

Title: **Responding to stormy weather: Choosing which journeys to make**

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Abstract:

This paper uses Mobile phone Network Data (MND) to analyse accessibility and how economic status and neighbourhood-level characteristics influence travel purpose priorities during two working weeks of multiple thunderstorms and incidents of flash flooding in June 2016 in the West Midlands, UK. Individuals and groups face different challenges in accessing employment, goods, and services depending upon their socio-economic position and where they live, work, and visit. These challenges can increase at times of severe weather, and offer an explanation for some changes in travel behaviour, beyond specific disruptions to transport services or infrastructure. Inspection of the MND used in this study indicates that the total number of trips taken under storm conditions is not dissimilar to the non-storm control period, but that there were significantly more commuting trips, or direct trips between home and work, and fewer trips between home and other destinations. By using MND to analyse the differences in trip purposes from / to different neighbourhoods, this paper discusses how population and land use characteristics enable more or less flexible and resilient accessibility under storm conditions, and explores the implications of changes in trip frequency and purpose, particularly the prioritisation of work journeys during an extended period of disruption.

Introduction

Severe weather events are occurring more frequently, and their impacts are not evenly distributed geographically. The UK has been identified as being at risk of more frequent coastal and river flooding, storm surges and more intense storms, with potentially increased infrastructure damage and disruption due to wind, lightening and pluvial flooding (Brown et al., 2014; Kovats et al., 2014; McColl et al., 2012). Yet whilst reviews of storm and flood events aim to identify and quantify the impacts and risks to infrastructure and assets due to their location, environment, use / load, and management (e.g. Chatterton et al. 2016; Jaroszweski et al., 2015), the patterns of public response to the transport disruptions caused by severe weather have often been ignored (Mattson and Jenelius, 2015). It is an understanding of this interaction of transport services with human behaviour that helps determine what combination of physical (re)design of transport systems and strategies of mitigation, coordination, and communication offer effective means of adaptation and response in specific geographies, particularly to sudden, unplanned weather impacts (Cox et al., 2011; Jaroszweski et al., 2014; Rogers et al., 2012). To assist in developing this understanding, this paper considers how neighbourhood geography and socio-economic obligations influence the resilience of travel behaviour and reactions for commuting and other trips.

Socio-economic characteristics such as gender, household structure, age, economic status, education, and income; and geographic characteristics like density, distance, and built form have all been shown to influence travel behaviour and the accessibility of different communities or groups of individuals (Hincks et al., 2018; Lovelace et al., 2014; Noulas et al., 2012). Analyses of these characteristics in parallel with changing travel patterns helps to explain why factors mainly external to transport operations are resulting in recent trends such as the decline in regular commuting trips, the increase in flexible working, the increase in time spent at home, and the substitution of technology to access activities (Chatterjee et al., 2018; Goodwin, 2012; Headicar and Stokes, 2016; Le Vine et al., 2017). Yet work remains an ‘anchor point’ for much of the employed population, a temporal constraint requiring a ‘non-discretionary’ journey within a concentrated timescale around which other daily travel is organised (Le Vine et al., 2017; Miller, 2005). Thus, more recent studies and methods measuring the accessibility to work and other activities for individuals and groups with different characteristics take account of variations in both space and time (Järv et al., 2018; Lee and Miller, 2018; Miller, 2005; Schwanen and Kwan, 2008). The importance of temporal flexibility, or lack thereof, is accentuated by severe weather events and the pressure extreme weather exerts upon the reliability of travel options, resulting in variation in the ability and capacity of people to avoid or minimise delay, disruption, and risk to personal safety and property, and maintain access to activities, especially work.

In extreme weather, there is a recognition that levels of resilience depend upon “intensity of use, the availability of alternatives and the economic importance of the route or service” (Brown et al., 2014, p.9). There is an understanding among some policy-makers that 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., 2016; Dawson et al., 2016). In other words, the level of risk and disruption will depend upon who lives, works, visits or travels through geographically distinct areas during the weather event. A flash flood on a country lane will clearly 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. Thus, 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. This impact is further increased when the nature of the weather event leaves little time for proactive planning, affecting the accessibility of not just

commuters, but other travellers and consequently the likely production or attraction of trips to / from different areas of origin / destination.

