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# WFH and broadband speed (title needs rework)

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**Abstract**
TBC

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

## 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 a new type of digital divide. 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 new digital divide has been viewed as mainly occupational, here we consider whether the divide is also technological.

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, may reinforce

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or redress the spatial and social dimensions of the digital division exposed by the pandemic. To do so, 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 both occupations and online accessibility intersect to enable or hinder the practice of telecommuting at a time of extreme demand. We will 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, and broadband services and infrastructure must be fit for purpose. **LET'S LEAVE IT FOR NOW, BUT I THINK WE CAN CRYSTALISE MORE THE RQ**

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 et al. 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), at least in the UK (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 than pre-Covid, 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 working force could work from home on an ongoing basis (Batty 2020). Similar figures have been reported for other countries (Felstead and Reuschke 2020). For instance, 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*, 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 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 et al. 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. The extreme level of demand for telecommuting fundamentally alters the potential returns of internet use for the user and wider community, assumes skills or functions that are present in some occupations but not in others, and relies upon access to high quality internet services.

As the quality of internet infrastructure and services, as well as variation in occupations are spatially dependent and clustered in space, our approach offers a framework for understanding the impact of and interactions between the different levels of digital division in different places with different characteristics. 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, not only during the pandemic, but also into the future. The structure of this paper is as follows. First we review the literature on telecommuting and digital divides to better understand the structural and spatial development of these practices 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 the UK local authorities and then assesses whether these clusters replicate or repudiate other socio-economic and geographic patterns of economic resilience. The paper ends with a conclusions section.

## Literature review

### *From telecommuting to #WFH*

In this analysis, the terms ‘telecommuting’ and ‘working from home’ 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, it should be noted that previous research has explored how telecommuting can occur in other places, including satellite offices or on public transport (Felstead

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

2012; Siha and Monroe 2006). Previous research has also used a variety of definitions to measure the level of telecommuting within different workforces, distinguishing, for example, 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 et al. 2015; Bailey and Kurland 2002; Haddad et al. 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. For example, 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 et al. 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, as well as 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 et al. 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).

## *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 et al. 2004; Siha and Monroe 2006; Singh et al. 2013). These returns have been even greater during the Covid-19 crisis, when those with the ability 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 and quality of internet connectivity at a time of extremely high demand. Salemink et al. (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 whether this variation in infrastructure quality affects the spatial footprint of telecommuting has not previously been measured, in part because telecommuting has not previously been the cause of greatest 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 variety of purposes (Hauge et al. 2011), and that there is a correlation between access to internet services and a reduction in household transport spend (Bris et al. 2017). Whether the implication is more internet use and less travel 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. Yet did the purchase of high speed connections and increased internet access also prepare households for long-term home-working, enforced by government restrictions? The extreme demand during the pandemic provides a new opportunity to understand how infrastructure accessibility, 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 contributes to or reduces 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 division on telecommuting, and whether this results in much more fundamental third level digital division than has previously been perceived.

Furthermore, these multi-layered digital divides intersect with material divides and the economic geography of the UK. Following the regional economic resilience literature, which underlines the differentiated capacity of cities and regions to escape or recover from economic crises (Martin 2012; Kitsos and Bishop 2018), different places have different industrial and occupational profiles, and these affect the aggregated potential capacity of places 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 regarding, for example, skills and human capital, unemployment, productivity and prosperity (Lee 2014; McCann 2020; Dorling 2018). Some scholars have even argued that the UK suffers some of the highest level of interregional inequalities in the global north (Gal and Egeland 2018; McCann 2016). Not only are all three levels of digital divides associated, to a certain extent, with or shaped by the geography of the UK, but the intersection of the digital and material divides affects the capacity of places to overcome some of the economic effects of the Covid-19 pandemic. Importantly, this is the first time that digital technologies became an essential tool for economic resilience for such a great part of the population.

## Methods and data

### *Time-Series Clustering*

The starting point of our methodological framework is cluster analysis, which can be defined within the modern machine learning framework as an unsupervised learning task, partitioning unlabelled observations into homogeneous groups known as clusters (Montero 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 et al. 2015). Therefore, cluster analysis is a widely used family of techniques in geography (Gordon

1977; Everitt 1974). For instance, clustering methods are the basis of *geodemographics*, a research domain which aims to create small area indicators or typologies of neighbourhoods based on various and sometimes diverse variables (Singleton and Longley 2009; Harris et al. 2005). Clustering techniques have also been employed to solve *regionalisation* problems (Niesterowicz et al. 2016).

