A multi-scale story of the diffusion of a new technology: the web

Abstract

This paper investigates the spatial diffusion of a new technology that is the Web in the UK. It employs novel data and machine learning methods to model the influence of well-established diffusion mechanisms. Contrary to previous studies, it adopts multiple scales, high spatial granularity and a long study period that captures the early stages of the Web until its maturity (1996-2012). Findings reveal the importance of such spatial mechanisms (namely distance, urban hierarchy and the S-shaped pattern of the cumulative level of adoption) even at granular scales. They also highlight spatial heterogeneity and instances of leapfrogging.

Keywords: diffusion, technologies, Web, digital

1. Introduction

Economic geographers were always interested in how new technologies and innovations diffuse across space and time with the work of Hägerstrand et al. (1968), which demonstrated the importance of communications as a mechanism for the diffusion of innovations, being the most impactful. It was followed by various empirical studies – see for instance Ormrod (1990) and Neumayer and Perkins (2005). However, the torch of exploring and modelling such diffusion 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; Ding et al., 2010). As a consequence, relevant studies did not investigate diffusion mechanisms at granular geographical scales to provide local policy insights, for instance, regarding infrastructural development and local technology policies. 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, a problem also highlighted by Neumayer and Perkins (2005) and Kemeny (2011). As Zook and McCanless (2022) pointed, digital activities are hardly ever captured in official data.

This paper offers such a contribution: an economic geography study revealing the importance of spatial mechanisms for the diffusion of a digital technology that is the Web in the UK at a high level of spatial granularity from the very early days until its maturity (1996-2012). It specifically focuses on the diffusion of commercial websites. It does so by employing a novel source of big data and machine learning algorithms to model the *active* engagement with Web – that is creating and maintaining instead of just browsing a website – during that period and tests how different spatial and temporal mechanisms shaped its diffusion. This paper also exemplifies how the combination of data sources and state-of-the-art research methods which escape the traditional social science domain can offer new lenses to geographical research regarding the understanding of technological diffusion.

The motivation for this paper lies in the fact that there are various stakeholders who are interested in knowing how new digital technologies diffuse over space and time and use this knowledge to make predictions about the diffusion of related future technologies. As per Leibowicz et al. (2016), historical studies agree that technologies diffuse differently in terms of times, rates, and geographies and can be driven by related

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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 is a scarcity of studies analysing the diffusion of new technologies at a detailed geographical level because of the lack of detailed enough data and adequate research methods.

This gap becomes even more prominent if we consider the importance of technology and its adoption in economic geography and macroeconomic growth theories. Simply put, differences in technological adoption and sophistication may lead to uneven development as new technologies can increase productivity and allow firms to introduce new products (Solow, 1957; Aghion, 1990; Kemeny, 2011). Linked to the subject of this paper, the Web and, more specifically, commercial websites can be considered as the underpinning technology for the transformative process identified by Capello et al. (2024) as the *digital service economy*. Importantly, the focus here is not the Web in general, but instead commercial websites. After all, diffusion together with invention and innovation are considered the pillars of technological change (Das, 2022). Findings from previous studies illustrated that early engagement with digital technologies such as the Web led to longstanding positive productivity gains for these regions that hosted early adopters (Tranos et al., 2021). Hence, obtaining a robust understanding of the spatial diffusion mechanisms is crucial in mapping future development trajectories.

Another line of motivation has to do with the very nature of the Web as a digital technology and how it evolved over time. The digital geographies field has debunked premature claims about the Internet's placeless-ness by mapping various of its facets and technological layers (Tranos and Nijkamp, 2013), but the lack of relevant long time-series data prevented researchers from observing digital phenomena overtime. Most of these studies focused on its hard infrastructure (e.g. Malecki, 2002; Moss and Townsend, 2000), on Internet subscribers (e.g. Blank et al., 2018), or on social media users (e.g. Crampton et al., 2013). Exceptions include early work from Zook (2000), Zook (2001) and Moss and Townsend (1997), which utilised domain name registration data and use it to map and illustrate the spatial footprint of the web content. Pivotal as these contributions have been in understanding the economic geographies of the Internet, they were based on cross-sectional, often spatially detailed, mapping and on short temporal comparisons (e.g. 1993-1998) and did not observe the evolution and diffusion of the Web until its maturity. As we know from the relevant literature, different technologies diffuse at different rates and there is no theory that can explain these differences (Leibowicz et al., 2016). Hence, mapping and modelling the diffusion of the Web can offer useful insights.

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 involved exclusively a 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 of a new technology that is the Web until its maturity. The former is a 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): while a static website facilitates one-way information dissemination, a platform like `github` enables cooperation between users and the creation of new information, meaning, and even knowledge (Faraj et al., 2016; Barassi and Treré, 2012). 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).

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

There is a broader theoretical discussion in the literature about the early adoption motives. As summarised by Perkins and Neumayer (2005), on 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 digital technologies 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).

The data used here depict the active engagement with the Web as they contain geolocated and time-stamped counts of commercial websites from the UK. Instead of adopting metrics reflecting the passive engagement with the Internet such as Internet adoption and speeds (e.g. Blank et al., 2018; DeStefano et al., 2022), this paper observes yearly counts of geolocated, commercial websites, which reflect the creation and maintenance of such websites. It needs to be highlighted here that although there are various types of underpinning web technologies – namely markup, stylesheet, client- and server-side coding languages as well as different web browsers and other related programming language – the focus here is on the diffusion of the Web as an overarching technology instead of more specific web technologies. For a such a detailed and cross-country technological diffusion study, see Papagiannidis et al. (2015).

To analyse these data, a diverse set of methods are employed. Firstly, cumulative adoption curves are estimated for the UK as a whole and for the Local Authority Districts (LAD), illustrating, for the first time, such S-shaped diffusion patterns for local areas. The exploratory spatial data analysis offers some first indications of the importance of the different spatial diffusion mechanisms in shaping the diffusion of the Web in the UK. Importantly, the analysis adopts two distinct geographical scales: the LAD and the most detailed scale of UK census areas, the Output Areas (OA). Then, a novel methodological framework based on Machine Learning (ML) algorithms is developed to test the role of such mechanisms at these two scales. The results reveal, for the first time, the importance of different spatial diffusion mechanisms in the diffusion of a digital technology at very granular geographical scales. The analysis also reveals that the diffusion of the Web is characterised by spatial heterogeneity, well-established spatial patterns and both stability and volatility.

The structure of the paper goes as follows. Section 2 reviews the mechanisms that shape the diffusion of a new technology and sets up the two hypotheses that are empirically tested in Section 4. Section 3 describes the data and methods used in this paper. The discussion of the results and the conclusions of the paper are offered in Section 5.

