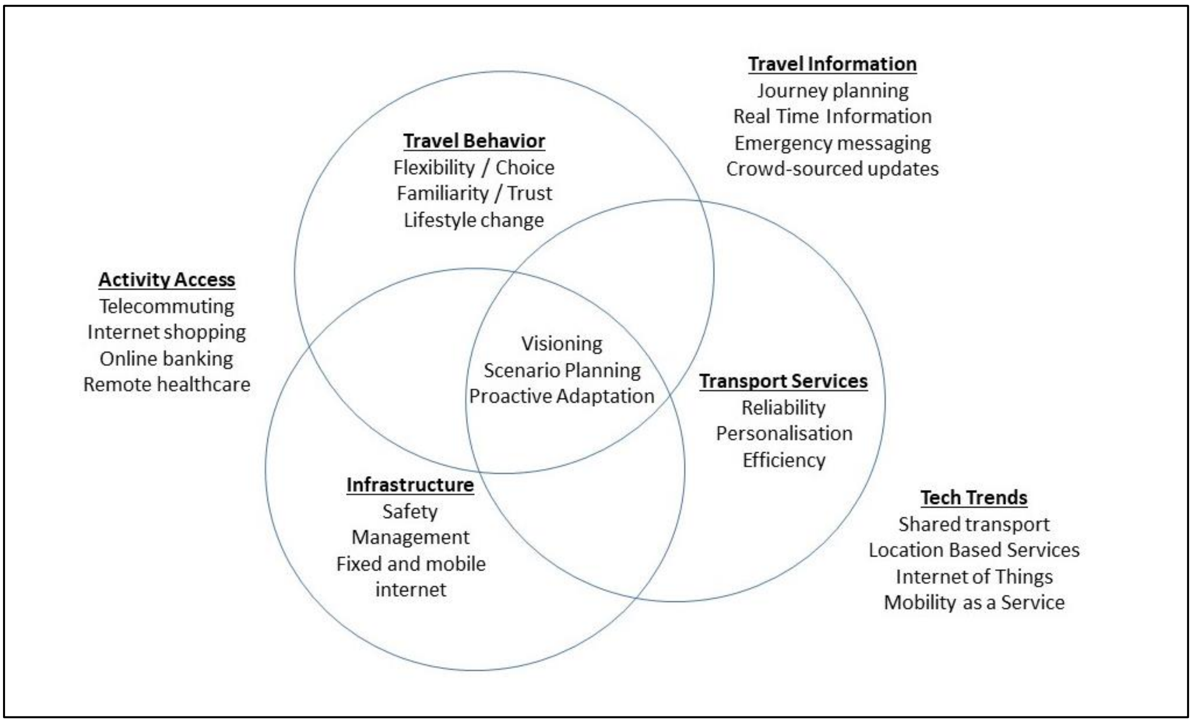

Figure 3.1: The study of ICT and Transport Interactions

3.1 Information Increases Efficiency: the next best thing to reliability?

Severe weather events can cause substantial disruption to transport networks and services, including not only road closures and rail cancellations, but also delays due to road traffic incidents, congestion, diversions, and speed restrictions. Delays increase individuals' capability constraints as they cannot be physically present at an activity if they are stuck somewhere on the transport network, and the increased time in transit reduces the time available for the activity. However, ICT has a major role to play in reducing temporal inefficiencies through travel information. Surveys have indicated that travellers' greatest concern is not the cost or total journey time, but rather the reliability of journey time for different modes or routes when used regularly (Lyons, 2006; Wang et al., 2009). Thus, it is not surprising that even when there is no adverse weather or other disruption, the demand for real-time, mobile journey planning is increasing and those who use such services are more likely to change their travel plans or have more flexible travel patterns (Wang et al., 2009; Wockatz and Schartau, 2015).

Indeed, over half of the 78% of UK adults who use a smartphone consider it essential for travel purposes and would share their data in exchange for improved services (OfCom, 2018; Wockatz and Schartau, 2015). Even basic information from variable message signing can encourage diversions, reducing local queueing, and potentially reduce travel times on a network with spare capacity elsewhere (Chatterjee and McDonald, 2004). More recent ICT developments allow travel information to be combined with location-based services to enable users to be notified of the quickest route to access goods, participate in activities, or to find others in their social network, all based on where they are at a given time (Arribas-Bel, 2014; Ratti et al., 2006). This can result in an increase in short, multi-purpose, linked trips to 'other' locations, for example if leisure opportunities are available near the workplace, and is one reason that direct home-work commuting is in decline (Astroza et al., 2017; Le Vine et al., 2017; Phithakkitnukoon et al., 2010; Wang and Law, 2007). Yet it also can have a substantial impact upon the ability to change timing, route, or mode of transport during a severe weather event or other disruption.

Information is often sought in response to the expectation of disruption, with an increased engagement and an improved perception of the reliability of alternative services if trustworthy information on delays, diversions and other options is available (Chorus et al., 2006; Cottrill et al., 2017; Lyons, 2006; Pender et al., 2014). The transport authorities in New York recorded large increases in the number of Twitter 'followers' before major storms and hurricanes, with few then 'unfollowing' after the event, suggesting that the overall level of engagement, and the rapidity and flexibility of future response increases through use of ICT (Chan and Schofer, 2014). Another study that used Twitter's geotagged data from natural disasters occurring around the world in 2013 and 2014 concluded that human mobility patterns in the most general sense of an individual's spatial area of travel and activity are highly resilient, and remain predictable in all but the most extreme scenarios (Wang and Taylor, 2016). As this study was informed by big data from an ICT source, one additional conclusion might be that ICT itself through geo-tagged social media was assisting users in maintaining their activity spaces. In Hong Kong during the Occupy Central Movement, the metro rail system was more resilient, and had enough spare and added capacity to cope with well-informed travellers shifting from disrupted road-based transport (Loo and Leung, 2017). In London during the 2012 Olympics, an extensive information, awareness and incentives campaign to minimise both disruption to normal travel and any negative experience of visitors to the Games generated substantial travel behaviour change during the games, and some sustained change afterwards (Parkes et al., 2016).

Meanwhile, data and records of the use of ICT by travellers can enable transport authorities and operators to make their services and information more efficient and relevant, providing real-time information to the right people in the right places during disruption, and creating a feedback loop that results in yet more efficient, sustainable, and resilient alternatives (Cats and Jenelius, 2014; Haworth et al., 2014; Nair et al., 2013). Apps and social media can encourage participation in this process, as they enable both the reporting of obstacles such as fallen trees and also requests for advice on alternatives (Cottrill and Derrible, 2015; Cottrill et al., 2017). Weather data is important too, although false warnings could actually reduce the level of response, so coordination between weather authorities, transport authorities or operators, and others who have a clear understanding of the timing, location, and extent of any potential impacts is essential (Lee et al., 2009). Yet the fewer the choices of modes and the longer the distance, the more likely not only that the available transport infrastructure or services will be disrupted by severe weather, but also that, if disruption is lengthy or recurrent, travellers will be forced to make decisions about rescheduling and relocating activities (Marsden et al., 2013). There is evidence that when faced with such decisions, people prefer advance planning, known routines, and space-time flexibilities with which they are already familiar, e.g. telecommuting (De Palma and Rochat, 1999; Marsden et al., 2016).

3.2 Telecommuting and Spatial Redundancy

Multi-modal studies in three different European countries indicate adverse weather results in the postponement or cancellation of many leisure journeys, but that commuters rarely cancel their trips, but may change mode, route, and timing of travel, with the latter being most common (Cools and Creemers, 2013; De Palma and Rochat, 1999; Khattak and De Palma, 1997; Sabir et al. 2010). This is because regularly employed commuters tend to prefer routine, organize their day around work obligations, and have less discretion to choose not to travel (De Palma and Rochat, 1999; Le Vine et al., 2017). Indeed, on a daily basis, people’s activities are least affected by changes in the weather during the normally compact morning rush hour between 8 and 9 AM (Horanont et al., 2013), more variable in the evening peak, partly because people appear to choose to leave work earlier or later during bad weather (Singhal et al., 2014), and most affected on the weekend when not just the travel, but also the activity itself may be cancelled due to bad weather (Arana et al., 2014; Sabir et al., 2008). This ‘fixed’ nature of work in time and place is largely due to coupling and authority constraints, such as the need for joint or team working, meetings, delivery of services to clients and customers, and management oversight. Yet that is changing as various spatially and temporally flexible working patterns including telecommuting or using ICT to replace all or some of the journey to and from work, are increasing, even if a lag in employer support has resulted in a slower trajectory than researchers might have expected (Cairns et al., 2004; Felstead, 2012; Siha and Monroe, 2006). Furthermore, the stated desire for telecommuting and the flexibility to work from home once or twice a week suggests considerable suppressed demand, particularly among women and part-time workers, fewer of whom telecommute regularly, but who are more likely to say they want to, perhaps due to additional care-giving responsibilities (Headicar and Stokes, 2016; Lavieri et al., 2018; Singh et al., 2013).

The level of telecommuting can be difficult to measure, as it is counted in different ways by different surveys, and depends upon the type of employment: directly employed, indirectly employed, self-employed, full-time, part-time; the definition of place: home, on transport, in alternative locations; the definition of time: full-days, part-days, overtime; and the work tasks (Allen et al., 2015; Bailey and Kurland, 2002; Haddad et al., 2009; Felstead, 2012). However, in all these definitions, telecommuting is reducing coupling constraints. For example, one of the material benefits of ICT is to reduce production costs through remote oversight, so early telecommuting practices often took the form of low-paid clerical work under contract or agency employment as firms used ICT to manage remote workers (Bailey and Kurland, 2002; Karlsson et al., 2010). Subsequently, the development of ICT and the knowledge economy with its autonomous, task-based work culture has been a fundamental component in changing patterns of work (Felstead and Henseke, 2017). Studies from the United States, the Netherlands, and the UK indicate that telecommuters are now most likely to be found among the professional, better educated, more internet-savvy sectors of the population, and many firms feel that to attract such people, flexibility needs to at least be available even if it is not chosen (Ellen and Hempstead, 2002; Headicar and Stokes, 2016; Peters et al., 2004; Singh et al., 2013; Walls et al., 2006).

As the popularity of telecommuting increases, it offers greater opportunities for increasing resilient travel behaviours, especially if employers are proactive. For example, the United States Federal Government's Telework Enhancement Act of 2010 required remote working be included in emergency planning strategies for its employees, and it was reported that a third of government employees telecommuted during Hurricane Sandy (Allen et al., 2015). Even without this strategic planning, a UK study surveying people in areas affected by the 2013-14 floods, a snow event in 2013, and the closure of a major road bridge in Scotland found evidence that some commuters adapted by working from home and from alternative destinations, or by temporally flexible working such as delayed starts and compressed work weeks (Marsden et al., 2016). Similar evidence was found in American studies of other major road / bridge closures and of commuters who were not employees of the Federal Government during Hurricane Sandy, the latter indicating that people also used ICT to 'crowdsource' shared transport and flexible office space with electricity (Kaufman et al., 2012; van Herick et al., 2012; Zhu et al., 2010). A large increase in internet traffic was tracked in London during a major snow event in 2018, which may have been due to increased remote working (Stubbings and Rowe, 2019). Commuters can also use ICT to coordinate non-work coupling constraints, such as arranging a trusted surrogate to pick up children when the parent, usually the mother, who may dedicate substantial time and effort to building networks of such surrogates, is delayed by disruption (Schwanen and Kwan, 2008).

Indeed, as developments in ICT, particularly cloud computing and 3-5G mobile internet enables access to information anywhere at any time, even when stranded on transport services, ever more people can participate in activities, including work, from unspecified locations (Lyons, 2018; Messenger and Gschwind, 2016). This may be beneficial during disruptions in the short term, but the debate over its longer-term sustainability and adaptive capacity continues. The potential for avoiding congestion in real time or connecting and multi-tasking in a traffic jam influences the marginal costs of time spent travelling, which is a concern for those attempting to forecast the potential use, benefits and impacts of both ICT and new transport technologies (Le Vine et al., 2015; Kwan et al., 2007; van Wee et al., 2013). A Canadian study suggested that mobile ICT increases the number of trips, distance travelled and therefore emissions, whilst a study from the UK correlates virtual accessibility, measured by variables such as possession of an ICT device and subscription to / coverage of a network, to more discretionary trips and longer distance tours (Lavieri et al., 2018; Miranda-Moreno et al., 2012). One international study questions whether the reduction in transport spend due to use of ICT for access implies less travel or enables more efficient travel over more dispersed networks (Bris et al., 2017).

Researchers speculate whether the long-term effects of ICT on travel demand will be more population dispersal and sprawl, as those who telecommute often live further from their workplace, but not only is the direction of this effect unclear, but also it is dependent upon geographic and economic characteristics, and whether the study includes only telecommuters, or their households, colleagues or the wider population

(Choo et al., 2005; de Abreu e Silva and Melo, 2018; de Vos et al., 2018; Ellen and Hempstead, 2002; Gubins et al., 2017; Hu and He, 2016; Kim, 2017; Qin et al., 2016; Zhu, 2013). Indeed, there is a socio-economic dimension to who is likely to be able to telecommute and whether they have the authority to decide when and how often they do so. If increased telecommuting does result in more travel and more sprawl, this might reduce the travel modes and options available, resulting in less dynamic accessibility and resilience. However, the flexibility telecommuting offers to coordinate with others, especially for work activities, and to avoid disruption, by staying home and reducing the pressure on key routes needed by emergency responders, indicates there is substantial scope for ICT to increase overall resilience and offer redundancy of access with appropriate interventions in transport, ICT, and land use planning.

3.3 Recovery and Long-term Change

ICT can relax the fixed nature of work travel for some categories of workers, but not for all, and not for an indefinite period of time. Telecommuting from home or alternative spaces may increase over a period of extended disruption perhaps because there are additional opportunities for communication between employers and employees using ICT after a weather event (Kaufman et al., 2012; Marsden et al., 2016). Yet, for those whose work is fixed in time and space because a manual task cannot be done elsewhere or a face-to-face interaction is required, then ICT enables the relaxation of other constraints on the spatial and temporal availability of services. ICT can direct people to local facilities of which they may not be aware, or help them continue to travel through ride-sourcing and reinforcing messages from the authorities about replacement options as networks recover (Loo and Leung, 2017). Online shopping and personal services such as banking and health offer more access outside business hours, and reduce the risks of travelling in severe weather, even if goods must be delivered at some point (Andreev et al., 2010; Chatterjee et al., 2018; Headicar and Stokes, 2016; Rohr et al., 2016). Personal business, food shopping, and other necessary if flexible trips may be undertaken on route to or from work as linked trips to increase travel efficiency and dynamic accessibility, although telecommuters cannot make such trips when they work from home and shift workers are limited by service opening hours (de Abreu e Silva and Melo, 2018; Allen et al., 2015; Järv et al., 2018; Susilo and Kitamura, 2005; Zhu, 2012). Likewise, many more commuters are limited by more time-consuming travel between work and home during disruption, such that, along with postponement and cancellation of non-work trips, reduced opportunity for linked trips is another response to adverse weather.

However, if work is available over the internet, perhaps other activities and services can be made available within walking distance, as adverse weather like extreme cold and flooding was associated in two studies with less disruption of active travel trips and increased walking distance (Marsden et al., 2016; Sabir et al., 2010). In another study, snow was also positively associated with more walking trips by commuters (Liu et al., 2015). Positive integration of urban planning and form can thus enable communities to make sustainable and resilient travel choices (Headicar, 2015; Hickman et al., 2013), and with the rise of telecommuting and other forms of flexible working, the push to increase sustainable travel choices must include non-work trips. Transport accessibility is dependent not only on the time, cost, or distance parameters of the transport systems and networks available, but also the gravitational pulls of land use, distribution of population and jobs, and the form of the built environment (Banister, 2008; Halás et al., 2014; Martinez and Viegas, 2013; Reggianni et al., 2011). If jobs and populations are unlikely to be distributed evenly, particularly if viewed in terms of employment sectors and labour skills, so flows are also unlikely to be even (Reggiani et al., 2011; Uboe, 2004). This uneven-ness can be exacerbated by ICT, as it undermines the traditional assumption that the main trade-off in residential location choice is between house prices and commuting costs (Clark et al., 2003; Ma and Banister, 2006). Telecommuters tend to live further from their regular workplace than those who don't telecommute, and although they may choose suburban or metropolitan areas with a diversity of jobs, employment and residential areas in the 21st century are often dispersed (de Abreu e Silva and Melo, 2018; Chowdhury et al., 2013; Ellen and Hempstead, 2002). Yet there is evidence that telecommuters travel more for activities like shopping and personal business, particularly those who live in mixed use neighbourhoods or areas of higher density (Asgari and Jin, 2017; Loo and Wang, 2018; Singh et al., 2013). Furthermore, even though trip chaining is associated with travelling further, perhaps because it often accompanies longer-distance commuting trips, people who live in high density areas are more likely to undertake complex trip chains yet travel shorter distances (Chen and Akar, 2017).

There is much academic speculation around whether ICT 'dematerializes' various goods and activities, making distance and geography less important in consumer choices and awareness of far-flung options, such as residential location or social connections, or whether the fragmentation and dynamism it introduces could increase the desire for dense, urban living and have a complementary impact on urban agglomeration and growth (Circella and Mokhtarian, 2017; Lyons, 2015; Qin et al., 2016; Tranos and Ioannides, 2015). For adaptation as well as mitigation purposes, policy and decision makers must discourage the former and encourage the latter.

Planning for services, shopping, and facilities in suburban areas can enable residents to make these trips by foot or bicycle if they so choose, and maintain access when more distant centres are made inaccessible by weather. About 20% of any given population are estimated to change jobs or move home each year, and whilst many of these individuals also change their mode and pattern of commuting, the choice to move home or job is influenced not only by commuting costs, but are also by socio-demographics, urban form, and the cost of moving itself (Clark et al., 2016; Dargay and Hanly, 2007; Van Acker et al., 2010; Van Ommeren et al., 1999). If ICT is reducing the importance of commuting costs to these decisions, then other factors like urban form or the presence of children in the household become more relevant, and planning neighbourhoods with key facilities has greater potential to increase the number of sustainable and resilient neighbourhoods over sprawling, car-dependent suburbs.

In conclusion, this section of the literature review demonstrates that ICT can enable a more resilient response to extreme weather events and other forms of disruption, particularly planned events or when unplanned disruption lasts long enough for coordinated communication of not only the problems, but potential solutions. It also shows there are numerous studies considering whether telecommuting and other online access practices are sustainable, but few of these consider the resilience or adaptation aspects of sustainability. Furthermore, analysis into the interactions between access to work and access to other activities by transport and ICT modes is very much an emerging field and the full potential of the co-benefits that might be realised by integrated planning of transport and ICT access to a variety of daily activities requires substantial further research. Together, Chapters 2 and 3 identify the gaps in the literature to which the empirical chapters of this thesis aim to contribute.

4. DATA AND METHODOLOGY[3]

This research project takes a quantitative approach to analysing the relationship between severe weather and changes in dynamic accessibility, including both travel and online access. As demonstrated in the literature review, weather impacts vary in space and time, and any response to them cannot be measured until after they occur. Thus not all data sources and methodologies are suitable for analysing the overarching research question. The volume, velocity, and variety of big data has the spatial breadth to map accessibility across relatively detailed geographies, and the longitudinal extent to compare patterns during selected case studies of storms or extreme weather to periods with more typical weather conditions. Furthermore, although the purpose of these secondary data sources and data privacy rules prevent in-depth analysis of the behaviour and characteristics of individuals, open socio-economic, demographic, geographic, and weather data can be matched to such big data sources by time and neighbourhood. This enables the addition of many of the control variables that are known to influence accessibility choices, irrespective of the weather. Such variables provide insights in both exploratory and econometric methodologies, which can then be considered further through more traditional data sources, such as surveys. The rest of this chapter discusses the opportunities and obstacles of different data sources, the methodologies which are appropriate for their analysis, and summarises which data and techniques are used in the empirical chapters, where more detailed context, sources, descriptive statistics, and equations are provided.

[3] As this Chapter provides an overview of the data and methodology from the author's papers cited in Chapters 5-8, some content from those papers have been integrated into this Chapter.

4.1 The Opportunities and Obstacles of Different Data Sources

Both transport supply and demand are affected by variability and uncertainty of travel times, cost, and safety during extreme weather events, among other factors, both within and outside of the control of the travellers who are making choices based on imperfect information (Bonsall, 2004). Even excluding extreme weather and climate change, uncertainty is growing due to the shifting economy, increased urbanisation, and disruptive technology, both within and outside of the transport sector (Marsden et al., 2018). These uncertainties apply differently to individuals depending upon a variety of socio-demographic characteristics which are relevant to both ICT penetration / service levels / use and to travel choices and behaviour; including wealth, education, deprivation, age, presence of children, and urban or rural living, each of which can be aligned to neighbourhood classifications and household features and can also vary spatially (Blank et al., 2018; Clark et al., 2016; Cottrill, 2018; Hauge et al., 2010; Hincks et al., 2018; Longley et al., 2008; Lovelace et al., 2014; Philip et al., 2017; Riddlesden and Singleton, 2014). Considering the relevance of such socio-demographics, a number of studies in the literature review highlight the benefits of using either stated or revealed preference surveys to determine how individuals would respond or had responded to different weather conditions (Böcker et al., 2013; Cools and Creemers, 2013; Khattak and De Palma, 1997; Meng et al., 2016).

However, due to the nature of severe weather, any disruptive impacts can only be confirmed after the fact, and few of these studies using primary data fully explore whether telecommuting or other ICT had been employed to overcome transport disruption, and there is even less evidence as to whether changes during disruption had an influence on long-term behaviour (Marsden and Docherty, 2013). Furthermore, those few case studies that do document such responses, whilst enlightening, are neither spatially nor temporally extensive due to the resource required for primary data collection, obscuring any trends. Meanwhile, larger, representative surveys rarely capture the response to irregular events, even if they can provide substantial detail on travel behaviour choices, use of ICT, and the access response(s) during typical weather variation (Sabir et al., 2010). Also, UK Government advice specifically recommends avoiding "times of extreme weather" when planning surveys, and that "data collection needs to be repeated if an unforeseen event occurs (such as an accident or adverse weather)" (Department for Transport, 2014, p5). Thus, surveys and travel diaries are useful to glean behavioural trends, such as the insights into the frequency of telecommuting and how often people travel for different purposes as explored in Chapter 8 using the NTS. They improve understanding of wider trends in space-time flexibility, such as the influence of geography on travel behaviour or the prevalence of trip chaining (Chen and Akar, 2017; Lavieri et al., 2018). However, to analyse actual access choices made during severe weather conditions, secondary sources of big data, generated and collected on an ongoing basis for other purposes, offer opportunities for behavioural records from the day of an extreme weather event, documenting responses such as awareness on social media, the detail of destination choice, and the change in passenger numbers on a diverted public transport service (Cottrill and Derrible, 2015).

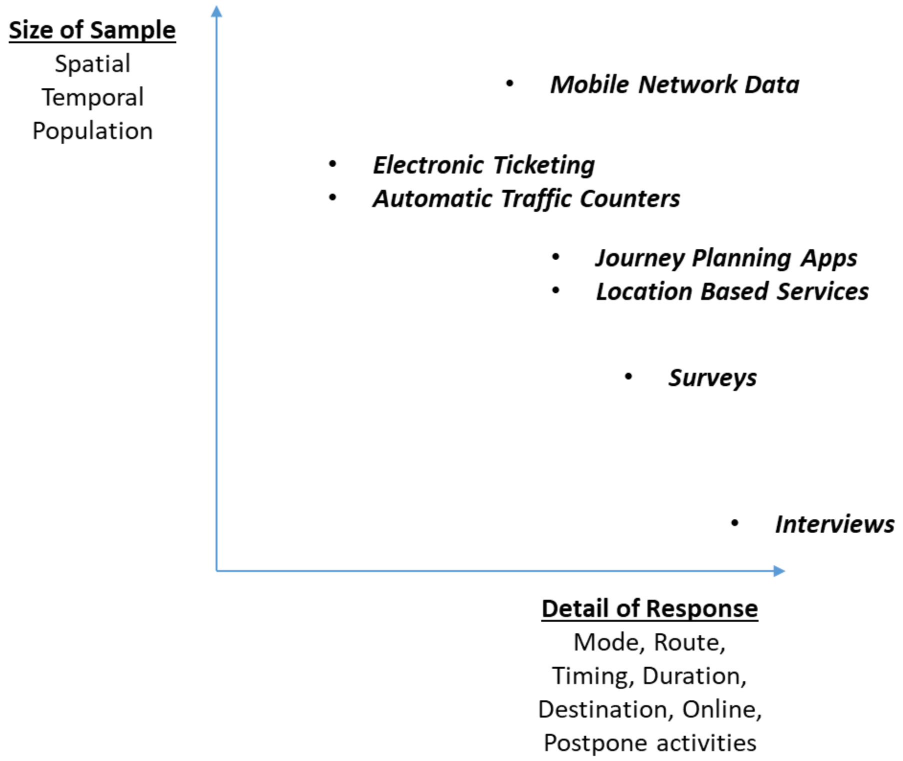

Figure 4.1: Trade-offs between sample size and detail of response by data source

Figure 4.1 provides a graphical representation of how automated, digitally collected 'big' data sources are likely to provide much more spatial and temporal granularity due to their large sample sizes. Thus, through matching to additional data sources, they reveal information about exposure to various environmental parameters. Big data sources contain less direct information on the access choices made by individuals, and even less so their motivations. However, although every data source has its own advantages, limitations, and biases, one of the aims of this research was to use secondary data sources which could enable a quantitative approach to assessing the influence of geographic and socio-economic characteristics on changes in space-time accessibility during cases of severe weather. Thus, three of the empirical chapters mainly utilise a variety of big data sources, whilst Chapter 8 uses the National Travel Survey, which, due to its size and consistency also enables the application of quantitative methodologies.

Many big data sources are internal to the transport sector, including electronic ticketing, traffic count loops, journey planners and other navigational aids or digital mobility platforms, CCTV and ANPR cameras, GPS trackers and on-board computers on public transport, freight and other vehicles, and sensors on transport infrastructure. The data are usually collected automatically by operators, authorities or other responsible parties for commercial or statutory purposes including the management, safety and security of transport networks and vehicle fleets, and to improve their reliability, efficiency, and comfort for users (Ricci et al., 2012). However, as reviewed above, a number of studies have used data from these sources to determine how weather and seasonal change influence passenger numbers on public transport, traffic volumes or speeds (Guo et al., 2007; Kalkstein et al., 2009; Cools et al., 2009; Tsapakis et al., 2013). Chapter 5 also uses the data generated by electronic ticketing transactions, but adds to this body of literature by focusing on an impactful winter storm rather than daily variation.

Transport data sources offer the potential to understand changes in route, mode, departure times, and cancellations, but there is no way of knowing whether online access has replaced travel. Many such records track a partial journey, rather than from home origin to final destination, and are therefore incomplete. Also, data sources such as electronic ticketing or traffic count loops are only relevant to a subset of transport modes, reducing how many behaviour changes might be measured without access to multiple datasets, usually with a variety of data owners and permissions to link them. Even cameras and sensors which do offer multi-modal output are unlikely to be comprehensive on local roads in urban areas, and pedestrians and other ‘slow’ modes are often overlooked or undercounted. Alternatively, there is the data produced by and for Information and Communication Technologies (ICT), including both mobile and fixed services, as form the inputs to Chapters 6 and 7 respectively.

ICT-derived data have the potential to capture large samples of space-time paths with minimal cost, and offer insights into the variability and short-term shifts and patterns of movement and user needs that cannot be captured by surveys (Arribas-Bel, 2014; Lovelace et al., 2016; Miller, 2005). Mobile phones and other connected devices and infrastructure are producing ever greater volumes of time-stamped data, via basic services, financial transactions, social media and apps; and spatial data through the provision of GPS-location-based services where voluntary geographic tagging is switched on for journey alerts, gaming, advertising, and social networking (Arribas-Bel, 2014; Blazquez and Viegas, 2018). These ICT sources are well-placed to uncover patterns of regular, but less frequent activity, such as secondary places of work, irregular trips for tourism or business travel, and atypical days when there are planned or unplanned events, including severe weather (Becker et al., 2013; Calabrese et al., 2010; Steenbruggen et al., 2015; Wang et al., 2017). They also have great potential to reveal how people access land uses other than employment, such as supermarkets and cafes or restaurants in both space and time (Järv et al., 2018; Wang et al., 2018). And whilst those using location-based services and mobile applications are still relatively small in number, the market share is increasing and key socio-economic characteristics can be linked to sample populations through their geography.

However, there are caveats. ICT infrastructure, operation, and use is as full of overlapping and uneven networks as are transport systems, with levels of accessibility and capacity dependent upon the end users' own capabilities, their placement in time and space, the Internet Service Provider involved, the type of connection, and the technology used to manage the connection (Blank et al., 2018; Graham, 2013; Nardotto et al., 2015; Philip et al., 2017; Tranos et al., 2013). Some of these data sources are much less granular than others, both spatially and temporally, and some have different spatial and temporal profiles than the transport movements they are being used to measure. For example, the basis for analysis in Chapter 7 is that the quality, or in other words, the download speeds of fixed broadband services are affected by increased online activity and data flows during severe weather events, although such speeds and flows are commonly tracked by time of day to estimate peak download demand after peak travel hours have ended (Fu et al., 2016; Nardotto et al., 2015; Riddlesden and Singleton, 2014; Stubbings and Rowe, 2019).

Furthermore, a mobile phone may not be in use or cell towers may be too far apart to capture shorter trips or short stops in a trip chain (Caceres et al., 2007). Aspects like mode, vehicle type, and occupancy can be inferred from mobile data, as road and rail trips are in Chapter 6, but these are not surveyed directly. The population that uses ICT the most tends to be younger, more urban, and better educated (Blank et al., 2018; Kwan, 2001), yet such socio-demographic characteristics are rarely included within ICT datasets due to concerns about privacy and data protection. Addressing privacy concerns in ICT datasets is an ongoing challenge, as there are contrasting regulatory and market-led approaches (Cottrill and Derrible, 2015). Studies have also recorded less mobile phone use and fewer social interactions in the morning peak (Aledavood et al., 2015; Louail et al., 2014), but this may not be the case during a severe weather event if people are using their ICT devices to track disruption (Lee et al., 2009). Thus, severe weather adds further layers of temporal and spatial variation in internet activity across ICT networks that has yet to be fully researched in parallel with transport accessibility, and adds uncertainties to the analyses in Chapters 6 and 7.

