Digital economy in the UK: a multi-scalar story of the diffusion of web technologies

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Abstract

This paper maps the participation in the digital economy and its evolution in the UK over space and time. Most of the existing economic geography literature which dealt with the spatiality of the internet employed supply-side measures, such as infrastructural capacity, in order to understand the geography of the digital economy and its potential spatial economic effects. Useful as these approaches might have been, they cannot capture the micro-processes and the characteristics of the individual online behaviour. Using large volumes of archived and geolocated web content, this paper models the diffusion of web technologies over space and time in the UK. The data and geolocation strategy allow to capture these processes at a very granular spatial scale. The modelling approach, which is based on simple spatial analytical methods and on the estimation of diffusion curves at various scales, enables to depict the role of geography and other cognitive factors which drove the diffusion of web technologies. Although the focus is on a recent historical period − 1996-2012 – the results of the analysis depict diffusion mechanisms which can be very useful in understanding the evolutionary patterns of the adoption of other newer technologies.

Keywords: keyword1, keyword2

1. Introduction

Geographers were always interested in how new technologies and innovations diffuse across space and time and, importantly, how such spatio-temporal processes can be modelled. After all, diffusion together with invention and innovation are considered the pillars of technological change (Das, 2022). The seminal contribution of Hägerstrand et al. (1968) is illustrative of this early interest. However, the torch of exploring and modelling such processes had been passed to other disciplines such as economics, business studies and sociology well before the 'cultural turn' of economic geography (Perkins and Neumayer, 2005). A potential explanation of the lack of geographical studies exploring the diffusion of new and, more specifically for this paper, digital technologies across *both* space and time can be attributed to the scarcity of relevant and granular enough data. As Zook and McCanless (2022) highlight, digital activities are hardly ever captured in official data.

This paper offers such a contribution: a geographical study illustrating how a new technology that is the web diffused over space and time in the UK at a high level of spatial granularity during the $1996 - 2012$ period. It does so by employing a novel source of big data which captures the active engagement with web technologies during that period. By addressing this empirical question this paper exemplifies how the combination of data sources which escape the traditional social science domain and adequate research methods can offer new lenses to geographical research regarding the understanding of technological diffusion.

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The motivation for this paper lies in the fact that there are various stakeholders who are interested in knowing how new digital technologies diffused over space and time and use this knowledge to make predictions regarding the diffusion of related *future* technologies. As per Leibowicz et al. (2016), historical studies agree on the fact that "technologies diffuse at different times, at different rates, and to different extents in different places, and can be significantly influenced by policies" (Victor, 1993). Meade and Islam (2021) highlight that a variety of actors have a direct interest in gaining such knowledge including network equipment suppliers; network operators, regulatory and local authorities. These processes and their effects vary a lot across scales: although the diffusion of a new technology might not be optimal at a local level, it might be beneficial from a global perspective as it could lead to faster diffusion to less advantaged places (Leibowicz et al., 2016). Despite the spatial heterogeneity of such diffusion mechanisms and the policy relevance, there are very limited attempts in the literature to analyse the diffusion of new digital technologies at a detailed geographical level.

Technological diffusion, which is by definition an aggregated process, can be discussed in parallel with individual adoption mechanisms. On the one hand, Rogers (2010) identifies early adopter of new technologies as 'knowledgeable risk takers' and Griliches (1957) as 'profit maximisers' (Ding et al., 2010). Such individual agents are rewarded because of their attitude towards new technologies and innovations. On the other hand, Perkins and Neumayer (2011) attribute diffusion to two processes: (i) epidemic-like mechanisms, which are governed by distance, proximity and social interactions, and (ii) by economic mechanisms as new innovations are adopted by users as they become more profitable, valueable and useful.

