Working from home and digital divides: resilience during the pandemic

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ABSTRACT
This paper offers a new perspective on telecommuting from the viewpoint of the complex web of digital divides. Using the UK as a case study, this paper studies how the quality and reliability of internet services, as reflected in *experienced* internet upload speeds during the spring 2020 lockdown, may reinforce or redress the spatial and social dimensions of digital divisions. Fast, reliable internet connections are necessary for the population to be able to work from home. Although not every place hosts individuals in occupations which allow for telecommuting nor with the necessary skills to effectively use the internet to telecommute, good internet connectivity is also essential to local economic resilience in a period like the current pandemic. Employing data on individual broadband speed tests and state-of-the-art time-series clustering methods, we create clusters of UK local authorities with similar temporal signatures of experienced upload speeds. We then associate these clusters of local authorities with their socioeconomic and geographic characteristics to explore how they overlap with or diverge from the existing economic and digital geography of the UK. Our analysis enables us to better understand how the spatial and social distribution of both occupations and online accessibility intersect to enable or hinder the practice of telecommuting at a time of extreme demand.

KEYWORDS
covid; internet; working from home; broadband speed; time-series clusters

1. Introduction

During the pandemic, working from home using digital technologies, whether partially or exclusively, was transformed from a niche means of accessing work, albeit one that had been on a slow, upward trend, to a widespread way of life in many countries. The ability to work from home or telecommute meant millions retained their jobs and, to a varying extent, maintained productivity during periods of strict lockdowns around the world. However, this ability has not been evenly distributed socially or spatially, creating new intersections of economic and digital divisions. On one side are those who can work from home, supported by digital technologies, and have thus been able to enjoy both economic resilience and greater personal safety. On the other side, previously employed individuals have been forced to accept furlough or redundancy packages unless they are part of the cadre of essential workers, who are potentially at high risk of infection. Whilst the basis for this pandemic-generated divide has been

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viewed as mainly occupational, here we consider whether it is also technological and, consequently, geographical.

Using the UK as a case study, this paper aims to understand how the quality and reliability of internet service, as reflected in *experienced* internet speeds during the spring 2020 lockdown, may reinforce or redress the spatial and social dimensions of digital divisions. We employ volunteered geographic data on individual broadband speed tests and state-of-the-art time-series clustering methods to create clusters of UK local authorities with similar temporal signatures of experienced internet speeds. We then associate these clusters of local authorities with their socioeconomic and geographic characteristics to explore how they overlap with or diverge from the existing economic and digital geography of the UK. Our analysis enables us to better understand how the spatial and social distribution of education, occupation and online accessibility intersect to enable or hinder the practice of telecommuting at a time of extreme demand. We also consider what lessons can be learned from this time for a future where telecommuting is likely to remain a more common means of accessing work, at least in comparison to the pre-Covid era.

The capability to work from home has previously been studied from the perspective of whether work tasks in a given occupation both can be and are allowed to be performed using digital technologies independently of location or co-location with colleagues, including supervisors (Allen, Golden, and Shockley 2015; Singh et al. 2013). However, successful telecommuting also requires that the quality and reliability of digital services, particularly home internet connection speeds, enable the completion of work tasks with a minimum of delay or interruption. Prior to the pandemic, the performance of broadband services with respect to telecommuters was never tested at scale, as working from home and connecting to colleagues and workplace resources via the internet was the purview of a small minority of workers. Instead, leisure use in the evening, when video streaming services are at their peak, has been used to benchmark broadband performance and service delivery by different Internet Service Providers (ISPs) (OfCom 2017).

Yet the shift towards telecommuting during various stages of lockdown around the world has been drastic and there are speculations that post-Covid, the tendency to work from home will be much higher, raising questions around whether internet services can accommodate the increased demand. For example, 47% of people in employment in the UK worked solely from home in April 2020, whilst the same figure only reached 5% the year before (ONS 2020a,b). A back of the envelope calculation suggests that up to 40% of the labour force could work from home on an ongoing basis (Batty 2020). Similar figures have been reported for other countries (Felstead and Reuschke 2020). Approximately 37% of the European workforce worked from home in April 2020 with countries like Finland reaching 60% (Eurofound 2020). In the US, almost half of the working population worked from home during the same period because of the pandemic (Brynjolfsson et al. 2020), and a recent estimate indicated that 37% of all jobs in the US can be permanently performed entirely from home (Dingel and Neiman 2020). None of these changes could have happened in the absence of reliable information and communication technology (ICT) infrastructure – both in terms of software and hardware. But while software innovations are easily diffused across space and society[1], the same does not apply for ICT hardware infrastructure such as internet broadband connectivity.

The literature describes first level digital divides in terms of the availability and

[1]See for example the huge success of videoconferencing apps such as Zoom (Marks 2020).

quality of internet connectivity, such as that manifest in different geographies in the UK (Riddlesden and Singleton 2014; Philip et al. 2017). Second level digital divides consider the presence or lack of the necessary skills to effectively utilise digital technologies and the internet (Blank and Groselj 2014; Van Deursen and Van Dijk 2011). The third level focuses on the heterogenous returns of internet usage among different socioeconomic groups and, consequently, how digital technologies can assist in bridging or further enhancing existing socioeconomic divides. (Stern, Adams, and Elsasser 2009; Van Deursen and Van Dijk 2014; Van Deursen and Helsper 2015). The capability to telecommute is related to all three levels of digital divides, but more importantly leads to differentiated outcomes regarding the economic resilience of people and places to overcome a systemic shock such as the current pandemic.

As the quality of internet infrastructure and services, as well as the concentration of different occupations are spatially dependent and clustered in space, our approach offers a framework for understanding the impact of and interactions between digital divisions geographically and socioeconomically. By asking how resilient broadband speeds, and particularly upload speeds, are as experienced in different parts of the UK during a time of extreme demand, we interrogate which places benefit from the greater economic resilience digital technologies can offer. The structure of this paper is as follows. First we review the literature on telecommuting and digital divides to better understand their structural and spatial development pre-pandemic, and thus their importance to the economic resilience of different places. We then describe our data and methodology. Our results section first offers a classification of how internet services vary across clusters of UK local authorities and then assesses whether these clusters replicate or repudiate other socio-economic and geographic patterns of economic resilience. We conclude with a discussion of the insights we have gained from our new perspective on digital divisions.

2. Literature review

2.1. *From telecommuting to #WFH*

In this analysis, the terms 'telecommuting' and 'working from home[2]' are used interchangeably, as most remote labour during the Covid-19 crisis was carried out in the homes of individual employees rather than any other location (Eurofound 2020). However, previous research has explored how telecommuting can occur in other places, including satellite offices or on public transport (Felstead 2012; Siha and Monroe 2006). Previous research has also used a variety of definitions to measure the level of telecommuting within different workforces, distinguishing between those directly employed, indirectly employed, self-employed, full-time or part-time, and those who use digital technologies to work remotely full-days or part-days (Allen, Golden, and Shockley 2015; Bailey and Kurland 2002; Haddad, Lyons, and Chatterjee 2009). No matter the definition, the option and capability to telecommute or work from home has never been equally distributed spatially or socio-economically any more than different industries and employment opportunities have. Studies from the United States, the Netherlands, and the UK found that telecommuters are most likely to hold professional, managerial, and technical occupations where the workforce is better educated and wealthier, and that there is suppressed demand among women and part-time workers (Headicar and Stokes 2016; Peters, Tijdens, and Wetzels 2004; Singh et al.

[2] See also the popular social media hashtag #WFM

2013).

Opportunities for working from home during the current pandemic have likewise not been equally spread across the workforce. Dingel and Neiman (2020) indicated that in the US, managers, educators, those working in computer-related occupations, finance, and law can easily work from home, and that occupations with opportunities to telecommute are associated with higher earnings. This is not the case for the workforce occupied in more spatially fixed occupations, from farming, construction and manufacturing to hospitality and care services. In the US, these occupations tend to be lower-income, non-white, without a university degree, live in rental accommodation and lack health insurance (Mongey, Pilossoph, and Weinberg 2020). Similar trends can be observed for other countries. For example, 75% of workers with tertiary education worked from home in Europe during spring 2020, whilst only 34% of workers with secondary education and 14% of those primary education did so (Eurofound 2020).

2.2. *Digital divides and economic resilience*

Our understanding of telecommuting as a product of enabled occupations can be described as a manifestation of the third level digital divide, as those who are able to use digital technologies to work from home benefit from a high rate of return on their use of the internet in terms of autonomy, flexibility, and time saved from commuting (Peters, Tijdens, and Wetzels 2004; Siha and Monroe 2006; Singh et al. 2013). These returns have been even greater during the Covid-19 crisis, when those with the capability to telecommute also have the ability to maintain their employment whilst protecting their health. However, the success of these arrangements has been dependent upon the first level digital divide, which is associated with access to and quality of internet connectivity. Salemink, Strijker, and Bosworth (2017) provides a systematic review of the pre-pandemic, first level digital divide in infrastructure quality between urban and rural areas in various advanced economies. Rural areas, predictably, fare worse, yet as Blank, Graham, and Calvino (2018) highlight, variation in individual internet uptake and use is a product of more complex spatial and demographic characteristics than simple rurality or urbanisation. Yet whether this variation in infrastructure quality affects the spatial footprint of telecommuting has not previously been investigated, in part because telecommuting has not previously been a cause of concentrated demand and pressure on internet services.

There are indications that those who purchase high speed connections consume more data of all sorts and use their connections for a greater variety of purposes (Hauge, Jamison, and Marcu 2011). There is also a correlation between access to internet services and a reduction in household transport spend (Bris, Pawlak, and Polak 2017). Independently of whether the additional internet use and reduced travel is because of increased telecommuting, these studies suggest that better internet services enable households to make savings and efficiencies, an example of the first level digital divide reinforcing the third level.