Table 4.1: Data Sources for each empirical chapter

Chapter 5	Chapter 6	Chapter 7	Chapter 8
Bus network electronic ticketing data	Mobile phone network data pre-processed into origin-destination matrices	Broadband speed tests (voluntary geographic information)	National Travel Survey 2009 – 2016 (England)
Local news reports and twitter feeds	2011 census tables / output areas 2016 population estimates (density) OpenStreetMap points of interest Media reports	2011 census tables / output areas Met Office archived weather records 2014 small area income estimates	

Although not all uncertainties can be removed from analyses such as those in Chapters 5 through 8, some are minimised through matching additional data sources, methodological choices, and sensitivity testing. The next section will discuss the methodologies used and how the strength of certain insights can be reinforced for subsets of the data. Table 4.1 lists the data sources used for each empirical chapter, including both the main data source and supporting data on geographic and demographic characteristics as well as information on weather events and impacts. It should be noted that the choice and use of secondary data sources was also dependent upon whether data were freely offered or otherwise made available in constrained formats. Transport and ICT big data is often proprietary, costly, and subject to stringent personal or commercial privacy regulations. However, the proprietary data could be linked to geographic and demographic data, which, at least at the neighbourhood scale, are generally open or crowd-sourced through voluntary agreement and thus available on APIs.

4.2 Identifying Appropriate and Mutually Reinforcing Methodologies

Severe weather events are irregular and extreme phenomena, ‘cases’ by nature, and the response to them is highly context-dependent, spatially and temporally, which is a key characteristic of case study research (Flyvbjerg, 2006). Investigating these atypical events also has greater potential to reveal whether trends in ICT diffusion and increasing flexibility of work and travel affect the resilience and access patterns of commuters, who respond little to mere daily weather variation. Furthermore, multiple case studies enable the emergence, rather than the deduction, of insights into opportunities for resilience, which is fitting for research that must find patterns in available data generated during particular weather events, rather than by experimental design (Eisenhardt and Graebner, 2007). Thus, the combination of secondary data sources with a methodological approach that builds on case study research is well suited to the research aims and objectives of this thesis.

Unusually for case study research, the central data sources for the empirical chapters all comprise thousands to millions of observations. Researchers are developing new methods of modelling the bigger data sources using machine learning techniques to infer greater insights into temporal variability, journey times, and even individual behaviour (Crawford et al., 2017; Haworth et al., 2014). The opportunities to use big data to build more concrete methodological foundations for the concept of time geography are also being identified (Arribas-Bel and Tranos, 2018; Miller, 2005; van Wee et al., 2013; Wang et al., 2018). However, big data sources, including those analysed in Chapters 5-7, often have challenges in terms of usability of format, missing data, or sampling / response biases, and each varies in scale and aggregation. Therefore, in each empirical chapter, it was essential to explore the data in tabular form, graphs, and maps, and interrogate the summary statistics. These in themselves can offer insights into travel patterns, and indeed, for a case study as spatially, temporally, and modally bounded as the one in Chapter 5, maps and graphs alone revealed an important change in travel behaviour, the context for which could be found in local news reports and Twitter feeds.

Graphs are also a common way to review and assess trends in data sources like the National Travel Survey (Chatterjee et al., 2018; Headicar and Stokes, 2016; Le Vine et al., 2017). Therefore, a proportion of the analysis in Chapter 8 focuses on graphs and summary statistics. However, the aim of using the National Travel Survey, where trip diaries are unlikely to have been recorded during extreme weather events was to consider the travel budget of telecommuters, not by distance or duration (Mokhtarian and Chen, 2004), but by journey purpose. Where journey purpose is the dependent, non-ordinal, categorical variable, similar to studies with modal choice as the dependent variable, multinomial logit modelling offers an appropriate methodology (Saneinejad et al., 2012; Zhou, 2012). Understanding the journey purpose of telecommuters provides insights into the types of non-work journeys which might be postponed or cancelled when commute journeys are prioritised during severe weather as is explored in Chapter 6.

Commuting patterns in Chapter 6 were derived from mobile phone network data pre-processed to mimic inputs into traditional transport modelling, and thus in the form of origin-destination matrices. This pre-processing is in line with a wider area of research supported by industry and governments to build transport models with mobile phone data inputs, as such data are larger and often less expensive than road side interviews and other survey techniques used to gather the same information (Caceres et al., 2007; Cuauhtemoc et al, 2017; Duduta et al., 2016; Tolouei et al., 2015; Vilarino et al., 2016; Wang et al., 2017). Furthermore, data analysts have built robust models that confirm that individual mobility follows certain patterns and is largely predictable, and have written algorithms that rank important places in people's lives, particularly work and home, to a high level of confidence as validated against national surveys and revealed travel (Gonzalez et al., 2008; Isaacman et al., 2011; Noulas et al., 2012; Song et al., 2010). Therefore, this confidence could be transferred to the assignment of trips as home-based work, home-based other, and non-home-based in the matrices built from mobile phone network data prior to their release for this research.

Yet although the data was designed to fit into a traditional transport model, the application of such a methodology had more limited value for comparing the *difference* in, rather than the total, trip generation for different land uses under storm conditions. Furthermore, transport models are a form of spatial interaction or 'gravity' models, a key element of which is a 'distance decay factor' or the ratio of cost to benefit, distance to attraction, even though these are based not on the laws of physics, but the vagaries of human behaviour (Halás et al., 2014). As various studies have noted, the perception of proximity alters according to route, mode, activity, environment, physical barriers, historic connections, and the diversity or homogeneity of neighbourhoods (Halás et al., 2014; Martinez and Viegas, 2013; Reggiani et al., 2011). It also varies with the weather, but within the context that certain major decisions, such as employment or residential location, will have been made based upon the economic and social opportunities and accessibility criteria at the time of decision (Noulas, et al., 2012), and are thus unlikely to account for how the journey may be affected during a period of disruption. Furthermore, in the case of differences in trip generation, using a gravity-style model and including distance decay masked other influences of primary interest to this research, such as socio-economic status and urban form, as well as resulting in a poor model fit. Therefore, linear regression rather than spatial modelling was used in Chapter 6.

The analysis in Chapter 7 is more complex and uses multi-level regression modelling, where intercepts were allowed to vary by a neighbourhood level statistical output area even though the speed tests themselves were geo-located. The reason for this is that ICT is not only a useful data source to track dynamic accessibility, but can also change it (Cats and Jenelius, 2014). As discussed in the last section, the quality of fixed broadband available is affected by both location-based supply options, such as the level of competition between Internet Service Providers and the types of connections they can provide, as well as the demographics of an area, which determine levels of demand independent of any adverse weather risks. Thus, controlling for the spatially fixed influences on broadband speeds within a spatial hierarchy enabled the model to better estimate the correlations between coefficients and temporal variation. The control variables were applied at the neighbourhood level because applying a random effect to these geographic units improved the model fit more than if larger areas were used, whilst more data was available at this level than if smaller areas were used.

Finally, to accommodate both key influences as defined in the literature and varying strengths of effects and significance of the coefficients within the model for socio-economic or geographic characteristics, the multinomial logit and multi-level models in

Chapters 7 and 8 were subject to sensitivity testing. The sensitivity tests were estimated for different subsets of the data included in the main model, and compared to other results from both the statistical modelling and the maps, graphs, and summary statistics of the data. By these means, the methodologies utilised in this thesis could either eliminate or further reinforce any insights into the changes in travel and online accessibility during severe weather and the key characteristics that most influenced those changes.

In summary, the empirical analyses in the next four chapters utilise a number of different secondary data sources, from electronic ticketing transactions to national travel survey responses, as well as ICT-derived big data. The quantitative methodologies employed complement the variables of interest and context is provided by matching the main data sources to information on weather parameters, weather impacts, and socio-economic statistics. This inductive and context-dependent approach is part of a case study based methodology, which fits the aims and objectives of the research to understand the response of commuters and other travellers to irregular and extreme phenomena such as severe weather events.

5. BUS AS THE RESILIENT TRAVEL CHOICE: A CASE STUDY FROM READING, UK[4]

This chapter describes an empirical case study which, as discussed in section 3.1, demonstrates one of the most basic ways in which ICT has made more resilient travel behaviours possible. ICT increases the awareness of alternatives if realistically available, provides the information required to successfully choose those alternatives, and enables prospective travellers to more rationally calculate the comparative cost, time, and reliability of the alternatives, in this case, between different modes of public transport during a major storm event. Weather events are a well-known risk to the reliability of journey times, particularly if infrastructure already operating close to design capacity is affected during busy periods such as morning and evening peaks (Koetse and Rietveld, 2009). *Storm Doris* struck on a Thursday, outside a holiday period, affecting congested urban areas at one or both peak periods. The case study in this chapter identifies the choice travellers and particularly commuters made to switch from delayed or cancelled train services to more reliable, if occasionally diverted bus services. Separate operating companies are responsible for the routes, timetables, fares and ticketing, and thus it is likely that ICT such as third party journey planners, as well as the communication channels of the operators helped customers be confident in making the switch. The analysis also provides some evidence of the importance of commuting trips over other journeys, as the co-location of a major employment site, small train station, and bus-based Park and Ride, generated a strong counter-flow trend in bus travel under storm conditions, taking advantage of spare capacity.

[4] The majority of this chapter has been published as Budnitz, H., Chapman, L., Tranos, E. (2018) 'Better by bus? Insights into public transport travel behaviour during Storm Doris in Reading, UK', *Weather*, 73(2), p54-60. https://doi.org/10.1002/wea.3058.

5.1 Storm Doris and the Public Transport Options in Reading, UK

On 23 February 2017 *Storm Doris* hit the British Isles with rain, snow and high winds. The strong winds felled trees and displaced signs, roof materials and other objects, which in turn severed power lines, blocked transport networks and caused substantial disruption. Alongside the physical damage, the cost of this event includes the extent to which it may have reduced economic productivity or impacted personal welfare, which is in turn determined by individual response to first the risk, and then the reality of the disruption. Although Reading was only issued amber warnings (Met Office, 2017a), and gusts reached no more than ~60mph, transport infrastructure and services were significantly affected by *Storm Doris*. This chapter explores how ticketing data from Reading Buses offer insights into the reactions of bus and, indirectly, rail passengers.

The UK Met Office coordinates with other agencies, including emergency responders, to issue severe weather warnings based upon expected impacts, such as travel disruption or flooding, rather than absolute levels of precipitation or wind speed (from correspondence with a Met Office weather desk advisor on 25 November 2016, pers. comm.). On 21 February 2017, the Met Office issued yellow and amber warnings relating to an approaching storm, which by the 22nd covered almost all of the country (Met Office, 2017b). It became *Storm Doris*, as the practice of naming storms with at least amber warnings, particularly if they were forecast to have strong winds and wind impacts, had been successfully piloted during the previous winter season in order to improve communication to the public (Eysenck, 2016; Met Office, 2016a). After *Storm Doris* passed, the national news reported that the damage caused by winds of up to 94mph had indeed been severe, including one death from fallen debris, power outages from East Anglia to Northern Ireland, cancelled flights and ferries, and closed train lines and bridges (BBC, 2017).

In Reading, the strong winds brought by *Storm Doris* also caused damage and disruption, particularly to the rail network. Over the course of the day, the online local news, *getreading*, reported trees or other obstructions blocking trains to London Paddington, Didcot, Bedwyn and Wokingham / Guildford, whilst all South West Trains, including those between Reading and London Waterloo, ran under speed restrictions that delayed journeys from late morning through most of the afternoon (Fort and Perryman, 2017). Of about 30 updates on their website over the course of the day, all but three were about rail disruption (Fort and Perryman, 2017). A Twitter search shortly after the event on the public transport operators' accounts and using key words such as '#stormdoris Reading' showed a similar ratio (Twitter, 2017). So many trees fell across the tracks on the line between Reading and Guildford that Great Western Railways reported the following on its social media page: An earlier large tree blocking the line has been cleared away… but response teams have now found several other fallen trees in the area (Great Western Railway, 2017).

Climate change risk assessments acknowledge that the UK's rail network is highly susceptible to strong winds, due to the presence of 2.5 million trees alongside the tracks (Dawson et al., 2016). For example, high winds during the winter 2013/2014 storms caused bridge closures on the country's Strategic Road Network, but operation returned to normal soon afterwards; conversely, the resources available for clearing trees blocking various rail lines were deemed insufficient, delaying recovery (Brown et al., 2014). In Reading, rail capacity was more disrupted than other transport modes by the high winds experienced during *Storm Doris*, with predictably more severe consequences considering trains are disproportionately important to the Reading conurbation. The population of Reading Borough was 155,700 in the 2011 census (Office for National Statistics, 2013), and even the wider urban area can count no more than double that number, yet Reading Station handled 20.7 million passengers entering, exiting or changing trains in 2015 / 2016 (Office of Rail and Road, 2016). This puts it in the top five busiest stations in England outside of London, and seventh overall for interchanges, with almost 4 million passengers logged changing between services (Office of Rail and Road, 2016). Figure 5.1 shows the rail network in Reading. Great Western Railway operate most trains serving Reading Station. South West Trains, Cross Country and many freight trains also use the facilities.

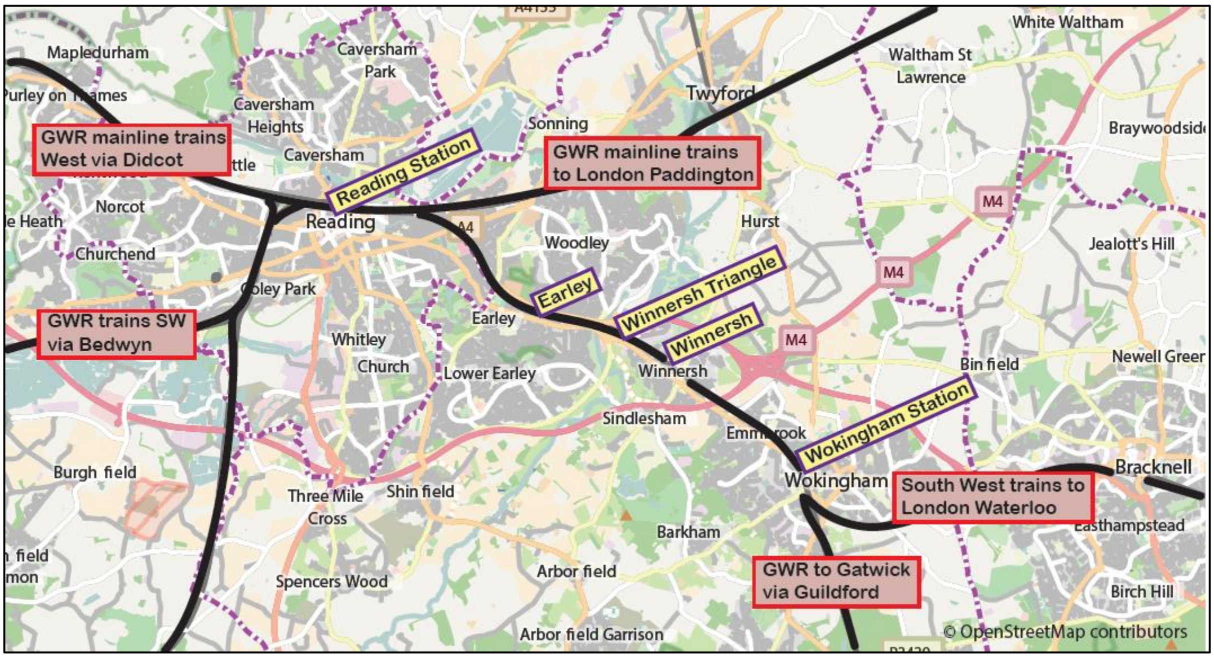

Figure 5.1: Rail network around Reading, UK[5]

During *Storm Doris*, many trains were delayed or cancelled, but that may not mean their passengers' journeys were too. Panel surveys of travellers affected by three major, recent weather and roadworks events indicate that commuters most often start

[5] *© OpenStreetMap contributors; see* *http://www.openstreetmap.org/copyright*

journeys slightly later in response to disruption, although over time compressing the work week and increasing the frequency of telecommuting become common coping responses (Marsden et al., 2016). Online interactions between individuals and the train operators confirmed that a few passengers re-routed along other train lines during *Storm Doris* (Twitter, 2017), but other reactions were not announced on social media. The Met Office claims that its severe weather warnings encourage more people to stay at home (Met Office, 2013). Other studies demonstrate that even normal weather variations cause some travellers to change mode, route or departure time, that is, by leaving early or postponing (Khattak and De Palma, 1997; De Palma and Rochat, 1999; Kilpelainen and Summala, 2007; Sabir et al., 2010; Cools and Creemers, 2013). If travellers in the Reading urban areas postponed on 23 February 2017, then their outbound journey may have been disrupted, but if they left early, they may have been stranded for hours trying to make an early return – unless they improvised by changing route or mode. The evidence from Reading Buses supports the latter hypothesis: some travellers adjusted their travel behaviour to the changing circumstances.

Reading Buses is a municipal bus company which operates over 95% of services in Reading Borough and the majority of services in neighbouring boroughs (Ottewell and Hyde, 2016). The dataset from their electronic bus ticketing system is thus a nearly complete record of bus patronage in the area for the period of analysis. Buses also hold a greater and growing share of the transport market in Reading compared with most other urban areas in the UK, with 20.4 million trips in 2015/16, the third highest rate of bus use per capita in England outside of London (Ottewell and Hyde, 2016). About 50% of trips are estimated to be made by commuters (T. Pettitt, pers. comm., 2017). For this research, Reading Buses provided summary data from their ticketing system of 303,000+ trips taken on Thursday 23 February 2017, during *Storm Doris*, and Thursday 2 March 2017, an 'average' day (Reading Buses, 2017a).

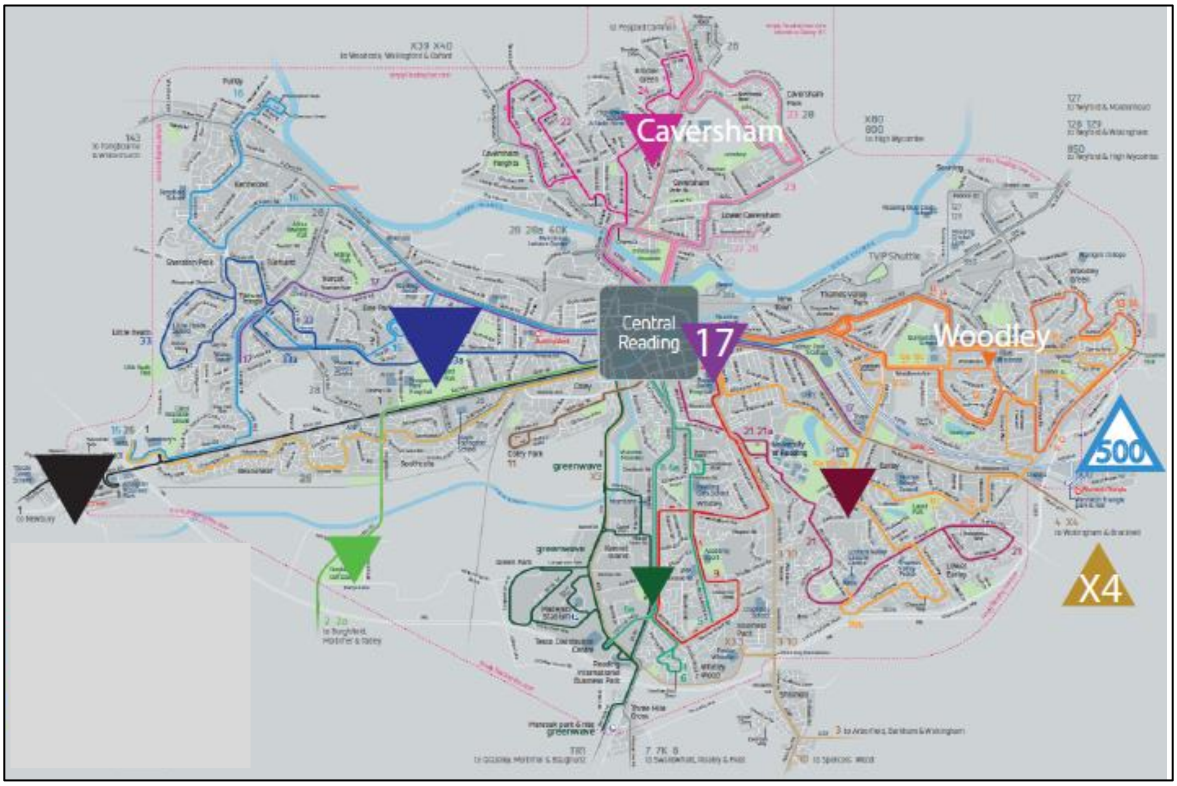

Figure 5.2: Map of Reading bus routes[6], with triangles added to indicate increase (pointing up) or decrease (pointing down) of passenger numbers. The triangles are scaled to match the percentage changes in daily passenger numbers on each colour-coded cluster of services during Storm Doris compared with an 'average' Thursday.

As is clear from Figure 5.2, the most obvious result from the summary data is that bus passenger trips were 4–8% lower on most services on 23 February than on an 'average' Thursday, except for the orange Woodley services, down by 1.5%, and the southeast Park and Ride route and inter-town services, which saw increases.

Lower patronage is expected, as studies of ticketing data in various cities over periods of up to 2 years conclude that ridership usually decreases in 'bad' weather and increases in 'good' weather; even with small percentage changes, many tests have had statistically significant results (Guo et al., 2007; Kalkstein et al., 2009; Stover and

[6] *Base map source: Reading Buses, 2017b*

McCormack, 2012; Singhal et al., 2014). Public transport passengers are thought to respond to a range of direct and indirect weather impacts (Guo et al., 2007; Adler and van Ommeren, 2016). People may decide not to travel by bus on rainy days because they would get wet walking to the bus stop, because their stop lacks a bus shelter, or because the bus is likely to be delayed by typically slower speeds on the road network (Guo et al., 2007; Stover and McCormack, 2012). They may also choose to postpone or cancel a weather-affected activity, and thus the trip to access the activity does not occur (Sabir et al., 2008).

Postponement or cancellation is most common for discretionary journeys, whilst far fewer people cancel their commuting or business journeys (Sabir et al., 2010). This conclusion appears to apply to the reduction in journeys around Reading. A majority of those using concessionary bus passes as tickets are not in work or education, as these passes are part of the national scheme only available to those of pensionable age travelling after 0930h or those with certain recognised disabilities. Therefore, excluding trips taken using concessionary bus passes, the percentage change in passenger numbers on the pink routes in Caversham falls to less than 1%, and in Woodley rises to 3% more passengers on 23 February. Other major service clusters still show decreases of 2–6%. Reviewing when fewer trips occurred provides further evidence of how few commuters cancelled trips. The graphs in Figure 5.3 show when and on which bus the almost 28,000 trips were taken on the eastern half of the cross-town, flagship Route 17 on the two successive Thursdays (Reading Buses, 2017a).

Figure 5.3: Route 17 passenger numbers for (a) inbound and (b) outbound journeys.

Whilst Route 17 saw 6.5% fewer trips during the day *Storm Doris* hit the UK, and 4.1% fewer trips excluding concessionary bus pass holders, that drop in passengers was spread throughout the day, inbound and outbound. Research suggests that mobility and activities are most consistent, no matter the weather, between 0800 and

0900h on weekdays: the morning rush hour (Horanont et al., 2013). In the dataset for Route 17 in Figure 5.3, there were actually 155 more passengers travelling on 23 February during this hour than on the following Thursday. If passengers during the entire peak period (0600–1000h) are included, there were 196 more AM peak trips on 2 March. Considering that the most common response to bad weather is for commuters to change the start time of a journey (Khattak and De Palma, 1997; De Palma and Rochat, 1999; Kilpelainen and Summala, 2007; Cools and Creemers, 2013; Marsden et al., 2016), the data suggest that a small number of commuters probably stayed at home on 23 February, but most travelled, some slightly later during the morning peak. Overall, therefore, this case study is consistent with the results of previous research: in severe as in merely 'bad' weather, most commuters will continue travelling.

Another question is whether those who do not travel, commuters or otherwise, are responding to weather parameters like rainfall and wind speeds, the focus of most previous research, or to weather impacts on network performance (e.g. bus routing, timetable adherence). From the company's operational summaries and its Twitter feed, it is known that falling trees and debris did affect a number of Reading Buses' services during the day of storm, causing delays and diversions. Yet the operator attributed far more lost mileage to ongoing roadworks than it did to the weather. For example, the Route 17 bus was diverted for almost two hours because a fallen billboard closed the road on which it normally runs along a bus lane, yet the redundancy built in to bus service delivery meant minimal lost mileage (Reading Buses, 2017a). Also, the difference in outbound passenger numbers during that period was negligible, and inbound passenger numbers dropped by only about 100, a small loss on such a popular service. Therefore, bus passengers appear to respond more to severe weather warnings and associated risks than to the resulting impacts as they occur.

5.2 Inferring the switch from rail to bus

It is less certain that rail passengers, who are dependent upon much less resilient services, respond likewise. Figure 5.2 reveals a clear aberration to the expected decrease in bus passengers. Routes serving the adjacent towns of Wokingham, Bracknell and intermediate areas with small railway stations recorded substantially more trips. These routes only carry about 7,000 passenger trips combined on an 'average' Thursday, but between them, they carried over 550 more passengers on the day of *Storm Doris* (Reading Buses, 2017a). It is not only a significant change but merits further investigation of the differences in trip patterns.

The service carrying the most inter-town passengers is the X4. On 23 February, during *Storm Doris*, these buses served 14.5%, or about 325 more trips than on 2 March, as shown in Figure 5.4. Unlike on Route 17, the difference in the number of trips does not appear to have been distributed randomly throughout the day or by direction. Most of the additional passengers were on two mid to late afternoon services, just before the typical evening peak hour, and 73% of the additional trips were inbound.

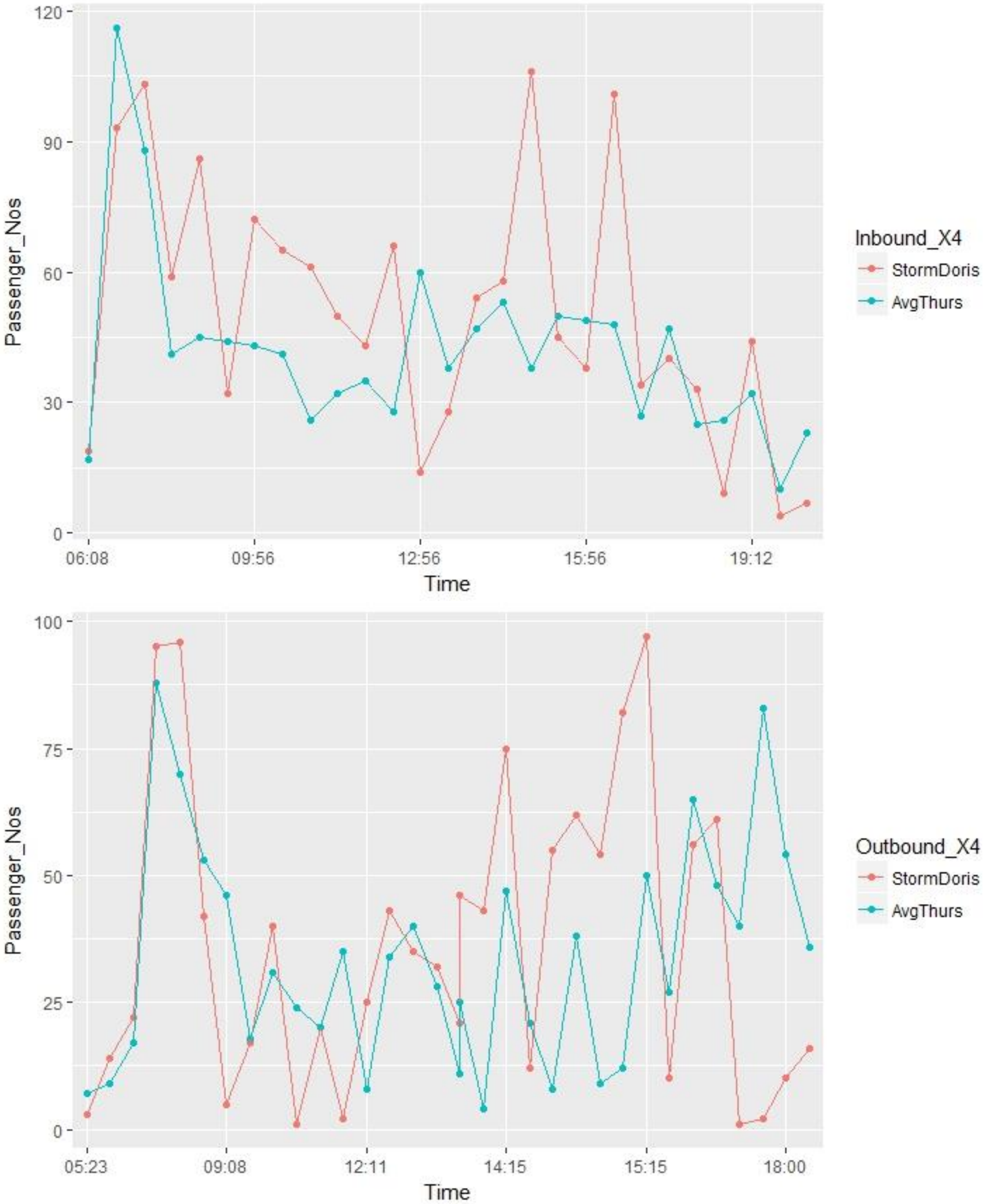

Figure 5.4: Route X4 passenger numbers for (a) inbound and (b) outbound journeys.

Although the reason for these extra trips cannot be confirmed from the data available, the parallel train lines suffered from severe disruption. Rail services between Reading and Guildford via Wokingham were delayed or cancelled on and off for about two hours in the morning, starting at the tail end of the rush hour, and then throughout most of the afternoon (Fort and Perryman, 2017; Great Western Railway, 2017). A limited bus replacement service was only offered at around 1600h (Fort and Perryman, 2017), and the train operator's Twitter feed estimated that the line would not be open until 1730h at the earliest and that tickets would be accepted on other operators' routes (Great Western Railway, 2017). According to *getreading*, the line reopened at 1717h,although delays continued for some time afterwards (Fort and Perryman, 2017).