Common characteristics of these studies are the cross-sectional nature of the data they employ. Indeed, 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 and, therefore, create clusters of local authorities in the UK with similar temporal signatures of experienced internet speeds. Hence, we deviate from the established geographical clustering tools and employ time-series clustering methods.

Time-series clustering methods have been developed in order 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 et al. 2001; Hyndman et al. 2015; Warren Liao 2005). The main challenge – and also the difference with cross-sectional clustering problems – is data dimensionality given the multiplicity of data points for every individual object, local authorities in our case, included in the data set. Time-series are dynamic data as the value of the observations change as a function of time (Aghabozorgi et al. 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 et al. 2015).

For this paper we utilise a category of time-series clustering methods known as shape-based approaches. These methods match two sperate time-series objects based on the similarity of their shapes through the calculation of distances between the shapes, and are thus better equipped to capture similarities between short length time-series (Aghabozorgi et al. 2015). This approach serves best this paper because (i) we identify clusters of UK local authorities with similar temporal signatures – i.e. shapes – of experienced internet speeds and (ii) the length of our time-series is short (see the data discussion in this section).

Another import element of time-series clustering is the actual clustering algorithm. Similar to the clustering of cross-sectional data, we can employ partitioning algorithms, which lead to non-overlapping clusters, hierarchical clustering, which classifies clusters at different levels, and fuzzy algorithms, which create overlapping clusters (Sardá-Espinosa 2019). Because of the simplicity of the implementation and the interpretability of the results, we utilise here partitioning clustering based on the widely used $k$-means algorithm. This is an iterative algorithm, which 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 above described application of $k$-means for cross-sectional data and its application for 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 in order 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). Using its underpinning dynamic programming algorithm, DTW compares 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).

## *Experienced Broadband Speeds*

To assess the quality and reliability of internet across local authorities in the UK during the time when the population were told to work from home if at all possible we utilise unique data comprising individual internet speed tests from Speedchecker Ltd[†]. 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 et al. 2015). By using volunteered geographic data, we are able to assess the *experienced* internet speed by users, which may differ from the *advertised* maximum speeds of 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 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 during the period of interest, 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. Meanwhile, the frequency of speed tests was important in identifying the temporal profile which would give us most insight into experienced internet service and resilience, and provide an indication of the volume of experience over particular units of time.

The first step in the workflow after dropping some outliers following Riddlesden and Singleton (2014) was to transform the individual, geolocated and time-stamped tests to more meaningful aggregates both in terms of space and time. The frequency of testing indicates that whilst there is an overall trend of increased testing from March to April and

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

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 experience of internet service quality was much more tied to the evening leisure peak and presumably to download speeds. Since the increase in testing during the working day in 2020 is an indication that users have a greater perception of the variable quality of internet service, particularly during a new morning peak of testing for service reliability, we decided to include a measure of hourly variation in our temporal profiles.

However, although this is a large data set – $241,088$ individual tests performed during weekday hours across the study period – there are not enough observations for each Local Authority District (LAD) and for each working hour of each working day – $631$ speed tests per LAD on average – to profile speeds at that level of detail. Therefore, we aggregate all the 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. We also aggregate these data spatially because we could not follow individuals or households and connect data points. 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, as well as the experienced speed characteristics of each cluster. Since the quality and reliability of internet services vary in time and space due to both supply and demand-side influences, we use a number of different measures to describe experienced upload speeds per cluster. These include: a) mean, experienced connection speed, b) standard deviation or the amount of fluctuation from the mean, and c) the variation in speeds at particular times of day when working from home is more likely to take place. We take account of all three measurements in our descriptive statistics of upload speeds 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 be different in different areas, as they may reflect either similarities in patterns of demand or similar 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 may cause slower speeds, less reliability and 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