This paper focuses on the diffusion of the web as new technology during the $1996-2012$ period. This was an exciting period for digital technologies as it corresponds with the commercialisation of the internet and, consequently, its almost universal adoption. The reader is reminded that it was only in 1994 when Netscape Navigator was introduced, a year before Microsoft's Internet Explorer [1]. Also, only 9 per cent of UK's households had access to the internet in 1998 (Office for National Statistics, 2018), the web included mostly static webpages, there were no social media and web browsing was happening exclusively from desktop PCs as there were no smartphones (Tranos et al., 2021). Hence, it is fair to say that the study period captures the very early stages of the diffusion on a new technology that is the web. This is key point in the lifecycle of a new technology. Firstly, during this period new technologies are expensive, crude and imperfect (Rosenberg, 1994; Wilson, 2012). A simple comparison between Web 1.0 and Web 3.0 applications clearly illustrates this (Tranos, 2020). During this period the performance of a new technology is the main attraction and not the cost to access and use it (Wilson and Grubler, 2011) There is a broader theoretical discussion in the literature regarding the motivation behind early adoption. As summarised by Perkins and Neumayer (2005), on the one hand, epidemic models highlight the role of interpersonal contacts as a way for new technologies to diffuse. On the other hand, economic models underline the importance of heterogeneity. Different firms have different structures and business plans, which define the potential economic returns of the adoption of a new technology and, therefore, the choice to adopt a new technology becomes an individual option. From a broader and evolutionary perspective, initial conditions are essential for the creation and evolution of path-dependent technological development trajectories (Neffke et al., 2011; Simmie et al., 2014). This argument is even more relevant when the focus is on Information and Communication Technologies (ICT) because of the commonly found lag between investment and economic returns as reflected in the Solow paradox (Acemoglu et al., 2014; Brynjolfsson et al., 2018).

Importantly, the data used here depicts the *active* engagement with the web in the UK as it contains all the commercial websites archived by the Internet Archive [2] that include a mention to at least one valid UK postcode in the web text. Websites are identified as commercial ones if they are part of the .co.uk second level domain (SLD). Also, the act of of creating a website is understood here as active engagement with the web vis-à-vis the more passive act of browsing the web or having an internet connection (Tranos et al., 2021). Previous studies have focused mostly on more passive notions of engaging with digital technologies

[1] https://www.theguardian.com/global/2015/mar/22/web-browser-came-back-haunt-microsoft
[2] https://archive.org/.

such as internet adoption and internet speeds (e.g. Blank et al., 2018; Riddlesden and Singleton, 2014). More details about the data and the data generation process can be found in Section XX. **ADD DATA DESCRIPTION, WHY .CO.UK**

Grubler (1990) Later Hagerstrand conceptualized physical "barrier" effects like lakes or uninhabited areas, which, in addition to distance, act as further retarding effects on diffusion. These are formalized in the form of "zero" or "half" contact multiplicators on the (distance decaying) message flows.

Grubler (1990) With respect to the formalization of the communication flows Hagerstrand defines a "mean information field" (MIF), in which the probability of communication is a negative function of distance between individuals

Wilson (2012) Logistic growth describes an initial period of gradual diffusion as a technology is introduced as a new commercial application, moving then through a rapid, exponential growth phase, before slowing and eventually saturating (Grübler et al., 1999). The substitution of incumbent technologies by new competitors leads to subsequent decline and eventual obsolescence.

2. Literature review

Geographical diffusion is a synthesis of different processes. On the one hand, we can identify purely spatial or, in other words, contagious processes. Adjacency and, more broadly, distance are the key drivers of diffusion. This perspective draws similarities with epidemics: innovation just like pathogens spreads because of contagion and, consequently, proximity and exposure (Hivner et al., 2003). On the other hand, we can identify hierarchical processes. Instead of horizontal distance-based diffusion mechanisms, the top-down hierarchy of urban systems drives diffusion. In reality, the synthesis of these two processes represents how new technologies diffuse over space and time (Morrill et al., 1988).