Multi-layered digital divides may also intersect with material divides and the economic geography of the UK. The regional economic resilience literature underlines the differentiated capacity of cities and regions to escape or recover from economic crises (Martin 2012; Kitsos and Bishop 2018). As different places have different industrial and occupational profiles, these affect their aggregated potential capacity for telecommuting. Such profiles are associated with longstanding inequalities in the UK and their spatial representation as a North-South divide (Martin 1988). Various studies have illustrated severe inequalities between the north and the south regions of England in terms of skills and human capital, unemployment, productivity and prosperity (Lee 2014; McCann 2020; Dorling 2018). Some scholars have even argued that the UK suffers from some of the highest levels of interregional inequalities in the global north (Gal and Egeland 2018; McCann 2016). All three levels of digital divides are associated with or shaped by the geography of the UK. Yet this is the first time that the intersection of digital and material divides is relevant to understanding the economic resilience of places and large swathes of the population, as digital technologies became an essential tool of productivity during the Covid-19 pandemic.

The extreme demand during the pandemic thus provides a new opportunity to understand how internet infrastructure quality, and reliability affects telecommuting, particularly in light of the high volumes of bandwidth-intensive video conferencing required in order to avoid the face-to-face contact that could increase the spread of infection. We seek to answer how internet service resilience could contributes to or reduce economic resilience when the latter is dependent upon the capability to work from home. We also aim to improve our understanding of the impact of first level digital divisions on telecommuting, and whether this results in more fundamental third level digital divisions than has previously been perceived.

3. Methods and data

3.1. *Time-Series clustering*

Our chosen methodological framework is cluster analysis, which can be defined within machine learning approaches as an unsupervised learning task, partitioning unlabelled observations into homogeneous groups known as clusters (Montero, Vilar et al. 2014). The key idea is that observations within clusters tend to be more similar than observations between clusters. Clustering is particularly useful for exploratory studies as it identifies structures within the data (Aghabozorgi, Shirkhorshidi, and Wah 2015). Cluster analysis is a widely used in geography (Gordon 1977; Everitt 1974), for example to solve *regionalisation* problems (Niesterowicz, Stepinski, and Jasiewicz 2016). Clustering methods are also the basis of *geodemographics*, a research domain which aims to create small area indicators or typologies of neighbourhoods based on diverse variables (Singleton and Longley 2009; Harris, Sleight, and Webber 2005). These studies usually employ cross-sectional data, and most clustering problems in geography deal with observations that are fixed in time. However, for this paper we are interested in internet speeds, which vary over time. Therefore, we create clusters of local authorities in the UK with similar temporal signatures of experienced internet speeds.

To do so, we employ time-series clustering methods, which have been developed to deal with clustering problems linked to, for instance, stock or other financial data, economic, governmental or medical data as well as machine monitoring (Aggarwal and Reddy 2013; Aggarwal, Hinneburg, and Keim 2001; Hyndman, Wang, and Laptev 2015; Warren Liao 2005). The main challenge, which does not apply to cross-sectional clustering problems, is data dimensionality, with a multiplicity of data points for every individual object included in the data set, and how their value changes dynamically as a function of time (Aghabozorgi, Shirkhorshidi, and Wah 2015). This high dimensionality leads to (i) computational and algorithmic challenges regarding handling these data and building algorithms to perform clustering over long time-series, and (ii) open questions regarding the choice of similarity measures in order to cluster similar times-series objects together considering the whole length of the time-series and overcoming issues around noise, outliers and shifts (Lin et al. 2004; Aghabozorgi, Shirkhorshidi, and Wah 2015).

For this paper we utilise a category of time-series clustering methods known as shape-based approaches. These methods match two separate time-series objects based on the similarity of their shapes through the calculation of distances between the shapes, and are better equipped to capture similarities between short length time-series (Aghabozorgi, Shirkhorshidi, and Wah 2015), such as our data. We thus identify clusters of UK local authorities with similar temporal signatures – i.e. shapes – of experienced internet speeds. The clusters are identified using the common partitioning algorithm, where no clusters overlap, known as k-means. This iterative algorithm is popular because of the simplicity of the implementation and the interpretability of the results. It begins with defining the desired number of clusters: k. Then each observation is randomly assigned to a cluster from the $[1, k]$ space. This initial cluster assignment is followed by iterations in order to minimise the distance between the centroids of the clusters and the observations assigned to these clusters (James et al. 2013).

There are a number of differences between the application of k-means for cross-sectional and times-series data. Instead of creating clusters around centroids, a common approach is to create clusters around *medoids*, which are representative time-series objects with a minimal distance to all other cluster objects (Sardá-Espinosa 2019). Also, instead of calculating the Euclidean distance between centroids and data points, more complex distance measures need to be employed to capture the similarity between a time-series object and a medoid. A common distance measure for shape-based time-series clustering is Dynamic Time Warping (DTW), an algorithm comparing two time-series objects to find the optimum warping path between them. DTW is widely used in order to overcome limitations linked to the use of Euclidean distance (Sardá-Espinosa 2019; Berndt and Clifford 1994; Ratanamahatana and Keogh 2004). The `R` package `dtwclust` has been used for the time-series clustering (Sarda-Espinosa 2019).

3.2. *Experienced Broadband Speeds*

To assess the internet quality and reliability across local authorities in the UK, we utilise unique data comprising individual internet speed tests from Speedchecker Ltd[3]. This is a private company that allows internet users to check their own broadband upload and download speeds, and stores every speed-check with timestamp and geolocation information. These data have been used before to assess digital divides (Riddlesden and Singleton 2014) and the impact of local loop unbundling regulatory processes (Nardotto, Valletti, and Verboven 2015), and we followed the former's approach to remove outliers. By using this volunteered geographic data, we are able to assess the internet speed *experienced* by users, which may differ from the maximum speeds *advertised* by ISPs. We are particularly interested in upload speeds and the frequency of speed tests over the period from March to May 2020, as government statements indicate this is when UK workers were first told to work from home if at all possible (GOV.UK 2020). Average upload speeds are slower than average download speeds, at 9.3Mb/s mean upload speed for the whole sample, compared to 29.6Mb/s for download speeds, but they are also less associated with internet-based, high-demand, leisure activities such as video streaming. Therefore, upload speeds are more relevant to work-related activities such as uploading documents or two-way audio, video, and text-based

[3] `https://www.broadbandspeedchecker.co.uk/`

communication systems.

The frequency of speed tests was important in identifying the temporal profile which would give us most insight into experienced internet service and resilience over units of time. Whilst there is an overall trend of increased testing from March to April and then a slight reduction from April to May, this trend masks substantial variation by not only the day of the week, but also time of day, as can be seen in Figure 1. Thus, a daily aggregation of upload speeds would mask the variation in experienced service over the course of each weekday. Furthermore, the importance of this variation is highlighted by a comparison with the same period in 2019, as in Figure 2, when the volume of testing and thus of experienced internet service quality peaked in the evening, presumably in response to demand for leisure activities and download speeds. In contrast, the majority of the increase in testing in 2020 is during the working day, creating a new morning peak in Figure 1. Therefore, we include a measure of hourly variation in our temporal profiles to reflect the change in users' perception of the workday reliability of internet services.

However, there were insufficient observations – only 631 speed tests per LAD on average – for each for each working hour of each working day in each Local Authority District (LAD) to profile speeds at that level of detail. Spatial aggregation was also necessary because we could not follow individuals or households and connect data points. Therefore, we aggregate the $241,088$ individual, geolocated and time-stamped speed-checks during the 13 weeks of March to May inclusive for weekdays in 2020 by each hour of the day and day of the week. As our research aims to identify the geography of internet service resilience for work purposes, bank holidays and the hours between midnight and $6:00$ were excluded, as well as weekend days. The composite week time-series thus comprise 18 hours multiplied by 5 weekdays or 90 time points per series. The time-series were calculated for each of the 382 LADs in the UK, standardised, and then a k-means partitioning around medoids clustering algorithm was applied using DTW. We initially run the algorithm for $k \in \mathbb{N} \bigcap [5, 15]$ and used cluster validity indices (CVIs) to pick the optimal solution of $k = 13$. Following Sardá-Espinosa (2019) the majority vote for the following CVIs was used: Silhouette (max), Score function (max), Calinski-Harabasz (max), Davies-Bouldin (min), Modified Davies-Bouldin (DB*, min), Dunn (max), COP (min).

In Section 4.1, we review the temporal profile of upload speed by hour of the day and day of the composite week for each cluster. Since the quality and reliability of internet services vary in time and space due to both supply and demand-side influences, we also use a number of different measures to describe experienced upload speeds per cluster. These include: i) mean, experienced connection speed, ii) standard deviation or the amount of fluctuation from the mean, and iii) the variation in speeds during the new morning peak of testing when working from home is more likely to take place. We take account of all three measurements in order to determine how resilient broadband speeds are as experienced in different parts of the UK during a time of extreme demand.