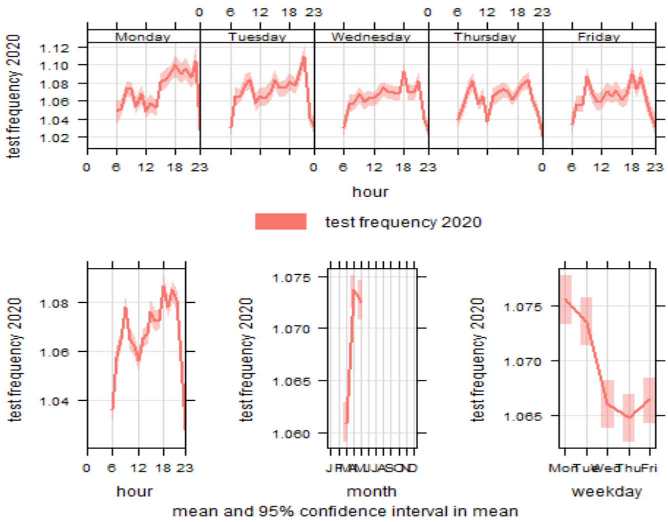


**Figure 1.** Speed tests over time, 2020

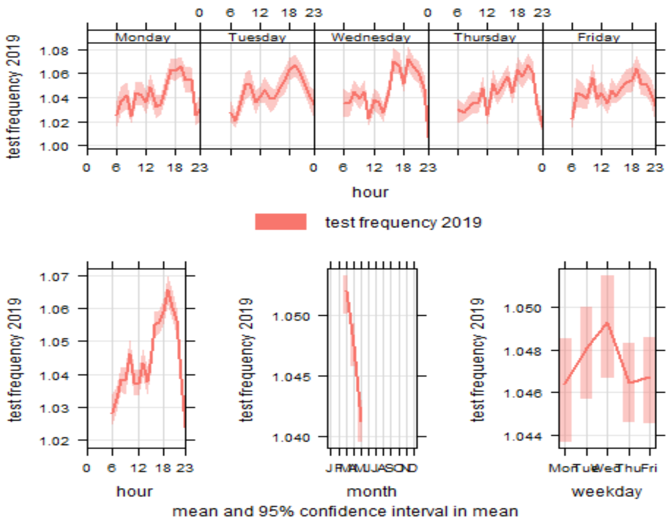


**Figure 2.** Speed tests over time, 2019

speeds. Instead, we run an auxiliary regression in order 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 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]](#sec:4.2), in order to explore how the different patterns might support or undermine efforts to work from home and maintain safe productivity and whether they reinforce existing spatial and social inequalities. This analysis enables us to provide a more nuanced understanding of how telecommuting and technology intersect at a time of extreme demand, and what lessons this time has for a future where telecommuting is likely to remain a common means of accessing work and broadband services, as well as infrastructure, must be fit for purpose.

## Results

### *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, in terms of the LAD membership and population, five clusters 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, the temporal clusters offering a novel approach to understanding spatial disparity.

The second largest cluster, comprising 126 local authorities and over 20 million people, is cluster 13. Cluster 13 has the slowest aggregate mean upload speed of any of the clusters, and the second 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, the variation in upload speeds in cluster 13, which can be an indication of its reliability, does not seem to disproportionately affect the morning peak from $9:00$-$10:59$, as upload speeds are, 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 that are home to 343 thousand people in cluster 1 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 home to 29.5 million people, experience 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. However, the time profile for cluster