These ideas were firstly introduced by Torsten Hägerstrand and his thesis entitled 'Innovation Diffusion as a Spatial Process' (Hägerstrand et al., 1968). Hägerstrand was the first one to identify diffusion as a geographical process. The starting point was the idea that diffusion is based on passing information through social networks, which themselves tend to be defined by geography. Hence, he identified the 'neighbourhood' effect of how information, and consequently, innovation diffuse. He used agricultural innovations to test and model his ideas using Monte Carlo simulations. Hägerstrand also incorporated the role of hierarchy and how some phenomena maybe firstly adopted in larger cities and then diffuse to second tier ones. This is a sequential instead of a simultaneous process, which resembles the 'lead-lag' spatial acceleration effect in market research (Bento et al., 2018; Peres et al., 2010). Hägerstrand is more widely known though for highlighting the role time plays in the diffusion of innovations: an early-pioneering period, a middle fast accelerating period and a final saturation one (Morrill et al., 1988).

The temporal dimension was further explored by Everett Rogers and his seminal work on 'Diffusion of Innovations' (Rogers, 2010). Rogers being a sociologist, his work focused not on the diffusion of innovations over space and time, but instead on the adoption of new technologies and innovations by individuals and the individual mechanisms that drive the decisions behind adoption. He identified five groups of individuals regarding their adoption speed: innovators, early adopters, early majority, late majority and laggards. Key mechanism of diffusion and adoption is always communication and how knowledge is transferred within a social system. Therefore, all approaches agree on the S-shaped diffusion and cumulative adoption pattern (Grubler, 1990).

Schmidt's Law empirically illustrates a similar pattern. *Core* and usually highly agglomerated regions is where new technologies are invented and commercially deployed [Grubler (1990); grubler1990rise]. This is where the first adopters tend to be based. Then, technologies spread to the *rim* and eventually to the *periphery*. Although adoption pace might be higher when new technologies finally arrive to the periphery, the saturation levels there may never reach the ones in the core because of the lack of infrastructure or other necessary institutions (Leibowicz et al., 2016). Grubler (1990) effectively summarises the three key characteristics of the spatial diffusion process: (i) the cumulative level of adoption follows an S-shaped pattern just like purely temporal models; (ii) diffusion is shaped by a hierarchy effect in a form of a centrifugal force: from core to periphery; and (iii) diffusion is also shaped by distance and a neighbourhood effect and contaminate nearby locations.

The remaining of this section reviews empirical studies which analysed the diffusion on new technologies over space and time. Although the spatial dimension is present in most of the following studies, the level of spatial detail is almost always more coarse than the one adopted here. Beardsell and Henderson (1999) studied the evolution of the computer industry in 317 US metro areas during the $1977-1992$ period using employment data. Their analysis indicated that the relative size distribution holds for urban computer employment and also urban heterogeneity is essential in explaining this distribution. in a recent study, Bednarz and Broekel (2020) focused on wind turbines and modelled their spatial diffusion across 402 German regions during $1970-2015$. Their key finding is that local demand than local supply was the main driving factor.

At a global scale Perkins and Neumayer (2005) explored whther the diffusion rate of new technologies is driven by a latecomer advantage and the engagement with the global economy via foreign direct investments and trade. Their results illustrate that indeed latecomers and developing countries experience diffusion of new technologies more rapidly than early adopter and developed countries. At the same scale, Perkins and Neumayer (2011) explored whether the adoption of previous communication technologies that is mail, telegrams and telephones was shaped by similar socioeconomic factors as the internet. Their results indicated common patterns regarding the drivers behind the adoption of different communication technologies.

Turning to studies that share more technological and scalar similarities with this paper, Ding et al. (2010) modelled the spatial diffusion of mobile telecommunications across regions in China. Their analysis indicated that socioeconomic characteristics are important determinants of the timing, speed and the level of mobile diffusion within China. Using data from a Hungarian online social network, Lengyel et al. (2020) analysed its adoption and the churn at a very granular spatial level. Their results are in agreement with early theoretical and empirical contributions reviewed here: assortativity, urban scaling and distance are the key drivers of spatial diffusion. At a global scale Papagiannidis et al. (2015) modelled the diffusion of different web technologies technologies and practices. Interestingly, they did so by using similar, but less extensive data as the one used here. Their analysis illustrated how the diffusion of different web technologies and practices follow an S-shaped pattern as well as the different diffusion rates of the different technologies and practices.