Using revealed preference survey techniques, previous studies of the impact of severe weather events on travel behaviour in the UK and the United States identify a variety of ways individuals avoid the disruption and still engage in activities such as work, depending upon the location and timing of the impacts (Kaufman et al., 2012; Marsden et al., 2013; Marsden et al., 2016). These include changing the time, route, or mode of travel, changing the destination, postponing or cancelling the trip, and potentially replacing physical travel with online access. Wider surveys of weather conditions over time, such as studies in Switzerland, Belgium and the Netherlands, indicate that 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). Changing modes is prevalent in specific scenarios, for example, if it is too cold or wet to cycle, and snow is the most likely reason for trip cancellations, although such shifts are moderated by cultural and climatological context, such as in the Netherlands where cycle mode shares are high or in Finland where heavy snow is common (Böcker et al., 2013; Cools and Creemers, 2013; Kilpelainen and Summala, 2007; Koetse and Rietveld, 2009; Sabir et al., 2010). Other studies have indicated that traveller reactions to weather are least variable during the morning commute, more variable in the afternoon, and most variable on weekends (Arana et al., 2014; Horanont et al., 2013; Singhal et al., 2014). There is evidence that people are most likely to choose alternatives with which they are already familiar, such as switching routes or public transport services, whilst responses such as compressed hours or telecommuting to reduce overall travel may become more widespread only when disruption is longer-term and / or there is substantial advance warning (Chorus et al., 2006; Marsden et al., 2016).

Although these diverse studies offer insights into individual perceptions and choices, and are indicative of the capacity for resilience, survey techniques lack the spatial breadth 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. In contrast, newer, 'big data sources' such as Mobile phone Network Data (MND), social media, and GPS-based location services provide opportunities to capture larger samples with minimal cost (Arribas-Bel, 2014; Lovelace, 2016; Miller, 2005; Wang et al., 2017). These data sources are particularly useful in identifying the reaction to irregular events, such as severe weather, which affects not only the resilience of transport infrastructure, but also the accessibility of opportunities to work or engage in other activities. By their nature, sudden, unplanned disruptions can only be considered in retrospect, and whilst surveys of those affected might provide greater insights into individual perceptions and reasons for choices, they are limited in breadth. Conversely, MND is ideally placed to enable quantitative analysis of the extent of changes in accessibility to both work and other purposes, and the influence of neighbourhood geography and socio-economic obligations on these patterns.

This paper uses MND to analyse 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 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.

Materials

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 due to unusual circumstances or irregular events (Becker et al., 2013; Isaacman et al., 2011; Steenbruggen et al., 2015). The main data used in this paper 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 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.