It is not unreasonable to speculate that some of the additional bus passengers were commuters and students who took trains in the morning, kept an eye on events and the uncertain extent of rail disruption, and improvised accordingly. Students often travel at that time, but commuters, too, were likely among the extra passengers, as their presence would better explain why so many trips were inbound. There are employment sites all along this corridor, but the majority of selective and specialist schools are in Reading, so more students would travel outbound in the afternoon. Furthermore, with bus and rail interchanges centralised in Reading, more employees working along the southeast corridor would need to travel inbound to access multiple residential neighbourhoods, whilst employees in central Reading would only travel outbound if they live in that direction.

The dataset for Route 500 also revealed a significantly different pattern on 23 February compared with 2 March. Route 500 is the express service into Reading from a Park and Ride site immediately adjacent to Winnersh Triangle railway station. Passengers may walk to the Park and Ride and ride Route 500 like any bus, or they may park their car at the Park and Ride site, or they may be dropped off and picked up. Parking and then riding offers less flexibility than the other choices, as passengers are expected to return to their car at the end of the day. Taking an alternative mode home, such as other public transport, would involve abandoning their personal vehicle. Being driven in somebody else's car to and from the Park and Ride offers the most flexibility, as the passenger could be dropped off and picked up at different places.

As shown in Figure 5.5, Reading's Winnersh Triangle Park and Ride carried 22% or almost 200 fewer passengers on 2 March than on 23 February. In contrast to the X4, 81% of those additional passengers were on outbound services.

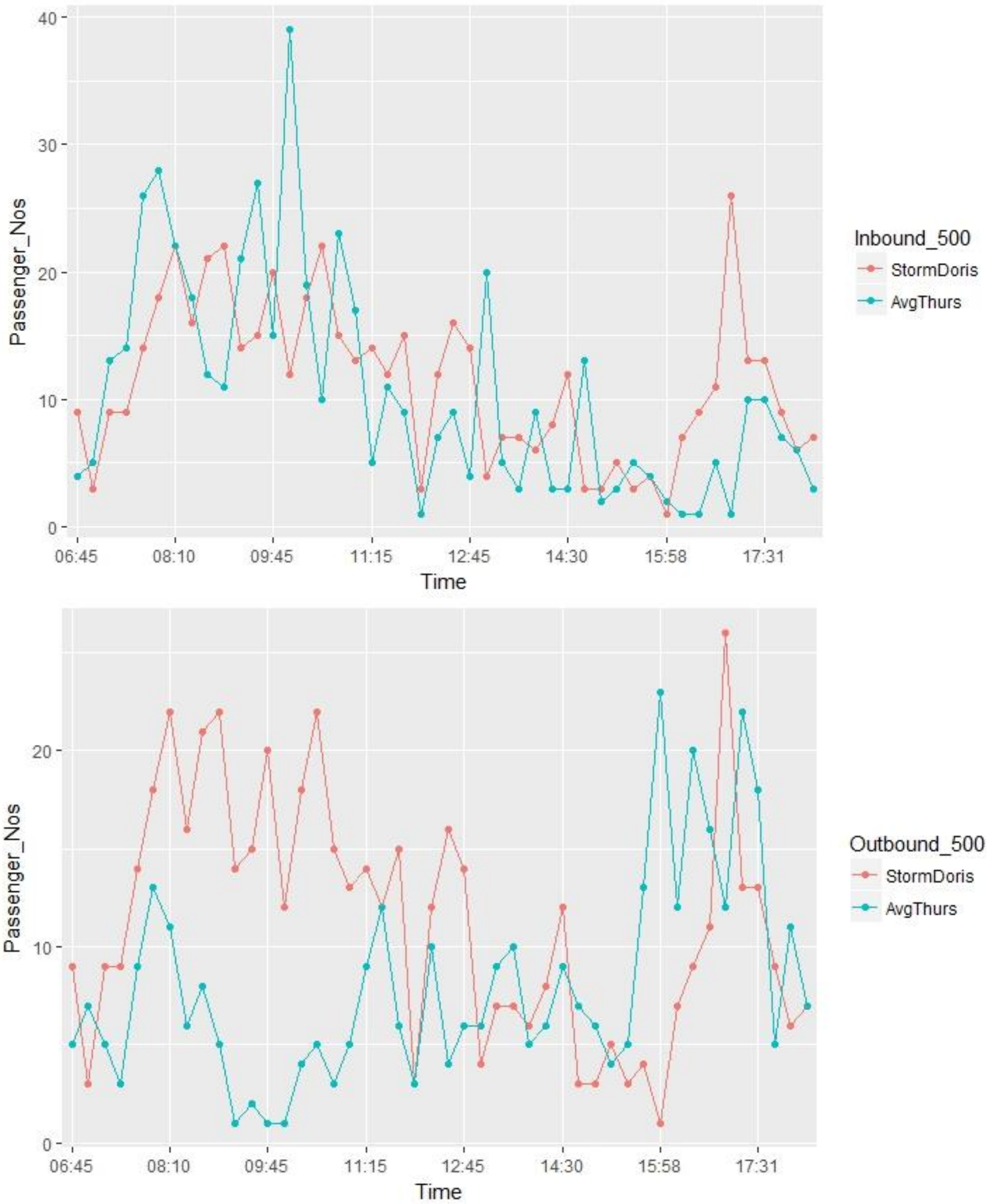

Figure 5.5: Route 500 passenger numbers for (a) inbound and (b) outbound journeys

Park and Ride sites are purposefully built to encourage daily commuters to use remote parking facilities and an express bus service as an alternative to parking in the centre of an urban area. Thus, they are designed for a high proportion of inbound trips in the morning and outbound in trips the evening. This was the pattern on 2 March, a ‘typical’ day. On 23 February, many more passengers were using the Park and Ride outbound in the morning. As it is unlikely they had left their cars the day before, their trips must have been made to access the business park and surrounding area where the Park and Ride facilities are located. Yet there are not enough inbound passengers recorded on Route 500 for those people to have returned home by that means in the afternoon.

The train delays at the end of the morning peak were between Reading and Wokingham, thus affecting both the South West trains that stop at Winnersh Triangle on their way to London Waterloo, and trains towards Guildford. In contrast, the speed restrictions on South West trains were lifted by mid-afternoon, even if those trains did still suffer delays, whilst the trains on the Reading–Guildford line weren’t running at all until a couple of hours later. Thus commuters who arrived at work at the tail end of the rush hour and left later in the evening could have been on the 500 bus in the morning and taken the train home in the evening. Others may have found the timetables of the heavily laden X4 buses more convenient in the afternoon.

In conclusion, the X4 and 500 bus routes attracted significantly more passengers on the day of Storm Doris. These services also lost concessionary trips during the storm, but non-concessionary trips more than made up for the loss. Thus, the evidence supports the hypothesis that those making non-discretionary journeys (i.e. commuters and students) were not cancelling their trips, but rather were seeking alternative, more resilient modes of travel. In this case study, the bus offered more resilience when faced with severely disrupted train services. The datasets from the slower, less direct Routes 4 and 10 also bolster this argument. Both carried more passengers on 23 February, although this applies to Route 4 only if concessionary trips are excluded. Route 10, which serves a number of smaller settlements, carried more passengers using all ticket types.

The above analysis demonstrates that the travel patterns of bus passengers in Reading changed significantly as a result of the storm. The overall reduction in passenger numbers on most services provides further evidence that public transport ridership tends to decrease in adverse weather conditions, despite previous studies often excluding the most severe weather events (Hofmann and O'Mahony, 2005; Guo et al., 2007; Kalkstein et al., 2009; Stover and McCormack, 2012; Singhal et al., 2014). It may be the case that bus passengers drive in bad weather, but it seems more likely that many discretionary journeys, particularly as measured by concessionary trips, are cancelled. Furthermore, as the Route 17 dataset demonstrated, the fall in trips is spread throughout the day, rather than tied to specific storm-related impacts on performance. This suggests that the Met Office weather warnings and publicity, including storm naming, is effective in encouraging people not to take risks and travel in severe weather (Met Office, 2013).

In contrast to public transport trips made for leisure or other more time-flexible purposes, commuters cancel fewer trips due to weather warnings, so their time at work and productivity may well be affected by disruption. Surveys suggest that if possible and acceptable to their employers, telecommuting increases during prolonged periods of travel disruption (Kaufman et al., 2012; Marsden et al., 2016), yet there is no such evidence for a single-day event. The empirical analysis above suggests that evasive action, such as travelling later or switching between rail and bus, may reduce the costs of delay, but without complete, clean and accessible datasets reflecting all modes of transport in an urban area, the exact shift between different modes of transport or proportion of cancelled trips cannot be determined. Nevertheless, Reading Buses' ticketing data does reveal patterns of travel behaviour change in response to Storm Doris. As the risk and impact is unequal for bus and rail services operating on parallel routes, the data suggest that passengers are willing to switch their mode of transport, as well as exhibiting flexibility and opportunism in the services they used, depending on the direction and time of travel. This case study thus provides insights into the complex relationship between non-discretionary travel behaviour and weather, and what this means for costing resilience and recovery planning.

6. ONGOING STORMY WEATHER AND ITS IMPACT ON ACTIVITY PARTICIPATION[7]

As highlighted in the previous chapter, it is difficult to measure quantitatively all types of travel behaviour response: changes in route, time of travel, mode, duration, destination, and prioritising some purposes whilst postponing others, as well as cancellation or online access; without datasets covering all modes, and information on internet activity as well. Acquiring datasets covering bus and rail passenger counts and local traffic volumes during storms is challenging in itself, but automated, comprehensive data that includes details of private vehicle occupancy, and numbers of pedestrians and cyclists is unlikely to exist in most urban areas, and online access rates are also absent. Furthermore, these transport big data sources provide little information on socio-demographics or journey purposes, other than ticket types such as the concessionary bus passes mentioned in Chapter 5, and do not provide an accurate account of the journeys' origin and destination end points, as the record begins at bus boarding and no further transaction occurs on alighting. As reviewed in section 2.1, some studies have used survey-based methodologies to identify how individuals avoid transport disruption and still engage in activities such as work during severe weather and other unplanned events, depending upon the location and timing of the impacts; and a few include questions about online access, journey purpose, and socio-demographics (Kaufman et al., 2012; Marsden et al., 2013; Marsden et al., 2016). Such studies provide useful insights into individual perceptions and choices, and are indicative of the capacity for resilience. However, they lack the spatial breadth

[7] The majority of this chapter has been published as: Budnitz, H., Tranos, E. and Chapman, L. (2020) Responding to stormy weather: Choosing which journeys to make. *Travel Behaviour and Society (special issue on "Changing Travel Behaviour in the Connected Era")*, 18: 94-105. https://doi.org/10.1016/j.tbs.2019.10.008

and granularity to offer insights into the production / attraction of trips, match responses to geographically specific transport disruption, such as that caused by flash flooding, and extrapolate socio-economic trends. Mobile phone Network Data (MND), in comparison, enables quantitative analysis of the extent of changes in accessibility to work and other purposes, and the influence of neighbourhood geography and socio-economic obligations on these patterns.

MND is, along with other big data sources discussed in section 4.1, particularly useful when disruptions are sudden and unplanned in nature, as the response to such events can only be analysed in retrospect from a data source that captures mobility or accessibility patterns on a continuous, uninterrupted basis. The type of weather event considered in this chapter was chosen in part for its suddenness and the likely reactive aspect of any response. The recurring convective storms that form the case study here, like the one-day wind impacts of Storm Doris, are more difficult for travellers to respond to resiliently than long-term flooding, when adjustments can be made over time, or during weather events like snow, which have impacts that are better understood and carry less uncertainty. In contrast, the level of risk and disruption from impacts like wind and flash-flooding will depend upon who lives, works, visits or travels through geographically distinct areas during the weather event. The severity of the impacts is related to existing patterns of human behaviour and the time and location at which the event and disruption occurs (Beiler et al., 2012; Dawson et al., 2016). In other words, a flash flood on a country lane will not have the same impact as a similar event on a major urban arterial road. A tree falling across a railway line in the middle of the night does not have the same consequences as one that has blocked the line during the commuter peak period. The severe weather events and any disruption they cause which occur at times when many people need to travel to or from work have a greater impact on accessibility, particularly for those commuters, than events at other times.

The most common response by commuters to bad weather is changing the departure time, either by postponing travel or leaving early to allow more time (Böcker et al., 2013; Cools and Creemers, 2013; De Palma and Rochat, 1999; Khattak and De Palma, 1997; Sabir et al., 2010). Yet these options are not available to commuters already at work who need to return home, and who may also already be locked into a mode of travel and do not have a telecommuting option. Commuting choices will influence other travel choices, and consequently the likely production or attraction of trips to / from different areas of origin / destination, and thus the accessibility of those areas or for those communities. Therefore, this chapter uses MND to analyse these patterns for a case study of two working weeks during which multiple convective storms caused pluvial flooding over a wide area and large sample population. The aim is to determine the impact of the storms on dynamic accessibility throughout the West Midlands metropolitan sub-region over a two-week period of disruption in June 2016. The storms occurred with little warning and mainly in the afternoon, when the majority of commuters would have made their initial choices of mode and destination. Thus, any behavioural response was inherently reactive, better highlighting the relevance of socio-economic and geographic characteristics to the changes in travel patterns and access to work and other activities.

6.1 Applying Mobile phone Network Data to a Severe Weather Case Study

MND is identified in the literature as a useful source for detecting patterns of travel between important origins and destinations such as home and work that can be validated against static data such as the Census to determine the influence of socio-economic or geographic characteristics, and, as it is collected continuously by mobile phone operators from their customers, to enable identification of divergences from normal patterns (Becker et al., 2013; Isaacman et al., 2011; Steenbruggen et al., 2015). The main data used in this chapter were prepared by Telefonica, a mobile phone operator with approximately 30% of the UK market share, including in the study area, using MND comprising of Call Detail Records (CDRs) from their private customers and certain minimal ‘passive’ network events generated by those customers, such as movements between clusters of cell towers (Duduta et al., 2016; Engelmann et al., 2018). CDRs include the coarse location of mobile phones whenever they are turned on / regain connection with the network; are in use for calls, texts, or the receipt of data; or switch between 2G / 3G / 4G bandwidths, resulting in large sample sizes with a low sampling bias (Becker et al., 2013; Engelmann et al., 2018; Tolouei et al., 2015; Wang et al., 2017). After working on smaller, urban area projects in the UK using 2014 data to apply MND to building traffic models and evaluating and validating it against both national and local survey data (Tolouei et al., 2015; Vilarino et al, 2016), Telefonica developed a much larger dataset of origin-destination trip matrices covering England, Scotland, and Wales for the whole of 2016. It was made available for academic research via the non-profit Transport Systems Catapult, an organisation set up by the UK government to foster innovation and industrial-academic collaboration.

Within the available dataset, a period of thunderstorms and flash flooding in June 2016 centred on Birmingham, UK offered an opportunity to assess the influence of geographic and socio-economic characteristics on travel choices, particularly which journeys are prioritised in these reactive circumstances. There are various spatial units covering the Birmingham metropolitan area, including the West Midlands Government

Office Region (GOR) and the West Midlands metropolitan county. This chapter uses a buffering technique to define the study area, as described below, which selected a spatial unit between the GOR and the metropolitan county in area. Socio-economically, the West Midlands metropolitan county performs worse economically than the national average for Great Britain, with 6.4% of the working-age population between 16 and 64 unemployed, 27% economically inactive for various reasons, and almost 13% having no qualifications; also, commuters are likely to have less spatial and temporal flexibility than in other regions, with a greater proportion of employees compared to those who are self-employed and a slightly higher percentage of employees working full time (ONS, 2019). However, mobile phone ownership in the West Midlands GOR is similar to the rest of the country, with about 95% of adults in Great Britain owning and using at least one mobile phone, although 10% of those over 64 and 31% of those over 75 do not (ONS, 2015).

The level of spatial and temporal granularity of MND varies depending upon the location and density of cell towers and the frequency of use of the device. This can result in the underestimation of short trips, whilst the accuracy of home and work trip identification is much higher than the identification of other destinations and thus journey purposes (Isaacman et al., 2011; Steenbruggen et al., 2015; Wang et al., 2017). There is inevitably also some age and temporal bias in using a dataset mainly based on mobile phone activity, as younger people are both more likely to have and to use their mobile phone more often, and phone use tends to peak in the afternoon / evening (Engelmann et al., 2018; Louail et al., 2014). Notably, people in the West Midlands were identified as being much more likely to switch their phone off regularly, which could reduce temporal bias, as the phone would be detected when switched on in the morning (ONS, 2015). Proprietary and privacy concerns mean that the product available is usually anonymised and aggregated at the mobile phone operator's discretion, which, depending upon the methods used in such pre-processing, may result in a dataset more or less suited for analysing travel behaviour and joining with socio-demographic data (Steenbruggen et al., 2015; Wang et al., 2017).

The pre-processing of Telefonica's dataset prior to it being made available to the authors involved extracting records from regular customers with personal contract mobile phones[8] for whom home locations could be reliably calculated, translating these records into trips made by anonymised residents, and then expanding the number of recorded trips made by each resident in a geographic area on a daily basis to match the population of that area and account for lower mobile phone use by age (Duduta et al., 2016; Engelmann et al., 2018). Some population bias may remain where the official statistics at a fine spatial scale used for expansion have not kept pace with newer residential or commercial development and thus population change (Engelmann et al., 2018). The data is disaggregated into the matrices shown in Figure 6.1 of road and rail trips; by periods within the 24-hour day: AM peak, inter-peak, PM peak, and night; and, very broadly, into journey purpose and direction, with 'commute trips' defined as direct journeys between home and a regular, identifiable place of work. Different types of road users, such as bus travellers, cyclists, or commercial vehicles are not disaggregated.

[8] Business contracts and the use of other devices such as tablets are excluded to avoid double counting individual users. There are also checks to exclude overseas tourists or others not regularly using the network.

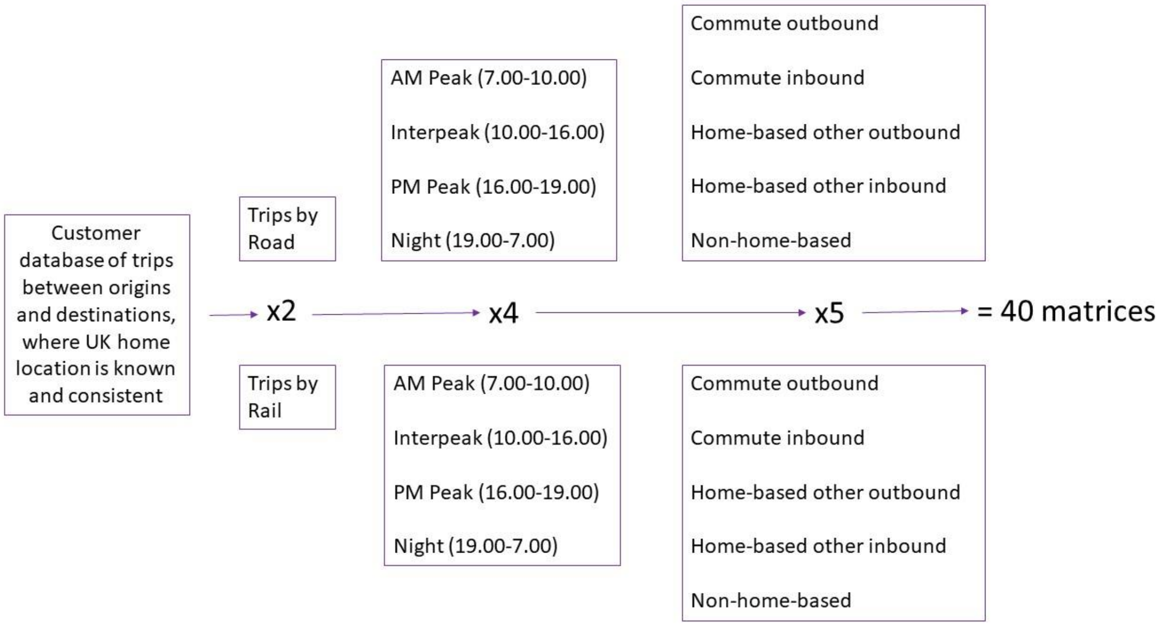

Figure 6.1: Structure of MND matrices

The journey purposes are determined through algorithms that identify 'points of interest' for customers, the most frequent ones with the longest dwell times being home and work (or education), and trips are inferred to occur between them, although short stops, like short trips, are often under-represented due to the more limited likelihood of mobile phone activity (Duduta et al., 2016; Engelmann et al., 2018). Therefore, although defined in the same manner in both this dataset and national surveys, the MND picks up more 'commuting' trips than the 15% of trips categorised as 'commuting' in the National Travel Survey (Department for Transport, 2017a). However, in both methodologies, travelling on business, travelling to workplaces which vary from day to day, or making linked trips, such as to escort a child to school, go shopping, or visit a gym, are all assigned to either 'home-based other' or 'non-home-based' trip categories. Thus, many journey purposes are not specified within the dataset, but there is clear delineation between commuting and other trips, which is of primary interest to this study of the journeys people make under storm conditions.

The contract between Telefonica and the Transport Systems Catapult and their interpretation of the European Union’s General Data Protection Regulation results in legal restrictions that any matrices provided to third parties aggregate trips into no more than 1000 geographic units no smaller than Middle layer Super Output Areas (MSOAs) and comprise a minimum sample of 10 days ‘averaged’ for each set of matrices provided. Thus, the dataset used in this chapter comprised a geographic subset of 573 MSOAs within a 40km or 25 mile buffer of Birmingham, UK during an extended period of thunderstorms, intense rainfall, and flash flooding occurring in the afternoons and / or evenings of Tuesday, 7 June, Wednesday, 8 June, Friday, 10 June, and Tuesday, 14 June, as well as during the mornings of 15 and 16 June, and later in the evening on 16 June. This run of storms and their timing was a key reason for choosing the study area. The 40 matrices representing ‘storm conditions’, were averaged from the trips made on weekdays between 6 and 17 June 2016, and enable analysis of recurrent severe weather that arrived with little warning and caused substantial disruption to urban transport networks, including road closures, accidents, rail delays / cancellations, and infrastructure damage during working days and peak periods. With two full working weeks, any noise from intra-weekly, intra-personal patterns of part-time or flexible working should not influence the analysis, nor should any geographic variation in the impacts of individual storms during the study period. A second set of 40 matrices for the same area was derived from approximately 5 weeks either side, 19 April to 22 July, excluding weekends, bank holidays and the school half-term, and offered a ‘non-storm conditions’ sample for comparison.

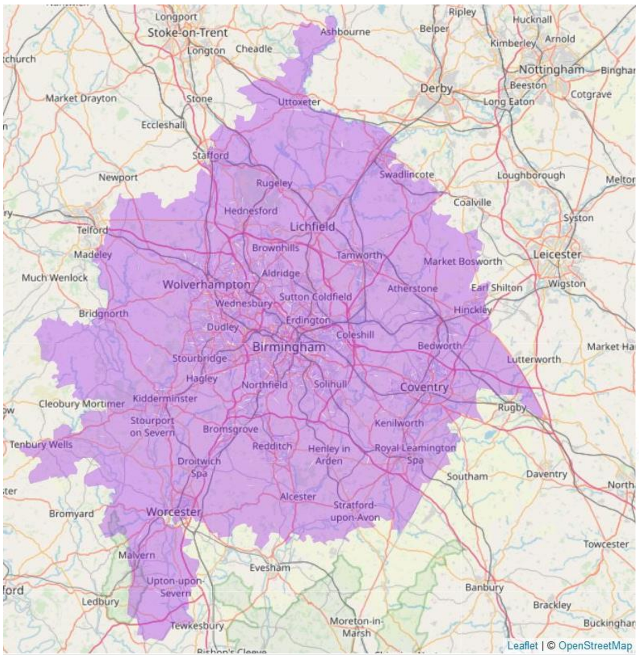

Figure 6.2a: Study Area

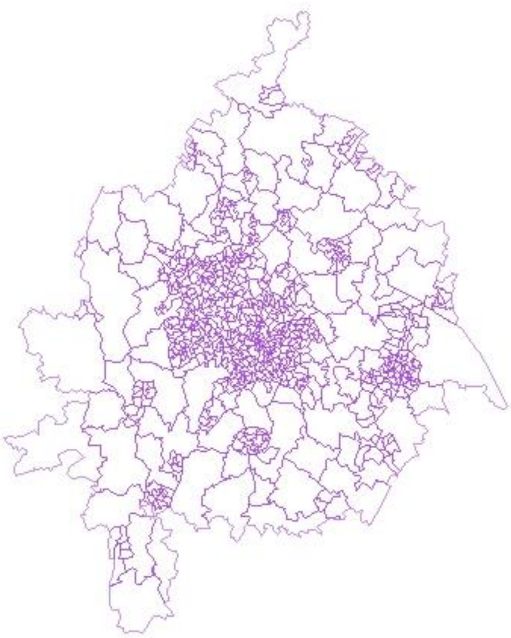

Figure 6.2b: MSOAs outlined in purple

The study area is depicted in Figure 6.2a, and extends beyond the major conurbation to encompass surrounding towns and also more rural areas. Figure 6.2b shows the MSOAs to which the trip data was aggregated. MSOAs are designed for the presentation and comparison of neighbourhood statistics, with populations of between 5,000 and 15,000 people or 2,000 and 6,000 households, and are also the level at which the UK Office of National Statistics (ONS) aligns 'workplace zones'. Such a level of spatial granularity offers little insight into changes of route or variation in short trips, particularly in the smaller urban MSOAs, which are often missed by MND in any case. However, the spatial unit is designed to capture socio-economic and geographic characteristics that tend to be consistent at the neighbourhood level and represent who lives, works or visits there. Since this chapter is particularly interested in comparing commuting and other trips made by the same groups of people, the key socio-economic characteristics are derived from 2011 census tables on economic activity, namely the ratio of the MSOA's resident population, aged 16-74, who are full time employees, part-time employees, self-employed, or retired (ONS, 2014). Also included is the residential population density from 2016 population estimates (ONS, 2017). Data for workplace population density and the employment status of the workplace population in destination MSOAs balance the resident population variables.

Whilst the census-derived statistics offer key explanatory variables for the production and attraction of commuting trips, it was important to include data on land use or amenities that might produce or attract trips for non-commuting purposes. Therefore, using data from the crowd-sourced Open Street Map platform[9] on ‘points of interest’; the locations of supermarkets, convenience stores, banks and post offices were mapped onto the MSOAs. These types of amenity were chosen because, especially over a two week period of storm conditions, food shopping and personal business are examples of regular maintenance trips not made for work or education. It should be noted that education trips are not considered in this study as the journey purpose categories in the Telefonica dataset class some education trips as commute trips (if they appear year-round rather than term-time), some as other trips, and would likely have missed the many education escort trips that are short in distance or dwell time. Rather, this chapter considers how fixed or flexible commute and non-commute trips appear to be for maintaining accessibility under storm conditions.

Finally, to enable some qualitative analysis of the alignment between changes in behaviour and physical access, details of the transport impacts of the storms (and school closures) were found in media reports (Authi et al., 2016a; 2016b; Brown, 2016; Campbell, 2016; Campbell and Richardson, 2016; Hurst, 2016; Hurst et al., 2016a; 2016b). Although the level of detail about lengths of road flooded or when precisely

[9]© OpenStreetMap contributors, licensed under the Open Database Licence. Information on this and the map tiles used in Figure 6.2a can be found at https://www.openstreetmap.org/copyright.

infrastructure was closed and reopened was not precise, some of the named locations and major routes listed in the media reports were entered into Google Maps to obtain approximate geographic coordinates of the disruption and plot them on Figure 6.3.

6.2 Methods

In order to explore and model the patterns in the data described in the section 6.1, further aggregation was required. The MND was provided in two sets of 40 matrices as shown in Figure 6.1. Each matrix comprised of 328,329 (or 573^2) cells, recording a total of over 16 million trips. Comparing the total trip numbers from each of these matrices did offer some insights, which will be discussed in section 6.4. However, for the visual and statistical analysis, the 40 matrices for the storm conditions sample were subtracted from the 40 for the non-storm conditions or control sample to provide 40 'difference' matrices. Naturally, these differences are sometimes positive, sometimes negative, and, in many cases, negligible, particularly in the reactive circumstances of the afternoon thunderstorms in this case study. Thus, the 'difference' matrices include a substantial proportion of null data. Some of these are integral to the analysis, but others are 'false' zeroes, as wherever a particular pair of MSOAs in the study area do not generate any flows between them, the null return in the 'differences' matrices provide no indication of behavioural change. There is precedent to remove any inter-MSOA flows lower than five prior to analysis (Hincks et al., 2018), but that was for commute trips only, whereas this study also considers other types of trips. If pairs are removed only where flows are low for all journey purposes, many uninformative observations will remain for each journey purpose individually. If flows for each journey purpose are removed for model estimations of that purpose, comparison of any effects that occur across journey purposes could be masked. Therefore, the maps and modelling are based upon the sum of the differences in flows by road from / to each MSOA to / from every other MSOA to create trip origin / destination vectors rather than matrices. This is the dependent variable in equations (6.1) and (6.2). The 573 origin MSOAs are represented by (*i*) and the 573 destination MSOAs by (*j*). These equations show only the explanatory variables used in the final models, as discussed in the third results section, 6.5.

$$\text{Non-Storm Day Trips}_i - \text{Storm Day Trips}_i = \alpha + \beta\text{Residential Population Density}_i + \beta\text{Food Shopping}_i + \beta\text{Personal Business}_i + \beta\text{Ratio of Part-time Employees}_i + \beta\text{Ratio of Self-employed}_i + \beta\text{Ratio of Retired Persons}_i + \beta\text{Personal Business}_i : \text{Ratio of Retired Persons}_i + \varepsilon_i \quad (6.1)$$

$$\text{Non-Storm Day Trips}_j - \text{Storm Day Trips}_j = \alpha + \beta\text{Workplace Population Density}_j + \beta\text{Personal Business}_j + \beta\text{Ratio of Self-employed}_j + \beta\text{Personal Business}_j : \text{Ratio of Self-employed}_j + \varepsilon_j \quad (6.2)$$

Modelling origin and destination separately also allows the relevant geographic and socio-demographic variables to be attached independently to each MSOA, i.e. workplace population variables are only attached to destinations. Thus, if geographic or socio-demographic characteristics do result in varying levels of dynamic accessibility and travel demand during adverse weather, measures to increase flexibility and resilience might be targeted at resident or workplace populations respectively. Journey purpose and the relationship between commuting and other trip-making during disruption when dynamic accessibility is significantly altered is of primary interest in this study. MND does not enable sufficient spatial granularity to identify route changes, modal switch (beyond the very broad ‘road-based’ and rail), changes in short trips, or other nuances of *how* flows shift around the transport network. Rather, it is ideal for considering where flows do or do not start and conclude during irregular events, and what might influence these patterns by trip purpose, which are also estimated separately for a more direct comparison of effects. Since ‘home’ is the origin for inbound as well as outbound ‘home-based’ trips, inbound and outbound trip numbers are summed to minimise confusion, although it is important to recall that not all of these will be ‘return’ trips between one O-D pair. Rail trips make up only 1% of the observations for both sample days, so they are considered qualitatively in section 6.3, but excluded from the statistical analysis. The various time periods are considered in section 6.4, but are also excluded from the statistical analysis in favour of daily totals, which offer greater variation between the storm and control samples.