3. Materials and Methods

For instance, we can approximate digital economic activities in a region by measuring the volume of commercial webpages by considering only .co.uk websites, which are dedicated to commercial activities (Thelwall, 2000). Such commercial websites are used to exchange information, support online transactions and share opinions (Blazquez & Domenech, 2018). Although nothing prevents a UK-based company from adopting a generic TLD such as.com and, indeed, such cases escape our data, we do not expect that such omissions could affect our results given the popularity of the .uk ccTLD: UK consumers prefer to visit a .uk website when they are searching for products or services (Hope, 2017); and anecdotal evidence indicates that during the first half of 2000, three .co.uk domains were registered every minute (OECD, 2001). Also, as Table 1 demonstrates, .co.uk was the most popular SLD under the .uk ccTLD in 2000. Hence, we use the total volume of all the archived webpages in a region as a proxy for the level of digitization. We start the analysis by focusing on commercial webpages (.co.uk).

Wilson (2012) growth function description in p. 86

from R: Asym/(1+exp((xmid-input)/scal)) using the terms from Wilson k/(1 + e^(t_0 - t)/scal)

Wilson: k(1 + e^-b(t - t_0)) So, scal = - 1/b

The curve is symmetric* around t_0

minimum R2 = 95%, see also Grubler (1990)

The literature usually uses the saturation level as the asymptote. I am using the total number of websites as we cannot compute a rate.

Moran's I as Ding et al. (2010) **TODO** for t_0, diffusion speed

4. Results

4.1. Old ideas

Hexagon density maps: reflect the spatial structure of Britain. Websites are associated in places where people live and work.

TODO maps at the local authority level per firms and discuss patterns

Neighbourhood effect: diffusion proceeds outwards from innovation centers, first "hitting" nearby rather than far-away locations (Grubler 1990)

- Moran's I: for OA and LAD over time
- LISA maps: for OA and LAD over time More and less expected clusters. Different scales show different results
- Website density regressions: for OA and LAD over time **TODO** add 0s Similar pattern

Hierarchy effect: from main centers to secondary ones – central places

- Gini coefficient. Almost perfect polarisation of web adoption in the early stages at a granular level More equally diffused at the Local Authority level Plateau overtime

S-shaped diffusion curves

- S for LADs per firm and OA.
- Fast and slow LAs map. There is clustering
- s_uk_firm_11
- ranks: there is stability and movement

4.2. New structure

1. S-shaped diffusion curves: S for LADs per firm. UK, fast/slow/examples
2. ranks: there is stability and movement
3. Neighbourhood effect: diffusion proceeds outwards from innovation centers, first "hitting" nearby rather than far-away locations (Grubler

1990)

- Moran's I: for OA and LAD over time
- LISA maps: for OA and LAD over time More and less expected clusters. Different scales show different results
- Website density regressions: for OA and LAD over time

4. Hierarchy effect: from main centers to secondary ones – central places

- Gini coefficient. Almost perfect polarisation of web adoption in the early stages at a granular level More equally diffused at the Local Authority level Plateau overtime

5. RF

- ideal: (i) train RF for all years and all (1) LADs and (2) OAs with CAST and report metrics. (ii) train for all years and all but one region for (1) LADs and (2) OAs to predict to the holdout region. Reports predictions as region similarities.