2. The mechanisms that shape the diffusion of a new technology

The diffusion of new technologies and innovations is driven by three different mechanisms (Grubler, 1990; Morrill et al., 1988): (i) distance and proximity, (ii) urban hierarchies in the form of a centrifugal forces as new technologies diffuse from core to periphery, and (iii) over time the cumulative level of adoption follows an S-shaped pattern. Hägerstrand et al. (1968) was the first 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 geographically bounded. Hence, he identified a 'neighbourhood' mechanism of how information, and consequently, innovations and new technologies diffuse. This perspective draws similarities with epidemics: new technologies and innovations, just like pathogens, spread because of contagion and, consequently, proximity and exposure (Hivner et al., 2003).

Hägerstrand et al. (1968) also emphasised the role of the top-down hierarchy of urban systems and highlighted that new technologies and innovations are 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). Schmidt's Law empirically illustrates a similar pattern (Grubler, 1990). Core and highly agglomerated regions is where new technologies are invented and commercially deployed. 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 may never reach the ones in the core because of the lack of infrastructure or other necessary institutions (Leibowicz et al., 2016).

Diffusion is naturally a dynamic process and Hägerstrand recognised the role time plays in the diffusion of innovations and new technologies: an early-pioneering period, a middle fast accelerating period and a final saturation one (Morrill et al., 1988). This was further explored by Rogers (2010), who identified five types of adopters of new technologies and innovations: innovators, early adopters, early majority, late majority and laggards. Hence, plotting the cumulative adoption of a new technology over time often leads to an S-shaped line plot (Grubler, 1990).

Although the above processes have been studied in innovation studies, the distancing of economic geographers from research questions about the diffusion of new technologies and innovations resulted to a knowledge gap regarding the explanatory power of these mechanisms at granular, local scales (Ding et al., 2010). As discussed in Section 1, such spatially explicit knowledge can directly inform local technology and infrastructure policies. Indeed, while the spatial dimension is present in the following studies, the geographical level of analysis is often too coarse to ascertain the role of the above mechanisms at the local scale. Beardsell and Henderson (1999) studied the evolution of the computer industry in 317 US metropolitan 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. Haller and Siedschlag (2011) employed firm panel data for Ireland during 2003-2005 and illustrated that when firms are located in a region or industry with high share of firms having a website, they are more likely to have a website too. At a global scale Perkins and Neumayer (2011) explored whether the adoption of previous communication technologies that is mail, telegrams and telephones were shaped by similar socioeconomic factors as the Internet. Their results indicated common patterns regarding the drivers behind the adoption of different communication technologies. Feldman et al. (2015) focused on inventions and used patent data to map how the the rDNA technology diffused among inventors across 366 US metropolitan areas. Ding et al. (2010) modelled the spatial diffusion of mobile telecommunications across the highest level of administrative division in China (29 regions in total). Their analysis indicated that socioeconomic characteristics are important determinants of the timing, speed and the level of mobile diffusion within China. Bakher Naseri and Elliott (2013) compared different growth curves as a means to model the diffusion of online shopping in Australia during the 1998-2009 period, but they did not consider any spatial mechanisms. At a global scale Papagiannidis et al. (2015) modelled the diffusion of different web technologies and practices across countries. Using similar but less extensive data as the one used here, their analysis illustrated how the diffusion of different web technologies and practices follows an S-shaped pattern as well as the different diffusion rates of the different technologies and practices. The most detailed consideration of the spatial footprint of the diffusion of a new technology comes from Lengyel et al. (2020), who analysed the adoption and churn of a Hungarian online social network. Their results were in agreement with the early theoretical and empirical contributions reviewed here: assortativity, urban scaling and distance are the key drivers of spatial diffusion. Based on the above, the main empirical hypothesis that is tested in this paper states:

> H_1: The three diffusion mechanisms namely distance, urban hierarchy and the S-shaped pattern of the cumulative level of adoption shaped the diffusion of the commercial Web in the UK even at granular geographical scales.

Understanding the diffusion of a new technology in multiple, detailed spatial scales is of interest to economic geography as potential local economic benefits may occur because of concentration of early adopters or through technological leapfrogging. On the one hand, early adopters are often rewarded because of their attitudes towards new technologies and innovations. Rogers (2010) identifies them as 'knowledgeable risk takers' and Griliches (1957) as 'profit maximisers' (Ding et al., 2010). On the other hand, latecomers can adopt and benefit from new technologies that have been developed elsewhere without incurring the hefty initial R&D costs (Teece, 2000). At a global scale Perkins and Neumayer (2005) explored whether 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 adopters and developed countries. At a regional scale, previous research highlighted the long term and sustained productivity benefit of the early adopters of web technologies in the UK (Tranos et al., 2021). Although the early adoption and leapfrogging literature has not paid much attention on cities and regions (Yu and Gibbs, 2018), the potential local economic benefits justify the need to investigate the dynamics of the web diffusion in different scales in the UK. Hence, the second empirical hypothesis states:

H_2: The diffusion of the commercial Web is shaped by both early adoption and latecomer effects.

These two hypotheses are empirically tested in Section 4 employing the data and methods described in the next section.

3. Data and Methods

To capture the diffusion of the commercial Web, a website density metric is developed for two different geographical scales that are discussed later in this section. The main data are counts of commercial websites that are calculated using data from the Internet Archive[2] and, specifically, the JISC UK Web Domain Dataset (Jackson, 2013). The Internet Archive is one of the most complete and oldest archive of webpages in the world operating since 1996 (Ainsworth et al., 2011; Holzmann et al., 2016). It is a web crawler, which discovers webpages by following the hyperlinks of every webpage it archives. This dataset, which is curated by the British Library, contains all the archived webpages from the UK country code top level domain (ccTLD - .uk) from the 1996–2012 period. In essence, this is a long list of 2.5 billion URLs of archived webpages including also the archival timestamp.

Instead of using the whole .uk ccTLD, this paper focuses on its commercial subset, the .co.uk second level domain (SLD). This choice is aligned with the topic of the paper – the diffusion of the Web for commercial functions – and decreases the heterogeneity of the web data as such commercial websites have specific aims: they are used to diffuse information, support online transactions and share opinions (Thelwall, 2000; Blazquez and Domenech, 2018). Although a UK company can adopt a generic TLD such as .com and these cases escape the data used here, such omissions should not affect the validity of the results given the popularity of the .uk ccTLD (Tranos et al., 2021): 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). Importantly, previous studies illustrated that .co.uk is the most popular UK SLD (Tranos et al., 2021). Henceforward any reference to websites will refer to commercial – .co.uk – websites.