The cause of these different experiences of broadband resilience may vary between and within clusters, as they may reflect either patterns of demand or quality of infrastructure. Our approach is also limited by potential endogeneity, as for example, better quality connections with high mean speeds may enable more working from home, but greater demand can cause slower speeds, less reliability, or greater variability of speed at different times of day or week. Therefore, we avoid attributing any cause to our analysis of the experienced level of quality and reliability of upload speeds. Instead, we run an auxiliary regression to understand how the spatial and temporal patterns

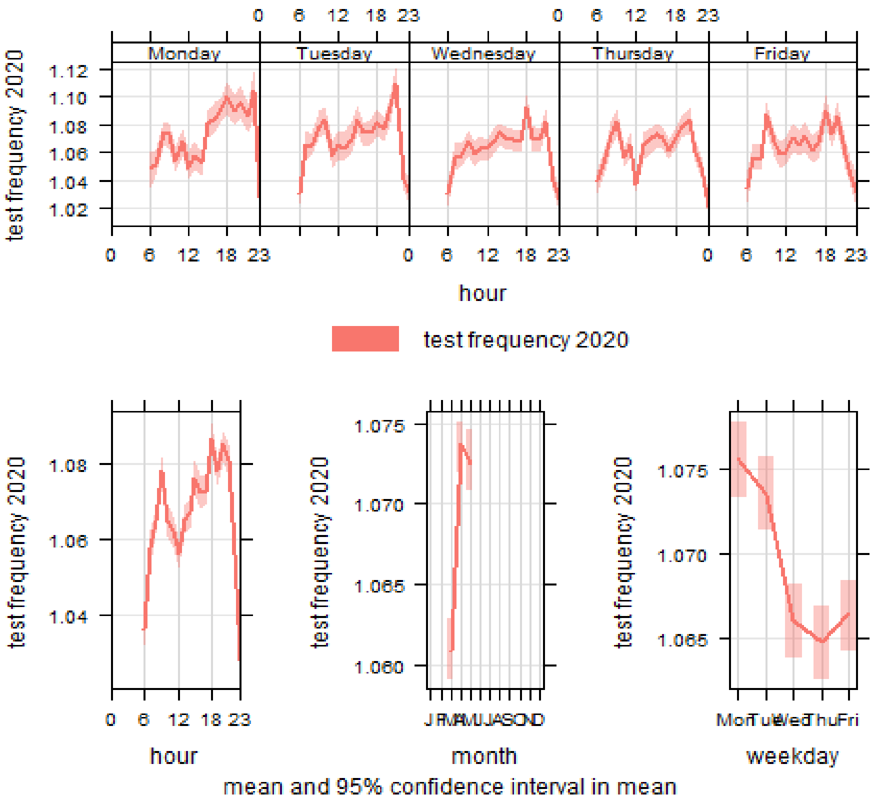

Figure 1. Speed tests over time, 2020

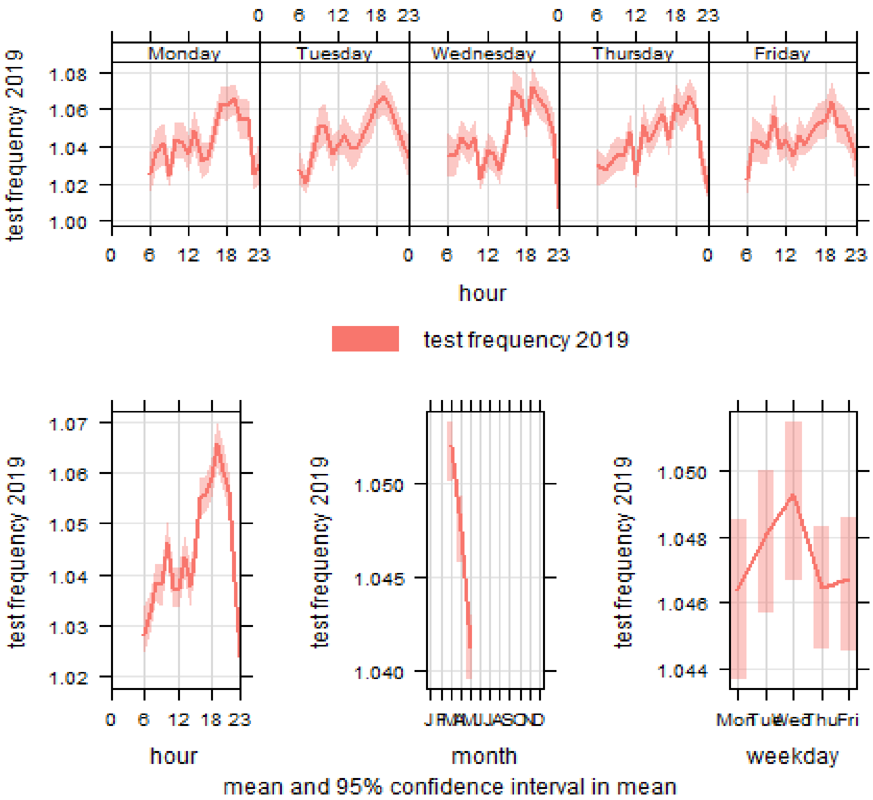

Figure 2. Speed tests over time, 2019

of internet service relate to the economic geography of the UK. More specifically, we estimate the following multinomial logit model:

$$Pr(Y_i = j) = \frac{exp^{X_i \beta_j}}{\sum_{i=1}^{j} exp^{X_i \beta_j}} \begin{cases} i = 1, 2, ..., N \\ j = 1, 2, ..., J \end{cases} \tag{1}$$

Based on the outcomes of the time-series clustering, we identify J distinct and crisp clusters. We then regress this cluster membership against a vector X_i of socio-economic and geographic variables, which are discussed in detail in the relevant Section 4.2. Because we cannot identify individuals or households and consequently aggregated our data at the LAD level, our results offer correlations between the socioeconomic characteristics of certain geographic locations and internet service quality, not a record of who was telecommuting. Such individual data could be found though surveys, but these offer less detailed information about the experience of internet resilience due to enforced demand, which is the main contribution of this paper. Our auxiliary regression, therefore, provides an indication of how internet connectivity can reinforce or redress existing spatial and social inequalities in different places. However, it opens a path to future research by highlighting the importance of understanding of how telecommuting capabilities and digital infrastructure divisions intersect.

4. Results

4.1. *Upload Clusters / cluster description*

The temporal profiles of the local authority clusters have been summarised in Figures 3 and 4 and Table 1. The graphs show a composite profile of mean upload speeds per hour per day for each cluster, with the largest five clusters, in terms of the LAD membership and population, in Figure 3, and the next six in Figure 4. These figures and table provide a comprehensive overview of the quality and reliability of experienced broadband in different parts of the UK.

Table 1. Upload speed cluster characteristics

Cluster	N. of LADs	LAD population	mean speed	SD speed	mean AM speed	mean PM speed
1	5	343100	8557	6139	7747	9563
2	2	265600	10922	6687	9674	10645
3	4	474700	10201	5658	9470	11236
4	1	91100	9689	6122	7816	9689
5	1	79800	10127	6024	9030	11101
6	155	29535700	9397	5839	9161	9580
7	4	559800	10119	6102	9813	11070
8	5	436300	9429	6254	8682	10434
9	32	6355500	10878	5957	10832	11071
10	4	699600	10795	6005	9258	10697
11	33	5771400	10845	5936	10781	10988
12	10	1544900	9551	6166	9254	9048
13	126	20277700	8392	5849	8299	8522

Note: All speed measures are upload speeds

The second largest cluster, comprising 126 local authorities and over 20 million people, is cluster 13, which has the slowest aggregate mean upload speed, and the second