4.2.1. RF results

The next section incorporates the above discussed spatial drivers of the diffusion of web technologies into the same modelling framework. The aim is to use variables depicting these spatial processes in order to predict the diffusion of web technologies in the UK over space and time and across different scales. Specifically, four different models are estimated. Firstly, all the data points at the OA and LAD are utilised in order to build RF models and assess their capacity to predict the adoption of web technologies. These two models will reveal the predictive capacity of the spatial processes and also allow to see how the importance of such variables changes across scales. The next two models will be again trained on web difusion at the two working scales: OA and LAD. However, instead of using all the data points, the OA and the LAD from one of the 12 UK regions are hold out and then the trained model is used to predict web adoption in the OA or the LAD of the held-out region. This process takes place recursively for all UK regions. The difference in the predictive capacity of the different samples will reveal how different are these spatial process across regions and, importantly, at different scales.

It needs to be highlighted here that the cross-validation for all models presented here is spatially and temporally sensitive. Instead of using 10 random folds, we employ the `CAST` package which allows holds back data points from specific years and spatial units and use them for testing in order to estimate the model performance (Meyer et al., 2018).

The models need to include variables that capture the three processes that the relevant literature and the descriptive analysis presented in the previous section highlighted. Namely, the models capture: (i) a hierarchy effect with diffusion running from main centres to secondary ones, (ii) a neighborhood effect according to which diffusion first hits nearby locations, and (iii) the rather canonical pattern of the diffusion over time as reflected in the S-shaped pattern in the cumulative level of adoption.

To capture the hierarchy effect the models include as predictors a one year lag of website density in London – the largest city in the UK, a one year lag of the website density in the nearest city and the same for the nearest retail centre. Due to the small sizes of the retail centres, the latter is only relevant for the OA-level models. In addition, the models include the distance to London, the nearest city and the nearest retail centre. The underlying logic is that the level of website adoption in a spatial unit depends on the level of the adoption in places further up in the urban hierarchy the previous year. To depict the neighbourhood effect, the web density of the neighbouring spatial units in the previous year is calculated. Again, the underpinning rationale is that the level of web adoption within a spatial unit depends on the level of web adoption in the neighbouring spatial units the year before. This is the 'hitting nearby locations first' argument. Therefore, the spatial and temporal lag of the website density in LAD and OA is calculated. Lastly, the time effect which is reflected on the S curve for the cumulative adoption is captured by trend variable. Hence, all four model will follow the following generic form 1:

$$
\begin{aligned}
Website\,Density_t \sim Distance\,London + Website\,density\,London_{t-1} + \\
Distance\,Nearest\,City + Website\,density\,Nearest\,City_{t-1} + \\
Distance\,Nearest\,Retail_i + Website\,density\,Nearest\,Retail_{t-1} + \\
W * Website\,density_{t-1} + \\
year_t
\end{aligned}
\tag{1}
$$

To assess the predictive capability of the model, three broadly utilised metrics are employed: the coefficient of determination (R squared), mean absolute error (MAE) and root mean square error (RMSE):

$$
R^2 = 1 - \frac{\sum_k (y_k - \hat{y_k})^2}{\sum_k (y_k - \overline{y_k})^2} \tag{2}
$$

$$MAE = \frac{1}{N}\sum_{k=1}^{N} |\hat{y_k} - y_k| \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}(\hat{y_k} - y_k)^2}{N}} \tag{4}$$

y_k is the k^{th} observation of the dataset, which consists of N observations in total. $\hat{y_k}$ is the k_{th} predicted value for the dependent variable and $\overline{y_k}$ is the average value of y. The last two metrics are expressed in the same units as the dependent variable – websites per firm for the LAD modes and the number of websites for the OA models – while the first one is the coefficient of determination between the observed and the predicted values of website adoption. Regarding MAE, it is the absolute difference between the observed and the predicted website adoption. While MAE does not penalise for large errors, $RSME$ does so as it is proportional to the squared difference between the observed and the predicted trade flows. Hence larger errors weigh more for $RMSE$ (**?**).