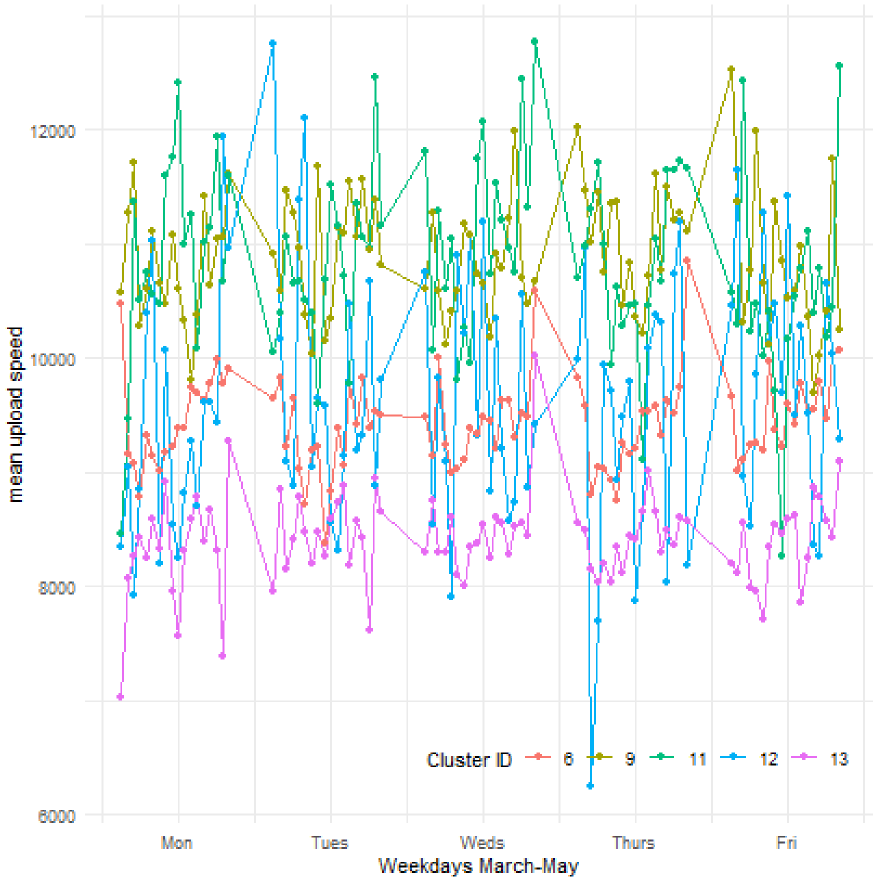


**Figure 3.** Temporal profilies for upload speed large clusters

6 in Figure 3 shows that upload speeds are highest at $6:00$ on a Monday morning and peak between $23:00$ and midnight on Wednesday and Thursday, but tend to be lower during the working day. Indeed, 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, but smaller than any of the clusters with temporal profiles shown in Figure 4. Clusters $8$ and $12$ also have mean upload speeds under $10$Mb/s, but higher than clusters $1$ and $13$, and their standard deviation is not dissimilar. However, this masks great variation in when lower speeds are experienced, with the mean upload speeds much lower between $9:00-10:59$ than between $19:00-20:59$ in cluster $8$, but slightly faster in the morning in cluster $12$.

Indeed cluster $12$ is the only cluster to experience higher speeds in the evening peak, compared to the morning peak, suggesting that widespread telecommuting has generally