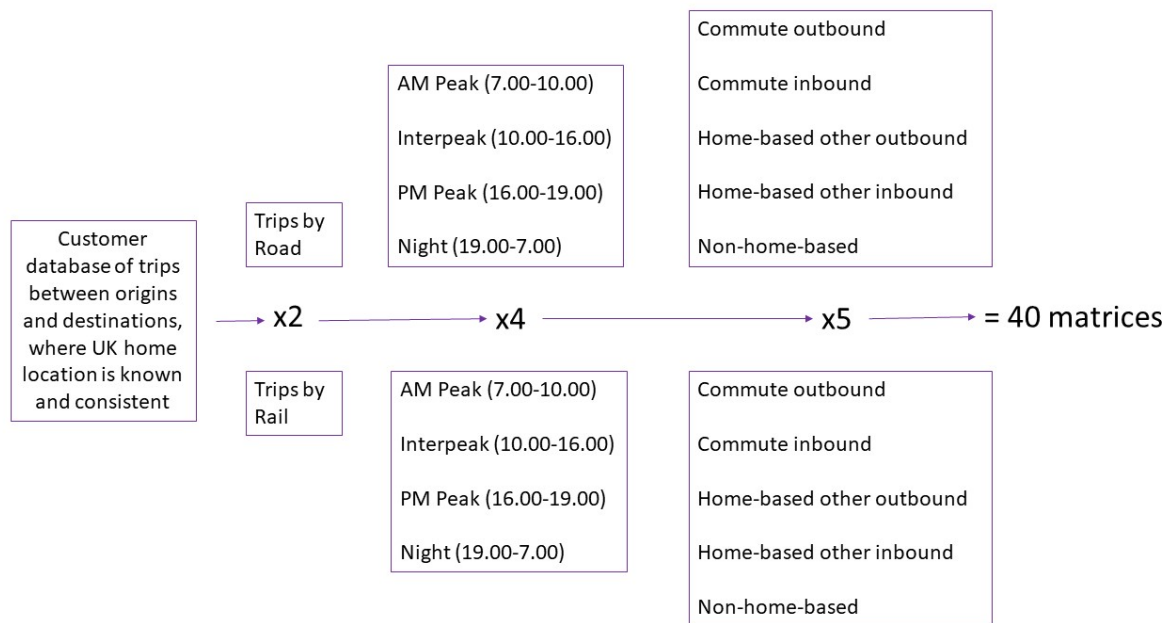
Within the available dataset, a period of thunderstorms and flash flooding in June 2016 centred on Birmingham, UK offered an opportunity to assess the influence of geographic and socio-economic characteristics on travel choices, particularly which journeys are prioritised in these reactive circumstances. 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 paper 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 phones¹ 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 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.

Figure 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

¹ 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.

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, 2017). 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 paper 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 2a: Study Area

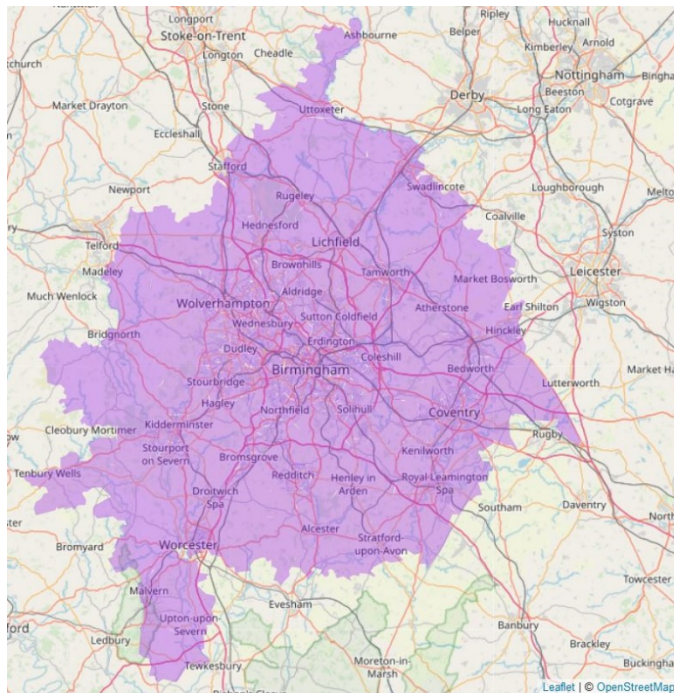
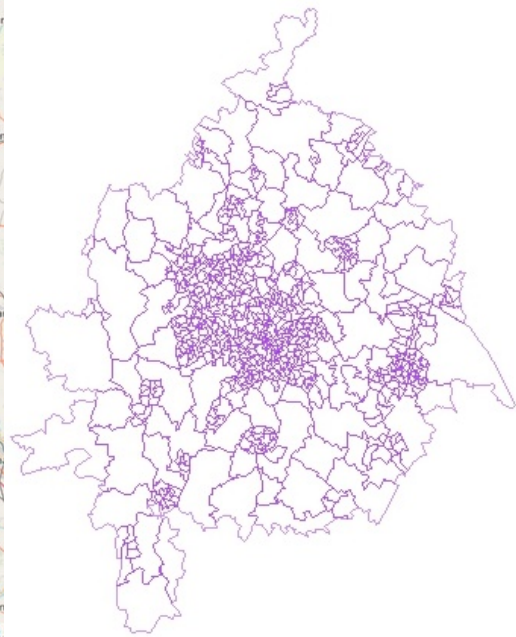