The text from these webpages was scanned using a regular expression (regex) to identify strings of text which resemble UK postcodes and one fifth of them included a mention to a postcode (Jackson, 2017a). This information allows the geolocation of the data and the creation of the LAD and OA counts. To prevent false positives, the resulted postcodes were matched against official postcode lookup files (Office for National Statistics, 2025).

The data cleaning process includes an aggregation step, through which the archived webpages are aggregated to the parent websites. This website reconstruction process lend itself to the construction of *website* instead of *webpage* density metrics. Websites tend to represent specific organisations or entities, and, arguably, are more meaningful observational units than webpages, which can ignore the upstream dependency

[2] https://archive.org/.

Table 1: Number of unique postcodes per .co.uk website, 2000.

Postcodes	F	F (%)	cumulative F
(0,1]	41,596	0.718	0.718
(1,2]	6,451	0.111	0.830
(2,10]	6,163	0.106	0.936
(10,100]	2,975	0.051	0.988
(100,1000]	646	0.011	0.999
(1000,10000]	62	0.001	1.000
(10000,100000]	4	0.000	1.000

Source: Tranos et al. 2021

of the website they belong to. Based on the following example, all three webpages are part of the same website (http://www.website.co.uk). Only the overall website and not the nested webpages are considered for the counts as otherwise the density metrics would have been biased towards large, place specific, websites. It is important to note here that websites commonly contain place references, with previous research estimating this share to be around 70% (Hill, 2009).

- http://www.website.co.uk/webpage_a B15 2TT
- http://www.website.co.uk/webpage_b BS8 1TH
- http://www.website.co.uk/webpage_c B15 2TT

What is challenging is that this aggregation approach, which has been used elsewhere (Tranos et al., 2021; Stich et al., 2023) may lead to websites with multiple postcodes. As per the above example, www.website.co.uk includes two unique postcodes: B15 2TT and BS8 1SS. The distribution of the number of postcodes per website for 2000 is presented in Table 1, which illustrates a wide range. At the left end of the distribution, there are websites anchored to a unique location (72% of all the reconstructed websites in 2000), which may represent a small company with a single trading location. At the right end, there are websites with thousands of different postcodes. Considering the time period of the analysis, such cases can represent directories which used to be popular in the pre-search engines early times of the commercial Internet as well as real estate websites (Tranos et al., 2021). Previous research which used the same methodology for a small subset of these data illustrates the robustness of the above approach: its results matched in terms of accuracy past rounds of research based on extensive qualitative work, interviews and observational studies for the same study area (Stich et al., 2023).

The analysis is firstly conducted on websites, which only contain one unique postcode. As a robustness check, the analysis is replicated for an extended subset of websites, which include up to 10 unique postcodes to capture commercial websites which point to multiple locations. They are geolocated by equally attaching them to these locations. This extended sample includes 94 percent of all the archived websites in 2000 (see Table 1).

Another data cleaning step deals with some extreme outliers. Figure 1 plots the website counts for the top 1000 postcodes. Some obvious outliers can be observed for the 2002-2006 period for a handful of postcodes, which can be attributed to link farms (Jackson, 2017b). The website counts for these postcodes (SE24 9HP, CV8 2ED, GL16 7YA, CW1 6GL, M28 2SL, DE21 7BF), which in 2004 or 2005 had more than 1,000 websites pointing to them, were replaced with predicted values based on a simple panel regression model with postcode fixed effects and yearly dummy variables. These postcodes refer to a residential area with a small park in South London, residential areas outside Warwick and Manchester, a rural area in the south border of England and Wales and small business parks in Crew and Derby. Hence, it is difficult to believe that these postcodes genuinely hosted such a large amounts of websites, which were later extensively declined. To put the magnitude of the data imputation into perspective, this process affected 6 out of the 557,808 postcodes included in the data. As Section 4 illustrates, this led to a small increase of the model predictive power.

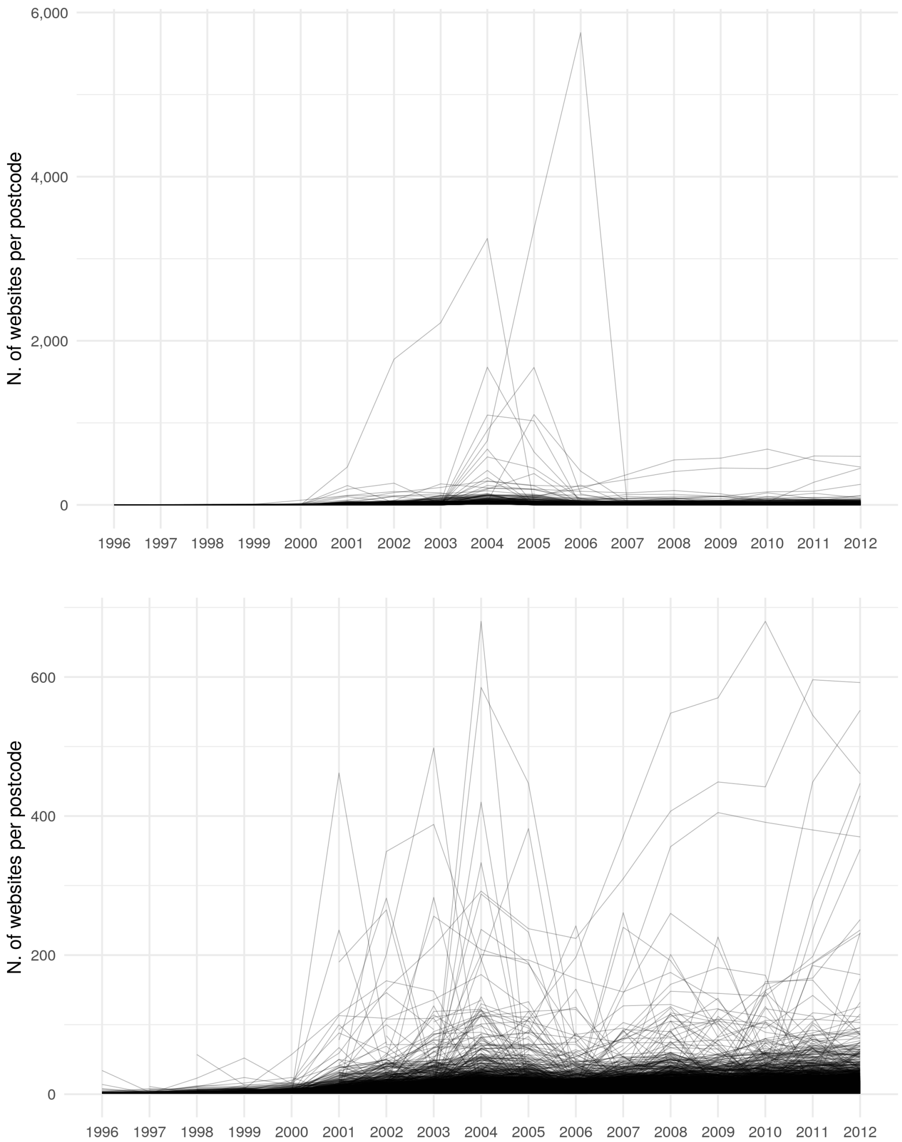

Figure 1: Yearly website counts per postcode (top 1000) before (top) and after (down) data imputation