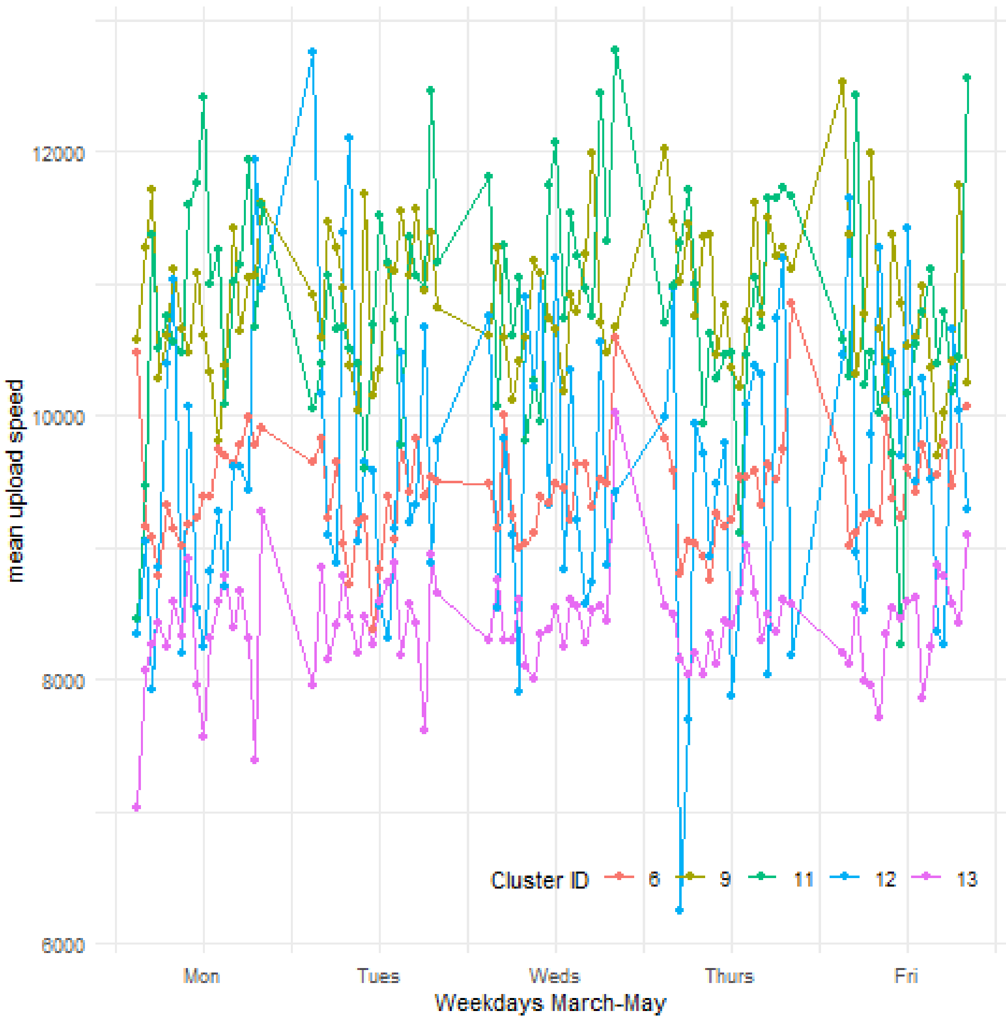

Figure 3. Temporal profilies for upload speed large clusters

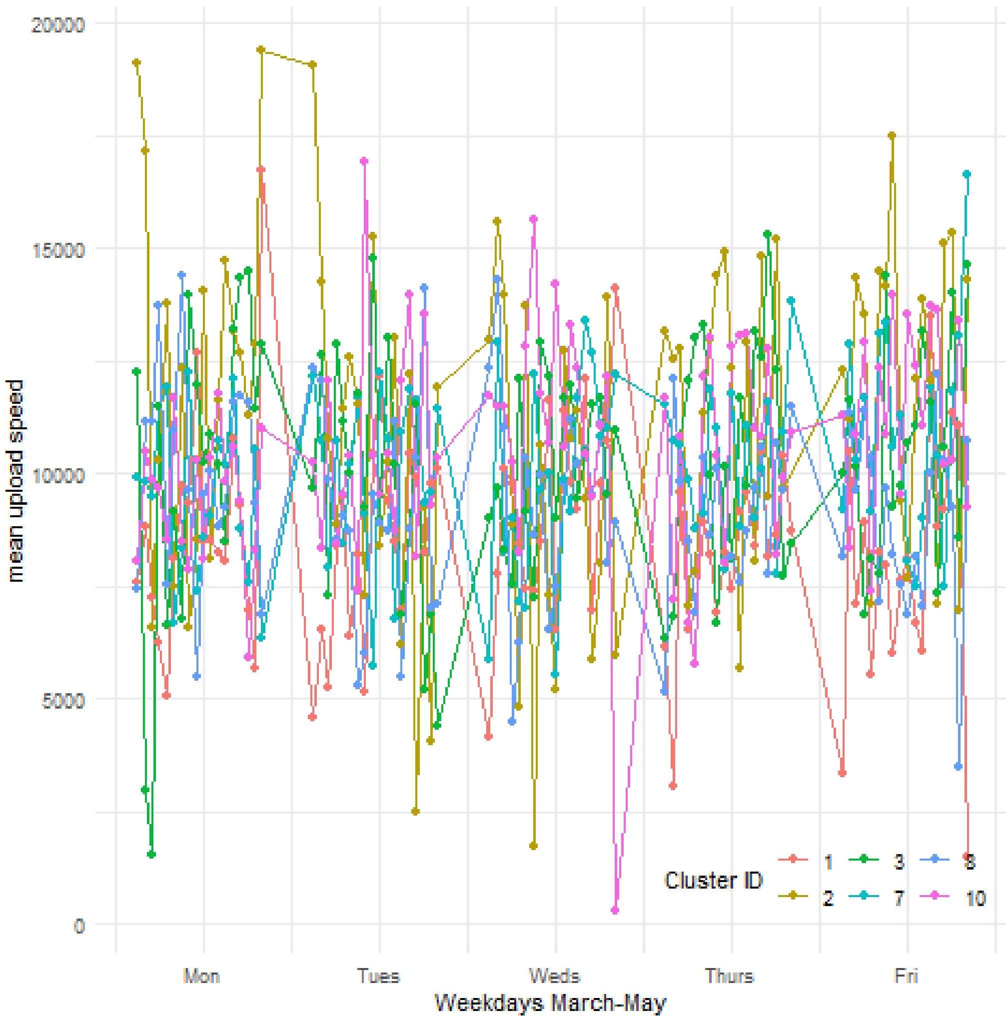

Figure 4. Temporal profilies for upload speed small clusters

highest ratio of the standard deviation to the mean. This suggests that those living in local authorities in this cluster experienced some of the lowest quality broadband services in terms of upload speeds in the UK. However, Figure 3 shows that the high standard deviation, which is one indication of unreliable internet, did not disproportionately affect the morning peak from $9:00$-$10:59$, when upload speeds were, on average, only 2.6% slower than in the evening peak period between $19:00$ and $20:59$, when entertainment purposes are likely to be using the most bandwidth. In comparison, the five LADs in cluster 1, home to 343 thousand people, not only experience the second slowest mean upload speeds and the highest ratio of standard deviation to the mean, but are also much more affected during the morning peak.

Meanwhile, those living in the largest cluster – 6, with 155 LADs and 29.5 million people – experienced aggregate mean upload speeds of about 1Mb/s faster than those in cluster 13, but still lower than the other three large clusters and most of the smaller clusters, suggesting a middling quality of service. The temporal profile for cluster 6 in Figure 3 shows that upload speeds are highest at $6:00$ on a Monday morning and between $23:00$ and midnight on Wednesday and Thursday, but tend to be lower during the working day. Furthermore, experienced mean upload speeds in the morning peak are 4.4% lower than in the evening peak – a greater, more noticeable change than any of the other large clusters experience, suggesting poorer reliability during the working day. This difference is less, however than any of the clusters included in Figure 4.

Clusters 8 and 12 also have mean upload speeds under 10Mb/s, but higher than clusters 1, 13, and 6. However, mean upload speeds are much lower between $9:00-10:59$ than between $19:00-20:59$ in cluster 8, but slightly faster in the morning than in the evening in cluster 12. Indeed, cluster 12 is the only cluster to experience higher speeds in the morning peak compared to the evening, and thus the only cluster where the temporal profile of internet use is closer to what might have been expected pre-pandemic. Among the other clusters, however, the reliability of internet services during the working day still varies considerably. Interpreting this variation from the large spikes and dips shown on Figures 3 and 4 is difficult, but the statistics in Table 1 show that clusters 9 and 11 have the most reliable internet services. The ratio of standard deviation to mean in both these clusters is lowest, and speeds are only about 2% slower in the morning than the evening. Mean speeds are also higher than in any other cluster, excluding cluster 2, where measures of reliability suggest poorer performance.

Thus, broadband services in clusters 9 and 11, home to over twelve million people, performed the best during the study period, in terms of both quality and reliability. In Figure 3, cluster 11 shows more noticeable peaks and troughs, with the lowest points occurring, on average, between $6:00-7:00$ on Monday morning, $14:00-15:00$ on Friday, and $16:00-17:00$ on Thursday, not the workday peak. Furthermore, these slow periods offer better speeds than the average hourly profile of cluster 13. Clusters 3, 7 and 10 also have relatively high mean upload speeds. Clusters 3 and 10 pair high mean speeds with low standard deviations relative to the mean speeds, suggesting reliability and resilience, as well as quality broadband services. Cluster 7 has a higher ratio of standard deviation to mean, but there is less difference in average speeds between the morning and evening peaks than in clusters 3 and 10.

In summary, LADs in clusters 9 and 11 experienced resilient broadband internet that could support high levels of telecommuting. Those in clusters 2, 3, 7, and 10 also experience higher than average mean speeds and rank middle to high on measures of service reliability. These LADs are *not* on the wrong side of the first level digital divide, but how likely are they to be able to take advantage of their resilient ICT infrastructure and services? Meanwhile, cluster 6 is not only the largest in terms of number of LADs and population, it has the closest mean upload speed to the pre-clustered average for the whole sample. As well as average quality internet services, those in cluster 6 also experience average reliability for work purposes, ranking fifth behind the four other clusters with populations over one million, but ahead of the smaller clusters. Clusters 8 and 12 are also close to average mean upload speeds, but show very different patterns in terms of reliability, whilst clusters 1 and 13 appear to suffer most from a lack of quality internet services, with slow speeds and high standard deviations. With those in cluster 1 more likely to experience that poor reliability during the morning peak, is this first level digital divide occurring in areas where few are occupationally able to telecommute anyway, and what are the implications for economic resilience?

4.2. *Post-clustering regression analysis*

Using an auxiliary multinomial logit regression, we test whether the clusters that have higher mean speeds and more reliable services consist of LADs that are more urban, affluent, and / or more likely to benefit from a choice of high quality internet services. We also estimate which of our clusters are more likely to have a higher proportion of occupations where the nature of the work enables telecommuting. The results of the auxiliary regression are presented in Table 2. The dependent variable is the LAD cluster membership as described in the methods and data section and equation 1. Each column represents a different cluster. The reference case is cluster 4, which includes only the local authority of Hambleton in North Yorkshire, a rural area of just over ninety thousand people. Mean, experienced upload speeds in cluster 4 (see Table 1) are between the average speeds for the 13 clusters (9.9Mb/s) and the pre-clustered average for the whole sample (9.3Mb/s). However, the standard deviation for cluster 4 and the difference between average speeds in the morning compared to the evening peak periods are indications of worse reliability than many of the other clusters. Hence, the results in Table 2 should be seen as relative rather than absolute probabilities.

First, we control for the number of speed tests run per cluster inhabitant between $9:00$-$10:59$ as well as the share of fast Virgin Media internet connections. Regarding the former, we expect people in LADs with more unreliable connections to test their internet speeds more often, and the results validate our priors. Meanwhile, fast Virgin Media cable connections have historically only been available to 45% of premises in the UK (OfCom 2016), where the more lucrative and competitive market originally attracted the cable TV provider. Those in clusters 2, 3, 9 and 11 benefit from a higher proportion of Virgin connections, which is an indication that people in these clusters are more likely to live in urban areas, with more choice of broadband services. In other words, they are more likely to be on the right side of the first level, infrastructure-based digital divide, as we expected from the analysis in Section 4.1.