Figure 2b: Outlines of MSOAs in study area



The study area is depicted in Figure 2a, and extends beyond the major conurbation to encompass surrounding towns and also more rural areas. Figure 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 paper 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 platform² 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 paper 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 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 3.

Methods

In order to explore and model the patterns in the data described in the Materials section, further aggregation was required. The MND was provided in two sets of 40 matrices as shown in Figure 1. Each matrix comprised of 328,329 (or 573²) 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 the Results II section. 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,

²© OpenStreetMap contributors, licensed under the Open Database Licence. Information on this and the map tiles used in Figure 2a can be found at <https://www.openstreetmap.org/copyright>.

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 (1) and (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.

$$\begin{aligned} \text{Non-Storm Day Trips}_i - \text{Storm Day Trips}_i = & \text{Residential Population Density}_i + \text{Food Shopping}_i + \\ & \text{Personal Business}_i + \text{Ratio of Part-time Employees}_i + \text{Ratio of Self-employed}_i + \\ & \text{Ratio of Retired Persons}_i + \text{Personal Business}_i : \text{Ratio of Retired Persons}_i + e_i \end{aligned} \quad (1)$$

$$\begin{aligned} \text{Non-Storm Day Trips}_j - \text{Storm Day Trips}_j = & \text{Workplace Population Density}_j + \text{Personal Business}_j + \\ & \text{Ratio of Self-employed}_j + \text{Personal Business}_j : \text{Ratio of Self-employed}_j + e_j \end{aligned} \quad (2)$$

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 the Results I section, but excluded from the statistical analysis. The various time periods are considered in the Results II section, 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 1. Those for the destination estimations are shown in Table 2. All descriptive statistics are the mean values and ranges by MSOA. The trip differences are as described in equations (1) and (2), whilst density and amenity statistics are numeric and socio-economic statistics are ratios.

Table 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 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%

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 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 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 paper: 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 the third results section.

Figure 3: Differences in total home-based trips by road for each Origin MSA; 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.