To empirically test the two hypotheses stated in Section 2, the website density metric was calculated for two different scales the Local Authority Districts (LAD) and the Output Areas (OA). The former is the lowest administrative unit in the UK and there are 374 LAD. The latter is the smallest census-based geographical unit and there are c. 230,000 of them in the UK. To create the website density metric, the yearly website counts at the LAD level are standardised by the number of firms in LAD to avoid biases associated with LAD hosting a large number of firms. Given that there is no such readily available statistic for the OA, the actual OA level counts are used. However, because of the the consistent spatial definition of OA (they host

40-250 households),[3] website counts in OA are interpreted as a density metric too.

These website density metrics are used for the different stages of the analysis. Starting with the first hypothesis (H_1), to test whether the S-curve accurately describes the cumulative adoption of the Web at a local scale, the following logistic function (Equation 1) is estimated for the whole of the UK and then for each LAD separately:

$$y = k/(1 + e^{-(t-t_o)}) \tag{1}$$

k is the asymptote or, in other words, the saturation level, b the overall growth rate, and t_0 the *inflection point* of maximum growth at $k/2$, where the logistic function is symmetrical (Wilson, 2012). The t_0 of each LAD is compared against the t_0 of the UK to delineate whether a LAD reached that point faster or slower than the country average. This heterogeneity is discussed further when testing the second hypothesis (H_2). Importantly, an accuracy criterion was imposed and only LAD with $R^2 > 0.9$ were included in this analysis. To estimate Equation 1 a self-starting logistic growth model was employed using the `nls` and `SSlogis` functions in `R`. This logistic growth model depicts the initial period of slow diffusion of a new technology, which is followed by the fast, exponential growth stage to then eventually slow down and saturate (Wilson, 2012; Grübler et al., 1999).

Next, exploratory spatial data analysis provides some first insights of whether the other two drivers of spatial diffusion – namely neighbourhood and hierarchy – underpin the diffusion of the Web in the UK. To capture the former and following Ding et al. (2010) the Moran's I and the Local Index of Spatial Association (LISA) are estimated for the website density. To capture the hierarchy mechanism, the Gini coefficient – an established metric of inequality – is calculated. All the above are computed and plotted longitudinally both for the LAD and the OA.

To formally test H_1 a modelling framework is developed to assess the above diffusion mechanisms. The overarching aim is to build a model that can test how well these three mechanisms can predict website density:

$$Website\,Density_t \sim Hierarchy_{t-1} + Neighbourhood_{t-1} + S\text{-}curve_t \tag{2}$$

To capture the hierarchical mechanism the model include as predictors a one year lag of website density in London, the largest city in the UK, and a one year lag of the website density in the nearest city. Both variables clearly illustrate the urban hierarchy in the UK. Especially for the OA models, a third predictor is added to capture hierarchy at a much more granular scale: a one year lag of the website density in the the nearest retail centre [4]. As the literature illustrates, retail centres are key components of urban systems (Dennis et al., 2002; Jones, 2021). Due to the small sizes of the retail centres, the latter is only relevant for and included in the OA models and not in the LAD models. In addition, the model includes 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. The inclusion of the distance variables incorporates spatial structure into the hierarchy argument. To depict the neighbourhood mechanism, the website density of the neighbouring spatial units in the previous year is employed. This is calculated using rook continuity. 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

[3] https://www.ons.gov.uk/methodology/geography/ukgeographies/statisticalgeographies

[4] The retail centres data have been obtained by the Consumer Data Research Centre, an ESRC data investment, under project ID CDRC 498-01, ES/L011840/1; ES/L011891/1: https://data.cdrc.ac.uk/dataset/retail-centre-boundaries-and-open-indicators.

spatial units the year before. This represents the 'hitting nearby locations first' argument. Therefore, the spatial and temporal lag of the website density in LAD and OA is calculated. Lastly, the temporal pattern of the cumulative adoption is captured by a time trend variable. Hence, the model will follow the following generic form (Eq. 3):

$$\begin{aligned} Website\,Density_t \sim Distance\,London + Website\,density\,London_{t-1} + \\ Distance\,Nearest\,City + Website\,density\,Nearest\,City_{t-1} + \\ Distance\,Nearest\,Retail_i + Website\,density\,Nearest\,Retail_{t-1} + \\ W * Website\,density_{t-1} + \\ year_t \end{aligned} \tag{3}$$

Specifically, four different models are estimated. Firstly, all the data points for the OA and LAD are utilised in order to build two models and assess their capacity to predict the adoption of the Web at the two different scales. These two models will reveal the predictive capacity of the diffusion mechanisms and also demonstrate how the importance of such variables changes across different scales. The next two sets of models are again trained at these two scales: OA and LAD. However, instead of using all the data points, the OA and the LAD from one of the twelve UK regions are held out for the model training. Then, the trained model is used to predict website density for the OA or the LAD of the held-out region. This process takes place recursively for all twelve UK regions. The regional differences in the predictive capacity of the different samples will reveal how dissimilar these spatial process are across regions and, importantly, at different scales.

Equation 3 is estimated using Random Forest (RF). This is a popular ML algorithm for both regression and classification problems (Biau, 2012). It was introduced by Breiman (2001) and has become a go-to data science tool. RF can effectively handle skewed distributions and outliers, model non-linear relationships, require minimal hyperparameter tuning, exhibit low sensitivity to these parameters, and have relatively short training times (Caruana et al., 2008; Liaw et al., 2002; Yan et al., 2020). These attributes match well with the website density data characteristics including skewness especially for the OA. Also, the large data size (c. 230k data points for each of the 17 years) calls for fast training times. Importantly, RF predictions tend to be more accurate than those from single regression trees and outperform Ordinary Least Squares in out-of-sample predictions, even with moderate-sized training data and a small number of predictors (Mullainathan and Spiess, 2017; Athey and Imbens, 2019; Sulaiman et al., 2011; Pourebrahim et al., 2019; Biau, 2012).