The descriptive statistics for the origin model estimations, including those not included in the final models, are shown in Table 6.1. Those for the destination estimations are shown in Table 6.2. All descriptive statistics are the mean values and ranges by MSOA. The trip differences are as described in equations (6.1) and (6.2), whilst density and amenity statistics are numeric and socio-economic statistics are ratios.

Table 6.1: Descriptive statistics of variables for Origin MSOAs

Origin MSOA Variables	Mean	St. Dev.	Min	Max
Difference home-based work trips by road	-268.4	189.8	-1999.0	87.0
Difference home-based other trips by road	265.9	265.0	-563.0	2406.0
Residential Population Density (per km^2)	3416.2	2267.7	46.4	17809.6
Food shopping (no. of supermarkets and convenience stores in MSOA)	1.7	1.8	0	13
Personal business (no. of banks and post offices in MSOA)	0.5	1.6	0	17
Ratio of Full-time Employees (within total residential population)	37%	7%	6%	54%
Ratio of Part-time Employees (16-30 hours per wk)	14%	2%	3%	18%
Ratio of Self-employed	8%	3%	1%	19%
Ratio of Retired Persons	14%	4%	1%	28%

Table 6.2: Descriptive statistics of variables for Destination MSOAs

Destination MSOA Variables	Mean	St. Dev.	Min	Max
Difference home-based work trips by road	-268.4	186.3	-1928.0	67.0
Difference home-based other trips by road	265.9	273.3	-687.0	2650.0
Food shopping (no. of supermarkets and convenience stores in MSOA)	1.7	1.8	0	13
Personal business (no. of banks and post offices in MSOA)	0.5	1.6	0	17
Workplace Population Density (per ha)	13.2	23.8	0.1	470.9
Ratio of Full-time Employees (within workplace population)	54%	11%	30%	87%
Ratio of Part-time Employees (16-30 hours per wk)	24%	5%	6%	41%
Ratio of Self-employed (full or part time)	18%	8%	3%	40%

6.3 Results I: The Geography of Storm Impacts and Response

Due to the nature and timing of the storms and the minimal warning, it was important to identify whether any major changes in travel patterns were simply reactions to the locations of disruption. Figure 6.3 shows key road impacts as crosses on a map of the differences in total home-based road trips by trip origin MSOA, and school closures (on 9 and 15 June) as crosses within rectangles. The darker shading is where fewer trips were generated under storm conditions compared to non-storm conditions, whilst the palest hues represent more trips during the storm sample beginning and ending at those home locations.

Figure 6.3 reveals few obvious connections between closed or flooded roads and schools and fewer trips generated under storm conditions. For example, around Leamington Spa and Warwick in the southeast of the study area, large reductions in the production of round trips cannot be matched to records of any major impacts in the media search. Nor is there a clear pattern around schools reported to have suffered closures, although it may be that the home locations and catchment areas of different schools are not closely aligned to the MSOAs. The exception is the urban MSOA that encompasses the area just to the north and east of Birmingham city centre, which had the greatest reduction in home-based return trips during storm conditions. Within this area, media reports indicate that the A38 Aston Expressway flooded at a junction known as Dartmouth Circus, and in both directions, including the Queensway tunnel into the city centre. This flooding occurred on the 8th, 10th, and 14th of June; 3 of the 6 stormy days in the study period, and on a fourth day a pothole attributed to the flooding caused further disruption. In comparison, most other reported incidents appeared to affect a specific link on only one or two of the storm days, rather than throughout the period. Overall, however, there is no discernible pattern between the difference in trips originating in MSOAs and the known impacts of the June storms. The absence of obvious links between infrastructure disruption and changes in trips numbers supports the hypothesis put forward in this chapter: changes in travel demand, particularly in reactive circumstances, are affected by pre-existing geographic or socio-economic characteristics that correlate with spatial and temporal flexibility as modelled in section 6.5.

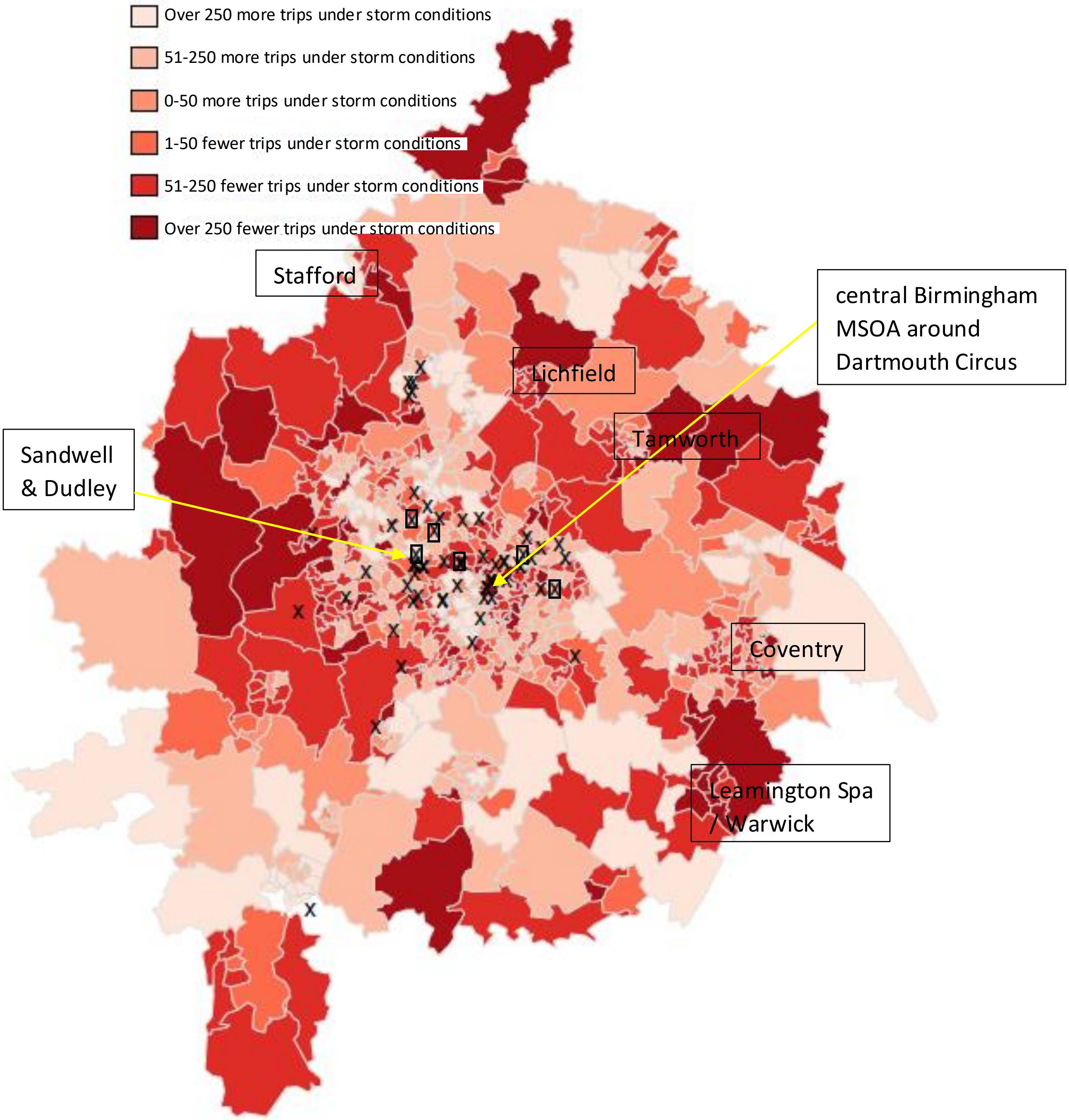

Figure 6.3: Differences in total home-based trips by road for each Origin MSOA; the darker the shading, the fewer trips under storm conditions. Also locations of major storm impacts on the road network indicated by crosses, school closures by crosses within rectangles. Key locations labelled.

Figure 6.3 does show that a number of areas with the greatest reduction in road trips under storm conditions are around the West Coast mainline stations of Stafford, Lichfield, Tamworth, Coventry, Sandwell and Dudley, and around the busy station at

Leamington Spa, raising the question of modal switch from road to rail. According to the media reports, inter-urban services and the West Coast Mainline appear to have been minimally affected, although certain local services to places such as Rugeley Trent Valley and Stourbridge Junction were subject to delays, cancellations and replacement bus services. As discussed in the next section, a comparison of the totals from the original matrices did show an increase in rail trips for the storm sample for all but the night time period. However, mapping the differences in rail journeys was not particularly enlightening, rail journeys make up just 1% of the total trips in both averaged sets of matrices, and without individual data or other qualitative sources such as social media and journey planning bulletins at the time, direct modal switch cannot be confirmed. MND appears not to be an ideal data source to identify modal switch in response to severe weather, even for road to rail. Instead, by focusing on the road-based trips in the modelling, most of the available dataset is used in the analysis in the next two sections.

6.4 Results II: A Summary of Travel Behaviour Change

Comparison of the total trip numbers recorded in each of the 40 matrices for storm and non-storm conditions revealed further insights. Time switching, which the literature suggests is likely to be the most common response, especially for a sudden event, appears to have occurred. There were more total trips by road in the AM peak period under storm conditions and fewer trips for the inter-peak, PM, and night, as shown in Figure 6.4, which matches what would be expected considering the afternoon and evening saw the worst storm impacts. Also, whilst there were more home-based work trips in every period in the storm sample, there were fewer home-based other trips outbound, but slightly more *inbound* in the AM peak. This suggests that some people may have been trying to complete certain personal business or other trips before the storms and return home early. However, since mobile phone use normally tends to be higher in the afternoon and evening, and conversely lowest between 2300 and 0800 (Louail et al., 2014), it may be that the use of mobile phones as well as travel behaviour changes when there are unusual events, if mobile phone users are more likely to check for updates, weather warnings, coordinating with others, etc. Whilst this could mean more AM trips are detected under storm conditions than non-storm, any increase in detections is also likely to reduce the daily expansion factor somewhat so that the changes both in physical travel and mobile phone use appear to balance out within the dataset of trip numbers. Furthermore, these temporal differences are less than 1% of the totals for each time period.

Figure 6.4 shows that there were more commute trips under storm conditions compared to the non-storm sample in every period, inbound and outbound, which partly reflects the lack of flexibility among commuters compared to other travellers, and is well-documented in the literature (Böcker et al., 2013; Liu et al., 2015; Sabir et al., 2010, Sabir, 2011). However, if commuting trips are fixed and there was no change in behaviour by commuters, little to no change would be expected in the numbers of commute trips. Yet, the increase in home-based work trips and decrease in home-based other trips within the study area for the storm sample matrices are both significant at $p < 2.2e-16$ for the former and $p = 1.01e-09$ (outbound) and $p = 3.919e-07$ (inbound) for the latter according to Welch's t-tests. Seen another way, commute trips, outbound and inbound, make up 18% of the total daily trips within the study area under non-storm conditions, but rise to 20% of the total daily trips under storm conditions (or 23% and 25% of all home-based trips). Meanwhile, the overall difference in trips if all modes and purposes are taken together is insignificant, comprising of only 0.3% of the total road trips.

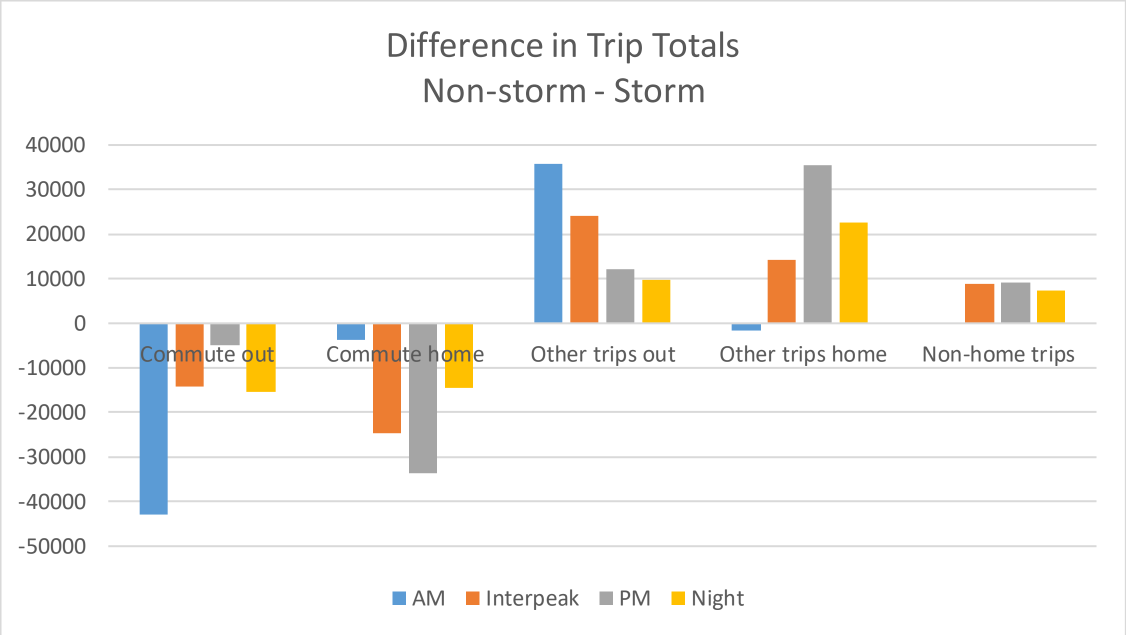

Figure 6.4: Difference in total trips by road between the non-storm and storm matrices by journey purpose and period.

One potential explanation for the increase in commuting trips and the decrease in other trip types is a reduction in linked trips or trip chaining, defined as “where people combine two or more trips for differing purposes” (Le Vine et al., 2017, p5). If it is more difficult or takes longer to get to and from work, then travellers reduce any intermediate stops they normally make, as reflected in the decrease of other and non-home-based trips, which may have actually been indirect trips to work. An extensive study of commuting and travel patterns using mobile phone data identified that those who travel further in their daily lives often travel to fewer regular locations, the predominant one being work, and are more predictable in their travel (Song et al., 2010). Under storm conditions, commuters are likely to travel ‘further’ if there are diversions, or for longer than normal if there is traffic or speed restrictions. Therefore, the reduction in an individual’s dynamic accessibility due to the weather, especially later in the day when they may already be ‘locked in’ to certain travel options makes them choose to switch not just their routes or timing, but also their journey purpose, prioritising their direct commute over other activities. Although individual level data could have further supported this argument, the analysis presented in the next section provides more evidence of such choices between journey purposes.

6.5 Results III: Modelling Origins and Destinations

Tables 6.3 and 6.4 show the results for the final model estimations for the MSOAs as origins and destinations respectively, as shown in equations (6.1) and (6.2). Multiple combinations of all the independent variables listed in Tables 6.1 and 6.2 were initially tested in the relevant model estimations to better compare between models for the different journey purposes and check for any unexpected interactions, even though logically some explanatory variables would not be relevant to certain travel behaviours, such as employee ratios for home-based other trips, whilst others may not have the expected influence due to their ubiquitous nature, such as the high volume of full-time employees within most MSOA workplace populations. Ultimately, only the variables with significant coefficients and / or interactions are included below. Positive coefficients describe how many fewer daily trips under storm conditions are likely for each incremental change in the independent variable for a given MSOA, whilst negative coefficients indicate more trips under storm conditions.

Table 6.3: Regressions for Origin MSOAs as equation (6.1)

Origin MSOA Variables	Difference in Commute Trips by Road	Difference in Home-based Other Trips by Road
Residential population density	*0.032****	
	(0.004)	
Food shopping	*-9.759***	*16.582***
	(3.907)	*(6.517)*
Personal business	*-88.288****	*102.822****
	(7.654)	*(12.543)*
Ratio of Part-time Employees	*1,838.477****	
	(412.780)	
Ratio of Self-employed	*847.197****	
	(265.903)	
Ratio of Retired Persons	*1,047.154****	*-236.091*
	(214.110)	*(253.889)*
Personal business : Ratio of Retired Persons	*415.915****	*-529.202****
	(63.848)	*(106.310)*
Constant	*-816.007****	*249.893****
	(63.310)	*(40.617)*
Observations	573	573
R^2	0.449	0.187
Adjusted R^2	0.442	0.181
Residual Std. Error	141.814 (df = 565)	239.770 (df = 568)
F Statistic	65.694*** (df = 7; 565)	32.656*** (df = 4; 568)
Note:	**p<0.1; **p<0.05; ***p<0.01*	

Table 6.4: Regressions for Destination MSOAs as equation (6.2)

Destination MSOA Variables	Difference in Commute Trips by Road	Difference in Home-based Other Trips by Road
Workplace Population Density	-1.952***	3.474***
	(0.335)	(0.577)
Personal business	-62.462***	54.658***
	(8.755)	15.054
Ratio of Self-employed	638.998***	-322.363**
	(74.652)	(128.359)
Personal Business: Ratio of Self-employed	297.675***	-200.185*
	(64.671)	(111.196)
Constant	-346.173***	263.257***
	(16.187)	(27.833)
Observations	573	573
R2	0.466	0.267
Adjusted R2	0.463	0.262
Residual Std. Error	136.554 (df = 568)	234.796 (df = 568)
F Statistic	124.126*** (df = 4; 568)	51.711*** (df = 4; 568)
Note:	*p<0.1; **p<0.05; ***p<0.01	

These tables reinforce the conclusions of section 6.4, that the influence of geographic and employment characteristics on travel behaviour response vary most between commute trips and other home-based trips. Every coefficient that is positive for commute trips is negative for other trips and vice versa. Since there were significantly more commute trips in the storm matrices than in the control sample, and significantly fewer other types of trips to / from identified home locations, the regressions above offer more insight into what this could mean in terms of the fixedness or flexibility of trip purposes.

First, it should be acknowledged that the overall reduction in ‘other’ trips, and even the reduction in commute trips in some MSOAs, does not necessarily mean that participation in the activities that generate those trips is cancelled or reduced. Some people can and do access work tasks, goods and services online or could have consolidated certain trips on the few days within the period of storms when there was less disruption, including the intermediary weekend, for which data was not included. The latter is particularly likely in the case of food shopping, and the model shows that the number of food shops in a destination MSOA had no significant correlation with any change in trip numbers. Even for origin MSOAs, the effect is fairly small and only of medium significance. Supermarkets and convenience stores are also relatively evenly distributed across the study area, and are within walking distance of home or workplaces for many, so the number of such trips recorded within both the storm or non-storm matrices could be underestimated by the MND. If residents still made a normal number of trips to food shopping destinations during the disruption, but chose those shops closer to home under storm conditions so they could make more direct journeys to work, this could explain the difference that does manifest in the model, where those living with more food shopping nearby are correlated with more commute trips and fewer ‘home-based other’ trips under storm conditions. Either way, food shopping is an example of an activity that is necessary, but not fixed in time or space, enabling people to choose to make fewer, more local trips to fulfil those needs whilst still prioritising the ‘direct’ commute.

In comparison, banks and post offices are much more scattered, as shown in Figure 6.5, have shorter opening hours / days, and their presence and number had a highly significant influence on more commuting trips and fewer other trips made under storm conditions. The inclusion of this variable also had a substantial effect on the model's goodness of fit, suggesting that it is of particular importance to travel behaviour change during the period of disruption. As banks and post offices tend to be located in commercial centres, it may be that this variable is highlighting the presence of a wider built environment and land use mix. In particular, there may be more commuting trips to and from such places because there are more jobs there, but fewer 'other' journeys ending in places where the shopping and services available are generally discretionary for those who do not work there. Indeed, the higher the density of working population in an MSOA, the more commute trips attracted under storm conditions and the fewer other trips, supporting the proposed explanation that people are visiting fewer 'other' destinations on the way to and from work, including perhaps personal services. Yet the relationship between working population density and trip differences might be due to the commuter pull of MSOAs with factories, business parks, or other large employers, rather than mixed-use commercial centres. Furthermore, the influence of a commercial centre in an MSOA of large area, but likely lower population, will not be the same as more densely populated MSOAs, yet the coefficient for neighbourhoods with higher *residential* population densities suggest they are attracting fewer commute trips under storm conditions. So whilst settlement pattern influences revealed travel demand and journey purpose during adverse weather, the response is complex and it is as difficult to identify patterns from Figure 6.5 as from Figure 6.3. Thus, the presence of amenities such as banks and post offices may relate more to who is making trips to use such services or access particular types of employment, rather than their location.

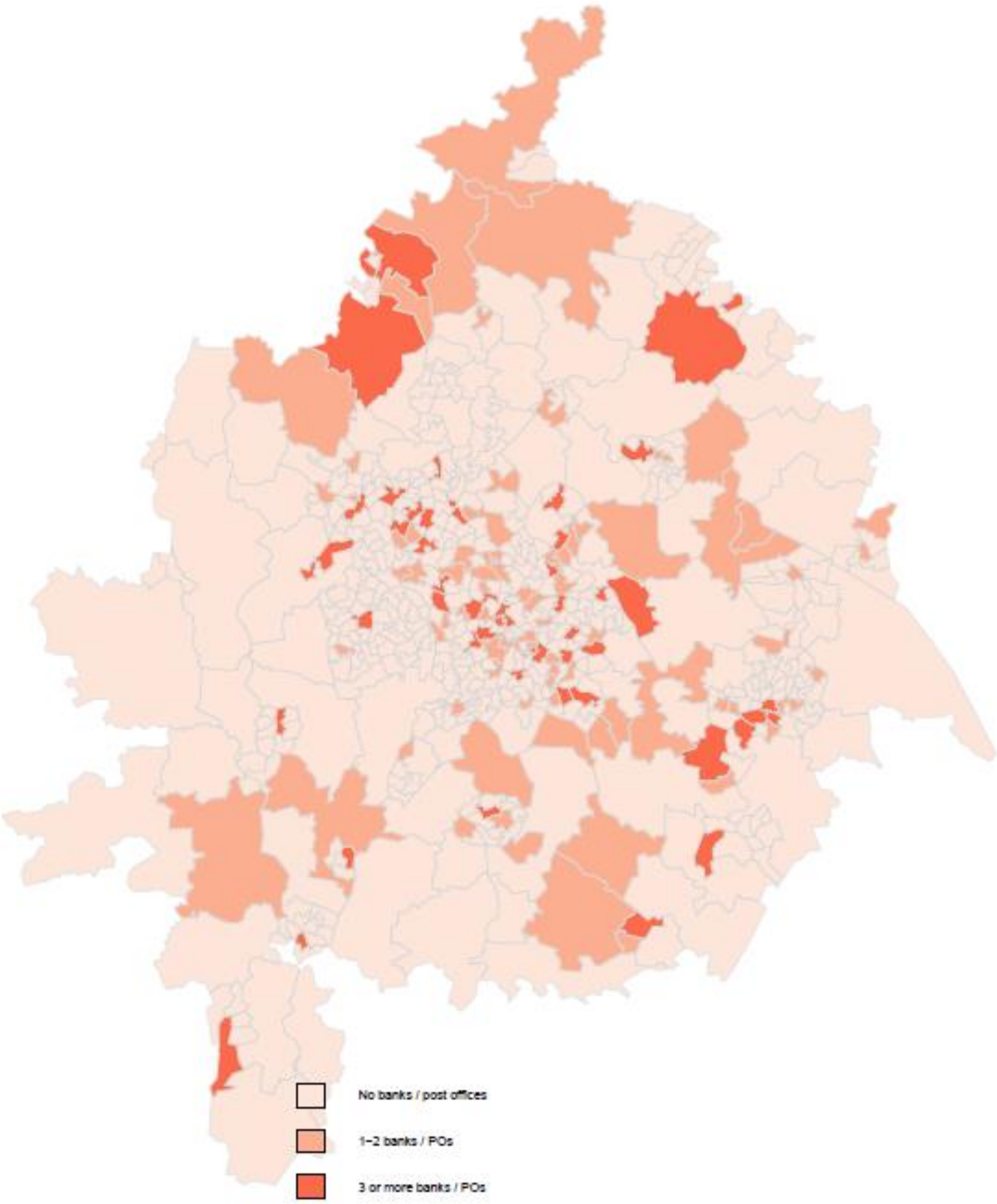

Figure 6.5: Density of personal business amenities (banks and post offices) in the study area.

Thus, the coefficients for the interaction terms of personal business with retired persons by origins, and personal business with self-employed people by destinations offer more insight into the non-discretionary journeys to places with banks and post offices. Within the working age resident and workplace populations, self-employed workers travelled less to their regular place of work, or in other words, commuted less under storm conditions, perhaps an indication of their greater flexibility to work elsewhere, as they travel more to ‘other’ destinations. However, ‘other’ destinations like banks and post offices may be important not as alternative workplaces, but for the business services provided, e.g. to deposit income or pay invoices, or due to other nearby amenities in commercial centres. The interaction term suggests that self-employed people may choose different commercial centres to which access may be less disrupted, but these types of trips are still being made. Likewise, retired people may have the flexibility to make fewer work journeys if they are still involved in the local labour market, but collecting their pension or visiting other services such as pharmacies, which tend to be in similar locations, is not so optional. Thus, the proportion of retired people is correlated with more ‘other’ trips and the interaction term with personal business is significant.

Whilst the correlation between retired persons and fewer commute trips generated under storm conditions requires little explanation, the models also show similar significant correlations between the proportion of self-employed workers and part-time employees within the working-age resident population of an MSOA. As the sample is taken from two working weeks of data, this effect cannot be attributed to any regular variation in which days of the week part-time and self-employed residents work. Also, the lack of significant effects that these variables had on the difference in ‘other’ trips suggests that the change is not due to a recorded switch in journey purpose, say because someone is working at a different destination. Therefore, perhaps enough part-time employees and self-employed residents were able to cancel their work trips altogether during the period of severe weather to result in these significant coefficients. Returning to the concept of dynamic accessibility, this in turn can be interpreted as part-time and self-employed workers having more spatial (if they worked from home) and temporal flexibility in terms of when, how long, and how often they work. Meanwhile, there were no significant effects on trip differences based upon the proportion of full-time employees, who did not change their travel behaviour enough to be identified in either the origin or destination models. This is more as would be expected from the literature, although considering the fewer commutes made by part-time and self-employed residents, the additional commutes attracted to places with high workplace population density, and the significant additional commute trips discussed in the previous section, it seems likely that full-time workers are making more direct commute trips under storm conditions, but the high proportion of such full-time employees in the working age population is masking this variation.

6.6 Discussion and Conclusion

This chapter considers a period of transport disruption that occurred due to storms that arrived with little warning, caused sudden pockets of localised flooding, and affected journeys mainly in the PM peak period. Unfortunately, the MND data only became available and the storm events selected in 2018, so further detail on the response to the storms that might have been gathered from social media, transport operators, and other responsible parties could not be sourced in retrospect, although other studies note the importance of such sources (Chan and Schofer, 2014; Pender et al., 2014). However, media reports show that residents, workers, and visitors to Birmingham and surrounding areas had little warning of these disruptions, and not just the infrastructure, but individual journeys were affected by the impacts, with hundreds of calls to emergency responders on the afternoon of Wednesday, 8th June alone (Hurst, 2016). As the detail of *how* travel behaviour may have changed in terms of not only other modes, but also route or travel time is not considered, it may be that some commuters and other travellers did make resilient choices for work journeys, such as taking an unaffected bus service or a less flood-prone route. Still, the MND from the averaged period of multiple days of on-and-off disruption demonstrated that there were significant and quantifiable changes in accessibility when compared to the 'non-storm' control period, and these could not be clearly linked to the locations of disruption. Instead, sections 6.4 and 6.5 support the insights that the delays and disruption caused by sudden, afternoon storms reduce dynamic accessibility, such that the travel behaviour response of working adults is to choose which journeys are fixed, usually commuting, and which are flexible in time and space.

For many, work is fixed, and the higher the density of employment, the more trips that are attracted to the destination under storm conditions than under non-storm conditions, suggesting commute journeys are rarely cancelled, as was expected from previous studies. Yet these survey-based studies focus on the minimal change in reported commuting trips, whereas this study identified a significant revealed increase in such trips between home and a regular place of work, counter to the decline in these narrowly-defined journeys observed over the last couple of decades in the UK. One major cause of this overall decline is identified as trip chaining, where multiple activities are accomplished more efficiently by reducing the number of round trips (Le Vine et al., 2017). If the opposite is happening under storm conditions, then, whilst the literature identifies switching routes, modes, and time of travel, this empirical study concludes that an additional individual travel behaviour response is, in simple terms, to switch the frequency of journeys for different purposes. The MND reveals this change in journey purpose as fewer home-based other and non-home-based trips and more direct commuting, and although travellers may be making more nuanced choices about their participation in different activities, the prioritisation of commuting has implications for resilience and policy.

In particular, if this switch results in less participation in non-work activities over a full two-week period, individual dynamic accessibility to a variety of essential activities and services for those who do not have or do not perceive they have the flexibility to avoid the risk of travelling to work at such times is affected. Furthermore, whilst switching from multi-purpose trips to commute-only trips might result in some reduction in total trips taken during times of adverse weather and disruption, the reduction in this case study was insignificant and did not mean less travel, less risk, or more resilience for the traveller. Retired adults (under 75) and part-time and self-employed workers appear to have more flexibility in time, space, or both; to cancel their commute, work from home, or work longer hours on fewer days, resulting in fewer home-to-work journeys from places where more of them live. This could mean such groups are more resilient, particularly if they are therefore still able to maintain access to other activities and services, such as personal business, which for retired and self-employed people could be more important or 'fixed' than their commute trips. Ideally, they are able to maintain this access by travelling during the periods without disruption, or substituting online access.