We employ distance from London and from the nearest metropolitan area (including London) as two variables depicting peripherality, urban structure and, potentially, first level digital divides. The broadband speed tests run in the authorities in cluster 3 are more likely to be taking place close to London than those run in any of the other clusters, and two of the four authorities in cluster 3 are the London commuter towns of Harlow and Luton. However, even though London was also included in the variable calculating distance from the centre of one of either the ten largest metropolitan areas in England, or Glasgow or Cardiff, tests run in cluster 3 are likely to be furthest away. Thus, it is important to consider the membership of each cluster as well as the

Table 2. Auxiliary multinomial regression of upload speed clusters on socio-economic and geographic LAD variables

	1	2	3	6	7	8	9	10	11	12	13
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
pop, 2018	−0.00004***	0.00002*	0.00001	0.00002***	0.00002***	0.00000	0.00002***	0.00002***	0.00002***	0.00002**	0.00002***
	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
job density, 2018	−0.536***	−1.834***	−0.132***	−0.925***	−1.208***	−0.299***	−1.746***	−1.436***	3.350***	3.400***	0.630***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
distance to nearest met. area	−0.034***	−0.014***	0.002***	−0.020***	−0.074***	−0.044***	−0.013***	−0.036***	−0.031***	−0.036***	−0.024***
	(0.0005)	(0.001)	(0.0002)	(0.002)	(0.0001)	(0.0002)	(0.002)	(0.0005)	(0.0003)	(0.0002)	(0.002)
distance to London	0.007***	0.002	−0.016***	0.001	0.004***	0.004***	−0.002*	0.005**	−0.002	0.003	0.006***
	(0.001)	(0.002)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
South of the UK	−0.410***	−1.451***	−0.039***	−0.111***	−0.048***	−0.841***	−0.798***	1.492***	0.610***	0.798***	2.403***
	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00001)
managerial jobs, 2020	0.939***	0.704***	0.435***	0.704***	0.316***	0.786***	0.576***	0.311***	0.476***	0.594***	0.615***
	(0.00004)	(0.0001)	(0.00004)	(0.00004)	(0.00002)	(0.0001)	(0.00003)	(0.00003)	(0.00002)	(0.00004)	(0.00003)
tech jobs, 2020	0.096***	−0.257***	−0.071***	−0.111***	−0.206***	0.199***	−0.126***	−0.606***	−0.180***	−0.398***	−0.112***
	(0.00004)	(0.00004)	(0.00004)	(0.00003)	(0.00003)	(0.0001)	(0.00003)	(0.00003)	(0.00002)	(0.00004)	(0.00003)
skilled trade jobs, 2020	0.651***	0.160***	−0.191***	0.236***	0.604***	−0.184***	0.205***	0.597***	0.108***	−0.022***	0.295***
	(0.00004)	(0.00004)	(0.00003)	(0.00003)	(0.00003)	(0.00004)	(0.00002)	(0.00003)	(0.00003)	(0.00004)	(0.00003)
professional jobs, 2020	−0.118***	−0.234***	−0.121***	−0.172***	−0.514***	−0.172***	−0.349***	−0.351***	−0.245***	−0.344***	−0.229***
	(0.00005)	(0.0001)	(0.0001)	(0.00005)	(0.00003)	(0.0001)	(0.00004)	(0.0001)	(0.00003)	(0.00005)	(0.0001)
administrative jobs, 2020	0.019***	−0.836***	−0.040***	−0.117***	−0.139***	0.206***	−0.058***	−0.200***	−0.055***	−0.168***	−0.177***
	(0.00003)	(0.00002)	(0.00004)	(0.00001)	(0.00003)	(0.00003)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
leisure jobs, 2020	−0.198***	−0.180***	−0.225***	−0.476***	−0.654***	−0.820***	−0.537***	−0.935***	−0.353***	−0.625***	−0.491***
	(0.00002)	(0.00004)	(0.00004)	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00001)	(0.00002)	(0.00003)	(0.00002)
machine operation jobs, 2020	−0.336***	0.207***	0.392***	0.010***	−0.433***	0.139***	−0.099***	−0.139***	−0.144***	0.098***	−0.179***
	(0.00002)	(0.00003)	(0.00003)	(0.00002)	(0.00001)	(0.00003)	(0.00002)	(0.00001)	(0.00001)	(0.00002)	(0.00001)
earnings, 2019	−0.003*	0.010***	0.012***	0.020***	0.027***	0.001	0.020***	0.016***	0.015***	0.025***	0.014***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
n. business est. per hab., 2019	0.126***	−0.120***	−0.094***	−0.133***	0.123***	−0.051***	−0.334***	−0.133***	−0.150***	0.289***	0.377***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
NVQ4+	−0.141***	0.064***	−0.091***	−0.070***	−0.010***	0.004***	0.016***	0.170***	−0.110***	−0.038***	−0.035***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AM tests per hab., 2020	0.0005***	−0.002***	−0.005***	0.010***	0.0004***	−0.001***	−0.002***	−0.005***	−0.013***	−0.001***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Virgin Media %, 2020	−0.044***	1.578***	1.210***	0.248***	−1.724***	−0.242***	3.109***	−0.085***	1.214***	−3.889***	−0.745***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Constant	0.321***	−0.436***	0.199***	−2.953***	0.278***	0.002***	−0.866***	0.788***	2.600***	0.017***	0.022***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
McFadden's R squared	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338
N	323	323	323	323	323	323	323	323	323	323	323
Akaike Inf. Crit.	1,148.027	1,148.027	1,148.027	1,148.027	1,148.027	1,148.027	1,148.027	1,148.027	1,148.027	1,148.027	1,148.027

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

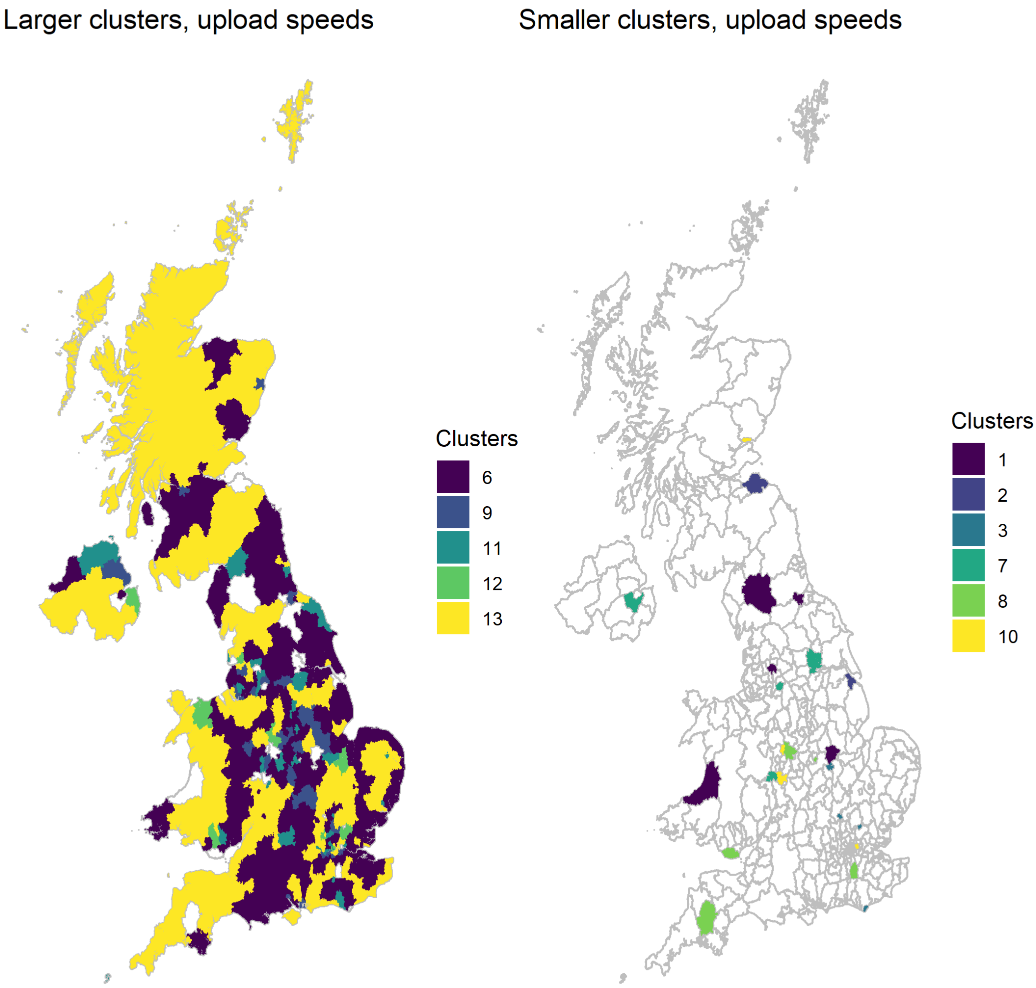

Figure 5. Upload speed clusters for LADs

regression results. Corby and Eastbourne, the other two authorities in cluster 3 are large, accessible towns, although not part of metropolitan areas.

Meanwhile, LADs in cluster 7 are most likely to be near the centre of a large metropolitan area, even though the four local authorities of cluster 7 include no central urban boroughs and only one LAD that is part of a metropolitan area of governance - Tameside in Greater Manchester. This may explain why those in cluster 7 are the second least likely to be served by Virgin Media. It is also a demonstration of the complexity of both experienced broadband upload speeds as captured by time-series clustering, and the geography of first level digital divides as a product of quality as well as availability. In comparison, cluster 1, which our analysis suggests lacks broadband resilience, contains five, mainly rural authorities, but they are closer to a metropolitan area than authorities in cluster 3, although furthest from London, perhaps because they are scattered around the country – see Figure 5.