RF is a tree-based ensemble learning algorithm (Breiman, 2001). It begins by generating random samples of the training data, which are then used to grow regression trees to predict the dependent variable. Data points and predictors are randomly sampled for the different trees. The trees are trained in parallel using their own bootstrapped samples of the training data. A crucial feature of RF is their ability not to overfit, meaning they can generalize well to unseen test data. While each tree may overfit individually, the ensemble of trees does not because the errors of individual trees are averaged, reducing the overall variance and preventing overfitting (Last et al., 2002). For regression problems, RF predictions are made by averaging the predictions of all decision trees.

RF have been widely employed to address regression research problems. Pourebrahim et al. (2019) combined a spatial interaction modelling framework with ML algorithms including RF to predict commuting flows in New York City. Sinha et al. (2019) advocated for adopting spatial ensemble learning approaches, such as RF, to model spatial data with high autocorrelation and heterogeneity. Credit (2021) predicted employment density in Los Angeles using spatially explicit RF. Guns and Rousseau (2014) used RF to build a recommendation system for research collaborations. Ren et al. (2019) trained RF to predict the socio-economic status of cities using various online and mobility predictors. Tranos et al. (2023) utilised hyperlinks data and RF to make out-of-sample predictions of interregional trade. Zhou et al. (2023) employed such a framework to assess whether key predictors of obesity differ across English cities.

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

To assess the predictive power of the model, three broadly utilised metrics are employed: the coefficient of determination (R^2), mean absolute error (MAE) and root mean square error (RMSE):

$$R^2 = 1 - \frac{\sum_k (y_k - \hat{y_k})^2}{\sum_k (y_k - \overline{y_k})^2} \tag{4}$$

$$MAE = \frac{1}{N} \sum_{k=1}^{N} |\hat{y_k} - y_k| \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N} (\hat{y_k} - y_k)^2}{N}} \tag{6}$$

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, as it is proportional to the squared difference between the observed and the predicted trade flows. Hence larger errors weigh more for $RMSE$ (Pontius et al., 2008).

An alternative specification could model the growth of website density. However, such a strategy is problematic because of the large frequency of OA without websites, which is to be expected given their small size and high granularity. Still, as a robustness text, the results of a growth model for LAD are presented in the Appendix.

Lastly, to test the second hypothesis (H_2) about the early adoption and the latecomer effects, a different research framework is developed. Firstly, the S-curve and the estimated t_0 for every LAD are employed and mapped in order to depict the spatial heterogeneity and specific patterns of the speed of the diffusion of the Web. Then, the volatility and the stability of the diffusion across the different LAD is analysed using tools from the complex systems domain (Batty, 2009) namely changes in rankings of LAD based on website density. Both the S-curve estimation and the volatility analysis focus only on LAD as the very large number of OA would have made such analysis difficult to visualise and interpret.

4. Results

4.1. The three diffusion mechanisms at granular geographical scales

Figure 2 plots the cumulative adoption of the Web in the UK as a whole during the 1996-2012 period. In line with the theoretical expectations discussed in the previous section, the cumulative adoption of the Web is well represented by a curve that resembles the letter S. The vertical line in the beginning of 2003 (2003.158) illustrates the point when the modelled cumulative adoption was equal to 50% of the maximum.

This t_0 point is known as the *inflection* point and signals the maximum adoption speed. The results remain unchanged when the extended subset of websites, which include up to 10 unique postcodes is used (see Figure A.1 in the Appendix). Importantly though, the extended subset of websites indicates a saturation level close to 100% at the end of the study period.

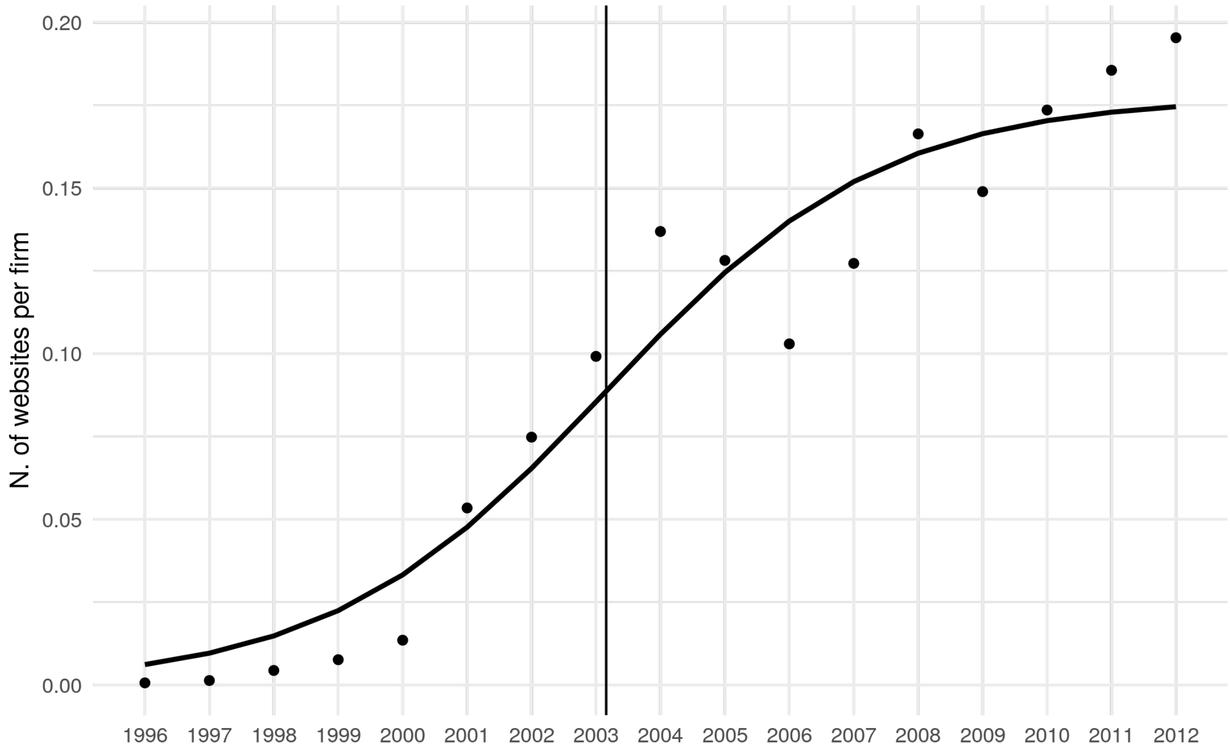

Figure 2: Cumulative adoption of the Web, UK

What escaped from previous studies was exploring whether such a pattern also describes cumulative adoption of new technologies at sub-national scales. To test this, the same logistic function is estimated for each of the 374 LAD. The detailed results are presented in Table A.1 in the Appendix. The key finding is that for 342 LAD (91% of all LAD) the $R^2 > 0.9$ for the logistic function, which indicates that even at local scale the cumulative adoption of the Web is characterised by a pattern similar to the one observed for countries. Graphically, all these LAD curves are plotted in Figure 3. The different colour lines illustrate whether a LAD reached t_0 faster or slower than the UK in total. This heterogeneity is further discussed later in this section.

