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 geographical.

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. High levels of demand are one of the main causes of reduced reliability and slower connection speeds, as network bandwidth becomes congested. Yet 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).

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). 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.

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. 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. Our analysis enables us to better understand how the spatial and social distribution of 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

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

common means of accessing work, at least in comparison to the pre-Covid era.

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. 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]See also the popular social media hashtag #WFM

2.2. *Digital divides and economic resilience*

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

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). In some aspects, these returns may have increased 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. This finding broadly applies in the UK, where studies that also analysed broadband speed checks concluded that average speeds are lower in rural areas, something that has not been improved by policy measures to increase competition (Riddlesden and Singleton 2014; Nardotto, Valletti, and Verboven 2015). In contrast, Riddlesden and Singleton (2014) found that levels of deprivation did not correlate with first level digital divides.

However, as Blank, Graham, and Calvino (2018) highlight, variation in individual internet availability and uptake is a product of more complex spatial and demographic characteristics than simple rurality or urbanisation. Dense urban areas were shown to suffer more from slowdown during peak hours, although these services were more likely to be improved by increased competition between providers, such as between new entrants and Virgin Media cable connections (Riddlesden and Singleton 2014; Nardotto, Valletti, and Verboven 2015). The latter were historically available to only 45% of premises in the UK (OfCom 2016), where the more lucrative and competitive market originally attracted the cable TV provider. Whether the variation in infrastructure quality and reliability 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.

Other intersections between digital divides have been subject to study. 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). 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. Such digital intersections and efficiencies have also changed transportation, connectivity and the structure of cities during the pandemic. We now have enough data to confirm the drastic alteration observed in the space-time geography of cities around the world in the last year (e.g. Google 2020; Shibayama et al. 2021). Yet, although there is a broad agreement that these changes during the pandemic have played a pivotal role in stopping the spread of the virus (Jia et al. 2020; Yang et al. 2020; Mu, Yeh, and Zhang 2020), the extent to which the increased levels of working from home, the consequent decrease in commuting flows, and the altered structure of cities will remain post-pandemic is the subject of considerable debate in the literature.

Meanwhile, 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 contribute 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. Indeed, those who seek to test their broadband are most likely to do so because they are experiencing slower speeds than expected, although any skew towards slower speeds is balanced by the likelihood that those who test their broadband are also more 'tech-savvy' and / or have purchased higher speed packages that are not delivering the promised level of service.

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 encompasses the period when UK workers were told to work from home if at all possible (GOV.UK 2020). Schools and various retail, leisure and hospitality businesses were closed from late March, and restrictions were gradually eased from late May. 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 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 [4]. 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 Local Authority District (LAD) on average – for each for each working hour of each working day in each 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

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

[4] Figures 1 and 2 were created with the `R` package `openair` (Carslaw and Ropkins 2012).

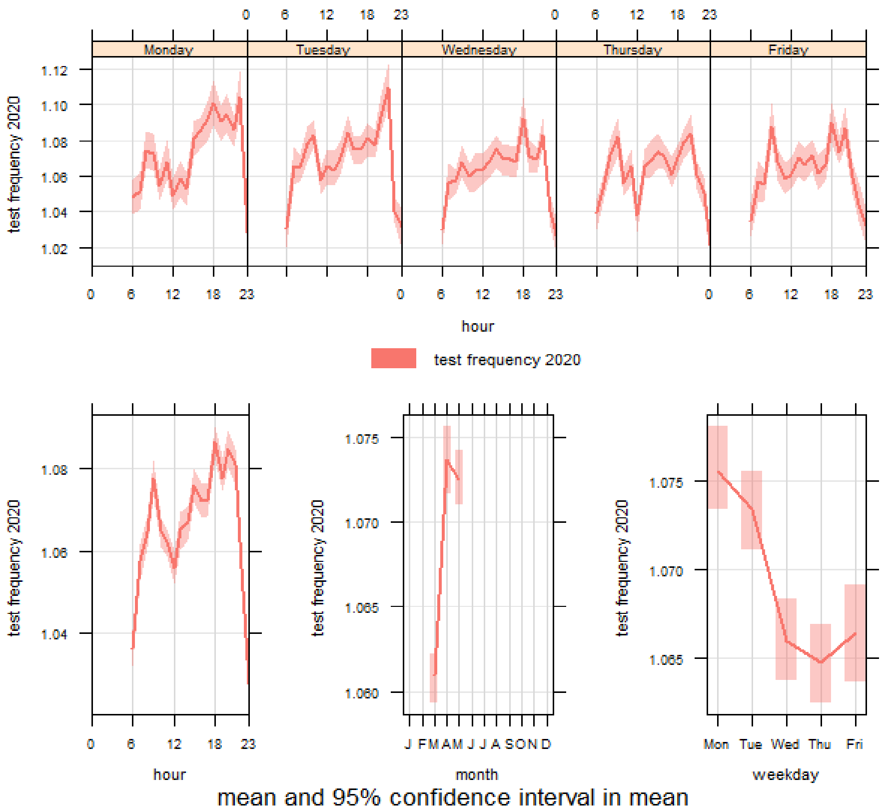

Figure 1. Speed tests over time, 2020

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 $k \in \mathbb{N} \bigcap [5, 15]$, calculated the cluster validity indices (CVIs) and then run the subsequent multinomial regression – see the end of this section for more details for the different k. Following Sardá-Espinosa (2019), to identify the optimal k we used the majority vote for the following CVIs: Silhouette (max), Score function (max), Calinski-Harabasz (max), Davies-Bouldin (min), Modified Davies-Bouldin (DB*, min), Dunn (max), COP (min). Nevertheless, we opted against using the optimal $k = 13$ solution as it was too large to allow for communicable LAD clusters. Instead we opted for a smaller $k = 9$, which led to a rather similar spatial pattern and, importantly, to a much higher R-squared in the subsequent explanatory regression (0.44 instead of 0.34).