Table **??** presents the model performance for the first set on models, for which all data points are employed for training and testing via cross validation. The first one is trained and tested on 374 LAD and the second on 232,296 OA for a 16 year period (1997-2012). The results are remarkably good considering that the are the outcome of space and time sensitive CV, so the the model does not suffer from overfit. At the LAD level we the model predicts 81% of the variation of website density. Both error metrics indicate that the model error is $(\frac{1}{20} - \frac{1}{30})$ of a website per firm. At the OA this score drops down to 21%. Considering its granularity, this is still a remarkable performance. To contextualise it, the model results in a MAE of one website for areas small enough to host less than 140 households.[3] Because of the small size of the spatial units, the distribution is highly skewed and a significant part of them is not linked to any websites. In 1997 only 1% of the UK OA were associated with a website. This should not come as a surprise as this was the very beginning of the commercial internet and any activities with a digital footprint were concentrated in a handful of areas. This was clearly illustrated in Section **ADD**. At the end of the study period almost half of the UK OA were not associated with a website. Again, given the granularity of the data this should not come as a surprise. Despite the large heterogeneity in website adoption, the model reached an R-Squared of 0.2.

Table 1: Model metrics {#table.metrics.all}

	RMSE	RSquared	MAE
Local Authorities	0.032	0.810	0.019
Output Areas	5.000	0.205	1.047

Figures 1 and 2 plot the importance of the difrerent predictors. When the focus is on the LAD, the website density in the nearest city, in London and on the neighbouring LADs the year before are the most important predictors. They are followed by the yearly trend, while the spatial configuration as reflected on distances to London or the nearest city only play a minor role. This can be attributed to the rather coarse spatial scale of analysis. Nevertheless, all previously discussed forces are at play in the diffusion of web technologies at the LAD: the first two predictors depict the hierarchical effect, the spatial and temporal lag of website density the neighbourhood effect and the yearly trend the time-sensitive cumulative adoption pattern.

[3] According to the Office for National Statistics, 80% of OA in England and Wales host 110-139 households, www.ons.gov.uk.

When the much more granular scale of OA is adopted, the picture is reversed. The most important predictors are the three distance variables to London, the nearest city and the nearest retail centre. They stil depict the hierarchical effect, but proximity to the different population centres is more important than their lagged web densities in predicting website diffusion. The neighbouring effect is less important at this scale. What is interesting is the almost negligible role of the yearly trend and London's website density. While the former probably illustrates the large heterogeneity in how web technologies have been adopted at this very fine scale, the later highlights that the importance of past web adoption rates in large population centres is surpassed by proximity to them and soatial configuration at this scale.