This is the first time that such cumulative adoption curves have been estimated for areal units as small as the UK LAD. Understanding and modelling the dynamics of technological diffusion and, ultimately, being able to predict diffusion rates at such small local scales can directly support the deployment of infrastructural networks (e.g. 5G) and local technology policies. The above are in line with previous studies exploring the diffusion of web technologies (Papagiannidis et al., 2015), social media (Lengyel et al., 2020) and online shopping (Bakher Naseri and Elliott, 2013).

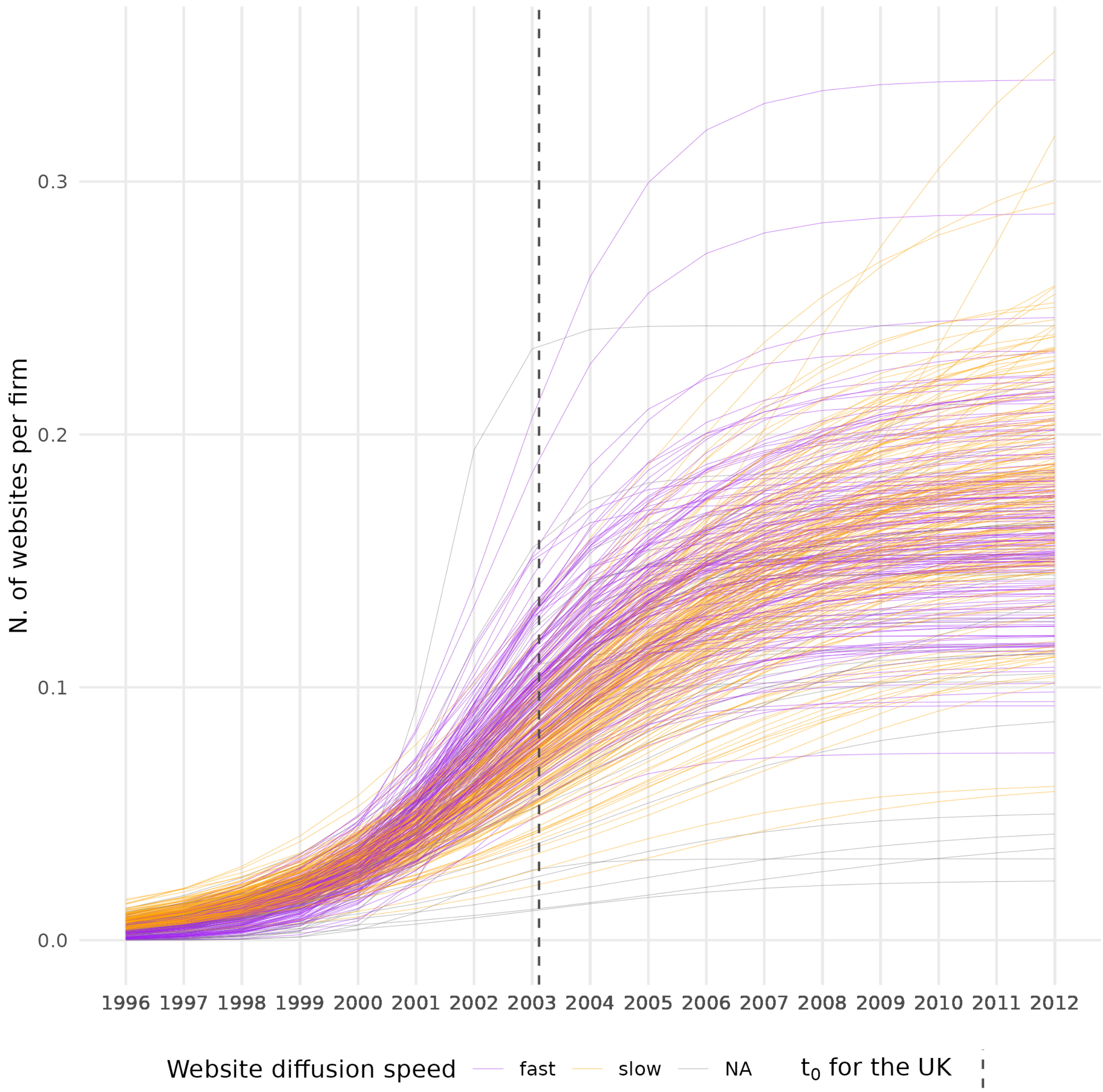

Figure 3: Cumulative adoption of the Web, LAD

To assess the second diffusion mechanisms, Figures 4 and 5 offer a first insight into whether a neighbourhood or, in other words, a distance mechanism underpins the diffusion of the Web in the UK as they present the Moran's I and the LISA maps of website density respectively for LAD and OA. Starting from the former, spatial autocorrelation was higher in the beginning of the study period and then after 2000 dropped slightly and stabilised around 0.2. This reflects the early concentration of high website density around London, which over time diffused as high website density clusters can be seen in other parts of the country away from London (Figure 5). An almost reverse pattern can be observed for OA. At the beginning of the study period Moran's I was around 0.5 and it plateaued after 2000 around 0.2. Because of the very small size of OA, at the early stages of the diffusion of web technologies their adoption was spatially scattered. This is reflected in the lack of any significant clusters in 1996 (Figure 5). Eventually, as the adoption rate increased, more such clusters of high website density were formed and this is reflected both in the Moran's I and the LISA maps in Figures 4 and 5. A similar pattern is observed for the extended dataset (see FiguresA.4 and A.5). In this case, the magnitude of spatial autocorrelation is slightly higher illustrating a stronger spatial clustering mechanism. All in all, the exploratory spatial data analysis advocates towards an underpinning neighbourhood mechanism, which is present at different scales. Interestingly, the magnitude of Moran's I is similar to the ones revealed by Ding et al. (2010) about mobile phone adoption in China albeit the much more detailed spatial scale of this paper.