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 of the clusters. 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

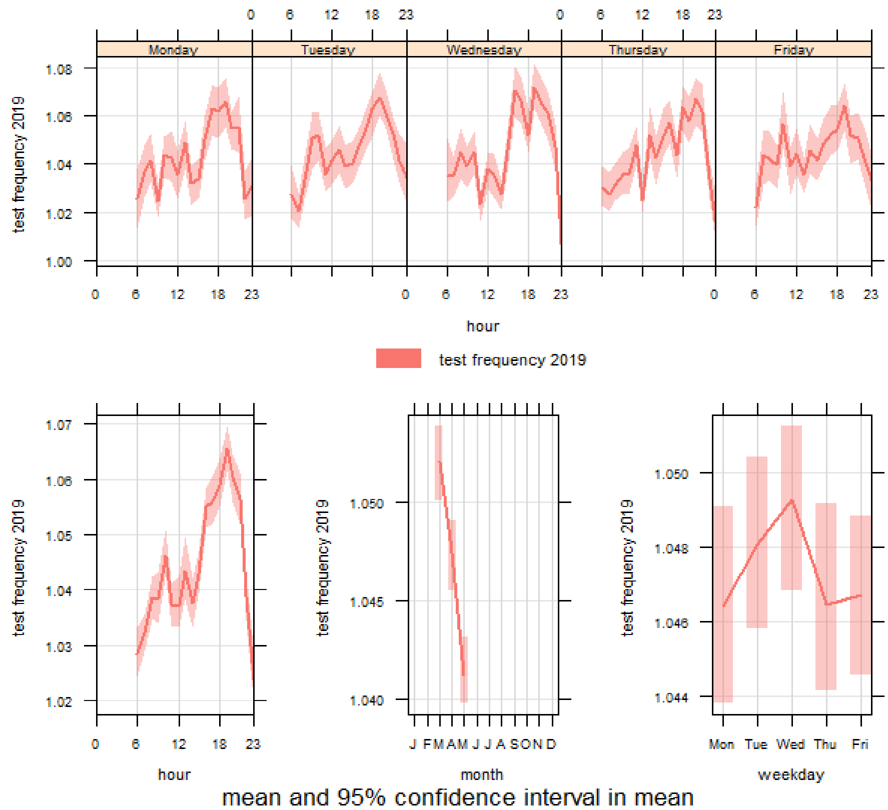

Figure 2. Speed tests over time, 2019

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 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 Figure 3 and Table 1, to provide an overview of the quality and reliability of experienced broadband in different parts of the UK. Figure 3 shows a composite profile of mean upload speeds per hour per day for each of the largest six clusters, in terms of the LAD membership and population.

The largest cluster, comprising 229 local authorities and over 40 million people, is cluster 6, which has the slowest aggregate mean upload speed of any cluster, and the 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 and reliability in the UK. However, as shown in Figure 4, some of the most rural areas of the UK are included in this cluster. If these areas suffer most from first level digital divides as described in the literature review,

Figure 3. Temporal profilies for upload speed clusters

Table 1. Upload speed cluster characteristics

Cluster	N. of LADs	LAD population	mean speed	SD speed	mean AM speed	mean PM speed
1	9	903200	9564	6314	8798	10457
2	2	162000	12085	6537	11882	10866
3	12	1785800	11047	6079	10029	11634
4	1	91100	9689	6122	7816	9689
5	3	280000	10802	6116	11010	10084
6	229	40552800	8761	5847	8555	8955
7	5	682500	10326	6102	10045	11149
8	6	510000	9769	6352	8989	10836
9	115	21467800	10328	5915	10283	10333