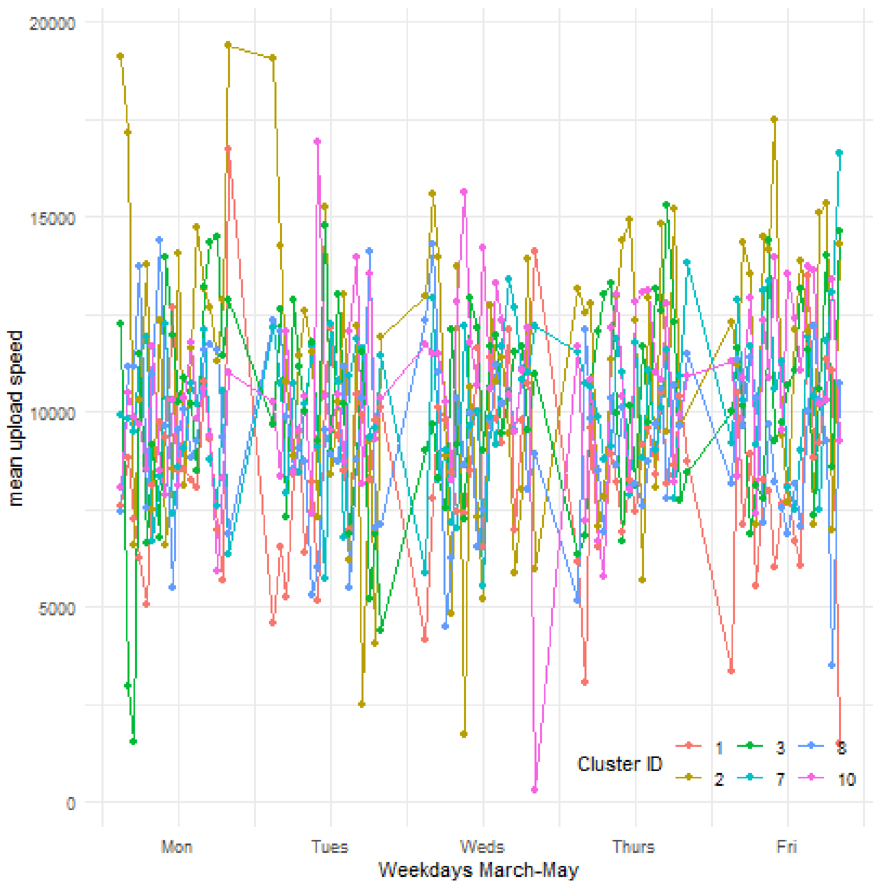


**Figure 4.** Temporal profilies for upload speed small clusters

changed the temporal profile of internet activity throughout the UK. Yet even if all but one cluster is showing slower speeds in the morning than the evening, the reliability of internet services in different clusters 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 below 55%, and the ratio of upload speeds in the peak periods indicates that 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 suggests 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

**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

Figure 3, cluster 11 shows more noticeable peaks and troughs, but the lowest points are not at the peak times described in Table 1. Rather, the slowest upload speeds on average occur between $6:00-7:00$ on Monday morning, $14:00-15:00$ on Friday, and $16:00-17:00$ on Thursday. These slowest times are still mostly faster than the average hourly upload speeds in cluster 13. Finally, ignoring the smallest clusters in terms of population, that is clusters 4 and 5, 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, the local authorities 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 in particular 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?

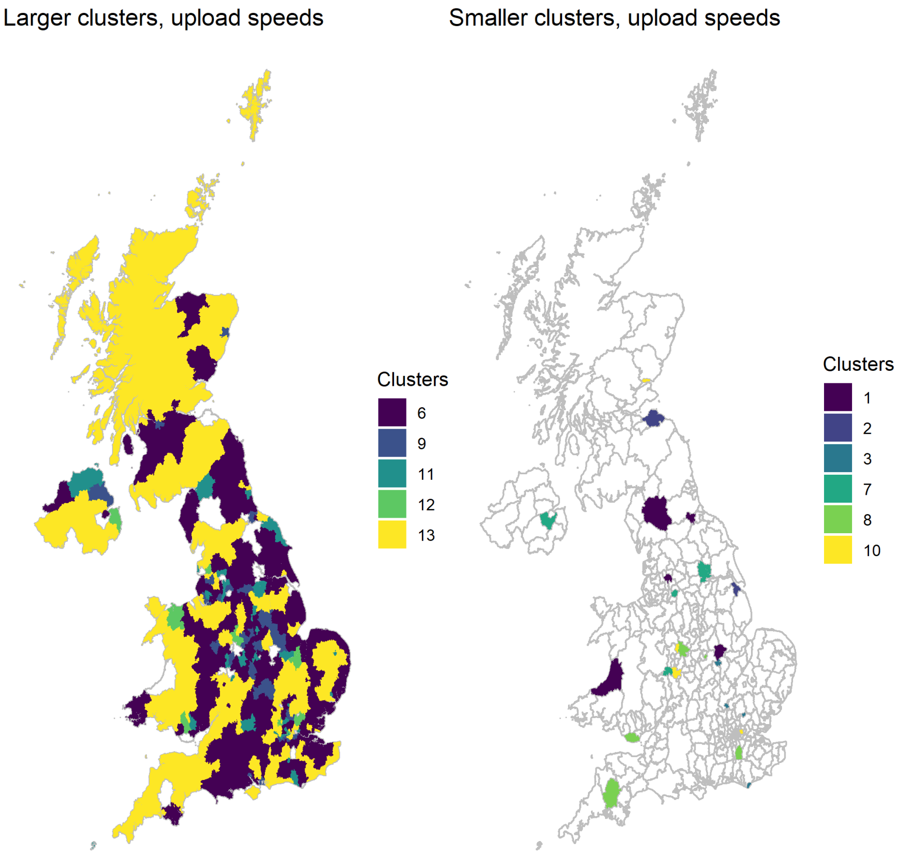


**Figure 5.** Upload speed clusters for LADs

## *Post-clustering regression analysis*

Using auxiliary regressions, 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 which enable telecommuting because of the nature of the work. The results of these auxiliary regressions are presented in Table 2. The dependent variable is the LAD cluster membership as described in the methods and data section and equation 1 and each column represent 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 are close to both the average speeds for the 13 clusters (9.9Mb/s) and the pre-clustered average for the whole sample