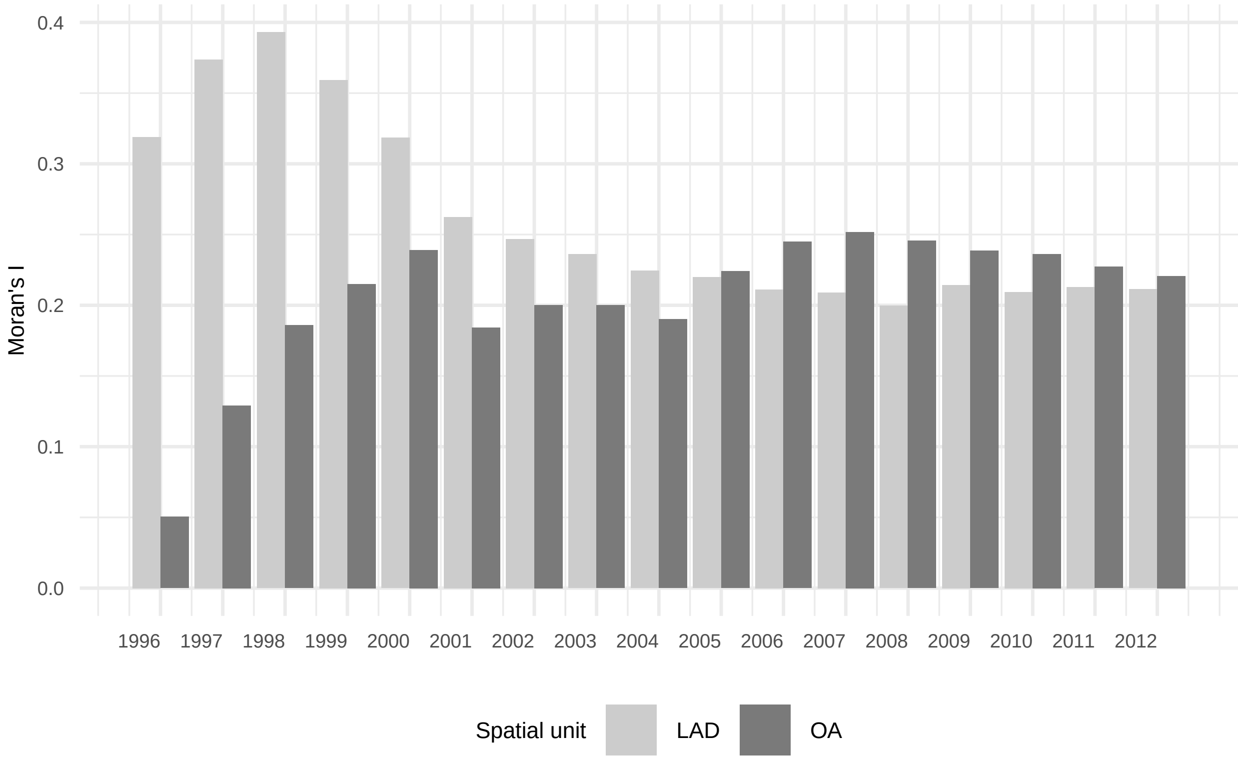

Figure 4: Website density Moran's I

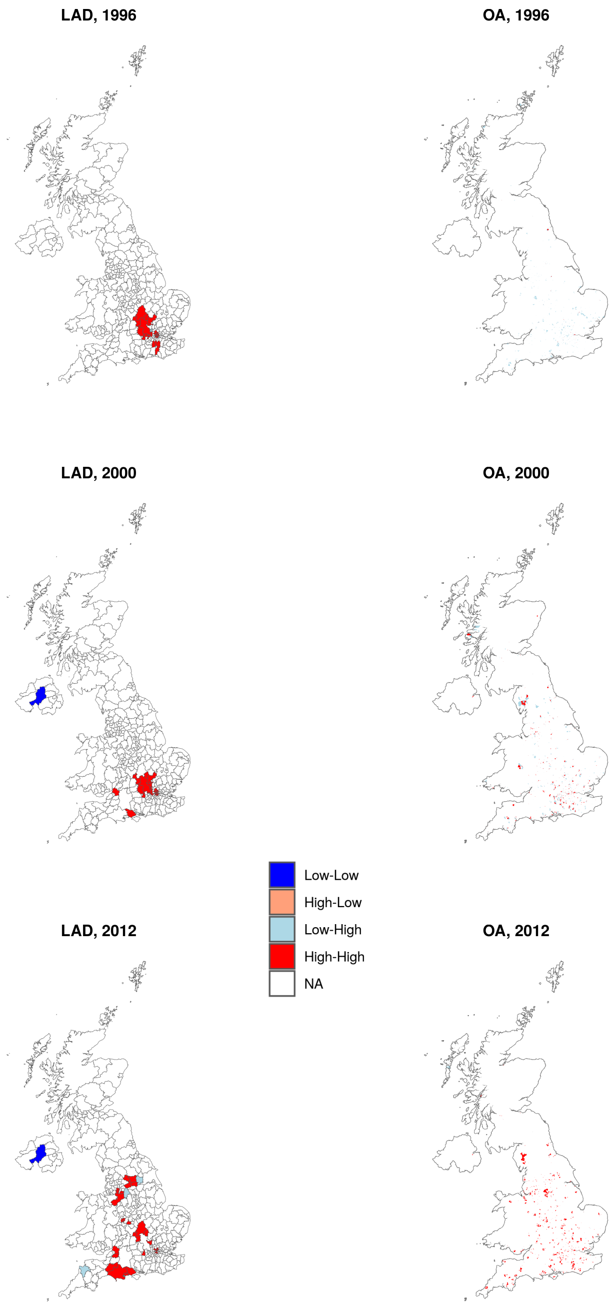

Figure 5: Website density LISA maps

To illustrate whether a hierarchical process also underpins the diffusion of web technologies – the third diffusion mechanism that is tested here – the Gini coefficient is calculated yearly both for LAD and OA. As a metric of inequality, the Gini coefficient demonstrates whether website density is concentrated in a small number of LAD or OA, or whether it is more equally spread across the country. Both scales of analysis in Figure 6 illustrate the same picture. At the beginning of the commercial Internet, website density was extremely unequal, or, in other words, only a few places had websites associated with them. Inequality dropped and plateaued after 2000 for both scales. This is illustrative of a hierarchical diffusion mechanism that led over time to a more equal spread. Interestingly, the year 2000 is again a period of change for this diffusion mechanism as it was for the neighbourhood process. There is a substantial difference between the Gini coefficient magnitude for LAD and OA, but this is expected as the very small size of OA equates to a lot of polygons without any websites pointing to them – for example residential OA.