Note: All speed measures are upload speeds

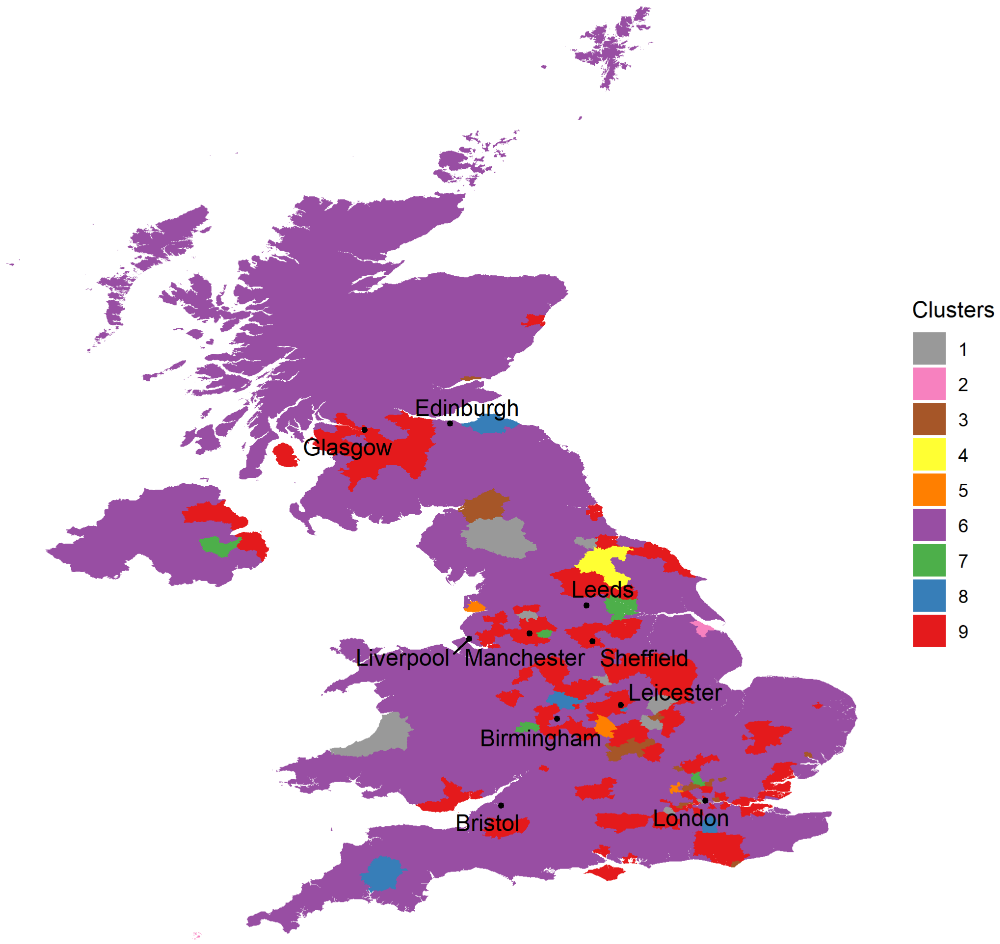

Figure 4. Upload speed clusters for LADs

the low speeds in rural areas might be pulling down the averages in other areas in this largest cluster. Also, since the areas are clustered by their temporal profile across the working week, the graph in Figure 3 indicates that speeds in cluster 6 are some of the more reliable. Table 1 confirms that upload speeds in cluster 6 during the morning peak from 9 : 00-10 : 59 were, on average, only 4.5% slower than in the evening peak period between 19 : 00 and 20 : 59, when entertainment purposes are likely to be using the most bandwidth.

Those living in the second largest cluster – 9, with 115 LADs and 21.5 million people – experienced aggregate mean upload speeds of more than 1.5Mb/s faster than those in cluster 6, a lower ratio of standard deviation to mean, and almost the same upload speeds in the AM Peak as the PM Peak. Indeed, the temporal profile for cluster 9 in Figure 3, like that for cluster 6, is fairly flat. Whilst it is likely that the large numbers of tests being performed by the large populations in these two clusters of LADs result in less varied averages to show in the graph, the method of shape-based clustering suggests that these results indicate that the majority of the population of the UK experience less temporal variation, and so belong in these two clusters. The results also confirm that those in cluster 9 experienced a consistently better service during lockdown than those in cluster 6, in terms of both average speed and reliability.

Of the smaller clusters, cluster 7 experiences quite similar mean speeds to cluster 9, and a not too dissimilar standard deviation, but mean speeds in the morning peak are almost 10% lower than the evening peak. Cluster 3 boasts speeds almost 1Mb/s higher again, but suffers from even greater slowdown in the morning peak. In comparison, clusters 2 and 5, home to a little less than half a million people, experience not only above average mean speeds, but also faster speeds in the morning peak compared to the evening. Thus, in the five LADs in these two clusters, the temporal profile of internet use may be closer to what might have been expected pre-pandemic. In comparison, the 15 LADs in clusters 1 and 8, home to over 1.4 million people, not only experience fairly average upload speeds and high ratios of standard deviation to the mean, but also experience much lower speeds during the morning peak than the evening peak. From the large spikes and dips shown on Figure 3, it is likely that this poor reliability or consistency of morning internet speeds was more noticeable to those in cluster 1, whilst those in cluster 8 experienced the lack of reliable service as a problem throughout the day.

It is worth noting here that clusters of LAD based on the upload speeds are very different to the ones occur when we apply the same methods to upload speed data for the same time period in 2019 – see Appendix 2. This drastic difference between the LAD upload speed profiles before and during the pandemic is an indication of the changes in internet usage that took place during the pandemic.

In summary, the reliability of internet services during the working day appears to have altered for the vast majority of locations due to increased use from residents told to stay at home, and, if they were fortunate, work from home. Yet this experience has been different in different locations. In particular, LADs in cluster 9 experienced higher speeds and more resilient broadband internet than those in the largest cluster, 6. Those in clusters 3 and 7 also experience higher mean speeds and better service reliability, and can be more confident that they are on the right side of the first level digital divide, and that their more resilient ICT infrastructure and services can robustly support higher levels of telecommuting. On the other hand, whilst high levels of telecommuting may be the cause of morning speeds over 15% lower than those in the evening, those in clusters 1 and 8 also experience lower mean speeds than clusters 3, 7, and 9, but not as low as cluster 6. Whilst the differences may not be large, the lower upload speeds in cluster 6 or the poor reliability in clusters 1 and 8 could still have had implications for economic resilience if combined with other types of digital divide. This potential will be explored in the next section.