Internet resilience is also more nuanced than our – arguably crude – dummy variable depicting the North-South economic divide, which assigns 1 to LADs located in Greater London, Southeast, Southwest and East of England regions, and 0 to the rest. The authorities most likely to be in the South are those in cluster 13, which was identified as having the slowest mean upload speeds of any of the clusters, and thus a low level of service. However, cluster 13 includes some rural, remote areas of the country, such as Northwest Scotland, Cornwall and Powys in Wales as shown on Figure 5. It also includes major metropolitan centres in the North – Liverpool, Newcastle – and South – Bristol, and nine (of 32) London Boroughs. There are also plenty of Southern home county and suburban areas. The standard deviation measure for cluster 13 is high, but speed variation is low during the morning peak, suggesting that the estimates for reliability are inconsistent. Considering that this is one of the largest clusters, and thus the averages incorporate more noise than some of the smaller clusters, it may be that the LADs in this cluster do not all suffer equally from a first level digital divide.

Yet we need to consider the results for other variables in Table 2 to better determine whether clusters 1 and 13, which appear to suffer most from poor quality internet services, are also more likely to have a low skilled workforce, less able to benefit from telecommuting. Cluster 1 has the lowest proportion of educated people, and the lowest earnings, despite recording the highest proportion of managerial and professional jobs, and the second highest proportion of tech jobs. Rural areas such as those in cluster 1 are home to many older, retired people (Blank, Graham, and Calvino 2018), which might explain these results or perhaps, as these figures are relative, we could note that cluster 1 also has a greater proportion of skilled trades than other clusters. In any case, it appears that the first level digital divide reinforces other inequities in cluster 1, where the even slower than average morning upload speeds shown in Table 1 suggest that internet users were more active during the working day. Meanwhile, those in cluster 13 are more likely to earn more and have a better education despite poor internet services. Cluster 13 also has the most businesses per inhabitant, but is somewhere in the middle in terms of job density. If this is an indication of a high number of SMEs, it could explain the variable internet quality, considering that small businesses have not been seen as the most valuable customers for higher speed broadband services if they are not located near residential customers (OfCom 2016).

Cluster 6 is the largest cluster, and thus, like cluster 13, there is more noise within the averages we use to measure internet quality and reliability. Our results indicate average mean speeds, and Table 2 shows that cluster 6 also falls towards the middle of the clusters on many of the socioeconomic variables. It ranks third or fourth out of the eleven in terms of the likelihood of having a higher proportion of managerial, professional, and tech jobs, as well as higher earnings, but is fourth from bottom for educational attainment. The LADs in cluster 6 are also diverse, with few truly remote areas, but urban areas throughout England, including Birmingham, Leeds, Sheffield, twelve London Boroughs, and many suburban areas and smaller cities like Oxford and Cambridge. The capital cities of the other UK nations, Belfast, Cardiff and Edinburgh, are also in this cluster, suggesting perhaps that the lower level of reliability discussed in Section 4.1 may be due to increased demand, e.g. for telecommuting, despite lacking the most resilient internet connections.

In contrast, Clusters 9 and 11 enjoy resilient internet connections, but LADs in Cluster 9 are more likely to host highly educated individuals with higher earnings than cluster 11, which has a negative coefficient for the NVQ4 variable. Cluster 11 has fewer businesses per inhabitant and the second highest job density and cluster 9 the second lowest. These coefficients might indicate that resilient broadband infrastructure generates higher returns for those in cluster 9, where slightly more slowdown in the AM peak was detected – see Table 1. LADs in cluster 9 are less likely to be in the South and those in cluster 11 more likely, although the coefficient for cluster 9 might be skewed by the presence of the Scottish cities of Glasgow and Aberdeen. Scotland has a different economic profile than England. Still, both clusters consist of larger LADs in terms of population, including districts within five of England's ten largest cities, and a number of other stand-alone urban areas and large market towns – see Appendix 1. These urban locations are on the right side of the first level digital divide, and the regression results suggest that internet resilience is supporting a wide range of small and large urban economies.

LADs in clusters 2, 3, 7, 10 are also on the right side of the first level digital divide, experiencing higher than average mean upload speeds and ranking high to middle on measures of service reliability. LADs in clusters 2 and 10 are also more likely to have highly skilled workers to take advantage of working from home opportunities. Cluster 2 is comprised of just two LADs, with the lowest job density of any cluster. Cluster 10 is comprised of four LADs, including two peripheral suburban areas of Birmingham, the East London Borough of Newham, and Dundee. Suburbs are considered the most likely urban form in which telecommuters live (e Silva and Melo 2018), and Dundee has a reputation for tech startups (UK 2018). LADs in cluster 7, which include the suburbs South of Belfast, a suburban district of Greater Manchester, and some other Midlands and North Yorkshire towns and villages have the highest earnings, and thus may also be making the most of their resilient internet. In contrast, LADs in cluster 3 are associated more with lower skills and have the highest proportion of individuals in machine operation jobs. Arguably, LADs in clusters 3 benefit the least from their resilient internet infrastructure in an era when working from home became a vehicle for economic resilience.

Finally, clusters 8 and 12 consist of LADs enjoying close to average mean upload speeds, but opposing patterns of internet reliability during the morning peak. LADs in cluster 8 are likely to host more individuals employed in tech and administrative occupations than any other cluster, as well as many in managerial occupations, whilst the opposite applies to skilled trade and leisure occupations. These LADs are characterised by a very small positive likelihood of more educated residents, but are not significantly likely to earn more than other clusters. Including suburbs near Leicester, Cardiff, and Birmingham and south of London, the LADs in cluster 8 seem to likely to have the skills and occupations that would benefit from quality internet services, but suffer from poor internet resilience and reliability.

In comparison, LADs in cluster 12 are less likely to be able to benefit from quality internet services if they had them, with fewer individuals achieving NVQ4 or better and lower levels of occupations that would benefit from homeworking. Yet LADs in this cluster benefit from the second highest level of earnings, and have the largest stock of businesses per inhabitant and the highest job density. This density of businesses could be why cluster 12 is the only cluster with higher speeds in the morning peak during the study period. If people are at home, business premises might well have been abandoned. Cluster 12 is home to 1.5 million people spread across twelve LADs, from London to Wales as listed in Appendix 1. This spatial diversity demonstrates that the temporal clustering of internet resilience is not necessarily spatially dependent, and digital divides do not necessarily overlap with economic ones.

5. Conclusions

This paper offers a new perspective on telecommuting from the viewpoint of the complex web of digital divides. We employ novel data regarding experienced upload speeds and time-series clustering methods, a family of unsupervised machine learning techniques which are rarely utilised in geographical research. Fast, reliable internet connections are necessary for the population to be able to work from home. Although not every place hosts individuals in occupations which allow for telecommuting nor with the necessary skills to effectively use the internet to telecommute, this paper raises the issue that places without good internet connectivity will still struggle more than other places to achieve economic resilience in a period like the current pandemic when internet resilience is so vital. Indeed, our analysis demonstrated that the temporal profiles of twelve of our thirteen clusters had slower upload speeds in the morning than in the evening. The opposite is likely to have been the norm prior to the pandemic, as level of demand and bandwidth management is the most common cause of temporal variation in experienced speeds, and why evening download speeds, rather than daytime upload speeds, have been used to benchmark the performance of internet services. Thus, the new patterns can be taken as evidence of widespread telecommuting and other daytime internet use which changed the temporal profile of internet activity throughout the UK, not just in areas with more digital industry or better skills.

Upload speeds have not previously been seen as integral to universal service, considering there has never before been such extreme demand for telecommuting and operations such as video calls. This may be why the average upload speeds for the largest two clusters – 6 and 13 – contain so many LADs that are centres of the knowledge economy, from Oxford and Cambridge in the former, to areas like Reading in the latter, which has the highest concentration of digital businesses in the country (UK 2018). Thus, whilst some areas suffer from an intersection of digital and economic divides, such as those in cluster 1, other areas, including cluster 8 as well as 6 and 13 also found their digital infrastructure to be less than reliable when confronted with the sudden change in the timing and type of demand. In contrast, LADs such as the digital hub, Milton Keynes, in cluster 9 were able to benefit both from reliable internet connections and populations which were familiar with working from home and could capitalise on their digital infrastructure. Yet the nuanced picture we gained through our analysis of the UK case study suggests that quality internet connectivity may also have enabled other LADs, such as those in cluster 3 or 11 to gain ground during the pandemic despite lower skill levels.

Digital infrastructure which considers upload speeds and working day reliability as well as availability are likely to be particularly important in a future where telecommuting might be a more common means of accessing work and broadband services must be fit for purpose, although the long-term effects of such drastic changes in telecommuting and attitudes towards working from home are difficult to predict. Nevertheless, they span various aspects of economy and society: from changes to transportation planning due to altered commuting patterns to changes in land use and urban planning to accommodate people who work from home (Budnitz, Tranos, and Chapman 2020; Elldér 2020), and from productivity and innovation changes to changes in agglomeration externalities and the attraction of large cities (Nathan and Overman 2020). Further research may be able to measure the economic resilience of the different clusters of places discussed in this paper once this pandemic is firmly past. However, our analysis demonstrates that the economic resilience made possible by working from home cannot be understood without considering the underpinning digital divides and cannot be achieved without planning for how the levels of digital, social and economic divides might intersect.

Appendix 1

This is the LAD cluster membership for the upload speed timeseries.