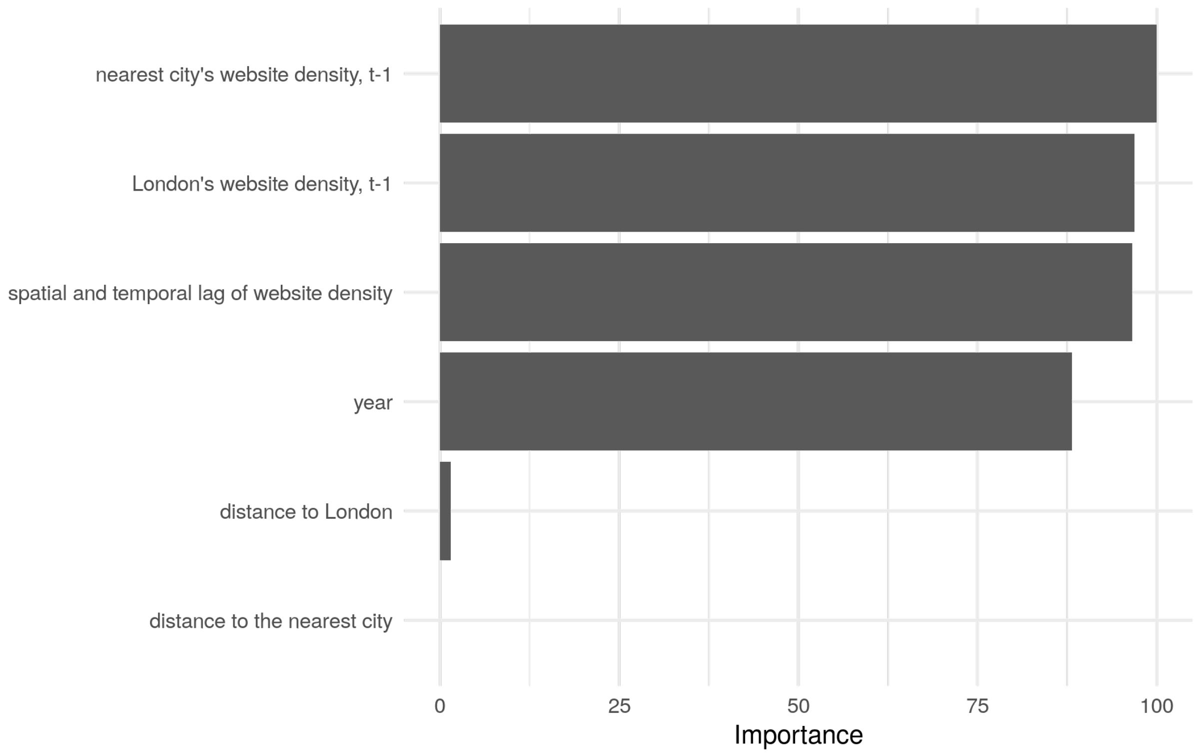

Figure 1: Variable importance, LAD

Table 2 presents the results of the recursive hold out models which aim to highlight potential regional heteorigeinty of the web diffusion spatial mechanisms. To begin with, as highlighted before, there is a difference of magnitude of one order between the LAD and the OA prediction errors, which is aligned with previous results that employed all data points. What is of interest here is the regional comparison. Table 2 illustrates some striking similarities, but also a few significant differences. The regions the web diffusion of which is better predicted using models trained in the rest of the country are the same despite the scale of analysis: South East, Wales, Yorkshire and The Humber and the North East of England. In other words, these are the regions whose spatial diffusion of web technologies is closer to the country's average. Despite the consistency across scales, this is a diverse set of regions: **ADD CHARACTERISTICS**.

At the other end of the spectrum, Scotland's and the North West's web diffusion mechanisms are consistently diverging from the country's average. This should not come as a surpise as these regions are characterised of high levels of rurality and remoteness. Similarly, London diffusion mechanisms diverge from the country's average and this is consistent across scales. London's uniqueness in UK's urban system and economy is also reflected in the spatial diffusion mechanisms of web technologies within its LAD and OA. It needs to be highlighted though that the difference between the RSquared of LAD and OA is more that an order of magnitude signaling how difficult is to predict diffusion at such a small spatial scale. North-