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 do indeed consist of LADs that are more urban or closer to major urban areas and are more likely to benefit from a choice of high quality internet services. This part of the regression aims to confirm any first level digital divides. Next, to better understand how the clusters fare in relation to the second level digital divide, we consider which LADs in which clusters have a higher proportion of occupations where the nature of the work and the skills that occupation employs enable telecommuting. Finally, we consider the rate of return on internet use, or third level digital divides, by reviewing which clusters have the highest earnings and job density, and also which clusters experienced the highest share of population

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

	1	2	3	5	6	7	8	9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
pop, 2018	−0.00004**	0.00002	0.00001	0.00002	0.00001	0.00002	−0.00000	0.00001
	(0.00002)	(0.00001)	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00002)	(0.00001)
job density, 2018	−0.534***	−0.362***	4.211***	−0.890***	3.516***	−8.624***	−3.259***	3.337***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
distance to nearest met. area	−0.007***	0.013***	0.002***	0.023***	−0.001	−0.158***	0.005***	−0.003**
	(0.0004)	(0.00001)	(0.0003)	(0.0002)	(0.002)	(0.0001)	(0.0003)	(0.002)
distance to London	0.011***	0.004***	0.005**	−0.013***	0.010***	0.012***	0.008***	0.008***
	(0.001)	(0.00004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
South of the UK	−3.628***	0.958***	4.936***	−10.243***	4.830***	3.919***	−1.140***	3.188***
	(0.000)	(0.000)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00001)
managerial jobs, 2020	0.944***	0.628***	0.593***	−0.544***	0.634***	−0.128***	0.725***	0.511***
	(0.00002)	(0.00000)	(0.00003)	(0.00003)	(0.00002)	(0.00003)	(0.00003)	(0.00002)
tech jobs, 2020	0.350***	−0.222***	−0.068***	−0.151***	0.018***	−0.139***	0.143***	−0.071***
	(0.00002)	(0.00000)	(0.00002)	(0.0001)	(0.00003)	(0.0001)	(0.00003)	(0.00003)
skilled trade jobs, 2020	0.521***	0.171***	0.214***	−0.578***	0.231***	1.067***	0.284***	0.049***
	(0.00002)	(0.00000)	(0.00004)	(0.00004)	(0.00004)	(0.0001)	(0.00003)	(0.00003)
professional jobs, 2020	−0.577***	−0.962***	−0.565***	−0.860***	−0.566***	−1.139***	−0.389***	−0.702***
	(0.00003)	(0.00000)	(0.00004)	(0.0001)	(0.00004)	(0.0001)	(0.0001)	(0.00004)
administrative jobs, 2020	0.200***	−1.324***	−0.050***	0.136***	−0.137***	−0.101***	−0.018***	−0.155***
	(0.00002)	(0.00000)	(0.00002)	(0.00004)	(0.00002)	(0.00005)	(0.00002)	(0.00002)
service jobs, 2020	−0.082***	−0.180***	−0.659***	−1.066***	−0.746***	−0.944***	−0.773***	−0.783***
	(0.00002)	(0.00000)	(0.00003)	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00001)
machine operation jobs, 2020	0.210***	0.574***	0.439***	−0.589***	0.229***	−0.260***	0.080***	0.127***
	(0.00001)	(0.00000)	(0.00002)	(0.00002)	(0.00001)	(0.00002)	(0.00001)	(0.00001)
earnings, 2019	−0.003***	0.029***	0.019***	0.069***	0.018***	0.050***	0.016***	0.026***
	(0.001)	(0.0001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
n. business est. per hab., 2019	1.930***	−0.377***	0.826***	0.251***	0.315***	1.515***	−0.948***	−4.011***
	(0.00000)	(0.000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
furloughed per hab., 2020	−1.518***	−0.152***	11.014***	0.972***	−26.969***	2.059***	4.236***	10.500***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
AM tests per hab., 2020	0.002***	−0.011***	−0.140***	0.015***	0.231***	0.005***	−0.025***	−0.078***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Virgin Media %, 2020	−0.349***	12.236***	5.619***	0.489***	1.721***	−16.289***	−5.581***	6.126***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Constant	−4.570***	−1.045***	−6.539***	5.629***	2.957***	3.386***	−2.531***	2.979***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
McFadden's R squared	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435
N	322	322	322	322	322	322	322	322
Akaike Inf. Crit.	742.901	742.901	742.901	742.901	742.901	742.901	742.901	742.901

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

furloughed during this period in the pandemic.