**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

(9.3Mb/s) as shown in Table 1. 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, the number of speed tests run per cluster inhabitant between $9:00$-$10:59$ is an indication of satisfaction or at least a lack of concern over broadband speeds and quality of service. People in LADs assigned to clusters 6 and 13 were more likely to run speed tests (at a per capita basis) at this time of day, whilst people in cluster 11 were the least likely to do so. This high level of satisfaction matches the high quality and reliability of service we would expect from the analysis in Section [4.1]](#sec:4.1). Those in clusters 2, 3, 9 and 10 were also less likely to ran speed tests per capita than those in the other six multi-authority clusters. Cluster 7 was the only cluster with higher mean speeds and middle to high measures of reliability which was more likely to run more speed tests per capita. This might be a reflection of the choice of ISP and connection options in those LADs, as, along with cluster 12, those in cluster 7 were least likely to have Virgin Media connections. 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, or in other words, are more likely to be on the right side of the first level, infrastructure-based digital divide.

We employ distance from London and for the nearest metropolitan area (including London) as two more 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, a result that makes sense considering 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. Still, whilst significant, the effect is tiny and the other members of cluster 3 are Corby and Eastbourne, two towns which, whilst not part of metropolitan areas, are also not in remote parts of the country, and are home to an estimated population of 175 thousand people between them. **move maps to here?**

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 be why those in cluster 7 are not served by Virgin Media. It also is a demonstration of the complexity of experienced broadband upload speeds as captured by time-series clustering, and their likely interaction with first level digital divides. Cluster 1, which our analysis suggests lacks broadband resilience, contains five, mainly rural authorities. However, they are scattered around the country – Ceredigion in West Wales, Darlington in the Northeast, Eden between the Lake District and the North Penines, Rossendale in the Northwest, and Rutland in the East Midlands –

and therefore, the results in Table 2 indicate that these authorities are not as far from the centre of a metropolitan area as authorities in cluster 3, but furthest from London.

Internet resilience, as measured here, seems to be more nuanced than our – arguably crude – dummy variable depicting the North-South economic divide either, which assigns 1 to LADs locates 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 does include some rural, remote areas of the country, such as Northwest Scotland, Cornwall and Powys in Wales as shown on Figure 5. It also includes the major metropolitan centres of Bristol, Liverpool, and Newcastle, as well as nine (of 32) London Boroughs, including the City of London and plenty of home county and suburban areas. Although by the standard deviation measure cluster 13 has unreliable internet services, speed variation was less 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 a lack of quality internet services, are also more likely to have a low skilled workforce, less able to benefit from telecommuting. Cluster 1 has the lowest propotion of educated people of any of the clusters, and the lowest earnings, despite recording the highest proportion of managerial, professional jobs, and the second highest proportion of tech jobs. Rural areas such as those in cluster 1 are often home to many retired people, 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. Either way, it seems likely that the first level digital divide reinforces other inequities in cluster 1. In comparison, those cluster 13 are more likely to earn more and have a better education. 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 might give some explanation for the variable internet quality, considering that small businesses have not been seen as the most valuable customers for higher speed broadband services **insert ref**.

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, and the result indicates an average level of service, even if better than LADs in cluster 13. Cluster 6 also falls towards the middle of the clusters on many of the socio- economic variables in Table 2. It ranks third or fourth out of the eleven clusters in the table in terms of having a higher proportion of managerial, professional, and tech jobs, as well as higher earnings, but is fourth from bottom in terms of education. The LADs in cluster 6 are also diverse, with few truly remote areas, but many urban areas in both the North, including Birmingham, Leeds and Sheffield, and South, including 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 as a result of increased demand, e.g. for telecommuting.

In comparison, clusters 9 and 11, which benefit from the most resilient internet connections, are characterised by lower share of occupations that are
may benefit from the ability to telecommute (e.g. managerial and technical). Cluster 9 is more highly educated and higher earning than cluster 11, has fewer businesses per inhabitant and less job density. Indeed, cluster 11 has a negative coefficient for the NVQ4 variable, whilst for cluster 9 the coefficient is positive, and cluster 11 has the second highest job density and cluster 9 the second lowest. The former might be an indication of the higher returns that resilient broadband infrastructure generates for cluster 9 versus cluster 11. Indeed, we did detect slightly more slowdown in the AM peak in cluster 9 than in cluster 11 (see Table 1). Meanwhile, a propensity for a high job density might indicate more labour intensive economic structures in cluster 11 than in the LADs in cluster 9.