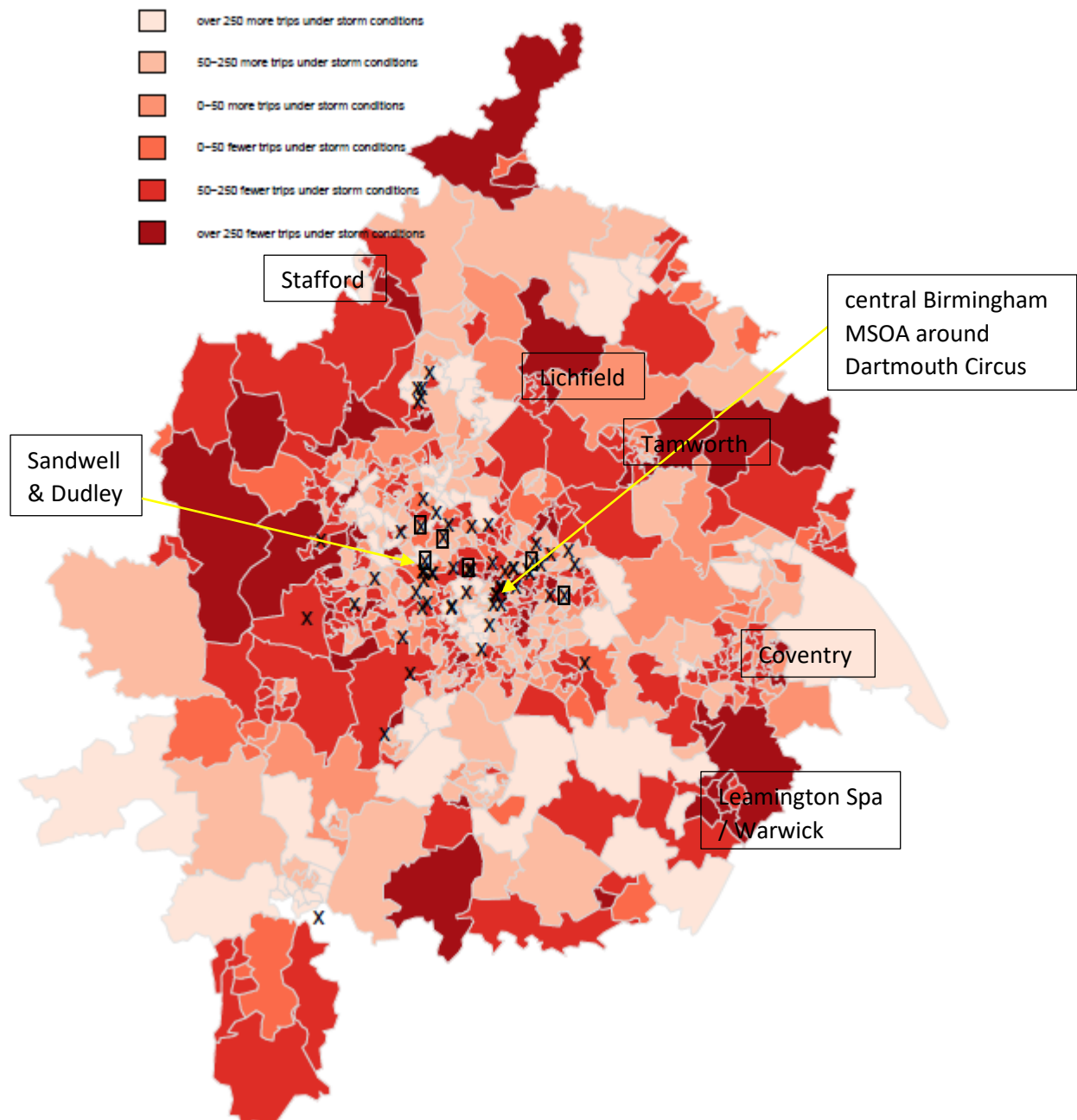


Figure 3 does show that a number of areas with the greatest reduction in road trips under storm conditions are around the West Coast mainline stations of Stafford, Lichfield, Tamworth, Coventry, Sandwell and Dudley, and around the busy station at Leamington Spa, raising the question of modal

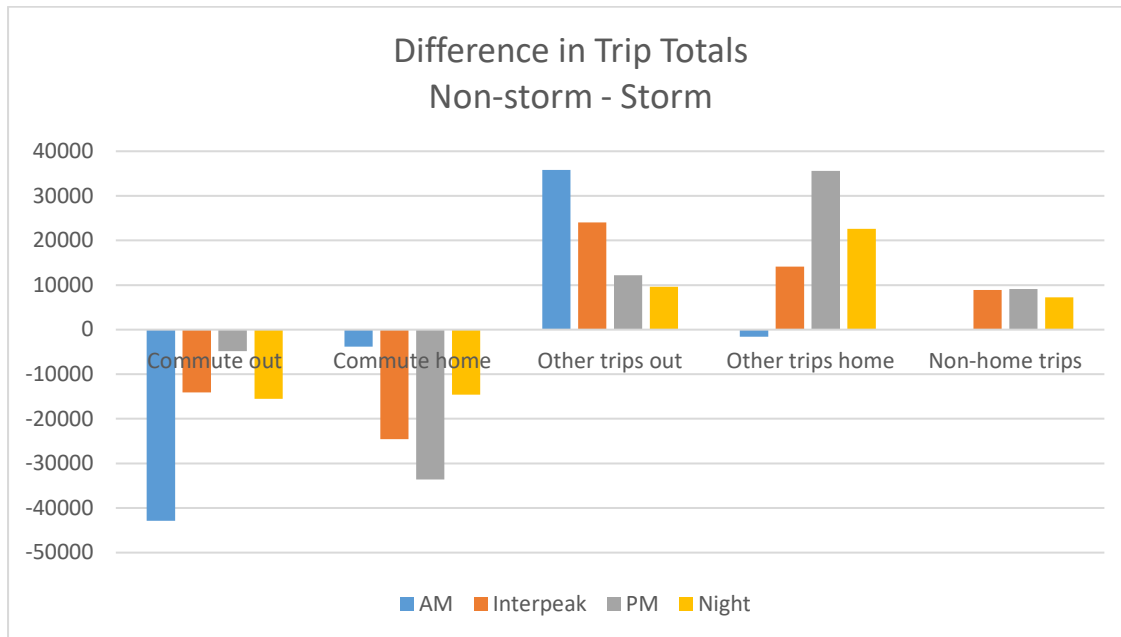
switch from road to rail. According to the media reports, inter-urban services and the West Coast Mainline appear to have been minimally affected, although certain local services to places such as Rugeley Trent Valley and Stourbridge Junction were subject to delays, cancellations and replacement bus 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. However, 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.