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 speed in cluster 4 (see Table 1) is close to 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 [5]. Regarding the former, we expect people in LADs with more unreliable connections to test their internet speeds more often, and the results show that those in cluster 6 are by far the most concerned about reliability at that time of day. Meanwhile, those in clusters 2, 3, and 9 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 profitable broadband markets, and a better choice of broadband services. We also employ distance from London and from the nearest metropolitan area (including London) as two variables depicting peripherality and urban structure. However, whilst significant, the pattern of coefficients of these variables is inconclusive in confirmed first level digital divides. Even though London was one of the ten largest metropolitan areas in England, which, along with Glasgow and Cardiff, were identified to calculate the variable estimating the impact of distance from the centre of a metropolitan area, the coefficients for the two variables are mostly small and the signs for some are opposite.

When looking at the constituent authorities (see full list of LADs in Appendix 1 as well as Figure 4), however, Cluster 9 is clearly more urban, including 13 of 32 London Boroughs, five of the seven constitutent LADs of the West Midlands conurbation, nine of the ten boroughs of Greater Manchester, and five of nine other large metropolitan areas coded in for the 'distance to nearest met area' variable. Cluster 9 also includes the other main cities in the East Midlands, Leicester and Derby, as well as smaller cities known for their knowledge economy, such as Oxford and Milton Keynes. However, as previously mentioned, there is more noise within the variables for the two largest clusters than the smaller ones, and cluster 6 also contains many urban areas. These include 16 London boroughs, Birmingham City, Bolton in Greater Manchester, Leeds, Liverpool, Newcastle and Bristol, as well as small cities with knowledge economies such as Cambridge, Edinburgh, and Reading and its neighbours in the high-tech agglomeration of the Thames Valley. And yet cluster 6 also includes some of the most rural areas in the country, showing how important it is to interpretation to consider the membership of the cluster as well as the regression results.

The coefficients in Table 2 demonstrate that those in cluster 6 were more likely to hold managerial, tech and professional jobs than those in cluster 9, and were the least likely to be furloughed of any cluster. Thus, although speeds were slow and not as reliable during the morning peak as in cluster 9, the skills that enabled telecommuting also enabled greater returns from doing so, despite lower than average earnings. Cluster 6 also has the second highest job density, with more jobs to keep. Likewise, those in

[5] See Appendix 3 for the descriptive statistics.

LADs in clusters 1 and 8 had the highest and second highest proportions of residents working in tech or managerial occupations despite suffering from lower speeds and unreliable services, another mismatch between first and second level digital divides. Yet unlike cluster 6 and despite occupations with better digital skills, cluster 8, with its five peripheral suburban areas in the Midlands, Scotland and south of London, as well as rural West Devon saw the third highest proportion of its working population furloughed. It also had the second lowest average earnings in 2019, suggesting that its population was more likely to be on the wrong side of the third level digital divide before, as well as during the pandemic. In contrast, the nine LADs of cluster 1, which include more rural areas, plus Westminster in central London had the lowest earnings of any cluster, but also lowest level of furlough after cluster 6.

The regression results for cluster 7 also reveal the complexity of intersecting and diverging digital divides. Along with 3 and 9, the analysis in Section 4.1 suggested this cluster was on the ‘right’ side of any first level digital divides, yet the regression shows that it has the lowest proportion of Virgin connections. It is furthest from a metropolitan area, but closest to London. The five LADs in cluster 7 are all suburban, making it sensible that the cluster is in the group with better infrastructure, but none are central urban boroughs and, along with a London suburb, Leeds suburb, Manchester suburb, and West Midlands suburb, the fifth LAD is outside Belfast. Belfast was not included among the metropolitan areas, and whilst there has been substantial investment in high speed broadband in Northern Ireland in recent years, including by Virgin, take-up may still lag behind historic networks in other urban markets.

Cluster 7 has the lowest proportion of residents currently employed in professional occupations, and among the lowest proportions in managerial or technical occupations. This suggests potentially a low level of skills to take advantage of the quality internet service available, a second level digital divide. Cluster 7 also has the lowest job density. However, with the largest proportion of skilled tradespeople, and the second highest number of businesses per inhabitant, those in cluster 7 ranked second in terms of earnings in 2019. On the other hand, the lack of some of the occupations most likely to telecommute during lockdown may have contributed both to a substantial proportion being furloughed in 2020, and even to the relative reliability of broadband speeds compared to many of the other smaller clusters.

Cluster 3, meanwhile, had the greatest proportion of its workforce furloughed of any cluster, despite having the highest job density and the second highest average speeds. Ranking in the middle for most of the occupations estimated, at least some of its population should have the skills to work from home. The geography would suggest economic advantage as well, with eight of its twelve LADs in the South of England, including two London Boroughs, four suburban areas north of London, and the two tightly bounded urban areas of Eastbourne and Ipswich – a greater proportion than any other cluster. Yet geographic position and job density do not appear to equate to particularly high average earnings in 2019, nor did they protect residents from furlough in 2020. In contrast, cluster 5, comprised of three suburban districts in the Northwest, Midlands, and the London green belt, had the highest average earnings in 2019, despite low levels of residents working in managerial, tech and professional occupations. Suburbs are considered the most likely urban form in which telecommuters live (e Silva and Melo 2018), yet the contrast between these small, mainly suburban clusters – 7, 3, and 5, suggest that they are not all equally economically resilient in a pandemic.