As this chapter has not considered the detail of *how* travel behaviour may have changed in terms of not only other modes, but also route or travel time, it may be that many commuters and other travellers did make resilient choices for what they considered mandatory journeys, such as taking an unaffected bus service or a less flood-prone route. The media reports confirm, however, that many travellers were stranded or so severely delayed in their journey that commuters' productivity was affected and essential, non-work trips may well have been postponed for up to two weeks. Therefore, the more flexibility in time and space that can be attached to different journey purposes, particularly journeys for work, the more resilient the travel behaviour response could be, especially where the disruption is neither expected nor long-term.

7. BROADBAND SPEEDS AND INTERNET ACTIVITY[10]

A key question that arises from the analyses in Chapters 5 and 6 is how to measure whether online access replaces travel during storm events, and to gain some insight into the spatial or temporal extent of the increases in internet activity that respondents reported in post-event surveys following case studies of long-term and extreme disruption (Allen et al., 2015; Kaufman et al., 2012; Marsden et al., 2016). As discussed in Chapter 3, ICT often increases both the spatial and temporal flexibility of individuals and groups of individuals, as well as offering alternative means of access, which, in turn, has the potential to make the response of those individuals to severe weather, risk and transport disruption more resilient in a number of ways. The previous two empirical chapters provide further evidence of the importance of spatial and temporal flexibility in enabling the avoidance of the risks of travelling during severe weather, as well as offering redundancy when disruption affects particular modes or geographic areas. Yet maintaining participation or access to the planned activity is also an essential part of resilience, and for those who are able to stay home and reduce their risk, online access may mean the difference between continued participation and productivity or reduced accessibility.

7.1 Contention in Context

Most online access from homes in the UK is achieved via fixed broadband networks. The geographic and demographic variation in internet availability, quality, skills, and accessibility is recognised as a policy concern by Government and researchers alike, who aim to bridge 'digital divides' in order to maximise the ability of citizens and

[10] The majority of this chapter is under review following submission as: Budnitz, H., Tranos, E., Chapman, L. 'Exploring the Influence of Weather Extremes on Internet Activity and Resilient Accessibility', *Applied Geography*.

businesses to participate fully in an increasingly online world, including in the transport sector (Blank et al., 2018; Cottrill, 2018; OfCom, 2014; Philip et al., 2017; Riddlesden and Singleton, 2014; Tranos et al., 2013). However, investment in the availability and speed of fixed broadband services can take priority over universal and reliable services (Philip et al., 2017), and the interaction between geographic and temporal variation in online access, whilst highlighted as an operational reality of internet service provision, has received less attention. Internet availability and quality, and thus its ability to offer an accessibility alternative to travel, is time-sensitive, subject not only to outages, but also to what OfCom, the industry regulator of Information and Communication Technologies (ICT) in the UK, calls "network contention (slowdown during busy periods)" (2017, p12). This slowdown is a measurement of relative broadband download speeds at different times, and how quickly information and content is either being copied from the internet for local storage or streamed in real time. Upload speeds are also affected.

OfCom measures contention during the evening peak of 8-10pm relative to a 24-hour average as an indicator of broadband performance for different Internet Service Providers (ISP). However, contention can occur at other times, such as during spikes in demand observed due to mass streaming of sporting and entertainment events taking place outside of 'prime time' (OfCom 2014). If online connectivity is to offer a resilient alternative for interactions beyond the domestic sphere during storms, floods, and other times of transport disruption due to extreme weather, such events can be expected to cause a spike in demand for robust, quality internet services (Fu et al., 2016). Indeed, a recent 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 Storm Emma and the 'Beast from the East' in early March 2018, which suggested that people were working remotely, checking traffic updates more, and streaming video (Stubbings and Rowe, 2019). It is here proposed that such increased traffic causes measurable contention if internet activities are in unusually high demand because household members are unexpectedly home due to such extreme weather events, such as the Beast from the East, those studied in Chapters 5 and 6, or more generally during severe weather conditions. Thus, this chapter compares time-stamped, geo-located broadband speed tests during the case study weather events to those during the control periods, and also regresses download speeds against a number of daily weather parameters to assess how the latter affect the daily variation in internet use at the neighbourhood level.

The exception to this is where the broadband connection is also disrupted and there is a time lag before operators can make repairs. During instances of weather-induced mass faults due to loss of power in the UK, such as during the high winds of Storm Jude on 28 October 2013 (Met Office, 2013), or when lightning strikes are widespread, outages, rather than delays, are most common and can result in increasing rather than decreasing broadband speeds, where services are still available. The flooding of ICT infrastructure, which can also cause outages, 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). Such time lags, along with the lack of consistent reporting make it difficult to pinpoint mass outages except via the occasional media report and add a layer of uncertainty to the analysis in this chapter. Where mass power or ICT outages are not reported in the media, the reports OfCom receives from ISPs, often during the later stages of an incident, are not available (John, 2017). There was a media report following Storm Jude, when, as highlighted in Figure 7.1, recorded download speeds were faster than surrounding working week-days (800-1800). This date was excluded as an outlier, but even where the dates of outages are unknown, there is some indication that unusual speed increases and decreases might balance each other in terms of ICT service quality.

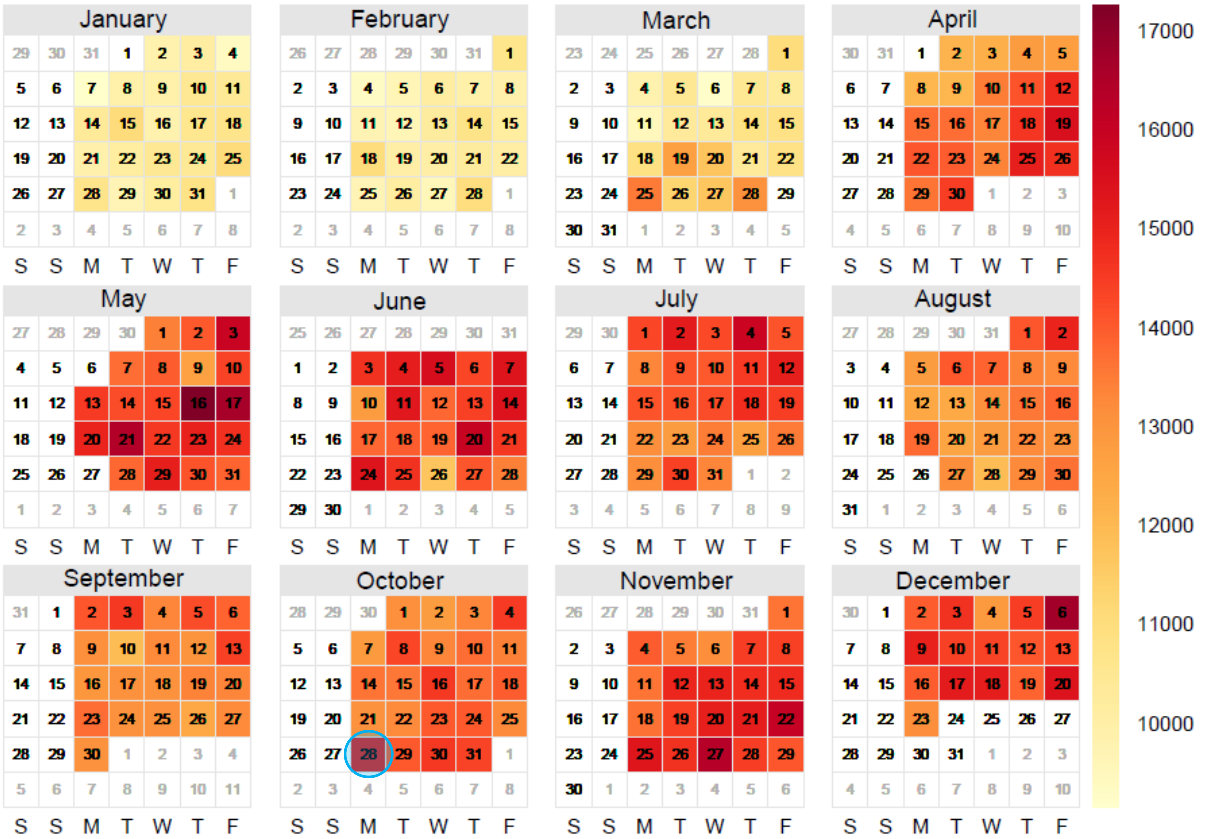

Figure 7.1: Calendar plot of mean download speeds (Kbps) in 2013 with 28 October circled in blue.[11]

Therefore, the proposed method of analysing ‘contention’ as a proxy for internet demand and choosing online connectivity over physical travel is considered valid. This research explores the concept of contention as a means to gain new insights into how the internet offers a resilient access alternative to transport, and evidence of increased online interactions and activity in response to extreme weather.

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

7.2 Data and Methods

In order to test the influence of weather conditions on internet activity, data was provided by *Speedchecker Ltd*[12], 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 captured using WiFi and GPS geolocation. Download speeds are "by far the most important feature for household users" (Nardotto et al., 2015, p336), and are more temporally variable, so are used here as a proxy for internet activity, although upload speeds are relevant, particularly for reliable video calling or transferring documents and will be discussed towards the end of the chapter (OfCom 2014). Datasets from *Speedchecker Ltd* have been the subject of previous studies on the geographic equity of broadband speeds (Riddlesden and Singleton, 2014), and on the service quality benefits of competition and local loop unbundling (Nardotto et. al, 2015), but whilst both studies investigated spatial variation, neither assessed the implications of daily variability or contention. Both mention that, even assuming fast connections to a property and proactive ISP management, speeds still vary throughout the day due to the level of use and 'congestion' at peak times, generally in the evening, when people are likely to be streaming video content for leisure purposes (Nardotto et al., 2015; OfCom, 2014; Riddlesden and Singleton, 2014), yet neither overtly considers differences during the working day or between working days dependent upon weather events.

In order to consider these differences, the first challenge is to match weather events which are known to have caused transport disruption during the working day to large enough samples of internet speeds in the same geography. The case study approach

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

enables specific date ranges with and without weather events and reported disruption to be matched to geographical and temporal subsets of the data, whilst local media records can provide information on the transport impacts and any power or ICT outages. However, the relatively low number of observations in any given case study limits further division of the data within the modelling. Thus, Welch's t-test methodology was applied to investigate the Storm Doris case study in Reading described in Chapter 4, although with a comparison to four Thursdays either side of the event rather than only a single subsequent Thursday, as a 9-day moving average appeared to offer more robust results (Kalkstein et al., 2009). A test was likewise applied to the June convective storms in Birmingham using the same days to represent 'storm' conditions and the control period as described in Chapter 6. The results of these tests are briefly described in section 7.4, but the bulk of the chapter aims to model the impacts of defined parameters of extreme weather on internet activity at a greater spatial and temporal scale. Therefore, a subset comprising a much larger proportion of the *Speedchecker Ltd* data, encompassing all working days, was selected and then linked to weather variables and other control factors.

The modelled subset incorporates 2,556,025 individual speed tests run on 1,239 days from 2012 to 2016 in England and Wales during the working hours of 0800 to 1800, Monday to Friday, excluding bank holidays and 24 December to 1 January inclusive.[13] Outlier tests recording download speeds of under 0.5Mbit/s or over 100Mbit/s were removed prior to analysis (Riddlesden and Singleton, 2014). The download speeds formed the dependent variable for a 'hierarchical' regression model

[13] 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.

that controls for characteristics relevant to individual tests as well as for higher-level, socio-economic and geographic attributes, which are assumed to be consistent over time and control for some differences of broadband supply and service ‘between’ defined areas, whilst testing for significant, time-variant or ‘within’ area effects such as weather (Bell and Jones, 2015). The model is set up as shown in equation (7.1), where *i* represents the individual speed tests, *l* represents the higher spatial level in which the speed tests fit, and *t* the time of the speed test. Nardotto et al. similarly varies predictor variables by higher geographic units, in his case the telephone exchange catchment (2015). The Test Speed variable represents the download speed for individual test *i* which took place in location *l* at time *t*. It is highly skewed, so a transformation using the logarithmic function is included in the model. B_1 is the vector of coefficients for the fixed attributes of each spatial unit.

$$\log(\text{Test Speed}_{ilt}) = = \alpha + \beta_{0r} + \beta_1\text{Distance to Nearest Exchange}_i + \beta_2\text{Internet Service Provider}_i + \beta_3\text{Annual Trend}_T + \beta_3\text{weekday}_t + \beta_4\text{Rainy Day}_{lt} + \beta_5\text{Windy Day}_{lt} + \beta_6\text{Heavy Rain}_{lt} + \beta_7\text{Storm}_{lt} + \beta_8\text{Freezing Day}_{lt} + \beta_9\text{Snowfall}_{lt} + \beta_{10}\text{Hot Day}_{lt} + \boldsymbol{\beta}_1\text{Control Variables}_l + \varepsilon_{ilt} \qquad (7.1)$$

As described in section 6.1, MSOAs capture geographic and socio-economic characteristics that tend to be consistent at the neighbourhood level: predominant land use, density, affluence, and accessibility, which affect not only travel behaviour, but also the ability to telecommute. Therefore, MSOAs were chosen as the most appropriate spatial unit, expressed with the index *l*, for applying the Control Variables in (7.1) which reflect the geographic and socio-economic context within which the individual tests occurred. MSOAs are also small enough geographic areas to control for supply-side variation, such as the type of connection available, technology used to manage the connection, and the length of wire from the street cabinet to a property, which often limits achievable broadband speeds for the end user in rural areas

(Nardotto et al., 2015; Philip et al., 2017). Data on street cabinet locations was not available, although the Distance to the Nearest [telephone] Exchange is included. To control for the choice of broadband package by individual households, the variable Internet Service Provider in (7.1) is divided into the broad categories of BT with 771,452 customer tests, Virgin Media cable, which usually offers faster speeds but has limited bandwidth available for connections that serve multiple properties and thus suffers more from contention, with 447,008 tests, and the remaining 1,337,565 tests in the sample, which are from over a dozen larger and hundreds of smaller ISPs, most of which use BT infrastructure through local loop unbundling (Nardotto et al., 2015). The latter was A chi-square, likelihood ratio test: $\chi^2(1) = 258516$, $p < .0001$ confirmed that a model with 'random' intercepts, in other words, constants or intercepts that can vary between each of the 7,201 MSOAs in England and Wales, offers a significantly better fit than one with a single, fixed intercept (Field et al., 2012). Furthermore, 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 (López-Bazo and Motellón, 2017).

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 dataset suggest that possible speeds are increasing faster than experienced speeds as shown in Table 7.1.

Table 7.1: UK annual mean speeds (Mbit/s) reported by OfCom (over 24 hours) and the annual means of the modelled dataset 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

Thus, the time trend variable, 'Annual Trend$_T$' in equation (7.1) controls for the annual, nation-wide improvement in broadband speeds, with 2012 coded as 1, 2013 as 2 and so on. The time-variant variables, however, expressed with an index *t* in (7.1), are all at a daily level of granularity to match a traditional working-day subset of broadband speed tests. This is because, as described in the Introduction and reviewed in section 3.2, work (or education) activities are the most frequent, 'non-discretionary' interactions external to the home around which daily trip and activity patterns coalesce (Le Vine et al., 2017, Miller, 2005). As work is an essential activity for those in 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), although an array of dummy variables (weekday in equation 7.1) representing days of the week (Monday, Tuesday, and so on) control for some residual variation.

However, it is also important to note that the working day is not normally considered the peak time for internet activity and contention, which occurs in the evening, nor does it include the early morning hours until 0600, when there are unusually high speeds because activity is extremely low (OfCom, 2014; Riddlesden and Singleton, 2014; Nardotto et al., 2015). As technology improves and proliferates in the 'digital age', remote or virtual access via ICT offer an alternative means to participate in a growing number of daily activities (Lyons, 2015), and those who purchase high speed connections consume more data of all sorts and use their connections for a variety of purposes (Hauge et al., 2010; OfCom, 2016). In other words, those who usually generate internet activity in the evening are likely to generate it during the working day if they are unexpectedly at home, whilst aggregation by working day also controls more for those who regularly generate internet activity during working hours, e.g. home workers, no matter the weather. Furthermore, weather impacts on transport infrastructure can be immediate or delayed, so aggregating weather parameters to identify daily extremes was deemed likely to capture more impacts than estimating weather effects at a more granular temporal scale.

The weather variables in (7.1) 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 hours, 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 and contain data from weather stations located throughout the UK (Met Office, 2006). However, weather doesn’t follow local administrative or statistical boundaries any more than does the transport infrastructure which is affected by that weather. Thunderstorms or other convective storms which may cause those 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 (Deljac et al., 2016; Schulman and Spring, 2011), but again such effects could cause increased speeds, as they did in this dataset during a major outage reported in the media on 20 July 2016 (Titcomb, 2016).

Therefore, synoptic, regional weather stations as shown in Figure 7.2 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 Organisation (Met Office, 2016b, Dobney et al., 2009). Minimising the number of weather stations from which data inputs were gathered also acted as a quality control on the data, increasing its consistency. In more rural regions, such 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. They are expressed with an index *lt* in (7.1), as the regional weather is assumed to apply at the MSOA level within the model, although admittedly this is a trade-off between accuracy at the neighbourhood level and data quality and consistency for England and Wales as a whole.

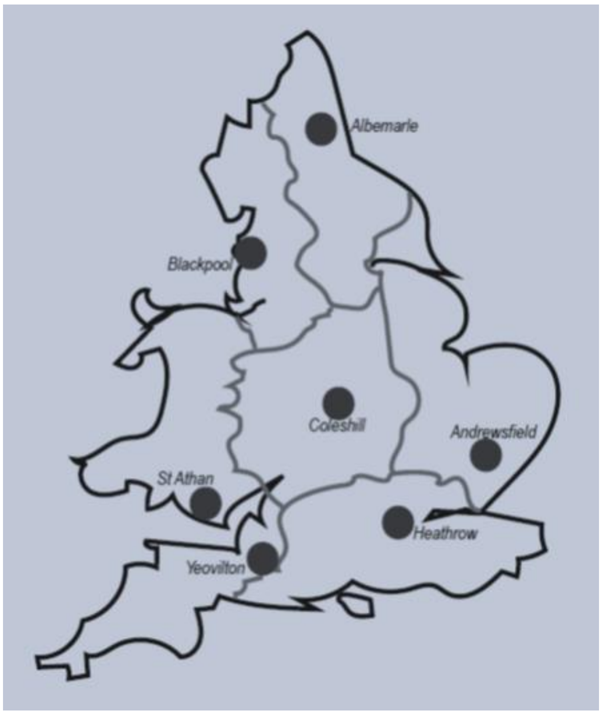

Figure 7.2: Representative weather stations chosen for each Met Office 'climate region' (2016b).

Daily, regional weather parameters were matched to the broadband speed tests by date and location, then transformed into binary dummy variables to better capture identifiable weather events. 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 >= 15mm in 24 hours 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 >= 2mm and < 15mm in 24 hours. The 'Windy Day' dummy captured days with wind speeds of levels 5 to 9 on the Beaufort Scale, whilst the Storm dummy captured any date / MSOA combinations with at least some precipitation and maximum gusts of level 10 '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 0ºC or below, and the snow dummy simply used the ‘snowfall’ record from the relevant dataset. 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, although it was 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 7.2[14]. 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 30ºC (2017c).

[14] Column 2 in Table 7.2 indicates the number or sample size of speed tests that could be matched to the independent variable in each row below ‘Mean Speed (Kbps)’ spatially and temporally. The other columns describe the key statistics of each variable respectively.

Table 7.2: Descriptive statistics for model variables

Variable	Sample size	Mean	St. Dev.	Min	Max
Mean Speed (Kbps)	2,556,025	16,432.98	17,734.98	513	102,397
Annual Trend	2,556,025	3.116	1.524	1	5
Day of the Week	2,556,025	4.021	1.408	2	6
Distance to nearest Exchange (km)	2,556,025	0.236	0.171	0	0.68
Ratio Speed Tests to population	2,556,025	0.074	0.162	0.007	1.689
Ratio of population working in High-tech industries	2,556,025	0.053	0.033	0.006	0.237
Ratio of population with higher professional status	2,556,025	0.231	0.072	0.042	0.582
Average Commuting Distance (km)	2,556,025	16.31	4.419	5.9	37.5
More urban location	2,556,025	0.843	0.364	0	1
Ratio of population who mainly work from home	2,556,025	0.031	0.018	0.002	0.116
Household net weekly income (£)	2,556,025	514.665	112.205	230	990
Rainy Day	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

The other Control Variables in (7.1) 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, and thus generate some of the background demand or daily variability not due to weather. According to the literature reviewed in section 3.2, the characteristics of those who telecommute, but are not home-based workers, include those holding professional or managerial positions, are often more educated and wealthier, have longer commutes when they do travel to their main place of work, and live in suburban/outer metropolitan neighbourhoods rather than fully rural areas (Ellen and Hempstead, 2002; Headicar and Stokes, 2016; Peters et al., 2004; Singh et al., 2013; Walls et al., 2006). As in Chapter 6, variables to represent these characteristics were derived mainly from census data compiled into 'neighbourhood statistics' tables produced by the Office of National Statistics at MSOA level. These included the ratio of the MSOA population who work mainly at or from home, average commute distance, numbers of residents working in information, communication, professional, scientific, and technical industries or Standard Industrial Classifications J and M (ONS, 2014), and numbers of residents holding managerial, professional, and administrative positions or Standard Occupational Classifications 1 and 2, and sub-classifications 31, 35, 41 and 72. The latter two were divided by the MSOA's home population. 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 versus the other four more urban classifications was included in the main model (ONS, 2016b). 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 individual supply variables, the Control Variables, and the annual trend and day of the week formed the base model of background variation. Each weather variable was inserted individually onto this base model to test for any effects on broadband speeds. Then they were tested jointly, 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 (7.1) 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.

7.3 Exploratory Analysis

Exploratory analysis prior to modelling 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 impact summaries (2012-2016a, 2012-2016b).

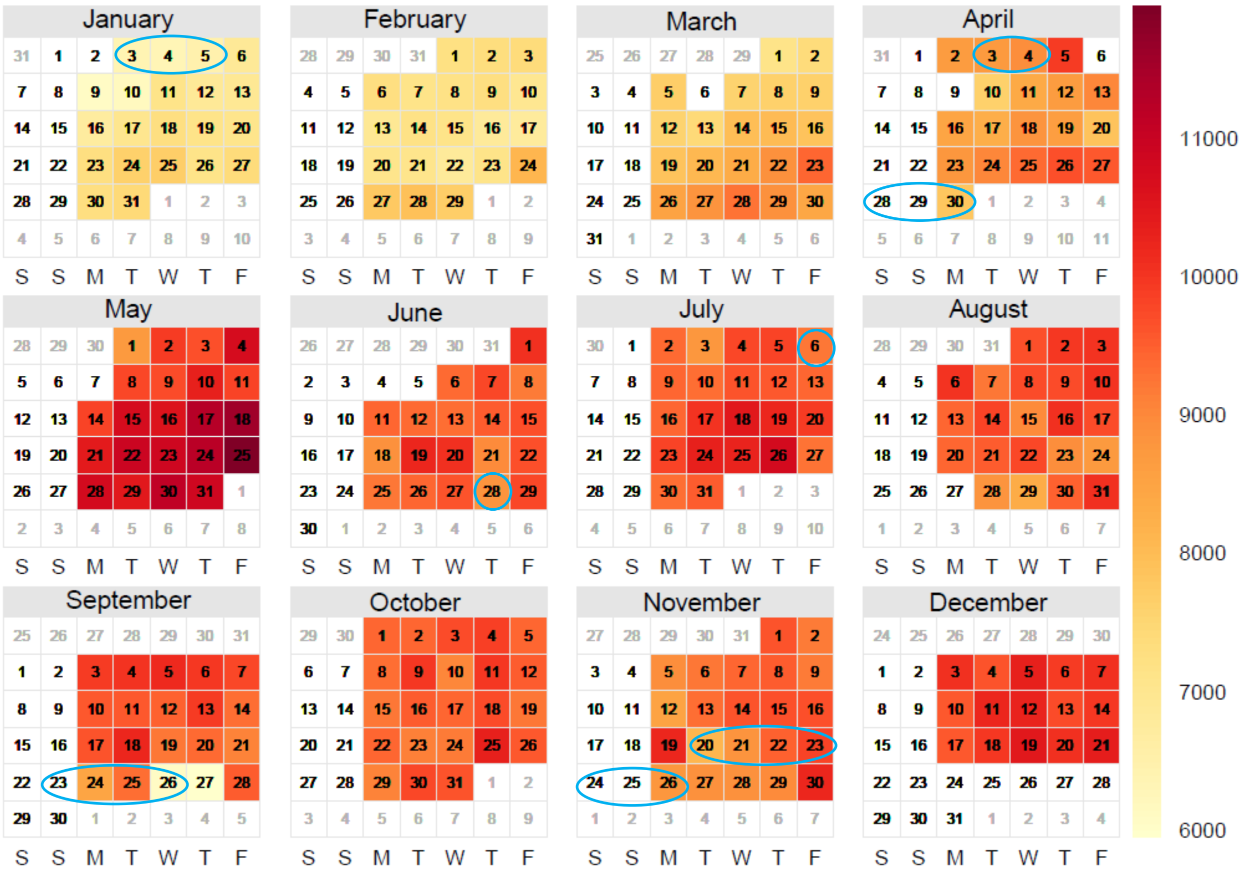

Figure 7.3: Calendar plot of mean download in speeds (Kbps) for all working days (0800-1800) in 2012. A selection of impactful storm days are circled in blue.

Calendar plots such as those in Figures 7.1 and 7.3 suggested that modelling the relationship between weather and internet activity beyond spatially and temporally restricted case studies would provide insights of interest. Manual checks further compared storm and snow dates captured by the dummies to those dates with weather impacts as noted and summarised 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 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 exploratory analysis highlights the temporal variation that might be attributed to the presence and timing of not only weather parameters, but also weather impacts, as well as other known and unknown influences on broadband activity. These influences include service upgrade promotions, different levels of internet activity on different days of the week, special events that generate weekday internet activity, or direct impacts on broadband infrastructure like power cuts or hardware failure, which 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. The available data thus do not explain all temporal variation, which also appears not to be completely unidirectional, but by dividing the model into a 4 year training period (2012-2015) and one year forecast period (2016), Figure 7.4 offers further confidence that the proposed model would capture some major temporal trends despite the noise.

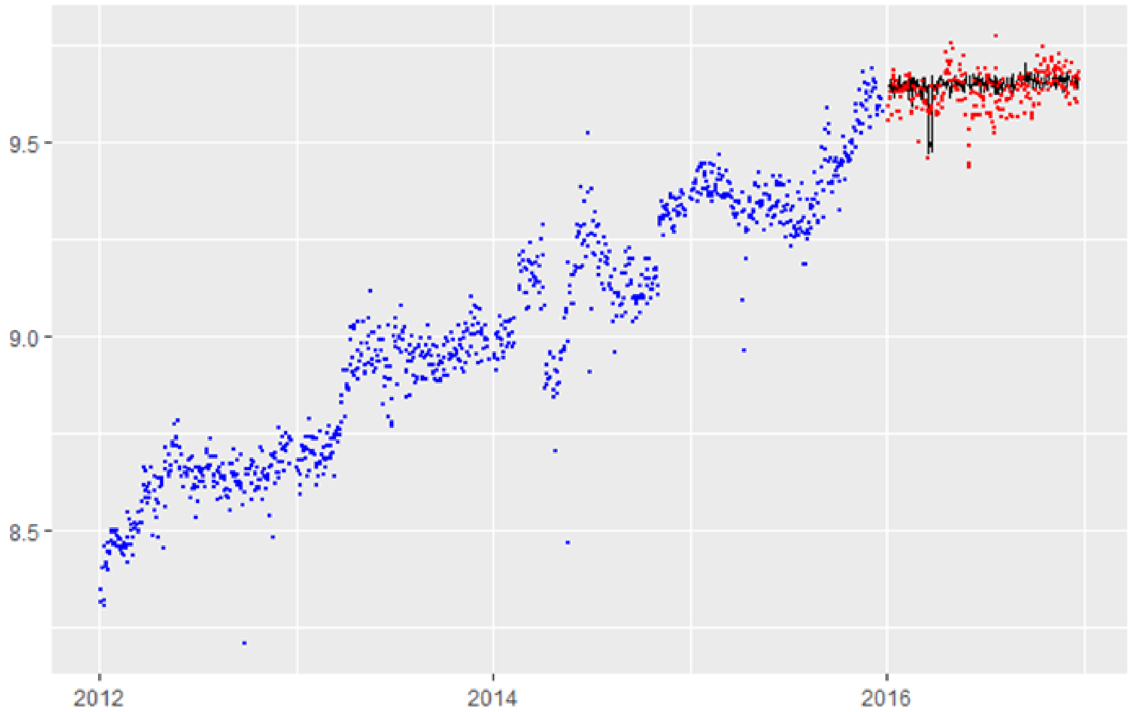

Figure 7.4: The average daily speeds calculated from the speed check data are graphed in red and blue, whilst the model forecast for 2016 are shown by the black line.

Meanwhile, the model also adds in the geography of weather events over an extensive and intensive spatial scale. Therefore, to explore how well the Storm dummy captured major storms in the locations that suffered transport disruption, the dates and MSOAs of speed tests run when the Storm Dummy registered as ‘1’ were extracted and mapped in Figure 7.5 for the period of well-documented storms between December 2013 and February 2014. These 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; breaches of security or reductions in availability, reported to them were attributed to severe weather (2014).