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 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 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; Sabir et al., 2010). 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 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.

Results III: Modelling Origins and Destinations

Tables 3 and 4 show the results for the final model estimations for the MSOAs as origins and destinations respectively, as shown in equations (1) and (2). Multiple combinations of all the independent variables listed in Tables 1 and 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 3: Regressions for Origin MSOAs as equation (1)

Origin MSOA Variables	Difference in Commute Trips by Road	Difference in Home-based Other Trips by Road
<i>Residential population density</i>	0.032*** (0.004)	
<i>Food shopping</i>	-9.759** (3.907)	16.582** (6.517)
<i>Personal business</i>	-88.288*** (7.654)	102.822*** (12.543)
<i>Ratio of Part-time Employees</i>	1,838.477*** (412.780)	
<i>Ratio of Self-employed</i>	847.197*** (265.903)	
<i>Ratio of Retired Persons</i>	1,047.154*** (214.110)	-236.091 (253.889)
<i>Personal business : Ratio of Retired Persons</i>	415.915*** (63.848)	-529.202*** (106.310)
<i>Constant</i>	-816.007*** (63.310)	249.893*** (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 4: Regressions for Destination MSOAs as equation (2)

Destination MSOA Variables	Difference in Commute Trips by Road	Difference in Home-based Other Trips by Road
<i>Workplace Population Density</i>	-1.952***	3.474***
	(0.335)	(0.577)
<i>Personal business</i>	-62.462***	54.658***
	(8.755)	15.054
<i>Ratio of Self-employed</i>	638.998***	-322.363**
	(74.652)	(128.359)
<i>Personal Business: Ratio of Self-employed</i>	297.675***	-200.185*
	(64.671)	(111.196)
<i>Constant</i>	-346.173***	263.257***
	(16.187)	(27.833)
Observations	573	573
R ²	0.466	0.267
Adjusted R ²	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)
<i>Note:</i>	* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$	