Cluster 2, which, like cluster 5, had faster morning broadband speeds than evening speeds, as shown in Table 1 contains two remote LADs, the Isles of Scilly and North-east Lincolnshire. Whilst the low demand may be due to the least residents in tech occupations, it may also be due to high numbers of retired people. Rural areas such as those in cluster 2 are often home to many older, retired people (Blank, Graham, and Calvino 2018), which may also explain some of the contradictions in cluster 1 with its low levels of furlough and low earnings, whilst the presence of Westminster in that cluster might be why there are the highest levels of tech and managerial occupations.

In summary, the regression results indicate the complexity of measuring second and third level digital divides within spatial aggregations where the geography of first level digital divides has been captured using time-series clustering of experienced broadband upload speeds as a product of reliability not just availability. Whilst the differences in mean speeds between clusters were not large, the temporal clustering of internet resilience showed much greater variation, and was not spatially dependent upon distance to large urban areas, or relative location. Internet resilience supports a wide range of small and large urban economies, but also fails, or at least frustrates a wide range of other urban economies, as demonstrated by the number of morning peak tests per capita run in cluster 6. Yet our analysis of the likelihood of furlough within the population, especially in the smaller suburban clusters 7, 3, 5, and 8 shows that digital divides were as likely to diverge as intersect during the pandemic, and did not necessarily overlap with prior economic divides. With a much greater share of the population likely to continue to work from home in the future, and with changing attitudes towards residential locations, our analysis suggests that first level digital divides should be seen as a function of reliability as well as availability, of upload speeds as well as download speeds, and of greater spatial variation than might have previously been considered.

5. Discussion and Conclusions

Our analysis demonstrated that the temporal profiles of seven of our nine 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. Furthermore, 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. Yet those in the largest cluster, 6, clearly experienced lower upload speeds. Their speeds were also less reliable, perhaps because they had higher levels of demand than the second largest cluster, 9, where many more employees were furloughed. Indeed, those with the skills and jobs to work from home were often left with the least robust services and greatest slowdown.

Therefore, home-based 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, the reliability of home broadband services deserve more consideration than in the past. This would represent a switch from previous demand-side broadband policies in the UK which tended to be aimed at supporting small and medium enterprises (Henderson 2020). SUch policies were based on previous research regarding the productivity effects of broadband infrastructure (DeStefano, Kneller, and Timmis 2018). However, this stream of research tended not to consider residential locations as places that host economic activity. Such policies also made some assumptions about the quality of service in residential markets that could be assured without government intervention – an assumption which our analysis suggest is not entirely accurate.

Policy and development proposals should also consider how the potential changes wrought by the pandemic span various aspects of economy and society. Changes to transportation planning due to altered commuting patterns also imply changes in land use and urban planning to accommodate people who work from home (Budnitz, Tranos, and Chapman 2020; Elldér 2020). Productivity and innovation changes will reflect upon 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. For example, our results suggest that broadband policies cannot improve the economic resilience of places where the industrial structure does not align with occupations that incorporate the digital skills and capabilities to work from home. Such places instead experienced higher proportions of their labour force being placed on furlough.

Early research on Covid-19 and cities also speculated upon the changes that potential extensive post-Covid working from home patterns might generate for spatial structure: from more walkable cities and more localised production and consumption patterns to more extensive urban sprawl, the decline in public transportation and increased private car usage (Batty 2020). Despite the essential role it played during the pandemic, less effort has been spent in understanding the current and future role of digital infrastructure. Our results indicate that probably for the first time the future of cities and spatial structure are so intertwined with digital infrastructure. If the post-covid world is a world with extensive working from home, then we need to build, among other things, resilient digital infrastructure capable of bridging the first layer of the digital divide. Contrary to previous broadband business and deployment plans, emphasis should be placed not only on download, but also on upload speeds (Brake 2020). In essence, Covid-19 accentuated the old argument, now more valid than ever: digital infrastructure, just like any other network infrastructure, only becomes visible when it stops working (STAR 1999; Tranos 2013).

On the other hand, the nuanced picture we gained through our analysis of the UK case study suggests that being on the right side of the second level digital divide had a greater impact on economic resilience and therefore the third level digital divide, than having quality internet connectivity. Our regressions results for cluster 1 and 6 are a demonstration of this. Our analysis shows both the intersections and divergences of digital and economic division. Almost all of the largest urban areas in the UK, as well as many smaller cities, were split between the largest two clusters – 6 and 9 – and both contain LADs that are centres of the knowledge economy, from Cambridge in the former to Oxford in the latter, or have high concentrations of digital businesses, like Reading in the former and Milton Keynes in the latter (UK 2018). Yet whilst LADs in cluster 9 were able to benefit both from reliable internet connections and populations familiar with working from home to capitalise on their digital infrastructure, they appeared to have a lower rate of return in the pandemic, with far greater numbers furloughed. Is this an indication of historic economic division, as well as the third level digital divide, in cities in the North and Midlands unable to capitalise on their digital infrastructure? Meanwhile, did the greater presence in London and the South of LADs in cluster 6, as well as the inclusion of many rural areas less impacted by the pandemic help those in this cluster be more resilient and gain greater returns, despite using less reliable internet services? Further research would be necessary to prise apart the detail, particularly in the largest clusters where averages are less distinct.

In conclusion, 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 may depend upon good internet reliability as well as connectivity to achieve economic resilience in a period like the current pandemic when internet resilience is so vital.