The LADs in clusters 9 and 11 also have opposite signs for their likelihood of being in the South of England. Those in cluster 9 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, as Scotland has a different economic profile than England. Still, both clusters consist of larger LADs in terms of population, including the urban centre of Manchester and three of the nine other districts of Greater Manchester, Nottingham, both Portsmouth and Southampton, eight London Boroughs, and four of the seven constituent authorities of the West Midlands Combined Authority. Among the 65 LADs are also a number of other tightly bounded urban areas, such as Blackpool, Ipswich, Norwich, Slough, and Stevenage, and urban areas at the centre of less confined districts like Burnley, the digital hub of Milton Keynes, and Northampton. Thus, our findings confirm the importance of geography and urban locations for being on the right side of the first level digital divide, and suggest that internet resilience cuts across other digital and economic divides.

A similarly divided picture can be built for the next tier of clusters: 2, 3, 7, 10. LADs in these clusters experience higher than average mean speeds and rank high to middle on measures of service reliability. LADs in these clusters are on the right side of the first level digital divide. However, only LADs in cluster 2 and 10 are more likely to have highly skilled work force, which might more easily take advantage of working from home opportunities. Cluster 2 is comprised of just two LADs, with the lowest job density of any cluster – these are East Lothian near Edinburgh, and North East Lincolnshire, home to Grimsby. 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, and Dundee has a reputation for tech startups **insert ref**. Yet although those in clusters 2 and 10 may be making the most of their resilient internet, those in cluster 7 have the highest earnings. The four LADs in cluster 7 include the suburbs South of Belfast, a suburban district of Greater Manchester, the villages between York and Leeds, and a couple of small West Midlands towns. LADs in cluster 3 are associated more with lower skills and have the highest proportion of individuals in machine operation jobs. They include the Southeast commuter towns of Harlow and Luton and the slightly more distant towns of

Eastbourne and Corby. 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, are characterised by LADs enjoying close to average mean upload speeds, but different patterns of internet reliability. 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 of Leicester, Cardiff, Birmingham, the green belt area south of London straddling the M25 motorway, and rural West Devon, 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 be abandoned. Cluster 12 is home to 1.5million people spread across twelve LADs, including the City of Westminster and the London Borough of Hammersmith. However, it also includes a LAD in Northern Ireland, two in Wales, two suburban areas North of London, Preston in the Northwest, East Staffordshire in the Midlands, and Fenland in the East of England. This spatial diversity demonstrates that the temporal clustering of internet resilience does not create spatial clusters, and digital divides do not necessarily overlap with economic ones.

## Conclusions

Upload speeds are not used as benchmarks in the UK, nor have been seen as integral to universal service, considering there has never before been such extreme demand for telecommuting and operations such as video calls.

Clusters 3, 9, 10 and 11 seem to benefit most from high quality and resilient broadband services. The dips in mean upload speeds in clusters 6, 3 and 10 during the morning peak are suggestive of more use during the working day, and potentially more telecommuting.

The long-term effects of such drastic changes in telecommuting and attitudes towards working from home are difficult to predict. Nevertheless, they span through various aspects of economy and society: from changes to transportation planning due to altered commuting patters, to changes in land use and urban planning to accommodate people who work from home (Budnitz et al. 2020)**also 2020 Swedish article from JTG**; and from productivity and innovation changes, to changes in agglomeration externalities and the attraction of large cities (Nathan and Overman 2020) just to name a few. This paper is positioned to support endeavours in understanding the effects of increased telecommuting by exposing the spatial and social dimensions of telecommuting including the resilience of broadband speeds in terms of both quality and reliability of service, and whether this reinforces or redresses prior digital divisions. **took this bit you wrote to put in the discussion at the end?**

## Acknowledgement(s)

An unnumbered section, e.g. `\section*{Acknowledgements}`, may be used for thanks, etc. if required and included *in the non-anonymous version* before any Notes or References.

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

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