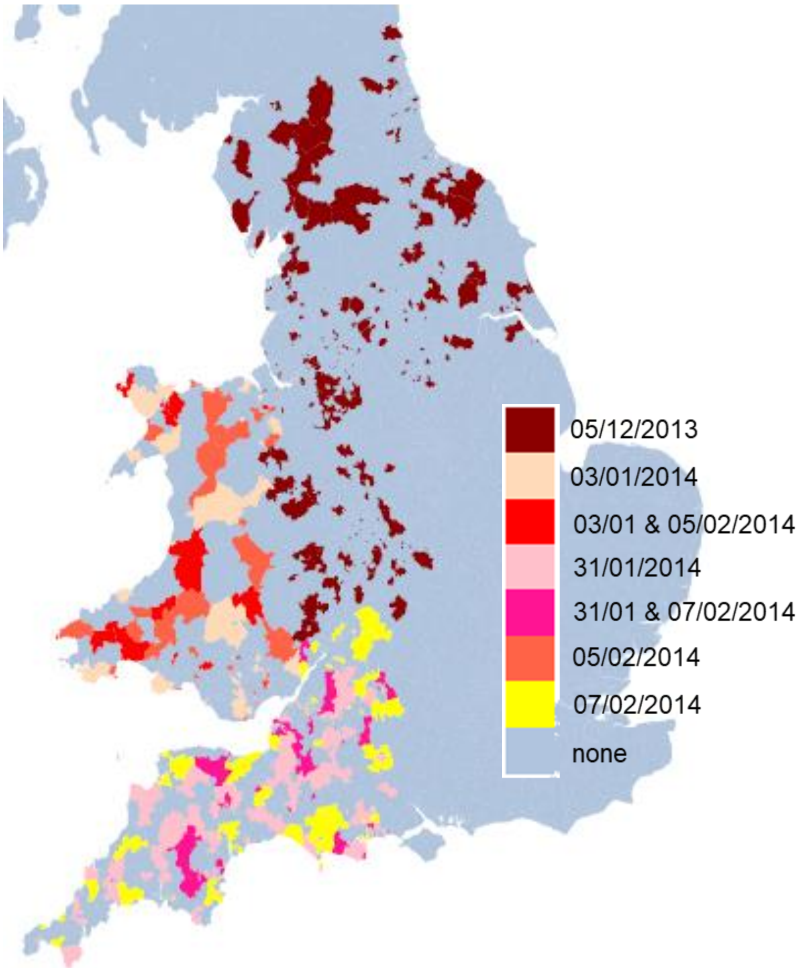

Figure 7.5: MSOAs with speed tests on 'Storm' dates as colour-coded during 2013−14 Winter Storms.

Figure 7.5 closely matches the known dates and impacts of that extreme winter's storms, other than in the Southeast region. This region was affected by the February storms, but the Storm dummy does not register '1' on these days. This may be because there was missing speed test data for the week 11-14 February 2014, which would have been when the Southeast felt the greatest impacts. Furthermore, the wind gusts, a key variable in setting the Storm dummy may not have been as strong in the Southeast, and flooding, which was substantial and impacted upon transport infrastructure, was not included in the dataset. Still, Figure 7.5 confirms that the Storm dummy successfully captures a selection of dates and places where changes in broadband speed due contention during storm conditions might be expected. The day of ‘Storm Jude’, mentioned in the introduction, was manually excluded from the storm dummy variable as an outlier, since the Met Office noted the extreme impacts of that storm were not exclusive to transport infrastructure, but included extensive power outages across the country (2013). Later investigations revealed a record number of faults reported to BT (Lazarus, 2014), such that those who did still have power and an internet connection appear to have benefitted from faster download speeds.

Despite the spatial granularity of individual speed tests, this is ‘volunteered geographic information’, so unsurprisingly, there are some MSOAs with no speed tests on a given date, and some with many tests on most days. However, the application of a random effects model addresses some of the concerns that might otherwise arise from analysing such a dataset, as these models better accommodate missing data and do not assume the independence of each observation (Field et al., 2012), i.e. that each observation comes from speed tests performed by different individuals or households. A variable to account for the number of Speed Tests per head of home population in each MSOA was added to the Control Variables in equation (7.1) in order to further moderate any sampling bias inherent in this crowd-sourced data. Furthermore, any bias resulting from the fact that tests in this dataset are more likely to be run “when there is other network activity ongoing” or speeds are lower than the customer expects (Riddlesden and 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.

7.4 Results

As with the exploratory analysis, the case study t-tests supported the hypothesis that download speeds and the level of internet activity would be affected by extreme weather events. In a subset of 152 MSOAs centred on the Reading area, the mean is 5,324 Kbps slower during Storm Doris than the average working day in the control period, with a significance of $t(149.96) = 3.28$, $p = 0.001$. Using the matching area and dates for the West Midlands case study, the mean is only 1,266 Kbps slower under storm conditions, but this is significant at $t(4465.1) = 3.21$, $p = 0.001$. However, as shown in Figure 7.6 and comparable to the road travel map in Figure 6.3, an obvious geographical pattern in this difference in broadband speeds is not apparent. Furthermore, there are many MSOAs with no speed check tests either during the control and / or storm periods, and therefore those neighbourhoods are ‘missing’ data in Figure 7.6. This is not surprising, as only 3,037 individual speed tests were recorded during the 10 storm days in the entire West Midlands study area, compared to the almost 8 million road trips that made up the matrices under storm conditions analysed in Chapter 6. Further modelling of such a dataset would neither be robust, nor likely to reveal any spatial patterns of online accessibility during the case study storms.

Figure 7.6: Difference in broadband speeds between control period and storm conditions. Darker pink shaded areas show those MSOAs with reduced broadband speeds under storm conditions. Paler areas had increased speeds, and grey indicates missing data.

Therefore, as discussed in section 7.2, records of over 2.5 million download speed checks over 5 years from throughout England and Wales provided the dependent variable, whilst weather parameters replaced definitive localised knowledge of weather impacts. The results of the main linear mixed-effects model based on equation (7.1) with intercepts that are allowed to vary by MSOA are shown in Table 7.3.[15]

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

Table 7.3: Main Regression model results with weekday coefficients hidden.

	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
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
Note:	*p<0.1; **p<0.05; ***p<0.01									

The annual improvement in broadband speeds captured by the 'Annual Trend' coefficient is intuitive, as the 26.3% average annual improvement that the coefficient represents is only slightly different from the average annual increases in *24-hour* broadband speed of about 26.7% as reported by OfCom for the UK between 2013 and 2016 – although admittedly in the first year of analysis from 2012 to 2013, 24-hour speeds rose much faster – see Table 7.1 (2016). Distance from the nearest telephone exchange becomes highly significant and positive only when the Control Variables are included, which may be because this variable is a somewhat imprecise reflection of the connection distance due to irregularly shaped catchment areas. Alternatively, it may be because the distance to the street cabinet, not the Exchange, has a greater impact on line speed, particularly in rural areas. Meanwhile, speeds are naturally faster for cable connections than for BT or for other copper-line based services, but the slower speeds from 'other' providers may mask a wide range of service packages. Finally, 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.

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.

Extreme 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. 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, not intensity. The coefficients are also likely to interact, as one weather parameter can affect another, such as high temperatures making intense rainfall more likely, or the temporal variation might reflect behavioural responses to weather warnings and / or impacts that last multiple days or have a greater than daily time lag. Thus, although the effects are clearly not cumulative, the last estimation includes all weather variables together, and 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. Furthermore, summer heatwaves 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.

The results in Table 7.3 provide some clear insights into the impact of weather on internet activity. However, it was deemed important to undertake sensitivity testing in order to reduce some of the statistical noise generated by a spatially and temporally heterogeneous dependent variable.

7.5 Spatial Sensitivity Testing

As mentioned in section 7.3 and shown in Figure 7.7, there is substantial variation in average speeds at MSOA level, with faster average speeds generally found in more urban areas.

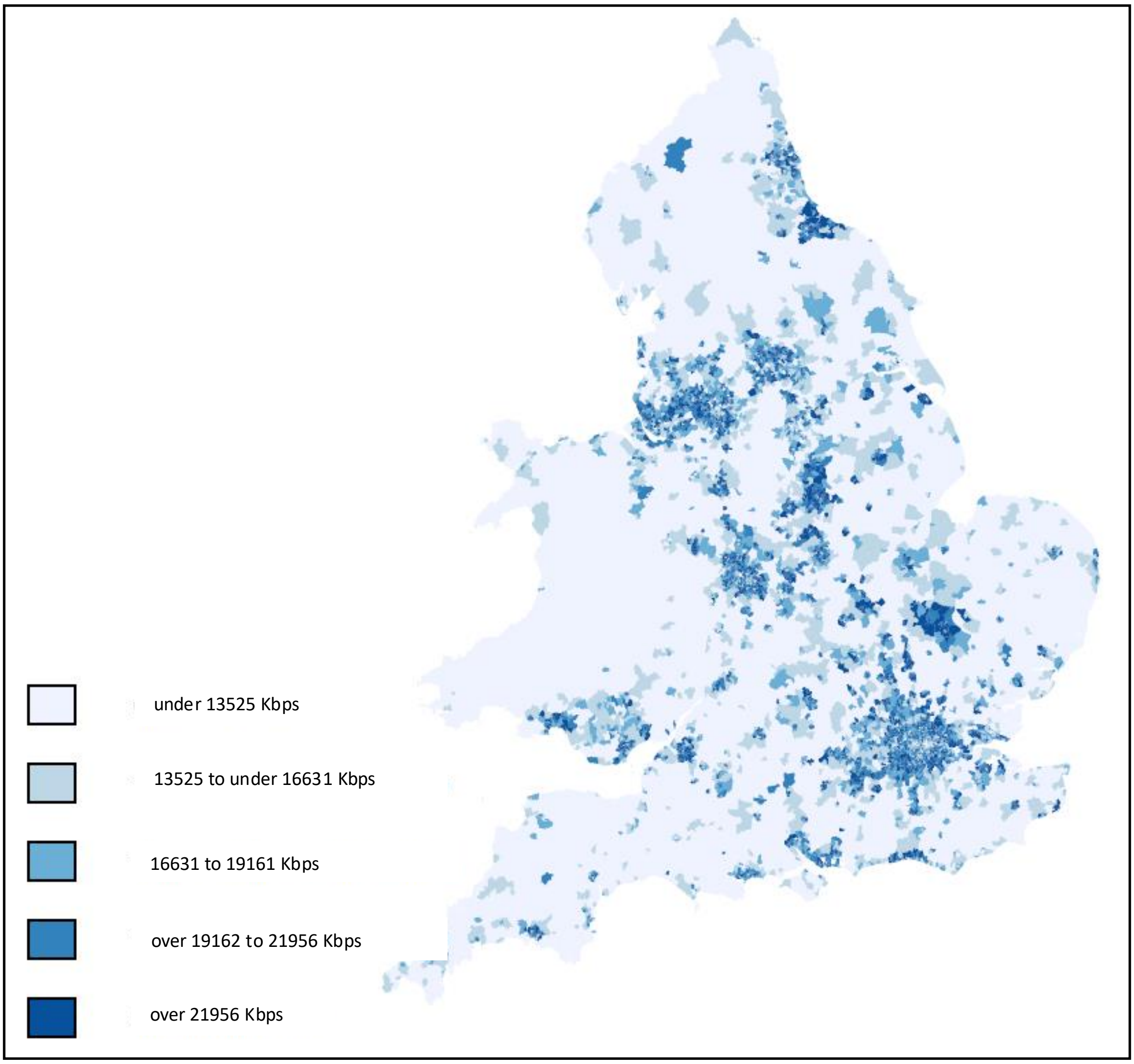

Figure 7.7: Mean speeds (Kbps) by MSOA for 2012-2016 working days

The main analysis discussed in section 7.4 addresses this spatial heterogeneity by applying a hierarchical, random effects model and including variables controlling for certain geographic and socio-economic characteristics. However, there are other methodologies, so a sensitivity test estimated the model by defining repeated observations for each MSOA by date as 'panel data' using the 'within effects transformation' applied to OLS regressions.[16] This estimation produced similar results as shown in Table 7.4.

[16] These regressions were estimated with the 'plm' package for R.

Table 7.4: 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
R^2	0.2	0.2	0.2	0.2	0.2	0.196	0.2	0.197
Adjusted R^2	0.198	0.198	0.198	0.198	0.198	0.194	0.198	0.194
F Statistic	70,740*** (df = 9; 2544000)	70,858*** (df = 9; 2545089)	70,739*** (df = 9; 2544000)	70,879*** (df = 9; 2546245)	70,945*** (df = 9; 2548341)	61,471*** (df = 9; 2265508)	70,903*** (df = 9; 2548341)	36,857*** (df = 15; 2260260)
Note:								*p<0.1; **p<0.05; ***p<0.01

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. Indeed, the results in Table 7.5 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 localised and thus affect a lower proportion of a dispersed population.

Table 7.5: 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	
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
Note:	*p<0.1; **p<0.05; ***p<0.01						

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. Yet these 'suburban' geographies and smaller urban areas are where the relationship between severe weather events and internet accessibility are likely to be most important, as they have neither rural economic activities and relatively slow speeds even under typical weather conditions, nor do they have the high densities of local employment options, other activities, and transport services of central cities. 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 15000 residents per km had mean speeds on 'Storm' days only half a Mb/s less than the average for non-stormy days, but 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 Figure 7.8, this subset excluded those exceptional, central London neighbourhoods where the density of transport options, population, employment, and other opportunities is at a scale some orders of magnitude greater than the rest of the UK, making these areas unusually resilient.

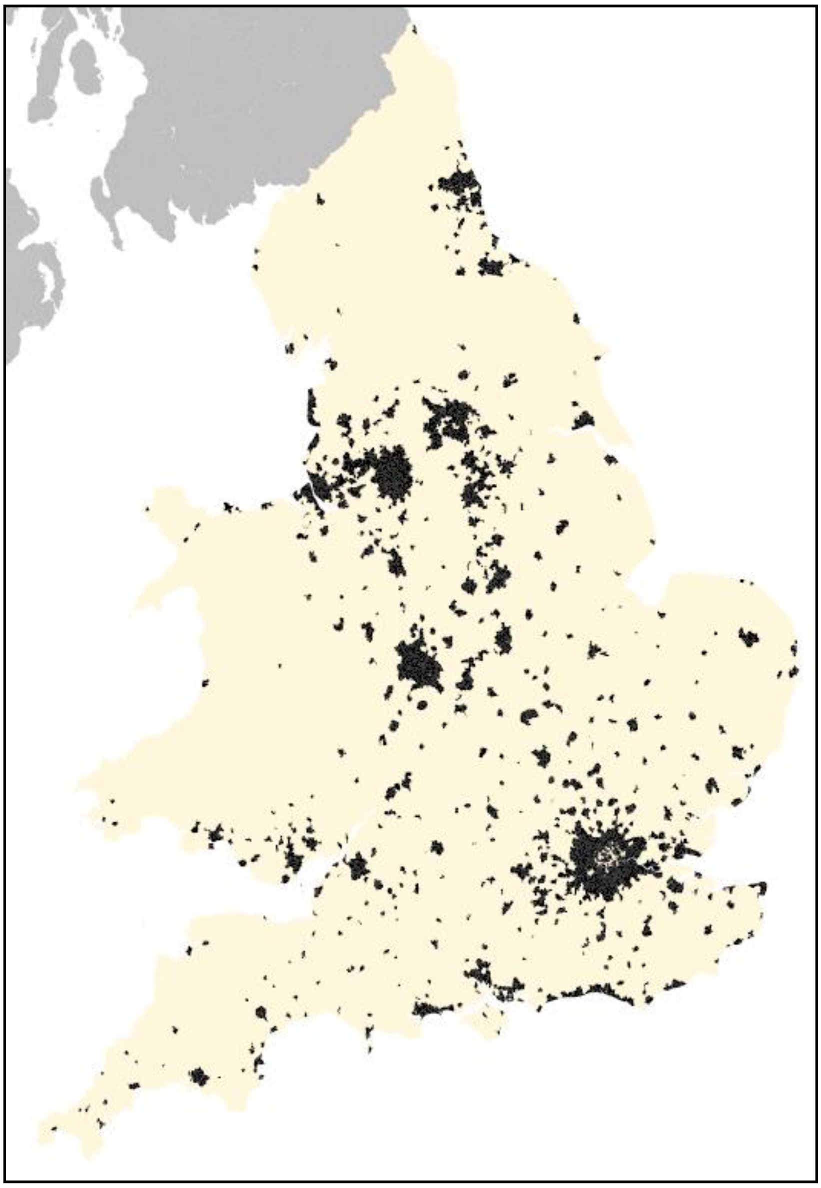

Figure 7.8: The subset of MSOAs with between 1000 and 15000 resident population / km in 2014.

The model results in Table 7.6 for this subset represent over half the total dataset 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. Meanwhile, the distance to the nearest exchange becomes insignificant, and the annual trend is less prominent with the exclusion of rural areas. In partial confirmation of the suggestion above 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 more urban locations who work mainly at or from home can choose 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, from more urban dwellers who usually commute. Overall, this sensitivity test offers additional evidence in support of the hypothesis put forward in this chapter, namely, that internet activity increases 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.

Table 7.6: Estimation of the subset of observations for MSOAs with a population density between 1000 and 15000 people per kilometre. The Urban / Rural classification is not included.

	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
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
Note:									*p<0.1; **p<0.05; ***p<0.01

7.6 Temporal Sensitivity Testing

The extent of known and unknown factors influencing temporal variation was discussed in section 7.3. This section explores these issues further. Figure 7.9 shows that whilst broadband speeds rose year on year, the trend within each year varied.

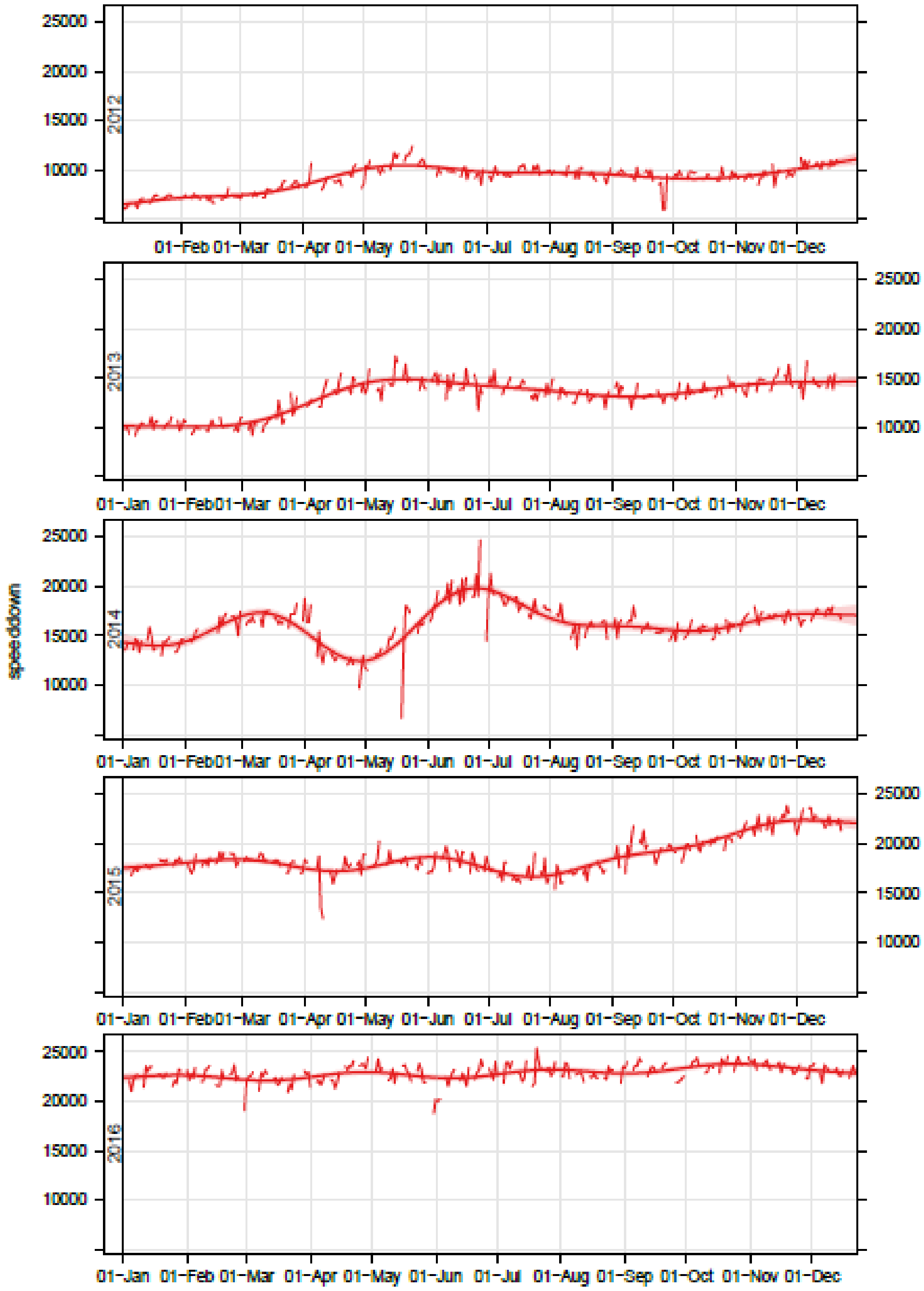

Figure 7.9: Mean broadband download speeds (Kbps) by date and year for working days.

The line is broadly a similar shape for 2012 and 2013, fluctuates widely in 2014, shows a different curve in 2015 and is fairly flat in 2016. In particular, there is great inconsistency within the annual rising trend in broadband speeds in 2014, which included missing data during the storms and flooding of February 2014. Furthermore, the manual checks described in section 7.3 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 the four named Storms in November / December 2015. Therefore, a regression was run on a subset including only 2012, 2013, and 2016, in order to sensitivity test whether effects might be greater if other temporal variation is more muted. The results in Table 7.7 include a Storm coefficient indicating speed reductions of 10%. This gives weight to the possibility that the patterns of significant effects on broadband speeds that suggest increased internet activity in response to extreme weather parameters in Table 7.3, whilst demonstrating a clear relationship between weather and internet activity, may underestimate the effects of weather disruption.

Table 7.7: 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
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
Note:										*p<0.1; **p<0.05; ***p<0.01

7.7 Discussion and Conclusion

This chapter argues that lower experienced internet speeds during the working day due to increased internet use and demand in areas of adverse weather conditions are an indication that people are choosing 'not travelling' as a viable, resilient alternative to avoid delay and disruption. The regression analysis supports this hypothesis with winter weather and storm-level winds showing significant, albeit small, negative effects on broadband speeds. Since weather impacts show more 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. However, 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 parameters and weather impacts and unidentified inconsistencies within the trend of rising broadband speeds and service quality delivery resulted in larger coefficients. Furthermore, storms can take diverse forms and have unpredictable impacts, which may well be dependent not upon the weather parameter itself, but where and when it occurs. Impacts vary depending on the location, season, 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 mixed effects models estimated in this chapter could also only imperfectly capture the geographic / socio-demographic constraints on internet use and quality of service, considering that the prevalence of tech-based employment, for example, might be more relevant at a larger spatial scale, or that there are local initiatives to improve broadband infrastructure in some rural areas, but not others. However, the spatial sensitivity tests demonstrate the heterogeneity in response between rural, suburban and central urban areas. Unfortunately, none of the sensitivity tests address the question of what activities the change in demand for online access represents. 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 creating the increased demand. For example, 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 recent 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 and Rowe, 2019).

Furthermore, although the data is not available to translate changes in working hours' internet activity into a quantified change in the number of trips taken on the day or the level of commuting or telecommuting, the broadband speed checks did include upload speeds, which could be a better indication of telecommuting activities rather than online leisure activities. The correlation coefficient between upload and download speeds is $r = 0.57$, so some of the effects could be broadly similar, and upload speeds show less range and variation than download speeds. Each year's range of speed checks and daily fluctuations fit within a scale of approximately 2 Mbit/s rather than 5 Mbit/s, and total mean speeds usually fall below 6 Mbit/s, even in 2016. Still, the model for upload speeds does offer some additional insights that may be more closely correlated with telecommuting behaviour, as shown in Table 7.8.

Table 7.8: Estimation of the main regression model in equation (7.1) with upload speeds as the dependent variable. Note that there are fewer observations as additional outliers were excluded.

	Dependent Variable: Upload 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	0.328***	0.328***	0.328***	0.328***	0.328***	0.328***	0.328***	0.326***	0.328***	0.326***
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Distance to Nearest Exchange	-0.050**	0.089***	0.089***	0.089***	0.089***	0.088***	0.089***	0.125***	0.089***	0.125***
	0.021	0.018	0.018	0.018	0.018	0.018	0.018	0.019	0.018	0.019
Virgin Media compared to BT	0.317***	0.309***	0.309***	0.309***	0.309***	0.309***	0.309***	0.318***	0.309***	0.318***
	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	-0.003
Other compared to BT	-0.508***	-0.510***	-0.510***	-0.510***	-0.510***	-0.510***	-0.510***	-0.501***	-0.510***	-0.501***
	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		-0.733***	-0.733***	-0.730***	-0.734***	-0.732***	-0.730***	-0.764***	-0.733***	-0.758***
		0.088	0.088	0.088	0.088	0.088	0.088	0.091	0.088	0.091
Ratio of pop working in High-tech industries		-0.177	-0.184	-0.197	-0.172	-0.182	-0.201	0.077	-0.172	0.042
		0.194	0.194	0.194	0.194	0.194	0.194	0.204	0.194	0.204
Ratio of pop with higher professional status		0.361***	0.364***	0.372***	0.358***	0.363***	0.373***	0.379***	0.358***	0.397***
		0.099	0.099	0.099	0.099	0.099	0.099	0.105	0.099	0.105
Average Commuting Distance (log)		-0.046***	-0.046***	-0.046***	-0.046***	-0.046***	-0.046***	-0.040**	-0.046***	-0.040**
		0.016	0.016	0.016	0.016	0.015	0.015	0.016	0.016	0.016
More urban location		0.286***	0.287***	0.286***	0.286***	0.286***	0.287***	0.283***	0.286***	0.283***
		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		-7.217***	-7.214***	-7.206***	-7.220***	-7.213***	-7.211***	-7.468***	-7.218***	-7.442***
		0.325	0.325	0.325	0.325	0.325	0.325	0.342	0.325	0.342
Household net weekly income (log)		0.400***	0.400***	0.397***	0.401***	0.399***	0.397***	0.363***	0.401***	0.358***
		0.023	0.023	0.023	0.023	0.023	0.023	0.024	0.023	0.024
Rainy Day			-0.011***							-0.014***
			0.002							0.002
Windy Day				-0.012***						-0.014***
				0.002						0.002
Heavy Rain					0.024***					0.020***
					0.005					0.005
Storm						-0.008				-0.009
						0.008				0.009
Freezing Day							-0.043***			-0.046***
							0.003			0.003
Snowfall								-0.049***		-0.025***
								0.005		0.005
Hot Day									-0.053***	-0.039***
									0.013	0.014
Constant	6.513***	4.029***	4.033***	4.049***	4.022***	4.033***	4.052***	4.224***	4.026***	4.264***
	0.007	0.126	0.126	0.126	0.126	0.126	0.126	0.133	-0.126	0.133
Observations	2,502,849	2,502,849	2,498,154	2,499,162	2,498,154	2,500,307	2,502,379	2,226,216	2,502,379	2,221,061
Log Likelihood	-4,016,174	-4,014,480	-4,006,933	-4,008,558	-4,006,941	-4,010,366	-4,013,654	-3,554,324	-4,013,788	-3,545,839
Akaike Inf. Crit.	8,032,364	8,028,991	8,013,897	8,017,148	8,013,914	8,020,764	8,027,339	7,108,680	8,027,609	7,091,722
Bayesian Inf. Crit.	8,032,466	8,029,182	8,014,101	8,017,352	8,014,117	8,020,968	8,027,543	7,108,882	8,027,813	7,092,000
Note:	*p<0.1; **p<0.05; ***p<0.01									

The first coefficients of interest are those comparing Virgin and other Internet Service Providers to BT. Virgin is still likely to offer faster broadband speeds than BT, but the smaller coefficients suggest that there is less differential between Virgin and BT for upload speeds, whilst providers other than Virgin and BT are already offering slower speeds on average for download, and even slower than that for upload. This may reflect the marketing and monitoring within the industry that prioritises and emphasises download speeds. Within the MSOA-level Control Variables, the coefficients for proportion working in ICT and other high-tech industries become insignificant, which is a big switch, whilst the effect of more people with higher professional status switches sign and is much greater, as is the effect of higher incomes. Although there is some overlap between industry and occupation, these correlations suggest that download speeds are more important than upload speeds to the tech-savvy, whilst internet service packages which include quality upload speeds are more important for those in more senior positions with higher incomes. The latter may be due to a need for more access to applications like video-conferencing when they do telecommute, as meetings may make up a larger proportion of the occupation of those with more managerial or client / customer service responsibilities. Finally, the hypothesis that telecommuting has a greater impact on upload speeds than download speeds is supported by the larger coefficients in Table 7.8 than in Table 7.3 for the proportion of home-workers, and although not shown in the tables, the effects of the days of the week, when different proportions of people may telecommute, e.g. on a Friday compared to a Monday, is also greater for upload than for download speeds.

The coefficients for the various weather parameters are more difficult to interpret. 'Light' rain and heavy rain show opposite effects, which are small, but significant, whilst there is no significant correlation between broadband speeds and the Storm dummy, but Hot Days show a significant negative relationship, even greater than Snowfall. One possibility is that upload speeds are more likely to reflect regular telecommuting by professionals, no matter the weather. Therefore, moderate adverse weather could be expected to have a small but significant negative effect on upload speeds, as regular telecommuters and home workers may interact more online as opposed to other offline or outdoor tasks if their normal days out of the office are wet and windy. Conversely, changes in upload speed due to telecommuting that occurs specifically in reaction to disruption, e.g. on days captured by the Storm dummy, may be masked by the relationship between upload and download speeds, where the effect on the latter is perhaps more attributable to internet use by others in the household or a combined effect and download activity consumes more bandwidth. This may also explain the weakening of the correlation between Snowfall and slower upload speeds in the final estimation including all weather parameters. Still another possible explanation relates to whether those weather parameters are linked to a proactive policy to telecommute for those who already regularly telecommute. Such a policy is more common in response to winter weather parameters, which do show significant negative coefficients.

In conclusion, the quantification of online *work* activities during weather disruption remains uncertain, but this chapter demonstrates that broadband speed variation during working hours can provide insights into patterns of internet activity and resilient accessibility. It does this at a level of temporal granularity and geographical scale such that a small, but significant response to events like storms and snowfall is detected, highlighting the ability of internet access to potentially replace travel during severe weather.

8. TELECOMMUTING AND OTHER TRIPS[17]

A key concern of policy makers when planning for storms, snow and other emergencies that will cause transport delay and disruption is the loss of productivity. The internet and telecommuting have the potential to provide robust accessibility options to work activities during extreme weather events, but the implications of this potential require further analysis of current trends towards online accessibility and telecommuting, and their interaction with travel behaviour. The decline in direct commuting trips in England over the last two decades has been partially attributed to increased telecommuting, although other impactful trends include increased trip chaining, more self-employment, contract and part-time working, and jobs where there is no fixed workplace (Le Vine et al., 2017). Of these trends, the additional flexibility telecommuting offers working adults in terms of time, location, and travel, as discussed in section 3.2 has great potential to increase resilience. However, as section 3.2 briefly reviews, the flexibility of telecommuting could either support sustainable travel behaviours or could result in more travel, more sprawl, and less resilient places. Which result occurs depends upon a more comprehensive analysis of the travel behaviour of known telecommuters, which is the aim of this chapter. When people choose to telecommute despite the presence of an external workplace or places, they are reducing the number of commute journeys they need to make, which in turn affects the number, distance, and environmental impact of both the remaining commuting journeys and the total trips taken by the individual, household, or local population (Choo et al., 2005; Gubins et al., 2017; Kim, 2017; Zhu, 2013). Research in China and

[17] The majority of this chapter is under review following submission as: Budnitz, H., Tranos, E., Chapman, L. 'Telecommuting and other trips', *Journal of Transport Geography*.

the United States concluded that telecommuters tend to make more trips for other purposes and that the demand for non-work activities may influence their choice to telecommute in the first place (Asgari and Jin, 2017; Loo and Wang, 2018; van Wee et al., 2013).