Appendix 1

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

Cluster 1: Ceredigion, Darlington, Eden, Erewash, Kettering, Rossendale, Runnymede, Rutland, Westminster

Cluster 2: Isles of Scilly, North East Lincolnshire

Cluster 3: Broxbourne, Carlisle, Corby, Dundee City, Eastbourne, Harlow, Hertsmere, Hounslow, Ipswich, Luton, Newham, South Northamptonshire

Cluster 4: Hambleton

Cluster 5: Fylde, Rugby, Three Rivers

Cluster 6: Aberdeenshire, Adur, Allerdale, Amber Valley, Angus, Antrim and Newtownabbey, Argyll and Bute, Armagh City, Banbridge and Craigavon, Arun, Ashford, Aylesbury Vale, Babergh, Barnet, Barrow-in-Furness, Basildon, Bassetlaw, Bath and North East Somerset, Bedford, Belfast, Birmingham, Blackburn with Darwen, Blackpool, Blaenau Gwent, Bolton, Boston, Bournemouth, Christchurch and Poole, Bracknell Forest, Bradford, Braintree, Breckland, Brentwood, Bridgend, Brighton and Hove, Bristol, City of, Broadland, Bromley, Calderdale, Cambridge, Camden, Canterbury, Carmarthenshire, Causeway Coast and Glens, Central Bedfordshire, Chelmsford, Cherwell, Cheshire East, Cheshire West and Chester, Chesterfield, Chichester, Chiltern, City of Edinburgh, City of London, Clackmannanshire, Conwy, Copeland, Cornwall, Cotswold, County Durham, Coventry, Craven, Croydon, Dacorum, Dartford, Denbighshire, Derbyshire Dales, Derry City and Strabane, Dorset, Dover, Dumfries and Galloway, Ealing, East Cambridgeshire, East Devon, East Dunbartonshire, East Hampshire, East Hertfordshire, East Lindsey, East Renfrewshire, East Riding of Yorkshire, East Suffolk, Elmbridge, Epping Forest, Epsom and Ewell, Exeter, Fareham, Fenland, Fermanagh and Omagh, Fife, Flintshire, Folkestone and Hythe, Forest of Dean, Gateshead, Gloucester, Gosport, Great Yarmouth, Greenwich, Gwynedd, Hackney, Harborough, Haringey, Hartlepool, Hastings, Havering, Herefordshire, County of, High Peak, Highland, Hillingdon, Horsham, Huntingdonshire, Inverclyde, Isle of Anglesey, King's Lynn and West Norfolk, Kingston upon Hull, City of, Kingston upon Thames, Kirklees, Lambeth, Lancaster, Leeds, Lincoln, Liverpool, Maidstone, Malvern Hills, Mansfield, Melton, Merthyr Tydfil, Mid Devon, Mid Suffolk, Mid Ulster, Midlothian, Mole Valley, Monmouthshire, Moray, Na h-Eileanan Siar, Neath Port Talbot, New Forest, Newcastle upon Tyne, Newry, Mourne and Down, North Devon, North East Derbyshire, North Lanarkshire, North Lincolnshire, North Norfolk, North Somerset, North Tyneside, North Warwickshire, North West Leicestershire, Northumberland, Orkney Islands, Pembrokeshire, Pendle, Perth and Kinross, Peterborough, Plymouth, Powys, Preston, Reading, Redcar and Cleveland, Reigate and Banstead, Rhondda Cynon Taf, Ribble Valley, Richmondshire, Rother, Rotherham, Rushcliffe, Rushmoor, Ryedale, Scottish Borders, Sedgemoor, Sefton, Sevenoaks, Shetland Islands, Shropshire, Somerset West and Taunton, South Ayrshire, South Bucks, South Cambridgeshire, South Gloucestershire, South Hams, South Holland, South Lakeland, South Norfolk, South Oxfordshire, South Ribble, South Somerset, South Staffordshire, Southend-on-Sea, Southwark, St Albans, Stafford, Stirling, Stoke-on-Trent, Stratford-on-Avon, Stroud, Swale, Swansea, Swindon, Teignbridge, Tendring, Test Valley, Tewkesbury, Thanet, Tonbridge and Malling, Torbay, Torfaen, Torridge, Tower Hamlets, Tunbridge Wells, Uttlesford, Wakefield, Waltham Forest, Wandsworth, Warrington, Watford, Waverley, Wellingborough, West Berkshire, West Lancashire, West Lindsey, West Oxfordshire, Wiltshire, Winchester, Windsor and Maidenhead, Wirral, Wokingham, Worcester, Worthing, Wrexham, Wychavon, Wycombe, Wyre

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

Cluster 8: Cannock Chase, East Lothian, Lichfield, Oadby and Wigston, Tandridge, West Devon