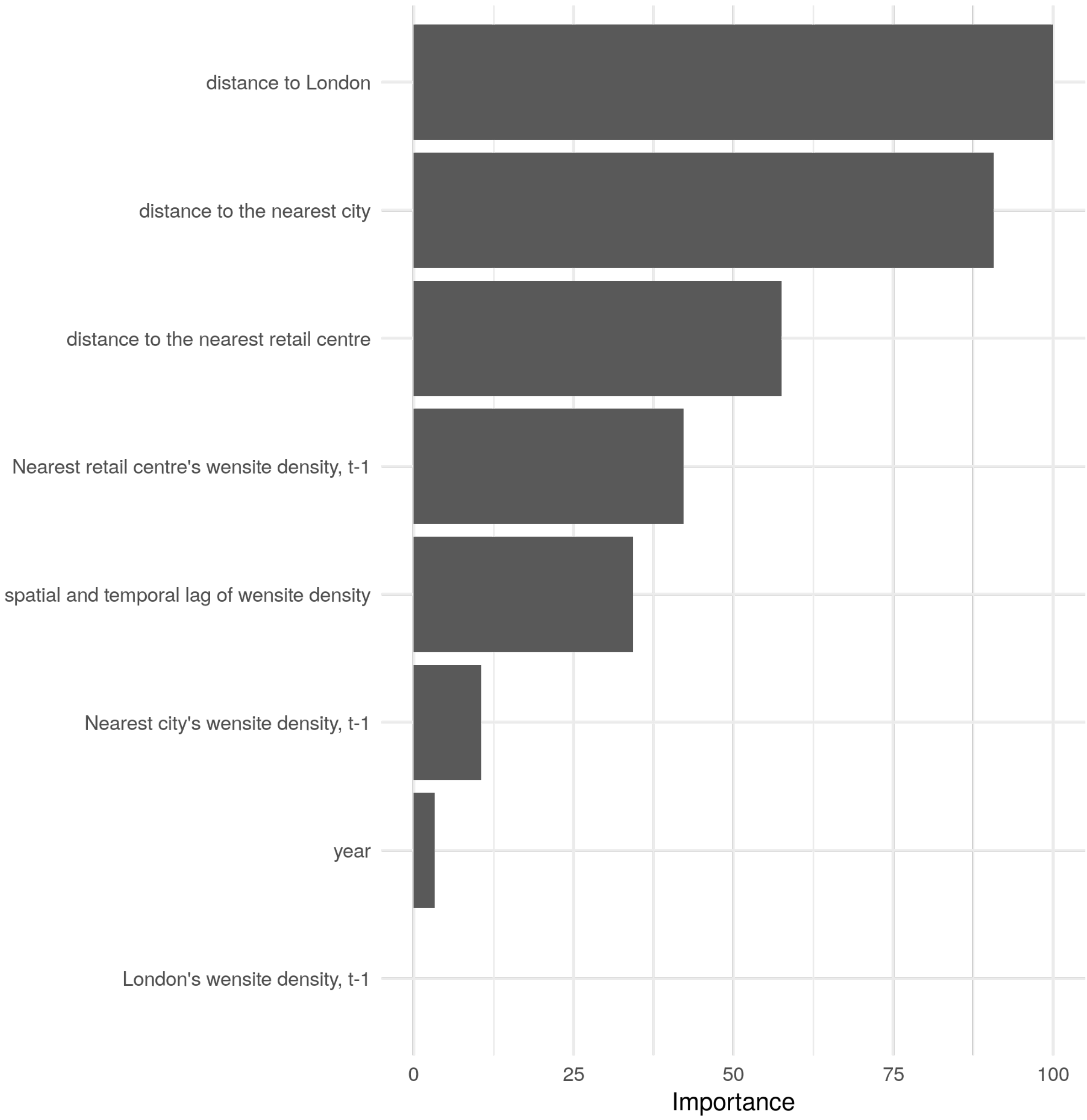

Figure 2: Variable importance, OA

ern Ireland is an interesting case. While it ranks at the bottom of the scale when the models are trained and tested on LAD data, when the modelling adopts the more granular OA scale, the spatial mechanisms that shape the web diffusion within this region appear to be closer to the country's average. At this scale, proximity or lack of in relative terms to the rest of the country become a less important and the internal to the region spatial structure predictors start playing a more important role **CHECK NI OA**.

Table 2: Regional differences

Region	RSquared LAD	Rank LAD	RSquared OA	Rank OA
South East	0.947	1	0.134	2
Wales	0.916	2	0.131	3
Yorkshire and The Humber	0.906	3	0.144	1
North East	0.895	4	0.128	4
West Midlands	0.883	5	0.070	9
East Midlands	0.882	6	0.088	8
East of England	0.876	7	0.106	6
South West	0.864	8	0.117	5
London	0.805	9	0.055	10
Scotland	0.770	10	0.035	11
North West	0.664	11	0.017	12
Nortern Ireland	0.576	12	0.101	7

5. Discussion and conclusions

contrary to results from future studies regarding social media (Lengyel et al., 2020), web technologies did not exclusively spread from a central location.

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