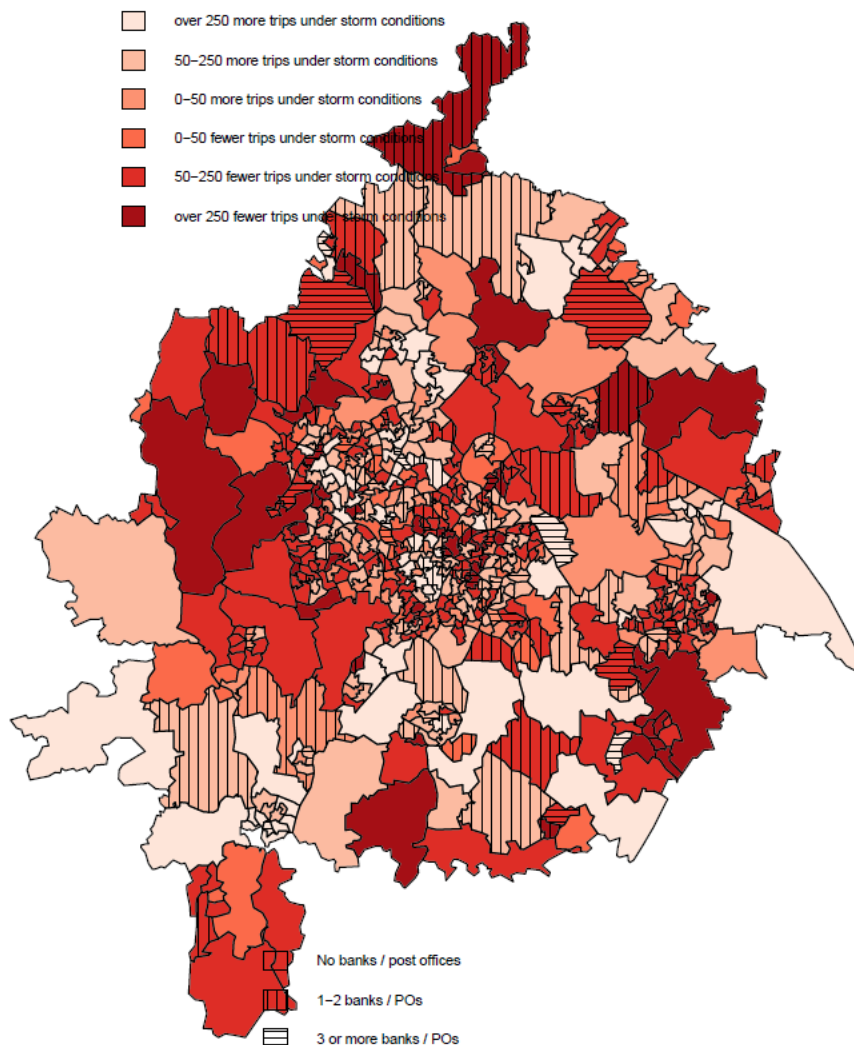
These tables reinforce the conclusions of the Results II section, that the influence of geographic and socio-economic characteristics on travel behaviour response vary most between commute trips and other home-based trips. Every coefficient that is positive for commute trips is negative for other trips 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 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 5 as from Figure 3. Thus, the presence of amenities such as banks and post offices may relate more to who is making trips to use such services, rather than their location.

Figure 5: Density of personal business amenities (banks and post offices) in the study area as hatching over differences in total home-based trips by road for each Origin MSOA as in Figure 3.



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.

Discussion and Conclusion

This paper 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). 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, Results sections II and III 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 recent 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 paper 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, but future research could benefit from either using other data sources in combination with MND or incorporating into surveys more questions about a wider variety of journey purposes, the priority given to work activities, the accessibility of non-work destinations, the importance of those destinations to personal resilience, and trade-offs between journey purposes.

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. However, 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 or to destinations without disruption. Therefore, the more flexibility in time and space that can be attached to different journey purposes, the more resilient the travel behaviour response could be, especially where the disruption is not constant nor long-term.

As this paper 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. Thus, employers, particularly those in business parks, industrial areas, and other places with high workplace population densities, might be encouraged to consider putting in place proactive measures maintain productivity and business continuity, such as enabling telecommuting when an area is under weather warnings, although this could be less effective in a region with more than the average proportion of manufacturing jobs (ONS, 2019). Still, 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). If employers are invested in providing such options to increase flexibility and maintain accessibility, then traveller responses in times of disruption would be more proactive rather than reactive no matter the nature and timing of the disruptive event.

Another useful policy measure would be integrating key amenities which are currently centralised in commercial areas, such as banks and post offices, into more communities and residential areas to enable greater access to important activities from home, rather than work. This would reduce the need for trip chaining, and making neighbourhoods more resilient. 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, and thus requires a different response from planners aiming to adapt to an uncertain future of more frequent weather extremes and other disruptive events.

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