Cluster 1: Ceredigion, Darlington, Eden, Rossendale, Rutland

Cluster 2: East Lothian, North East Lincolnshire

Cluster 3: Corby, Eastbourne, Harlow, Luton

Cluster 4: Hambleton

Cluster 5: Fylde

Cluster 6: Allerdale, Amber Valley, Angus, Ashfield, Ashford, Aylesbury Vale, Barnet, Basingstoke and Deane, Bath and North East Somerset, Belfast, Bexley, Birmingham, Blaenau Gwent, Bournemouth, Christchurch and Poole, Bradford, Braintree, Brentwood, Bridgend, Bromley, Broxtowe, Bury, Calderdale, Cambridge, Canterbury, Cardiff, Castle Point, Chelmsford, Cheltenham, Cherwell, Chesterfield, City of Edinburgh, Clackmannanshire, Colchester, Copeland, County Durham, Coventry, Croydon, Dartford, Daventry, Denbighshire, Derby, Derry City and Strabane, Dorset, Ealing, East Ayrshire, East Hampshire, East Lindsey, East Northamptonshire, East Renfrewshire, East Riding of Yorkshire, East Suffolk, Eastleigh, Elmbridge, Enfield, Falkirk, Fareham, Gateshead, Gedling, Gosport, Gravesham, Great Yarmouth, Guildford, Harborough, Haringey, Harrogate, Harrow, Hart, Hartlepool, Havering, Herefordshire, County of, High Peak, Hinckley and Bosworth, Horsham, Islington, Kettering, King's Lynn and West Norfolk, Kingston upon Thames, Kirklees, Leeds, Leicester, Lincoln, Maidstone, Maldon, Mansfield, Medway, Mendip, Mid Sussex, Middlesbrough, Monmouthshire, Moray, New Forest, Newcastle-under-Lyme, Newport, North Ayrshire, North East Derbyshire, North Hertfordshire, North Kesteven, North Lanarkshire, North Lincolnshire, North Norfolk, North Tyneside, North West Leicestershire, Northumberland, Nuneaton and Bedworth, Oxford, Pembrokeshire, Pendle, Renfrewshire, Ribble Valley, Rochford, Runnymede, Rushcliffe, Ryedale, Salford, Sefton, Sheffield, Shropshire, Solihull, South Ayrshire, South Hams, South Holland, South Lanarkshire, South Oxfordshire, South Staffordshire, St Albans, Staffordshire Moorlands, Stockport, Stoke-on-Trent, Surrey Heath, Sutton, Swale, Tamworth, Tendring, Test Valley, Thurrock, Tonbridge and Malling, Torfaen, Wakefield, Warrington, Warwick, Wealden, Wellingborough, West Berkshire, West Dunbartonshire, West Lancashire, West Lothian, West Oxfordshire, West Suffolk, Wigan, Wiltshire, Woking, Worcester, Wrexham, Wycombe, York

Cluster 7: Lisburn and Castlereagh, Selby, Tameside, Wyre Forest

Cluster 8: Lichfield, Oadby and Wigston, Tandridge, Vale of Glamorgan, West Devon

Cluster 9: Aberdeen City, Barnsley, Broxbourne, Charnwood, Chorley, Erewash, Glasgow City, Greenwich, Halton, Havant, Knowsley, Lewisham, Merton, Mid and East Antrim, Milton Keynes, Newark and Sherwood, Northampton, Oldham, Portsmouth, Richmond upon Thames, Rugby, Sandwell, South Derbyshire, South Kesteven, South Northamptonshire, Southampton, Spelthorne, Stockton-on-Tees, Telford and Wrekin, Trafford, Walsall, Welwyn Hatfield

Cluster 10: Bromsgrove, Cannock Chase, Dundee City, Newham

Cluster 11: Barking and Dagenham, Blaby, Blackpool, Bolsover, Brent, Burnley, Caerphilly, Carlisle, Causeway Coast and Glens, Crawley, Doncaster, Dudley, Hertsmere, Hounslow, Hyndburn, Ipswich, Isles of Scilly, Kensington and Chelsea, Lewes, Manchester, North Warwickshire, Norwich, Nottingham, Peterborough, Redditch, Rochdale, Scarborough, Slough, St. Helens, Stevenage, Sunderland, Vale of White Horse, Wolverhampton

Cluster 12: Ards and North Down, Conwy, East Staffordshire, Epping Forest, Fenland, Hammersmith and Fulham, Preston, Rhondda Cynon Taf, Three Rivers, Westminster

Cluster 13: Aberdeenshire, Adur, Antrim and Newtownabbey, Argyll and Bute, Armagh City, Banbridge and Craigavon, Arun, Babergh, Barrow-in-Furness, Basildon, Bassetlaw, Bedford, Blackburn with Darwen, Bolton, Boston, Bracknell Forest, Breckland, Brighton and Hove, Bristol, City of, Broadland, Camden, Carmarthenshire, Central Bedfordshire, Cheshire East, Cheshire West and Chester, Chichester, Chiltern, City of London, Cornwall, Cotswold, Craven, Dacorum, Derbyshire Dales, Dover, Dumfries and Galloway, East Cambridgeshire, East Devon, East Dunbartonshire, East Hertfordshire, Epsom and Ewell, Exeter, Fermanagh and Omagh, Fife, Flintshire, Folkestone and Hythe, Forest of Dean, Gloucester, Gwynedd, Hackney, Hastings, Highland, Hillingdon, Huntingdonshire, Inverclyde, Isle of Anglesey, Isle of Wight, Kingston upon Hull, City of, Lambeth, Lancaster, Liverpool, Malvern Hills, Melton, Merthyr Tydfil, Mid Devon, Mid Suffolk, Mid Ulster, Midlothian, Mole Valley, Na h-Eileanan Siar, Neath Port Talbot, Newcastle upon Tyne, Newry, Mourne and Down, North Devon, North Somerset, Orkney Islands, Perth and Kinross, Plymouth, Powys, Reading, Redbridge, Redcar and Cleveland, Reigate and Banstead, Richmondshire, Rother, Rotherham, Rushmoor, Scottish Borders, Sedgemoor, Sevenoaks, Shetland Islands, Somerset West and Taunton, South Bucks, South Cambridgeshire, South Gloucestershire, South Lakeland, South Norfolk, South Ribble, South Somerset, South Tyneside, Southend-on-Sea, Southwark, Stafford, Stirling, Stratford-on-Avon, Stroud, Swansea, Swindon, Teignbridge, Tewkesbury, Thanet, Torbay, Torridge, Tower Hamlets, Tunbridge Wells, Uttlesford, Waltham Forest, Wandsworth, Watford, Waverley, West Lindsey, Winchester, Windsor and Maidenhead, Wirral, Wokingham, Worthing, Wychavon, Wyre

Appendix 2

Table 3. Descriptive statistics for the auxiliary regression explanatory variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
pop, 2018	365	174,952.100	119,557.100	8,700	100,400	214,900	1,141,400
job density, 2018	365	1.137	5.726	0.400	0.700	0.930	110.110
distance to nearest met. area	365	53.269	57.700	0.150	22.050	69.290	544.090
distance to London	365	201.558	173.634	0.150	76.180	278.880	1,003.950
south of the UK	365	0.463	0.499	0	0	1	1
managerial jobs, 2020	363	12.009	4.013	3.600	9.000	14.300	27.900
tech jobs, 2020	364	14.505	4.057	3.500	11.800	16.900	29.600
skilled trade jobs, 2020	358	10.513	3.764	1.000	8.025	12.500	21.600
professional jobs, 2020	364	21.223	6.902	4.400	16.775	24.850	71.600
administrative jobs, 2020	359	9.965	2.738	3.200	8.100	11.400	21.300
leisure jobs, 2020	362	9.261	2.827	2.800	7.300	11.400	17.800
machine operation jobs, 2020	337	6.339	2.847	1.200	4.400	7.900	19.800
earnings, 2019	360	592.184	81.129	437.600	534.625	633.875	893.200
NVQ4+	365	39.329	11.076	15.000	31.800	45.300	100.000
Virgin Media %, 2020	365	0.152	0.141	0.000	0.018	0.241	0.753
n. business est. per hab., 2019	365	0.057	0.164	0.023	0.038	0.056	3.174
AM tests per hab., 2020	365	0.0005	0.0002	0.0001	0.0003	0.001	0.001

References

Aggarwal, CC, and CK Reddy. 2013. "Time-series data clustering." *Data Clustering: Algorithms and Applications* 1.

Aggarwal, Charu C, Alexander Hinneburg, and Daniel A Keim. 2001. "On the surprising behavior of distance metrics in high dimensional space." In *International conference on database theory*, 420–434. Springer.

Aghabozorgi, Saeed, Ali Seyed Shirkhorshidi, and Teh Ying Wah. 2015. "Time-series clustering–a decade review." *Information Systems* 53: 16–38.

Allen, Tammy D, Timothy D Golden, and Kristen M Shockley. 2015. "How effective is telecommuting? Assessing the status of our scientific findings." *Psychological Science in the Public Interest* 16 (2): 40–68.

Bailey, Diane E, and Nancy B Kurland. 2002. "A review of telework research: Findings, new directions, and lessons for the study of modern work." *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior* 23 (4): 383–400.

Batty, Michael. 2020. "The Coronavirus crisis: What will the post-pandemic city look like?" *Environment and Planning B: Urban Analytics and City Science* 47 (4): 547–552. `https://doi.org/10.1177/2399808320926912`.

Berndt, Donald J, and James Clifford. 1994. "Using dynamic time warping to find patterns in time series." In *KDD workshop*, Vol. 10, 359–370. Seattle, WA, USA:.

Blank, Grant, Mark Graham, and Claudio Calvino. 2018. "Local geographies of digital inequality." *Social Science Computer Review* 36 (1): 82–102.

Blank, Grant, and Darja Groselj. 2014. "Dimensions of Internet use: amount, variety, and types." *Information, Communication & Society* 17 (4): 417–435.

Bris, Myriam, Jacek Pawlak, and John W Polak. 2017. "How is ICT use linked to household transport expenditure? A cross-national macro analysis of the influence of home broadband access." *Journal of Transport Geography* 60: 231–242.