Cluster 9: Aberdeen City, Ards and North Down, Ashfield, Barking and Dagenham, Barnsley, Basingstoke and Deane, Bexley, Blaby, Bolsover, Brent, Bromsgrove, Broxtowe, Burnley, Bury, Caerphilly, Cardiff, Castle Point, Charnwood, Cheltenham, Chorley, Colchester, Crawley, Daventry, Derby, Doncaster, Dudley, East Ayrshire, East Northamptonshire, East Staffordshire, Eastleigh, Enfield, Falkirk, Gedling, Glasgow City, Gravesham, Guildford, Halton, Hammersmith and Fulham, Harrogate, Harrow, Hart, Havant, Hinckley and Bosworth, Hyndburn, Isle of Wight, Islington, Kensington and Chelsea, Knowsley, Leicester, Lewes, Lewisham, Maldon, Manchester, Medway, Mendip, Merton, Mid and East Antrim, Mid Sussex, Middlesbrough, Milton Keynes, Newark and Sherwood, Newcastle-under-Lyme, Newport, North Ayrshire, North Hertfordshire, North Kesteven, Northampton, Norwich, Nottingham, Nuneaton and Bedworth, Oldham, Oxford, Portsmouth, Redbridge, Redditch, Renfrewshire, Richmond upon Thames, Rochdale, Rochford, Salford, Sandwell, Scarborough, Sheffield, Slough, Solihull, South Derbyshire, South Kesteven, South Lanarkshire, South Tyneside, Southampton, Spelthorne, St. Helens, Staffordshire Moorlands, Stevenage, Stockport, Stockton-on-Tees, Sunderland, Surrey Heath, Sutton, Tamworth, Telford and Wrekin, Thurrock, Trafford, Vale of Glamorgan, Vale of White Horse, Walsall, Warwick, Wealden, West Dunbartonshire, West Lothian, West Suffolk, Wigan, Woking, Wolverhampton, York

Appendix 2

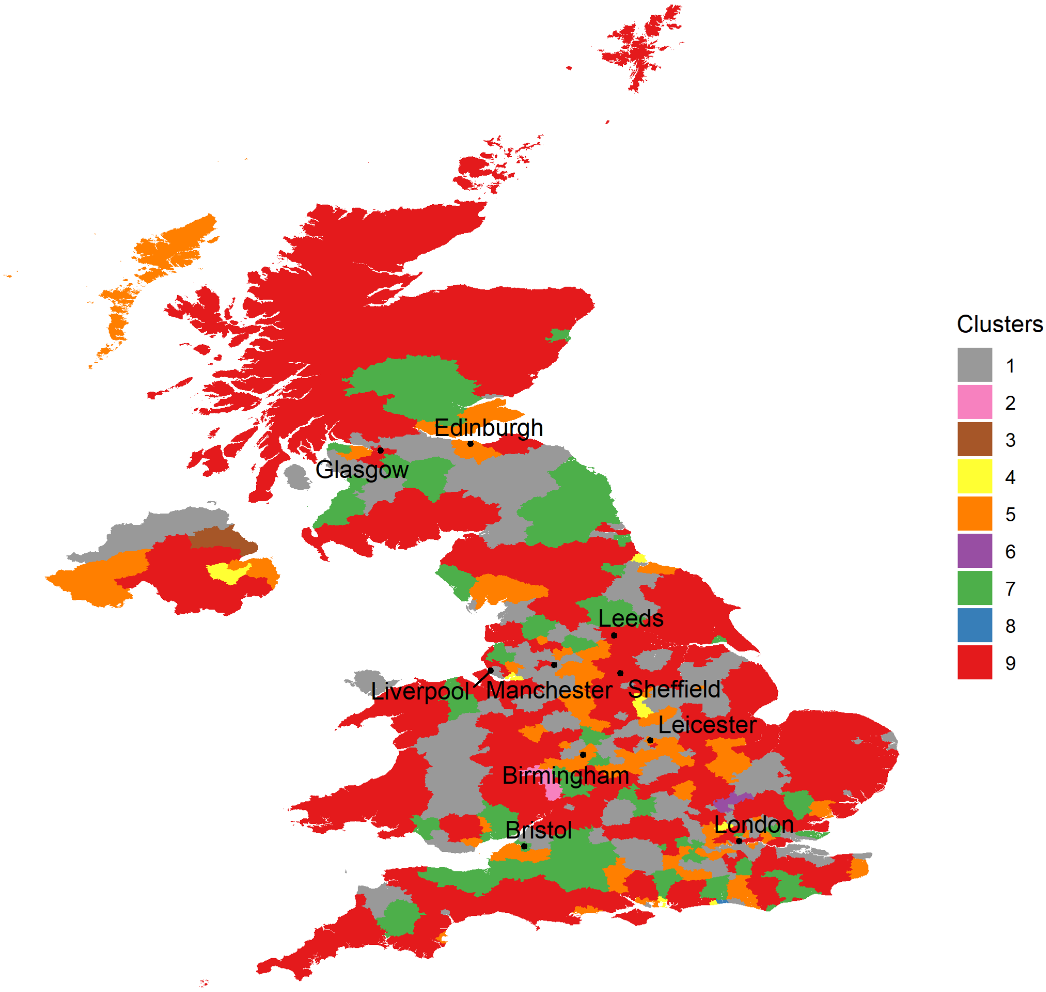

Figure 5. Upload speed clusters for LADs in before the pandemic (2019)

Appendix 3

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	8,700.000	100,400.000	214,900.000	1,141,400.000
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	0.000	0.000	1.000	1.000
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
service 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
Virgin Media %, 2020	381	0.150	0.140	0.000	0.018	0.238	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
furloughed per hab., 2020	362	0.115	0.013	0.077	0.107	0.122	0.178

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