The empirical analysis in this chapter builds on such literature by exploring the behavioural variation in out-of-home activity participation in England, by measuring and modelling the frequency of trips for different purposes by those who self-identify as telecommuters, excluding those whose workplace is home. By considering trip budgets rather than 'travel time budgets' (Mokhtarian and Chen, 2004), the analysis reviews how online work activities change the balance of external activity participation. Previous activity-based studies tend to measure only one or two journey purposes or categorise out-of-home and online activities into 'mandatory', 'maintenance', and 'discretionary' (Asgari and Jin, 2017). This methodology may enable an understanding of behavioural patterns, but offers little insight into the level of travel demand for different purposes, and thus the implications for accessibility and sustainability. Therefore, this study reviews 11 separate journey purposes. Purpose is considered independently of distance or mode, because the aim of the research is how planners might increase the potential for telecommuters and others with flexible working arrangements to choose sustainable travel patterns, rather than assess whether they are already sustainable.

The data source employed here is the National Travel Survey (NTS), which includes both a week's travel diary with records of all trips taken for different purposes during that week, plus an interview component for the same participants that includes a question on how frequently individuals work from home. The research aims to demonstrate how those who work from home at least once a week are different from other working adults in how they balance their demand for both travel and activity participation. This difference is explored through summary and statistical analysis, with the latter used as a tool to highlight the probability that a participant's status as a frequent telecommuter is more or less relevant to the variation in travel patterns than other basic socio-economic and demographic characteristics. Insights into this difference can better inform policies on the integration of land use, transport and online accessibility, which in turn are key determinants of the distance and impact of travel on sustainability and resilience.

8.1 Telecommuting in Context

In transport research, telecommuting tends to refer to the direct replacement of commute journeys with remote participation, usually using ICT; and investigation has focused on the potential of telecommuting to reduce vehicle miles and impacts in order to contribute to the sustainable transport agenda (Cairns et al., 2004; Choo et al., 2005; White et al., 2007). And yet, a number of studies show this assumption is flawed. Telecommuters tend to have longer commute distances and durations on the days they do commute, and telecommuting households have longer total one-way commute distances (de Vos et al., 2018; Peters et al., 2004; Singh et al., 2013; Zhu, 2013). Furthermore, telecommuters make more business and non-work trips and fewer high-efficiency linked trips, raising concerns that increased online access may have a neutral or unsustainable impact on total trips and distance travelled, particularly if telecommuters tend to live in more suburban, perhaps car-dependent areas (de Abreu e Silva and Melo, 2018; Gubins et al., 2017; Kim, 2017; Wang and Law, 2007).

Whilst there is some evidence that telecommuters are concentrated in suburban areas (Ellen and Hempstead, 2002), given the availability of other modes of transport, these commuters are not necessarily car-dependent. For example, since frequent telecommuters, who make up 8% of the working population in England, are more likely than non-telecommuters to travel by heavy rail when they do commute as shown in Figure 8.1, then some of those travelling longer distances may be doing so sustainably. It may be that any link between telecommuting and rail commuting is more related to the socio-economic characteristics telecommuters and rail commuters share, but it is still notable that working from home and commuting by rail are the only two 'modes' of accessing work which are increasing in England outside London, whilst 'multi-modality' more generally appears to be decreasing (Headicar and Stokes, 2016; Heinen and Mattioli, 2017; Le Vine et al., 2017). Therefore, the possibility that the two complement each other suggests that telecommuting and living further from the workplace does not necessarily have to be an unsustainable trend.

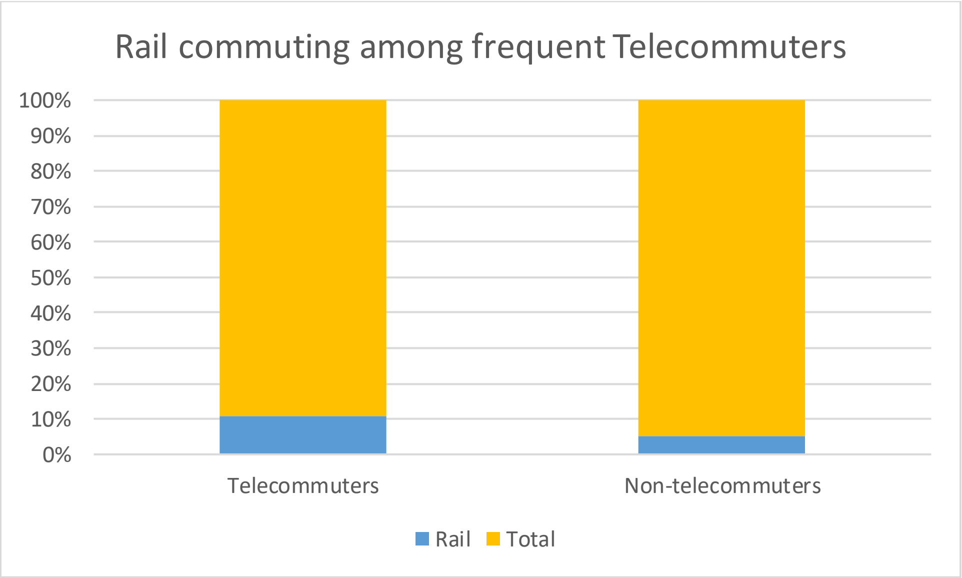

Figure 8.1: Main mode of travel to work for frequent telecommuters and non-telecommuters.[18]

[18] Data Source: Department for Transport, 2017b. Own calculation.

Furthermore, accessibility is as much a product of the density and distribution of work and other opportunities, as it is of the transport networks or absolute measures of distance (Noulas et al., 2012). If we move on from the sustainability of 'excess commuting' or commuting further than the optimum as derived from utility-based accessibility models, the sustainability of non-work journeys becomes a key policy implication (Ma and Banister, 2006). Indeed, both long commutes and the growing importance of non-work travel relative to commuting may affect not only the propensity to telecommute, but also the search for a residential location that better balances travel requirements with different lifestyles, land uses, or attitudes about travel (Aditjandra et al., 2011; Hu and He, 2016; Melia et al., 2018). Modelling such behavioural feedback and interaction is complex, and the measures of accessibility and choice are often limited by the data available (Lavieri et al., 2018; van Wee et al., 2013). Still, there are studies that indicate not only that telecommuters make more non-work trips, but also that those living in areas with greater densities of local, non-work destinations or by commercial / retail centres, are more likely to telecommute (Andreev et al., 2010; Loo and Wang, 2018; Singh et al., 2013). Therefore, understanding the demand for work flexibility and access to amenities could enable a better land-use planning response to people's needs (Banister, 2008; Kwan et al., 2007).

Questions around flexibility and access apply to both people whose work and lifestyles are already flexible and fragmented in time and/or space, and also those who aspire to work from home one to two days per week, such as women and part-time workers who may have additional care-giving responsibilities (Headicar and Stokes, 2016; Lavieri et al., 2018; Singh et al., 2013). Other trends can also have an influence. For example, trip chaining is associated with travelling further, often because it accompanies longer-distance commuting trips, yet where people live in high density areas, trip-chaining and complex 'tours' are likely to involve travelling shorter distances (Chen and Akar, 2017). Thus, whilst this chapter argues for the importance of non-work trips and accessibility for telecommuters, other trends may undermine or reinforce the potential for places which enable more sustainable, healthy, and resilient access to non-work activities.

8.2 Materials and Methods

The main data source used in this chapter is the *National Travel Survey: 2002-2016* (NTS), administered annually to approximately 16,000 individuals in 7,000 households selected through stratified, clustered, random sampling in order "to monitor long-term changes in personal travel" (Department for Transport, 2017b, *Data Extract User Guide, 1995-2016*: p5). Although the survey has a history which dates back over 50 years, there are regularly minor changes to the questionnaire, and occasionally more major reviews and alterations to data collection. Since 2013, the survey has only sampled households in England, so data from the other British nations from earlier surveys was excluded from this analysis. In 2016, there was a major change to the recording of short walks in the travel diary, defined as those under one mile, from collecting the data only on the last day of the travel diary to only on the first day, so rather than lose an entire year of data, all 'short walk' trips are excluded from the main analysis. Finally, as this chapter is interested in the travel patterns of telecommuters, of most relevance are the questionnaire changes in 2009 to who was asked about frequency of working from home, namely all participants of 16 years or over in employment, rather than only those who responded to binary questions about whether they did work from home in the previous week, or if they didn't, could work from home

(Department for Transport, 2017b). As a result, almost all working participants answered the question from 2009 onwards, even if they never telecommute. Pre-2009, a follow-up question recording which days someone had telecommuted in the previous week was used to calculate the frequency of telecommuting days per year by different groups (Le Vine et al., 2017). In comparison, this chapter uses the complete data from 2009 to 2016 and the question directed at all employed adults to compare the non-work travel of individuals who self-identify as working from home at least once a week to that of those who say they telecommute either more occasionally or never.

The questionnaire or interview portion of the survey is accompanied by a week-long travel diary of trips. As this chapter is interested in whether the frequency of participation in activities other than work varies according to different working patterns, the analysis aims to measure the effect of individual and household characteristics from the interview, particularly regular telecommuting, on the number of trips recorded in the diary categorised by journey purpose. Other household and individual level characteristics are selected based upon the literature review of the socio-economic-demographic and geographic factors that most influence not just telecommuting patterns, as applied in Chapter 7, but travel and access patterns more generally, including the choice to telecommute (Clark et al., 2016; Hincks et al., 2018; Lovelace et al., 2014). These include: the presence of dependent children in the household, whether the household is within the top income quintile, whether the individual is full-time not part-time, an employee not self-employed, and usually works in the same place on at least two consecutive days a week not different places. For the purpose of controlling for the sustainability of travel patterns, variables were included to account for the presence of one or more motorised vehicles per adult in the household and whether the individual identifies the car as their usual mode of commuting, either as driver or passenger. To control for geography and land use, we include a binary variable indicating urban or rural location. The above characteristics are weighted according to the NTS guidance to control for non-response bias, addressing, for example, those who did not complete the travel diary, whilst the weighting for trip numbers additionally controls for drop-off in response over the course of the diary week, which varies by journey purpose (Department for Transport, 2017b).

The survey breaks trips down into either eight or 23 different purposes, and as trip numbers for some of the latter categories are very small, this study uses mainly the eight broad trip types, but divides 'shopping' into food and non-food, and 'leisure' into recreational activities such as sport and entertainment, visiting in residential areas, and holidays / days out. These divisions capture where different journey purposes involve different land uses, are likely to be influenced differently by socio-economic characteristics, and manifest different travel behaviours. It should be noted that the final category of the broader trip types is 'other including just walk', and mainly consists of 'just walk' trips where walking or other forms of movement without a destination are therefore activities in and of themselves, occur on the public highway, and where the distance is over 1 mile. In other words, the short walk trips are not double-counted, nor is there any record in the NTS of walking, jogging, cycling, etc in a park or along public rights of way. The result is a single, dependent variable for journey purpose that is categorical and choice-based, with 11 binary options. Therefore, a multinomial logit model (8.1) is estimated in order to provide insight into which influences affect the probability of a person recording different journey purposes for their trips, and specifically additional non-work trips. Furthermore, the model estimates whether an individual being a self-declared telecommuter has a greater or lesser effect than the other socio-economic-demographic and geographic influences.

$$\ln(Pr_t \neq \text{Commute}) = \alpha + \beta_1\text{Telecommuter} + \beta_2\text{Household} + \beta_3\text{Individual} + \varepsilon \quad (8.1)$$

Such models have been used in transport studies before, usually with modal choice as the non-ordinal, categorical, dependent variable (Saneinejad et al., 2012; Zhou, 2012), but in this case, Pr_t is the probability that a given trip is made for one of ten journey purposes rather than the reference or base journey purpose choice of commuting in equation (8.1). The model coefficients are the log odds of the stated choice to telecommute regularly (β_1), and of other household (β_2) and individual (β_3) level characteristics making it more or less likely that each trip taken within the week will be to access one of the 10 activities other than the usual place of work. A chi-square test of the log-likelihoods of the model with the single explanatory variable for telecommuting, and for the complete model, both show a significant difference from the null model, and the model fit further improved with the addition of the other relevant variables.

8.3 Results: The Odds of Other Travel

The eight-year dataset analysed here includes a total of 958,167 trips made by 54,048 working individuals from 32,940 households once those who were not relevant to the analysis were excluded, e.g. due to not being of working age, being unemployed, identifying ‘home’ as their usual workplace location. Telecommuters, or those who work from home at least once a week make up 8% of the total. Table 8.1 shows the percentage of telecommuters that can be characterised by each binary variable, and the percentage of those who either never telecommute or telecommute less frequently with the same characteristics.

Table 8.1: Percentage of Sample for each Explanatory Variable

Variable	Telecommuters	Non-Telecommuters
Full Time not Part Time	78%	76%
Employee not Self-Employed	70%	91%
Have Regular Workplace	58%	86%
Have Degree	56%	29%
Male not Female	58%	53%
Over 40	64%	52%
Car to work	67%	67%
Urban not Rural	76%	83%
Have Children	39%	36%
Have at least 1 Car per Adult in household	94%	97%
Income Top Quintile	48%	26%

Considering the large sample size, it is not surprising that any correlation between being a telecommuter and the independent variables is 0.15 or less, but there are differences in the characteristics of telecommuters and non-telecommuters. As Table 8.1 shows, more frequent telecommuters are older, wealthier and better educated than non-telecommuters, all of which characteristics fit with the results of other studies, which also indicate more telecommuting among workers with professional and managerial roles (de Abreu e Silva and Melo, 2018; Gubins et al., 2017; Singh et al., 2013). More men than women, more individuals with dependent children in the house, and a higher percentage of those who work full-time telecommute, although these differences are not as large. It is interesting that, after rounding, the same proportion of telecommuters and non-telecommuters say their usual mode of commuting is by car and that a slightly lower percentage of telecommuters live in households with at least 1 car per adult, despite a higher proportion living in 'rural' areas. This could be an indication, albeit a small one, that telecommuting practices can reduce the car access and dependency requirements of a household, and perhaps opens the door to a more sustainable lifestyle, which may even be a reason why some choose to telecommute.

Certainly, Table 8.1 shows that compared to those who do not telecommute regularly, more telecommuters are self-employed and / or do not have a regular place of work, which are two key characteristics that will also affect how their journey purposes are recorded. In particular, having multiple workplaces or no regular workplace can change the journey purpose recorded from ‘commute’ to ‘business’. Indeed, all work journeys by those who never go to an identified usual workplace are counted as ‘business’ trips, and for self-employed people there might be additional ambiguity between ‘commute’, ‘business’, and ‘personal business’ journey purposes. Table 8.2 shows how differences in the journey patterns by purpose for telecommuters and non-telecommuters remain, even where those with overlapping flexibilities such as no regular place of work or self-employment are removed from the total.

Table 8.2: Journey purposes by total number of trips for non-telecommuters, telecommuters, telecommuters with a regular, external workplace, and telecommuters who are employees with a regular workplace

	Non-Telecommuters	Telecommuters	Telecommuters, regular workplace	Employee, telecommute, regular workplace
Commute	33%	17%	23%	24%
Business	6%	13%	8%	7%
Escort Education	4%	6%	6%	6%
Other Escort	8%	11%	11%	11%
Food Shopping	8%	8%	8%	8%
Other Shopping	8%	9%	9%	8%
Errands	8%	9%	9%	9%
Leisure Trips	10%	13%	12%	12%
Visiting	9%	7%	7%	7%
Holidays	4%	5%	5%	5%
Other (just walk)	2%	2%	2%	2%

Table 8.2 demonstrates that a greater share of telecommuters' trips are for other purposes. Telecommuters are also making more trips for other purposes in terms of absolute numbers. This is explored graphically in Figure 8.2. Regular telecommuters take about half as many commute trips per person in the diary week as those who telecommute less than once a week or not at all, but make almost 1.4 more 'business' trips from work or for other work purposes, although these do include all the work trips of those with no usual place of work. Telecommuters also record 0.6 more escort trips, 0.2 more errands or 'personal business' trips, and 0.4 more journeys to places for leisure and recreation per person per week than non-telecommuters. Yet there is little

difference in shopping trips, both for food and other goods. Since, in total, telecommuters make an average of 19 trips per person during the diary week, compared to 19.9 trips per non-telecommuter, this analysis suggests that working adults have a similar trip-making ‘budget’ whether they telecommute or not, but telecommuting allows for substantial shifts in the purpose of those journeys.

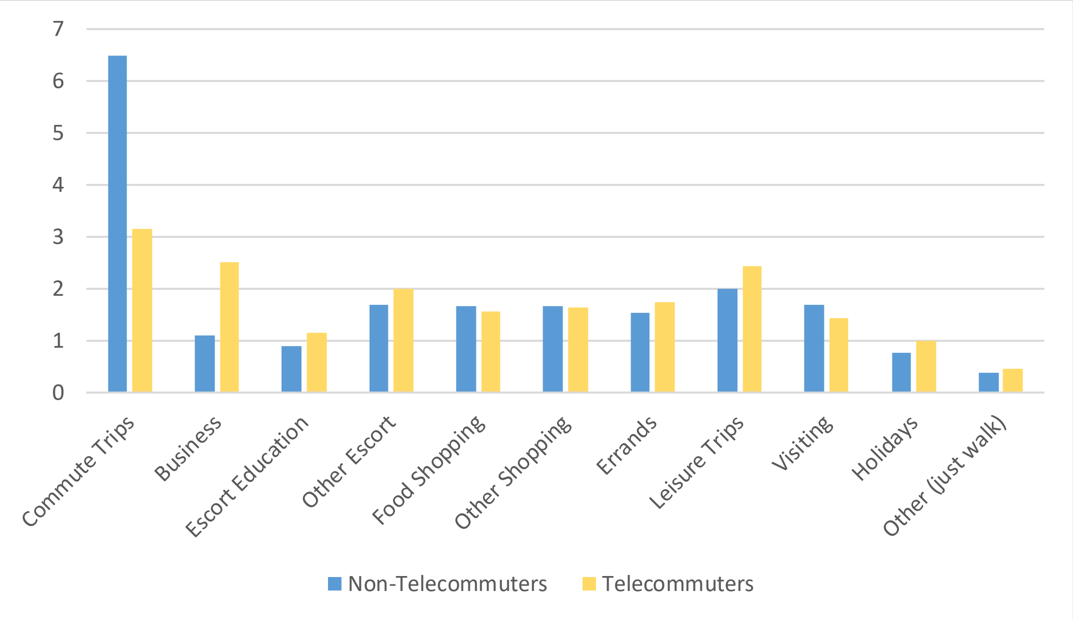

Figure 8.2: Trips per person in the diary week by journey purpose and telecommuting status.

The multinomial logit model supports this conclusion, as Table 8.3 shows that being a frequent telecommuter increases the likelihood of making more trips for non-commuting purposes and does so significantly and at a scale greater than most of the other socio-demographic characteristics across the 10 categories of non-commute journey purpose assessed. The coefficients are log odds, which can be difficult to understand intuitively, so it is useful to transform them using the expression $e^{\beta} – 1$ * 100 to obtain the percentage change in the odds that a switch of status in the binary variable, for example, from a non-telecommuter to a telecommuter, will result in an additional non-commuting trip. We use the term ‘additional’ here, as the intercepts are negative, meaning that in the sample as a whole, if all the independent variables are held at 0, it is more likely that a given trip will be for commuting, which remains the most common journey purpose in a usual week for most working adults. It should also be noted that the transformation of negative log odds result in smaller percentage figures.

Table 8.3: Results from the multinomial logit model for the influence of 2009-2016 NTS individual and household characteristics on the week's travel diary recorded trip purposes. The coefficients in bold are those discussed in subsequent paragraphs with similar / greater effect levels as telecommuting.

	Business	Escort Education	Other Escort	Food Shopping	Shopping	Errands	Leisure	Visiting	Holidays	Other
Telecommute at least weekly	0.696***	0.756***	0.620***	0.516***	0.500***	0.597***	0.593***	0.439***	0.657***	0.639***
	0.014	0.018	0.014	0.015	0.015	0.015	0.013	0.016	0.018	0.025
Full Time not Part Time	-0.042***	***-1.322******	*-0.589****	-0.491***	-0.501***	-0.517***	-0.497***	-0.492***	-0.542***	-0.499***
	0.012	0.011	0.009	0.009	0.009	0.009	0.008	0.009	0.012	0.017
Employee not Self-Employed	-0.102***	-0.307***	-0.073***	0.029**	0.043***	-0.159***	-0.001	0.063***	-0.038***	0.125***
	0.012	0.017	0.013	0.013	0.013	0.013	0.012	0.014	0.017	0.024
Have Regular Workplace	***-1.845******	-0.542***	-0.562***	-0.493***	-0.522***	-0.401***	-0.607***	-0.540***	-0.588***	-0.659***
	0.011	0.015	0.011	0.012	0.012	0.012	0.01	0.012	0.015	0.02
Have Degree	***0.471******	0.047***	0.163***	0.069***	0.107***	0.234***	0.296***	0.008	0.310***	0.061***
	0.009	0.011	0.008	0.008	0.008	0.008	0.007	0.008	0.011	0.016
Male not Female	-0.061***	-0.393***	-0.227***	-0.331***	-0.291***	-0.227***	-0.008	-0.282***	-0.065***	-0.198***
	0.009	0.011	0.008	0.008	0.008	0.008	0.007	0.007	0.011	0.015
Over 40	0.261***	-0.127***	0.249***	0.264***	0.215***	0.187***	-0.097***	-0.243***	0.179***	0.351***
	0.009	0.01	0.008	0.008	0.008	0.008	0.007	0.008	0.011	0.015
Car to work	***0.447******	0.342***	***0.658******	0.274***	0.239***	*0.375****	0.144***	0.313***	0.218***	0.052***
	0.01	0.011	0.009	0.008	0.008	0.009	0.007	0.008	0.011	0.015
Urban not Rural	-0.086***	0.019	0.024**	0.056***	0.046***	-0.057***	0.020**	0.110***	-0.222***	-0.237***
	0.011	0.013	0.009	0.01	0.01	0.01	0.009	0.01	0.012	0.017
Have Children	0.034***	***1.823******	***0.927******	0.208***	0.166***	0.277***	0.013*	-0.060***	0.105***	0.124***
	0.009	0.012	0.007	0.008	0.008	0.008	0.007	0.008	0.011	0.015
Cars Available	0.190***	-0.151***	-0.013	0.209***	0.147***	0.072***	0.211***	0.308***	0.042**	0.256***
	0.017	0.021	0.015	0.016	0.016	0.016	0.015	0.017	0.021	0.031
Income Top Quintile	0.185***	-0.124***	0.043***	0.051***	0.089***	0.130***	0.249***	0.018**	0.219***	0.230***
	0.01	0.013	0.009	0.009	0.009	0.009	0.008	0.009	0.011	0.016
Constant	-0.877***	-1.184***	-1.267***	-1.039***	-0.906***	-0.940***	-0.615***	-0.801***	-1.340***	-2.197***
	0.018	0.021	0.015	0.015	0.016	0.016	0.014	0.016	0.022	0.029
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$									

Once transformed, being a telecommuter makes it 55-115% more likely that a given trip will be for a non-commuting purpose, and the wide range reflects the variation between probabilities for particular journey purposes from visiting friends and family to escorting children to school. The bold, italicised cells in Table 8.3 show which other variables change the odds of making or not making certain trips at a rate similar to or greater than the influence of regular telecommuting, as transformed and highlighted in this and the following paragraphs. For example, after transformation, someone who self-identifies as a telecommuter is 101% more likely to record a 'business' trip rather than a commuting trip compared to a non-telecommuter, whilst someone who has a regular workplace is 84% less likely to record a business trip. The large effect for the latter is unsurprising as the survey categorises all work-related trips for those who do not have a regular place of work as 'business' rather than 'commuting', including trips to visit clients and customers. Since, as shown in Table 8.1, 42% of telecommuters do not have a regular workplace, a large proportion of the effect could be due to this segment of telecommuters. Many of these may also be self-employed. However, a sensitivity test was estimated for only employees with a regular workplace, whether they telecommute once a week or not, and as shown in Table 8.4 the telecommuters in this group were still 88% more likely to record a business trip.

Table 8.4: Results from the multinomial logit model for the influence of 2009-2016 NTS individual and household characteristics on the week's travel diary recorded trip purposes, with only telecommuters (and non-telecommuters) who are employed and have a regular workplace included.

	Business	Escort Education	Other Escort	Food Shopping	Shopping	Errands	Leisure	Visiting	Holidays	Other
Telecommute at least weekly	0.632^{***}	0.894^{***}	0.569^{***}	0.343^{***}	0.254^{***}	0.323^{***}	0.305^{***}	0.559^{***}	0.559^{***}	0.630^{***}
	-0.023	-0.024	-0.019	-0.021	-0.021	-0.021	-0.018	-0.019	-0.024	-0.032
Full Time not Part Time	-0.274^{***}	-1.490^{***}	-0.638^{***}	-0.552^{***}	-0.538^{***}	-0.606^{***}	-0.575^{***}	-0.581^{***}	-0.746^{***}	-0.733^{***}
	-0.016	-0.013	-0.01	-0.01	-0.01	-0.01	-0.009	-0.01	-0.013	-0.018
Have Degree	0.552^{***}	-0.176^{***}	0.118^{***}	0.122^{***}	0.126^{***}	0.251^{***}	0.268^{***}	0.009	0.222^{***}	0.339^{***}
	-0.012	-0.013	-0.009	-0.009	-0.009	-0.009	-0.008	-0.009	-0.012	-0.017
Male not Female	0.024^{**}	-0.245^{***}	-0.179^{***}	-0.330^{***}	-0.300^{***}	-0.227^{***}	-0.020^{***}	-0.276^{***}	-0.069^{***}	-0.141^{***}
	-0.012	-0.013	-0.009	-0.008	-0.008	-0.009	-0.008	-0.008	-0.012	-0.016
Over 40	0.265^{***}	-0.201^{***}	0.260^{***}	0.269^{***}	0.204^{***}	0.121^{***}	-0.089^{***}	-0.252^{***}	0.251^{***}	0.527^{***}
	-0.012	-0.012	-0.008	-0.008	-0.008	-0.009	-0.008	-0.009	-0.012	-0.017
Car to work	0.420^{***}	0.324^{***}	0.627^{***}	0.262^{***}	0.211^{***}	0.420^{***}	0.174^{***}	0.317^{***}	0.027^{**}	0.004
	-0.013	-0.012	-0.009	-0.009	-0.009	-0.009	-0.008	-0.009	-0.012	-0.017
Urban not Rural	-0.321^{***}	-0.041^{***}	-0.033^{***}	-0.044^{***}	-0.035^{***}	-0.150^{***}	-0.022^{**}	0.072^{***}	-0.106^{***}	-0.328^{***}
	-0.014	-0.014	-0.01	-0.011	-0.011	-0.011	-0.01	-0.011	-0.015	-0.019
Have Children	0.129^{***}	1.778^{***}	0.935^{***}	0.205^{***}	0.125^{***}	0.298^{***}	0.045^{***}	-0.086^{***}	0.104^{***}	0.226^{***}
	-0.013	-0.013	-0.008	-0.009	-0.009	-0.009	-0.008	-0.009	-0.013	-0.017
Cars Available	-0.379^{***}	-0.595^{***}	-0.494^{***}	-0.039^{**}	-0.062^{***}	-0.135^{***}	-0.138^{***}	-0.030^{*}	-0.117^{***}	-0.232^{***}
	-0.022	-0.022	-0.016	-0.017	-0.017	-0.018	-0.016	-0.017	-0.023	-0.031
Income Top Quintile	0.309^{***}	-0.063^{***}	0.126^{***}	0.030^{***}	0.025^{***}	0.103^{***}	0.228^{***}	-0.013	0.357^{***}	0.139^{***}
	-0.013	-0.015	-0.01	-0.01	-0.01	-0.01	-0.008	-0.01	-0.013	-0.018
Constant	-2.247^{***}	-1.406^{***}	-1.378^{***}	-1.155^{***}	-1.038^{***}	-1.188^{***}	-0.786^{***}	-0.869^{***}	-1.730^{***}	-2.215^{***}
	-0.022	-0.022	-0.016	-0.017	-0.017	-0.017	-0.015	-0.017	-0.023	-0.032
Note:										$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Having a degree and normally commuting by car also make it over 55% more likely that an individual will take a business trip, probabilities that are maintained even once those without a regular place of work and the self-employed are excluded. The former might relate to the types of jobs that those with degrees have, that require business travel, and the latter may suggest a reverse causal relationship – in other words those that need to travel for business during the working day or on the way to or from work are also more likely to commute by car so that the car is available for these other linked trips. Indeed, a similar connection might be drawn from the odds that those who commute by car are 45% more likely to record trips for 'personal business' or errands as for commuting, as commuting by car allows more trip-chaining. Still, a telecommuter is over 67% more likely to make an additional food shopping trip and 82% more likely to run more errands.

The highest probability of a trip purpose other than commuting being recorded by a telecommuter is for escort education. Again transforming the coefficients, a regular telecommuter is 113% more likely to record this type of trip than one who doesn't telecommute every week. To put this in perspective, someone with dependent children in the household is over 500% as likely as someone without dependent children to travel in order to escort a child to education. The only other characteristic with a sizeable effect on making escort education trips is those within the household who work full-time, who are 73% less likely to make such trips. Together, these coefficients or odds suggest that those with work flexibility, such as telecommuters and part-time workers are more likely to have responsibility for the school run in households with dependent children than adults in the same household with less flexibility. Indeed, as discussed in the literature, the causal effect may be that workers choose to telecommute or switch to part-time work because they have children and caring responsibilities, including escort duties. The results of a sensitivity test looking at those without dependent children in the household in Table 8.5, show these telecommuters only 35% more likely to make a trip for the purposes of escorting someone to education – which could be education trips other than the school run.