Brynjolfsson, Erik, John J Horton, Adam Ozimek, Daniel Rock, Garima Sharma, and Hong-Yi TuYe. 2020. *COVID-19 and remote work: an early look at US data.* Technical Report. National Bureau of Economic Research.

Budnitz, Hannah, Emmanouil Tranos, and Lee Chapman. 2020. "Telecommuting and other trips: an English case study." *Journal of Transport Geography* 85: 102713. `http://www.sciencedirect.com/science/article/pii/S0966692319305472`.

Dingel, Jonathan I, and Brent Neiman. 2020. *How Many Jobs Can be Done at Home?* Working Paper 26948. National Bureau of Economic Research. `http://www.nber.org/papers/w26948`.

Dorling, Danny. 2018. *Peak Inequality: Britain's ticking time bomb.* Policy Press.

e Silva, João de Abreu, and Patrícia C Melo. 2018. "Does home-based telework reduce household total travel? A path analysis using single and two worker British households." *Journal of Transport Geography* 73: 148–162.

Elldér, Erik. 2020. "Telework and daily travel: New evidence from Sweden." *Journal of Transport Geography* 86: 102777. `http://www.sciencedirect.com/science/article/pii/S0966692319311305`.

Eurofound. 2020. "Living, working and COVID-19." *COVID-19 series* `https://www.eurofound.europa.eu/publications/report/2020/living-working-and-covid-19`.

Everitt, B. 1974. "Cluster Analysis Heinemann Educational London." .

Felstead, Alan. 2012. "Rapid change or slow evolution? Changing places of work and their consequences in the UK." *Journal of Transport Geography* 21: 31–38.

Felstead, Alan, and Darja Reuschke. 2020. "Homeworking in the UK: before and during the 2020 lockdown." .

Gal, Peter, and Jagoda Egeland. 2018. "Reducing regional disparities in productivity in the United Kingdom." .

Gordon, AD. 1977. "Classification: methods for the exploratory analysis of multivariate data."

Wiley.
GOV.UK. 2020. "News and Communications." https://www.gov.uk/search/news-and-communications?level_one_taxon=5b7b9532-a775-4bd2-a3aa-6ce380184b6c&order=updated-oldest.
Haddad, Hebba, Glenn Lyons, and Kiron Chatterjee. 2009. "An examination of determinants influencing the desire for and frequency of part-day and whole-day homeworking." *Journal of Transport Geography* 17 (2): 124–133.
Harris, Richard, Peter Sleight, and Richard Webber. 2005. *Geodemographics, GIS and neighbourhood targeting.* Vol. 8. John Wiley & Sons.
Hauge, Janice, Mark Jamison, and Mircea Marcu. 2011. "Consumer Usage of Broadband Internet Services: an analysis of the case of Portugal." In *Adoption, Usage, and Global Impact of Broadband Technologies: Diffusion, Practice and Policy*, 198–213. IGI Global.
Headicar, P, and G Stokes. 2016. *On the Move 2: Making sense of travel trends in England 1995–2014.* Technical Report. Technical Report. Independent Transport Commission. http://www. theitc. org ....
Hyndman, Rob J, Earo Wang, and Nikolay Laptev. 2015. "Large-scale unusual time series detection." In *2015 IEEE international conference on data mining workshop (ICDMW)*, 1616–1619. IEEE.
James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani. 2013. *An introduction to statistical learning.* Vol. 112. Springer.
Kitsos, Anastasios, and Paul Bishop. 2018. "Economic resilience in Great Britain: the crisis impact and its determining factors for local authority districts." *The Annals of Regional Science* 60 (2): 329–347.
Lee, Neil. 2014. "Grim down South? The determinants of unemployment increases in British cities in the 2008–2009 recession." *Regional Studies* 48 (11): 1761–1778.
Lin, Jessica, Michail Vlachos, Eamonn Keogh, and Dimitrios Gunopulos. 2004. "Iterative incremental clustering of time series." In *International Conference on Extending Database Technology*, 106–122. Springer.
Marks, Paul. 2020. "News: Virtual collaboration in the age of the coronavirus." *Communications of the ACM* 63 (9): 21–23.
Martin, Ron. 1988. "The Political Economy of Britain's North-South Divide." *Transactions of the Institute of British Geographers* 13 (4): 389–418. http://www.jstor.org/stable/622738.
Martin, Ron. 2012. "Regional economic resilience, hysteresis and recessionary shocks." *Journal of economic geography* 12 (1): 1–32.
McCann, Philip. 2016. *The UK regional-national economic problem: Geography, globalisation and governance.* Routledge.
McCann, Philip. 2020. "Perceptions of regional inequality and the geography of discontent: Insights from the UK." *Regional Studies* 54 (2): 256–267.
Mongey, Simon, Laura Pilossoph, and Alex Weinberg. 2020. *Which Workers Bear the Burden of Social Distancing Policies?* Working Paper 27085. National Bureau of Economic Research. http://www.nber.org/papers/w27085.
Montero, Pablo, José A Vilar, et al. 2014. "TSclust: An R package for time series clustering." *Journal of Statistical Software* 62 (1): 1–43.
Nardotto, Mattia, Tommaso Valletti, and Frank Verboven. 2015. "Unbundling the incumbent: Evidence from UK broadband." *Journal of the European Economic Association* 13 (2): 330–362.
Nathan, Max, and Henry Overman. 2020. "Will coronavirus cause a big city exodus?" *Environment and Planning B: Urban Analytics and City Science* 47 (9): 1537–1542. https://doi.org/10.1177/2399808320971910.
Niesterowicz, J., T.F. Stepinski, and J. Jasiewicz. 2016. "Unsupervised regionalization of the United States into landscape pattern types." *International Journal of Geographical Information Science* 30 (7): 1450–1468. https://doi.org/10.1080/13658816.2015.1134796.
OfCom. 2016. "Connected Nations Report 2016." https://www.ofcom.org.uk/__data/

assets/pdf_file/0035/95876/CN-Report-2016.pdf.

OfCom. 2017. "UK Home Broadband Performance: The performance of fixed-line broadband delivered to UK residential consumers. Research Report." https://www.ofcom.org.uk/__data/assets/pdf_file/0015/100761/UK-home-broadband-performance,-November-2016-Technical-report.pdf.

ONS. 2020a. "Coronavirus and homeworking in the UK: April 2020." https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/coronavirusandhomeworkingintheuk/april2020.

ONS. 2020b. "Coronavirus and Homeworking in the UK Labour Market: 2019." https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/coronavirusandhomeworkingintheuklabourmarket/2019.

Peters, Pascale, Kea G Tijdens, and Cécile Wetzels. 2004. "Employees' opportunities, preferences, and practices in telecommuting adoption." *Information & Management* 41 (4): 469–482.

Philip, Lorna, Caitlin Cottrill, John Farrington, Fiona Williams, and Fiona Ashmore. 2017. "The digital divide: Patterns, policy and scenarios for connecting the 'final few'in rural communities across Great Britain." *Journal of Rural Studies* 54: 386–398.

Ratanamahatana, Chotirat Ann, and Eamonn Keogh. 2004. "Everything you know about dynamic time warping is wrong." In *Third workshop on mining temporal and sequential data*, Vol. 32. Citeseer.

Riddlesden, Dean, and Alex D Singleton. 2014. "Broadband speed equity: A new digital divide?" *Applied Geography* 52: 25–33.

Salemink, Koen, Dirk Strijker, and Gary Bosworth. 2017. "Rural development in the digital age: A systematic literature review on unequal ICT availability, adoption, and use in rural areas." *Journal of Rural Studies* 54: 360 – 371. http://www.sciencedirect.com/science/article/pii/S0743016715300176.

Sardá-Espinosa, Alexis. 2019. "Time-Series Clustering in R Using the dtwclust Package." *The R Journal* 11 (1): 22–43. https://doi.org/10.32614/RJ-2019-023.

Sarda-Espinosa, Alexis. 2019. *dtwclust: Time Series Clustering Along with Optimizations for the Dynamic Time Warping Distance.* R package version 5.5.6, https://CRAN.R-project.org/package=dtwclust.

Siha, Samia M, and Richard W Monroe. 2006. "Telecommuting's past and future: a literature review and research agenda." *Business Process Management Journal* .

Singh, Palvinder, Rajesh Paleti, Syndney Jenkins, and Chandra R Bhat. 2013. "On modeling telecommuting behavior: Option, choice, and frequency." *Transportation* 40 (2): 373–396.

Singleton, Alexander D., and Paul A. Longley. 2009. "Geodemographics, visualisation, and social networks in applied geography." *Applied Geography* 29 (3): 289 – 298. http://www.sciencedirect.com/science/article/pii/S0143622808000726.

Stern, M, Alison Adams, and Shaun Elsasser. 2009. "How levels of Internet proficiency affect usefulness of access across rural, suburban, and urban communities." *Sociological Inquiry* 79 (4): 391–417.

UK, Tech City. 2018. "Tech Nation 2017." https://technation.io/wp-content/uploads/2018/04/Tech_City_2017_report_full_web.pdf.

Van Deursen, Alexander, and Jan Van Dijk. 2011. "Internet skills and the digital divide." *New media & society* 13 (6): 893–911.

Van Deursen, Alexander JAM, and Ellen J Helsper. 2015. "The third-level digital divide: Who benefits most from being online?" In *Communication and information technologies annual*, edited by Laura Robinson, Shelia R. Cotten, and Jeremy Schulz, 29 – 52. Emerald Group Publishing Limited.

Van Deursen, Alexander JAM, and Jan AGM Van Dijk. 2014. "The digital divide shifts to differences in usage." *New media & society* 16 (3): 507–526.

Warren Liao, T. 2005. "Clustering of time series data—a survey." *Pattern Recognition* 38 (11): 1857 – 1874. http://www.sciencedirect.com/science/article/pii/

S0031320305001305.