Table 8.5: Results from the multinomial logit model for the influence of 2009-2016 NTS individual and household characteristics on the week's travel diary recorded trip purposes, with only telecommuters (and non-telecommuters) without dependent children in the household included.

	Business	Escort Education	Other Escort	Food Shopping	Shopping	Errands	Leisure	Visiting	Holidays	Other
Telecommute at least weekly	0.742***	0.303***	0.604***	0.508***	0.505***	0.610***	0.626***	0.463***	0.630***	0.722***
	-0.018	-0.049	-0.021	-0.019	-0.019	-0.019	-0.016	-0.019	-0.023	-0.03
Full Time not Part Time	-0.065***	-1.678***	-0.487***	-0.412***	-0.461***	-0.513***	-0.486***	-0.434***	-0.535***	-0.437***
	-0.014	-0.021	-0.013	-0.011	-0.011	-0.012	-0.01	-0.011	-0.015	-0.021
Employee not Self-Employed	-0.203***	0.109***	-0.149***	-0.058***	-0.026	-0.241***	-0.074***	-0.034**	-0.094***	0.047
	-0.015	-0.04	-0.018	-0.017	-0.017	-0.017	-0.015	-0.017	-0.021	-0.029
Have Regular Workplace	-1.792***	-0.400***	-0.510***	-0.474***	-0.502***	-0.416***	-0.572***	-0.496***	-0.545***	-0.678***
	-0.013	-0.033	-0.016	-0.015	-0.015	-0.015	-0.013	-0.014	-0.019	-0.024
Have Degree	0.480***	-0.211***	0.049***	0.104***	0.073***	0.240***	0.312***	0.01	0.347***	0.122***
	-0.011	-0.022	-0.012	-0.01	-0.01	-0.011	-0.009	-0.01	-0.014	-0.019
Male not Female	-0.064***	-0.034*	0.096***	-0.235***	-0.191***	-0.086***	0.064***	-0.194***	0.008	-0.102***
	-0.011	-0.019	-0.011	-0.009	-0.009	-0.01	-0.008	-0.009	-0.013	-0.017
Over 40	0.254***	-0.808***	0.494***	0.372***	0.269***	0.271***	-0.177***	-0.205***	0.305***	0.432***
	-0.012	-0.023	-0.012	-0.01	-0.01	-0.011	-0.009	-0.01	-0.014	-0.019
Car to work	0.446***	0.140***	0.727***	0.236***	0.185***	0.319***	0.121***	0.282***	0.183***	0.001
	-0.012	-0.02	-0.013	-0.01	-0.01	-0.011	-0.009	-0.01	-0.014	-0.018
Urban not Rural	-0.063***	-0.015	0.003	0.003	0.034***	-0.142***	0.047***	0.109***	-0.223***	-0.219***
	-0.013	-0.027	-0.014	-0.012	-0.012	-0.012	-0.011	-0.012	-0.015	-0.021
Cars Available	0.202***	0.906***	0.197***	0.168***	0.099***	0.160***	0.201***	0.200***	0.044*	0.155***
	-0.021	-0.05	-0.022	-0.02	-0.019	-0.02	-0.018	-0.02	-0.025	-0.035
Income Top Quintile	0.193***	-0.028	-0.101***	0.019*	0.076***	0.111***	0.209***	-0.016	0.214***	0.157***
	-0.011	-0.024	-0.012	-0.01	-0.01	-0.011	-0.009	-0.01	-0.014	-0.018
Constant	-0.829***	-2.160***	-1.903***	-1.048***	-0.858***	-0.952***	-0.571***	-0.719***	-1.435***	-2.081***
	-0.022	-0.038	-0.02	-0.019	-0.019	-0.02	-0.017	-0.019	-0.026	-0.035
Note:										*p<0.1; **p<0.05; ***p<0.01

Escort duties include more than education too, and almost double the number of trips in the travel diaries are categorised as 'other escort'. Telecommuters are 86% more likely to record such trips than non-telecommuters, and the presence of children in a household increases the likelihood of additional 'other escort' trips by 153%. Those who work full-time are 44.5% less likely to make such trips, whilst those who commute by car are 93% more likely. The latter may be another example of car commuters, whether driver or passenger, not commuting directly, who, as well as making linked trips, may be involved in car sharing, perhaps to adjacent workplaces, or otherwise escorting someone on their commute. Other escort trips do not necessarily involve children, and could be non-child-related care-giving responsibilities that fall to working adults with more locational and temporal flexibility, such as telecommuters. In the sensitivity test without children, telecommuters are still 83% more likely to make an ‘other escort’ trip as non-telecommuters.

Although the size of the effects vary, telecommuting at least once a week has consistent, significant, and relatively large effects on the probability of making additional journeys for all other purposes compared to the reference case of commuting. Conversely, working full time and working in the same place or the same place on at least 2 consecutive days, has a consistently negative, but always significant effects on an individual’s likelihood of recording frequent journeys for any purposes other than commuting. This reinforces the message described in the previous two paragraphs, that people working full time at a regular workplace away from home have the least flexibility, whereas regular telecommuters have a substantial amount of spatial flexibility in terms of where they work, and have more temporal flexibility as well, by freeing up commute time if not in other ways, which allows them to take trips to alternative activities more regularly. In contrast, the model suggests that being an employee or self-employed has less influence on the probability of choosing to make non-commuting trips, which may imply that being self-employed offers less additional flexibility than telecommuting or part time work in a normal week. However, the findings in Chapter 6 suggest that those who are self-employed do make fewer trips during disruption, perhaps because they have more autonomy and a greater awareness of risk than other full-time employees, and act accordingly.

To return to the model in this chapter, those who commute by car, whether driver or passenger, and households with car availability to match the resident adults had a higher probability of recording trips for non-commuting purposes, although that effect was mostly lower than for telecommuters. This could mean that the flexibility that the private vehicle offers an individual or family results in more trips in total, and of all types. However, this chapter does not aim to analyse modal share or vehicle mileage by trip purpose, but rather aims to highlight that telecommuters do make more trips for non-commuting purposes, both in relative and absolute terms, and policy should reflect the need for more non-work destinations to be accessible locally and by sustainable modes. It should not be assumed that travellers do not want to walk. The 'other' category mainly refers to "walking trips for pleasure or exercise along public highways, including taking the dog for a walk and jogging" (Department for Transport, 2017b, *National Travel Survey 2016: Notes and Definitions*: p11). Frequent telecommuters are 89% more likely to make such trips, indicating they not only have the time and perhaps the dog-walking responsibilities, but also the desire to walk along pavements and local streets. Yet they may have insufficient amenities which they are willing to walk a mile or more to reach, and so these walks are not categorised as other journey purposes.

Walks under a mile are excluded from the main analysis, but a brief review of the un-weighted single day of short walk trips recorded in the travel diaries each year between 2009-2015 shows that regular telecommuters not only make more short walk trips per person than those who don't regularly telecommute, but also make more short walk trips for purposes other than commuting, as shown in Figure 8.3.

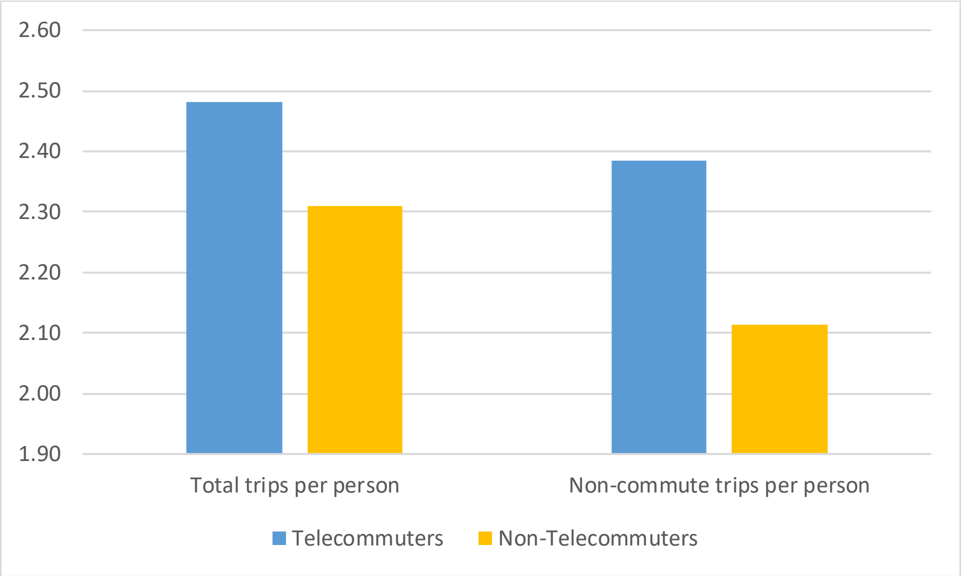

Figure 8.3: One day's short walk trips per person by telecommuting status 2009-2015.

8.4 Discussion and Conclusion

Telecommuting in and of itself may not reduce car travel or increase sustainability. Although regular telecommuting reduces the number of commuting trips that workers make, the willingness of frequent telecommuters to live further from their place of work and to make more journeys for non-work purposes has led other researchers to question whether telecommuting practices result in fewer trips or mileage, or more than a marginal reduction in car travel at the household or even national scale (Gubins et al., 2017; Kim, 2017; Zhu, 2013). Yet even a study sceptical of the sustainability of telecommuting noted that two-worker households with one regular telecommuter appear to make more efficient journeys and redistribute travel to minimise mileage (de Abreu e Silva, 2018). And although no attitudinal data is included in this study, research into residential self-selection indicates that people do want to move to areas where they can drive less, including younger generational cohorts, but this will only be possible if such areas are available to them (Aditjandra et al., 2011; Melia et al., 2018). The density of local shopping and leisure options, as well as the proximity of schools and other escort and business destinations, is more relevant to the travel behaviour of telecommuters than of non-telecommuters, especially if, as one study identified, the difference of travel patterns does not occur on ‘commuting work days’ (Kim, 2017). Thus, accessible, mixed use areas could enable frequent telecommuters, who have time to make more trips for purposes other than commuting, to do so more sustainably.

The purpose of the research in this chapter is to assess the relationship between a common form of online accessibility, namely accessing work activities from home through telecommuting, and the demand of those telecommuters for spatial accessibility to other activities. The accessibility of such activities in terms of distance, transport options, and the convenience of ‘intervening opportunities’ will have a major influence on travel patterns and their resultant impact (Noulas et al., 2012), particularly for telecommuters. Other benefits from telecommuting and flexible working can be achieved with little effort, as fewer peak hour commute trips can result in reductions in congestion, smoother flows, and thus less emissions. Furthermore, if flexible working patterns result in more flexible travel patterns, it can lead to more resilient travel behaviour as more people have an option that is recognised and supported by their employer not to travel during disruption (Marsden and Docherty, 2013).

Through focusing on journey purposes independently of distance or mode of travel, the empirical analysis clearly shows that those who telecommute at least once a week take half the number of commute trips, but more trips for most other purposes. These include business trips to places other than their normal place of work, escort journeys, whether to school or other destinations, errands, and destinations for local leisure and recreation activities. Furthermore, the multinomial logit model estimations demonstrate that the probability of taking more trips for all these purposes other than commuting is greater if an individual frequently telecommutes than for most other socio-economic characteristics tested. Indeed, even where there are stronger effects for other characteristics, such as having no regular workplace on the probability of business trips or the presence of children in the household on the probability of escort trips, the effect of being a telecommuter remains consistently high. Considering that the analysis also suggests that frequent telecommuters are slightly more likely to commute by train when they do go to work, take slightly greater numbers of short walks per person, and a slightly higher proportion live in households with fewer cars per adult, these are not the characteristics of a demographic intent on car dependency. The numbers are small, but significant, and the numbers of working adults who telecommute or otherwise have more flexible working patterns is growing, whilst the number and proportion of commuting trips is in decline (Le Vine et al., 2017).

Therefore, individuals who telecommute replace the commuting time they save on days they work from home not just with longer commute trips when they do go to work, but also with more trips for other purposes. This does not mean they want to spend more time travelling in congestion for those trips, nor are all those trips likely to be by car. In fact, frequent telecommuters appear to favour walking, as they not only make additional short walk trips per person, but also are 89% more likely to make trips over a mile in the 'other (just walk)' category. This has major implications for future transport and land use planning policy and the environmental impact of transport. A narrow focus on housing numbers, mobility technologies, or a traffic-based 'predict and provide' approach will not deliver a sustainable future (Marsden et al., 2018). There are many studies that highlight the benefits of mixed use development with residential densities that support accessible, local amenities (Banister, 2008; Headicar, 2015). This chapter provides additional evidence by considering how telecommuting practices also support the drive to plan for accessible neighbourhoods. Similar to other current technological trends, telecommuting will only enable sustainable, resilient communities if planning takes an active role in ensuring that result.

9. CONCLUSION

The overarching research objective of this thesis was to investigate the opportunities that improving ICT and increasing space-time flexibility create for commuters and other travellers to respond to severe weather, risk, and transport disruption. Previous research suggests that work-related travel is the least responsive to transport disruption or risk of disruption and delay, compared to travel for other purposes (De Palma and Rochat, 1999). This is because work is still the central activity around which most employed adults plan their daily schedule, despite the trend in the UK towards fewer regular commuting trips, which in turn is partially due to ICT and the increasing space-time flexibility it offers for activities such as telecommuting (Le Vine et al., 2017). Meanwhile, the literature on telecommuting tends to ignore the resilience aspect and potential of remote work and online access. Reviews of the costs of severe weather events also discount the potential of remote working and telecommuting, assuming a loss of productivity corresponding to a daily commuting 'average' (Chatterton et al., 2016). These gaps and oversights were the initial focus of the research that resulted in this thesis, originally entitled '(Tele)commuting, Cities and Weather Conditions'. Although the research aim and objectives expanded to encompass other interactions between travel choices, internet accessibility, and extreme weather, this thesis describes and in some ways quantifies the resilience potential of access behaviours like telecommuting and other online activity.

Resilient responses are more a matter of accessibility than mobility because the key metric is whether affected travellers are still able to participate in activities as planned, even if they cannot use a particular transport service to travel to a particular place. Thus, maintaining accessibility during disruption involves choices of mode, route, and timing of travel, as well as any alternatives or flexibility in where, for how long, and how often activities are undertaken. The more access options available, the more potentially resilient an individual or community will be. Since the variety and quality of transport and ICT options available during a severe weather event is dependent upon the geographic and socio-economic characteristics of particular groups in particular places, secondary data sources and quantitative methodologies were used to measure differences in space-time flexibility and accessibility. The findings therefore provide insights into the wider role ICT have to play in increasing resilience by providing information about disruption or alternatives and by enabling online accessibility to work activities and other goods, services, and social interactions. The research also highlights the priority given to work purposes, and the commensurate reduction in accessibility to other activities. The overarching conclusion is that if policy actions can improve space-time flexibility through increasing internet accessibility and transport alternatives to more geographies and socio-economic groups, the result will be more resilient and sustainable access choices during extreme weather.

9.1 Summary of Main Findings

This thesis is as much about identifying the potential capability of commuters and their households to be more resilient in severe weather as it is about understanding whether they are already taking resilient actions. Both the literature review and empirical analyses confirm the importance of work activities to the organisation of daily travel, and also provide evidence that the robustness of ICT infrastructure, and the increasing space-time flexibility of working patterns offer significant opportunities for commuters in particular to make more resilient access choices and maintain productivity even where they cannot get to work or caring responsibilities, e.g. due to school closures, keep them home. Furthermore, if resilience is viewed as an integral part of sustainability, online access and flexibility of access have a greater role to play than is often highlighted in research on 'sustainable travel' and how it can mitigate climate change through the reduction of greenhouse gas emissions. As discussed in Chapter 3, ICT can increase the knowledge available on travel, destination, and activity choices where available, as well as offer online access as an independent choice. In order to analyse the breadth of interactions between internet accessibility and travel choice, a number of data sources informed the empirical chapters. These include electronic ticketing transactions, mobile phone network data, broadband speed data, weather records, and the National Travel Survey, along with a variety of complementary data to control for socio-economic and geographic characteristics.

Due to the use of secondary data sources throughout this research, which are not designed to capture perceptions, the empirical chapters cannot answer whether a proportion of commuters and other travellers take heed of weather warnings and if this is the reason they work or access other activities from home. Nor have any surveys been undertaken to measure the level of awareness among commuters and other travellers of the risks described in section 2.2, namely that delays, lost productivity, personal and property damage during travel are all more likely during extreme weather. Transport authorities are aware of these risks but assume travellers are not; as mentioned in section 2.1; they calculate the welfare costs of severe weather events by assuming that any delay and disruption affect all those who would 'normally' be on the network, as based upon traffic models calibrated to the 'average' day.

Yet Chapters 5 and 6 indicate that people who have spatial flexibility, in that they have alternative means to access workplaces or work tasks, or who have temporal flexibility, such as part-time workers, are more likely to change their behaviour during extreme weather events. Both chapters therefore meet research objectives a) and b). Specifically, in Reading, employees used a Park and Ride service in the outbound direction to access a local business park, rather than waiting for a severely delayed or cancelled train. In the West Midlands, residential areas with higher proportions of part time and self-employed residents were more likely to generate fewer trips under storm conditions. Furthermore, whilst a similar number of trips were taken overall, significantly more of these were direct commuting journeys, indicating a reduction in linked trips and a switch in journey purposes, a choice underrepresented in previous studies and thus meeting research objective c). Chapters 5 and 6 also demonstrate that the presence of certain socio-economic groups is associated with staying at home under storm conditions, and whilst the bus data in Chapter 5 indicates these cancelled trips are more likely to be discretionary ones made by the elderly, Chapter 6 suggests that self-employed workers may well be choosing to telecommute.

The potential for online access to replace travel and reduce travel risk during disruption is investigated in the most detail in Chapter 7, which describes how internet activity increases during both the storm periods chosen as case studies in Chapters 5 and 6, and also more broadly during adverse weather as defined by a broad set of parameters in Chapter 7. The uncertainties of using weather parameters in the models estimated in Chapter 7 rather than known impacts and the inability to ascertain whether the increased internet activity is due to telecommuting are both acknowledged, but the focus is on research objectives b) and c), rather than a). Furthermore, the novel approach to analysing broadband speed data does offer evidence of the relationship between ICT, weather and travel risk. Internet activity increases in adverse weather, and where post-storm surveys have been administered as discussed in section 3.2, respondents indicated an increase in telecommuting and temporally flexible working or commute choices.

However, as also discussed in section 3.2 and further in section 8.1, the literature on telecommuting questions the sustainability of the practice if regular telecommuters travel further to work and business when they do work outside the home and also make more non-work trips. Therefore, Chapter 8 seeks to challenge this framing of regular telecommuting as unsustainable, not only because of its resilience potential as frequent telecommuters are empowered to stay at home during extreme weather, but also because of its potential to enable more non-work journeys by sustainable modes. Indeed, whilst the analysis in Chapter 8 supports the hypothesis that telecommuters make more non-work trips, it suggests that these are not automatically by car, as telecommuters are more likely to commute by train and make more trips per person on foot, even if the latter may not be for purposes of access to goods and services. By using a quantitative methodology which can interrogate the influence of geographic and socio-economic characteristics, as in research objective b), this chapter thus offers significant insights into telecommuting as a potential resilient response, thus meeting objective c). The implication is that telecommuting enables the temporal flexibility to dedicate more time to travelling sustainably, but not always the spatial flexibility if neighbourhoods are not designed to accommodate accessibility to non-work destinations. Redesigning neighbourhoods to improve access to more activities than employment would also assist those who cannot telecommute and therefore prioritise work journeys during severe weather events, as found in Chapter 6, when there was reduced accessibility to ‘other’ activities if they were not available close to home.

9.2 Policy Implications

If telecommuting is to result in not only a redistribution of motorised travel, but also less motorised travel in total, more attention must be given to the accessibility of land uses, activities and journeys other than the home to work commute. According to the NTS, the proportion not only of telecommuters, but also other workers with spatial and / or temporal flexibility is increasing in the UK. This increases the variability of work trips, leading to the decline of the traditional or 'average' commute, and thus the importance of non-work travel. The planning and policy implications are to invest in walkable neighbourhoods with well-dispersed basic services and amenities that can support more active travel, as well as road layouts and street design that physically prioritise such modes within what might traditionally be considered the 'first / last mile' from people's homes (Banister, 2008; Tight et al., 2016). Key amenities, such as post offices, which are currently centralised in commercial areas should be integrated into residential areas to enable greater access to important activities from home, rather than work. This would reduce the need for work-based trip chaining, and make neighbourhoods and communities with less flexibility more resilient to severe weather and other disruptions. It is often possible to walk if other modes are unavailable, and regular, but less frequent activities (e.g. food shopping) can be more easily maintained.

In the West Midlands in June 2016, it was not the location of disruption so much as who was travelling, what amenities were available to them, and where they lived and worked which influenced their spatial and temporal accessibility so as to create a significant pattern of change in travel by journey purpose. This has implications for understanding resilient accessibility behaviours that are separate from the physical constraints of travel and impacts on infrastructure. Issues such as land use, urban form, working patterns, investment in enabling ICT, and community engagement all demand consideration. Denser urban areas with better fixed and mobile internet access, more transport alternatives, and more opportunities for multiple activities in close proximity offer many more options in terms of accessibility and therefore resilience, as well as various co-benefits in terms of social equity and environmental sustainability. Indeed, whilst the resilience of transport infrastructure may continue to be the purview of transport engineers, transport planners must consider the sustainability of travel behaviour, or more accurately, 'access' behaviour from the point of view not only of mitigating climate change, but also adapting to an uncertain future of more frequent weather extremes and other disruptive events.

One option is to introduce flexibility between travel options or for work access as part of emergency or contingency planning separate from any policy proposals developed as part of a strategic sustainable transport package. For example, following Storm Doris and a few subsequent, unplanned disruptions to the public transport network through Berkshire, Reading Buses came to a formal agreement with the main train operator, First Great Western. Although separate business models have made a fully integrated ticketing system difficult to negotiate,[19] the bus drivers know to accept rail tickets on the buses whenever they are informed of disruption to the relevant train services, and the operators have agreed reimbursement terms. Similar contingency plans could also be arranged between policy-makers and employers, particularly those in business parks, industrial areas, and other places with high workplace population densities, to encourage and enable more employees to connect remotely if it is the

[19] Other than 'PlusBus' a nationally recognised and organised scheme for rail passengers who indicate they will need onward bus travel at the time they purchase their rail tickets. Reading is one of the 'top destinations' for PlusBus according to the scheme's website https://www.plusbus.info/home accessed 5 October 2019.

most resilient and least risky choice, such as when an area is under weather warnings. In the United States, statutory telework arrangements as part of federal government emergency planning meant that a third of employees worked remotely during Hurricane Sandy in 2012 (Allen et al., 2015). Although such measures could be less effective in a region with more than the average proportion of manufacturing or retail / hospitality jobs, if employers are invested in providing such options to increase flexibility and maintain accessibility, then traveller responses in times of disruption could be more proactive no matter the nature and timing of the disruptive event. Employers may even be able to measure how well such policies maintain productivity and business continuity during extreme weather events by monitoring and managing online work activities.

Indeed, as transport and ICT technology become more interwoven, and as economic and social behaviours become more flexible, policy decisions are usefully supported by evidence of the internet's ability to overcome traditional time and space constraints, and make planning for and investing in the weather resilience of such technology, including bandwidth, more efficient and effective. This thesis adds insights into the temporal variability of online access and quality of service to the existing literature that focuses on the demographic and spatial inequities of ICT penetration and levels of service (Blank et al., 2018; Philip et al., 2017; Riddlesden and Singleton, 2014). Some of the temporal variability is due to supply side issues, such as bandwidth and redundancy. These issues can overlap with identified spatial inequities, such as in rural areas where there is less choice in connection technologies and especially in those which are robust in adverse weather. Supply side temporal vulnerabilities can also be highly localised, such as where the location of ICT infrastructure is susceptible to flooding or likely to be exposed to lightning strikes or fallen trees. Other temporal variability is due to demand, including the issue of contention analysed in Chapter 7, which, to my knowledge, has not been previously researched in this context.

The policy implication is that proposals to improve the country's digital networks should explicitly consider temporal as well as spatial and demographic 'digital divides' and address these in an integrated fashion. The capability to use ICT is not universal and the option, opportunity, preference, and practice of online access is not available consistently in time or space or across socio-economic groups. However, as local governments around the UK develop strategies to bridge digital divides or better connect rural areas to superfast broadband, these strategies should take account of the potential of different connection options to suffer from contention or be vulnerable to irregular events like storms due to their location.

9.3 Future Research

Therefore, the policy implications of this work are as much to do with addressing the inequity of access to ICT, particularly with reference to the findings on temporal variability of access and flexibility of working patterns, as they are about planning transport access and preparing for extreme weather events. Further research into patterns of broadband services in all their spatial and temporal granularity could uncover additional patterns in the interaction between spatial and temporal quality of service levels. It could be enlightening to assess different urban, suburban, and rural geographies with different weather thresholds applied for different seasons and during holiday periods, rather than working days. It may even be possible to predict the impact of weather on broadband speed and availability, thus enabling improved messaging to the public around weather risks and their options for response in real time, including going ‘online’.

To develop such tools, it would be useful to have a complete set of data on internet and travel access, but a major limitation on this type of research is data availability: when, from whom, for how much, in what format, and in what way pre-processed. For example, in neither of the case studies described in Chapters 5 and 6 were data available on the full range of movements during the severe weather events. The electronic bus ticketing data in Reading obviously only allowed analysis of movements by a single mode, although at the most detailed level of temporal and spatial granularity for that mode. The MND provided a greater breadth of movements, including all trips by regular customers by whichever mode, even if undefined. However, many short trips were likely overlooked, the only specified trip purpose was commuting, and the spatial and temporal granularity was much more limited. Both case studies therefore captured a proportion of changes in travel behaviour, but not the full range. The changes identified fill some gaps in the literature, such as using electronic ticketing data to describe what occurs during a storm on public transport run by different operators rather than changes in daily travel for a single operator in response to normal weather variations. However, other aspects of travel response are still left unstudied.

One gap is consideration of active travel during extreme weather. The literature indicates that rain, wind, and certain temperature bands induce modal switch away from walking and cycling to more sheltered transport, but there is no consideration of whether this pattern still applies during storms or flooding, when walking and cycling routes may be more passable or less damaged than other infrastructure. Further research in this area would be useful to add to the adaptation side of the sustainability debate and the potential co-benefits between designing for resilience as well as mitigation.

Furthermore, if multiple big data sources offering spatial and temporal granularity were available for a particular case study that included a period of weather disruption, it might be possible to understand the influence of the time of day and the location of impacts on transport, other infrastructure, and service availability on all modes of travel / online accessibility behaviour. Additional case studies would help highlight whether locally-specific characteristics of a city's infrastructure or its population are significant to the resilience of that community. Combining data sources could enable more research into the accessibility choices available in a particular place. For example, the data sources used in Chapters 6 and 7 together show which MSOAs, with a population density between 1,000 and 15,000 persons per square kilometre and a median area of 2.17km^2, have a reasonable level of both online access and access to key non-work services:

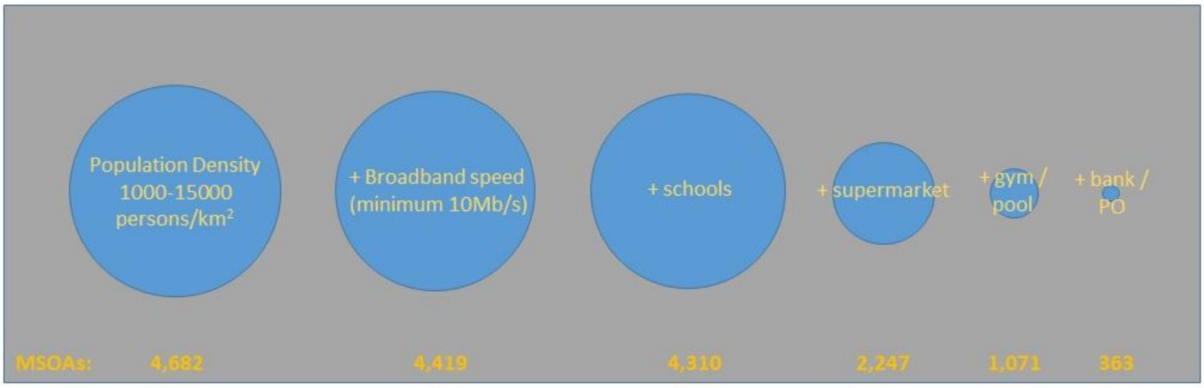

Figure 9.1: The diameter of the circles is scaled by the number of MSOAs populated by between 1,000 and 15,000 people per square km, plus which have median broadband speeds of at least 10Mb/s in 2016, plus the presence of at least one of each common amenity within the MSOA. The land uses are geo-located using crowd-sourced data from OpenStreetMap (Geofabrik GmbH, 2017).

If a survey-based or qualitative approach were added to this sort of analysis, it would improve understanding of local perceptions of accessibility to non-work destinations from residential neighbourhoods, the importance of those destinations to personal resilience, and trade-offs between journey purposes. More insights might be garnered on these questions from the National Travel Survey as well, by looking at different types of flexible workers and their patterns of non-work travel. With insights into which activities should be prioritised to provide more robust access or more access options, and whether online access is an option likely to be chosen for certain activities, it would become possible to map accessibility in new and more precise ways, rather than the rough estimations in Figure 9.1. Also, as all the empirical analysis in this project is focused within the UK, future research might investigate whether the insights apply in other countries and cultures. The analysis in this thesis aims to provide meaningful insights, but also highlights the many directions for future research.

In conclusion, the results and policy implications of this research project are all about the need for integration. Integrate policies for adaptation with those for mitigation to make travel behaviour more sustainable and realise co-benefits. Integrate ticketing and increase the transport modes available for redundancy. Integrate transport access with ICT access. Replace spatial and temporal barriers to travel and online access with quality services and infrastructure that can meet irregular demand. Increase and proactively plan for the varied spatial and temporal flexibilities available to commuters during disruption. To summarise, current and emerging trends in space-time flexibility, which are characteristic of the digital age, do offer opportunities to expand the access options available in extreme weather or during other disruptions, and to reduce their economic and social impact. To take advantage of these opportunities and induce more resilient responses to transport disruption and risk, sustainable policy must take an integrated approach to travel choice and internet accessibility.

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