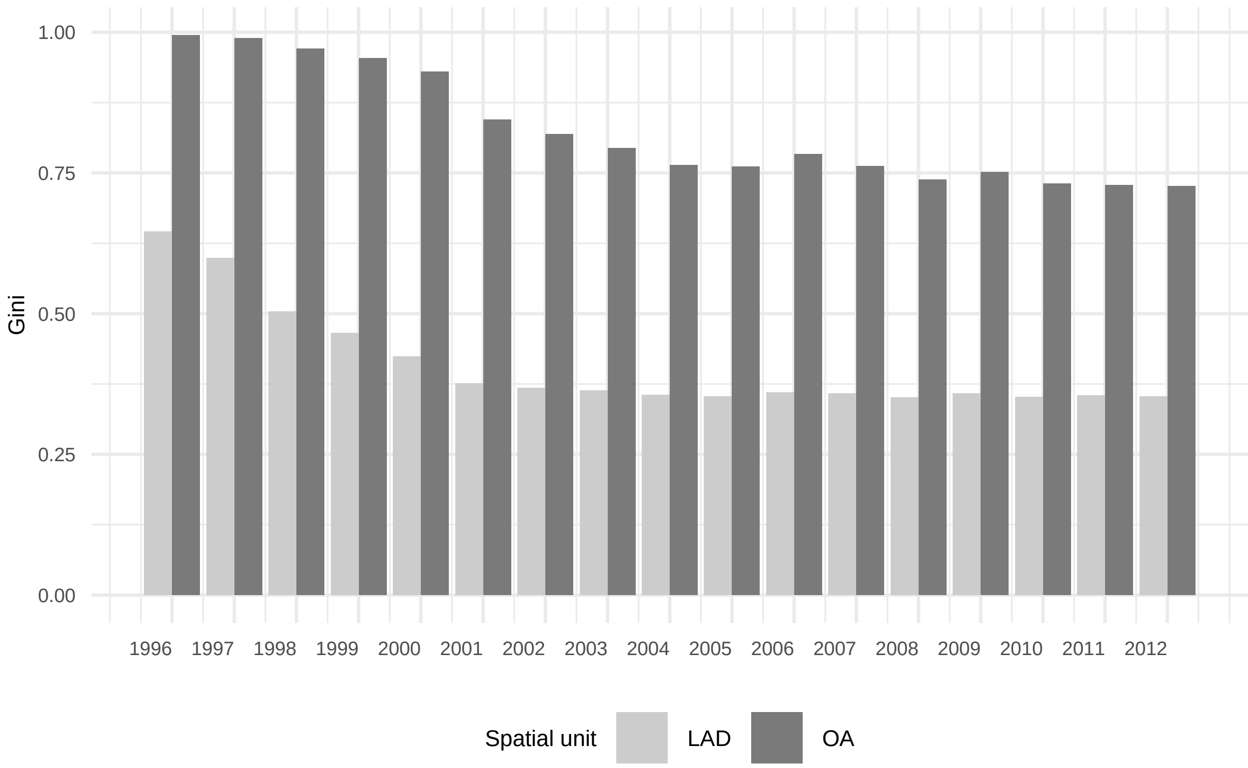

Figure 6: Website density Gini coefficient

After discussing the descriptive findings, the validity of the above diffusion mechanisms at the local scale is assessed with a predictive modelling framework described in Section 3. The reader is reminded that four models are estimated: for the OA and LAD, firstly all data points are employed to assess the capacity of the three mechanisms to to predict the adoption of the Web at these two scales; then, the LAD/OA from one of the twelve regions are recursively held out to assess the spatial heterogeneity of these mechanisms across the different UK regions.

Table 2 presents the model performance for the first set of models, for which all data points are employed for training and testing via CV. The first one is trained and tested on 374 LAD and the second on 232,296 OA, both for the 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 overfitting. At the LAD level the model predicts 83% of the variation of website density. Both error metrics indicate that the model error is fraction of a website per firm (0.020 and 0.029). At the OA the R^2 drops down to 33%. Considering its granularity, this is still a remarkable performance. To contextualise it, the model results in a MAE equal to 1.2 websites for areas small enough to host 40-250 households. 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 at least one website. This should not come as a surprise given that this was the very beginning of the commercial Internet and any activities with a digital footprint were concentrated in a handful of areas, as illustrated in Figure 5. 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 was expected.

Table 2: Model metrics

	$RMSE$	R^2	MAE
Local Authorities	0.029	0.824	0.020
Output Areas	3.218	0.333	1.233

The results in Table 2 are robust against different specifications. As noted earlier, the data imputation process resulted in a modest improvement of the predictive capacity of the model. As per Table 3, all accuracy metrics are only slightly worst when the data imputation is not applied. As expected, the improvement is higher for the more detailed scale of analysis. Then, Table 4 presents the model results for the extended dataset, which includes websites with up to 10 unique postcodes. While the results for LAD are only slightly less accurate, the R^2 of the OA model is much higher in comparison to the base results in Table 2. In addition, Table A.3 in the Appendix presents the accuracy results of a LAD model, the dependent variable of which is the yearly growth rate of website density. Even for such a specification (see Equation 7 in the Appendix) the predictive capacity of the model is exceptionally high ($R^2 = 0.5$). All in all, the modelling exercise revealed how well the three diffusion mechanisms predict the diffusion of the Web as a new technology. Importantly, this predictive power is highly robust against against different scales and delineations of the diffusion of the web.

Table 3: Model metrics without data imputation

	$RMSE$	R^2	MAE
Local Authorities	0.032	0.781	0.021
Output Areas	4.644	0.244	1.237

Table 4: Model metrics for the extended dataset

	$RMSE$	R^2	MAE
Local Authorities	0.190	0.749	0.129
Output Areas	21.591	0.455	6.845

Figure 7 plots the importance of the different predictors. When the focus is on LAD, the website density in the neighbouring LAD, in the nearest city and in London the year before are the most important predictors. They are followed by the yearly trend, while the spatial configuration as reflected in distances to London or to the nearest city only plays a minor role. This can be attributed to the relatively coarse spatial scale of LAD. Nevertheless, all previously discussed spatial processes are at play in the diffusion of the Web at the LAD level: the first two predictors depict the hierarchical mechanism, the spatial and temporal lag of website density the neighbourhood mechanism, and the yearly trend the time-sensitive cumulative adoption pattern.

At the much more granular scale of OA, the picture is almost reversed. The two most important predictors are the distance to London and to the nearest city followed by the spatial and temporal lag of website density and the distance to the nearest retail centre. They still depict a hierarchical mechanism, but proximity to the different population centres is more important than their lagged web densities in predicting website diffusion. The neighbourhood mechanism is still strong but 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 the Web has been adopted at this very fine scale, the latter highlights that the importance of past web adoption rates in large population centres is surpassed by proximity to them and spatial configuration at this scale.

The above pattern of variable importance is largely in accordance with the models estimated for the extended dataset. A comparison with Figure A.7 illustrates that the main difference is the importance of the neighbourhood mechanism for the OA as the space and time lag of the website density is by far the most important predictor when the extended dataset is employed. For the LAD, the importance of the distance to the nearest city increases in favour to its website density the previous year. But still, the variable importance patterns for the two datasets are not dissimilar.

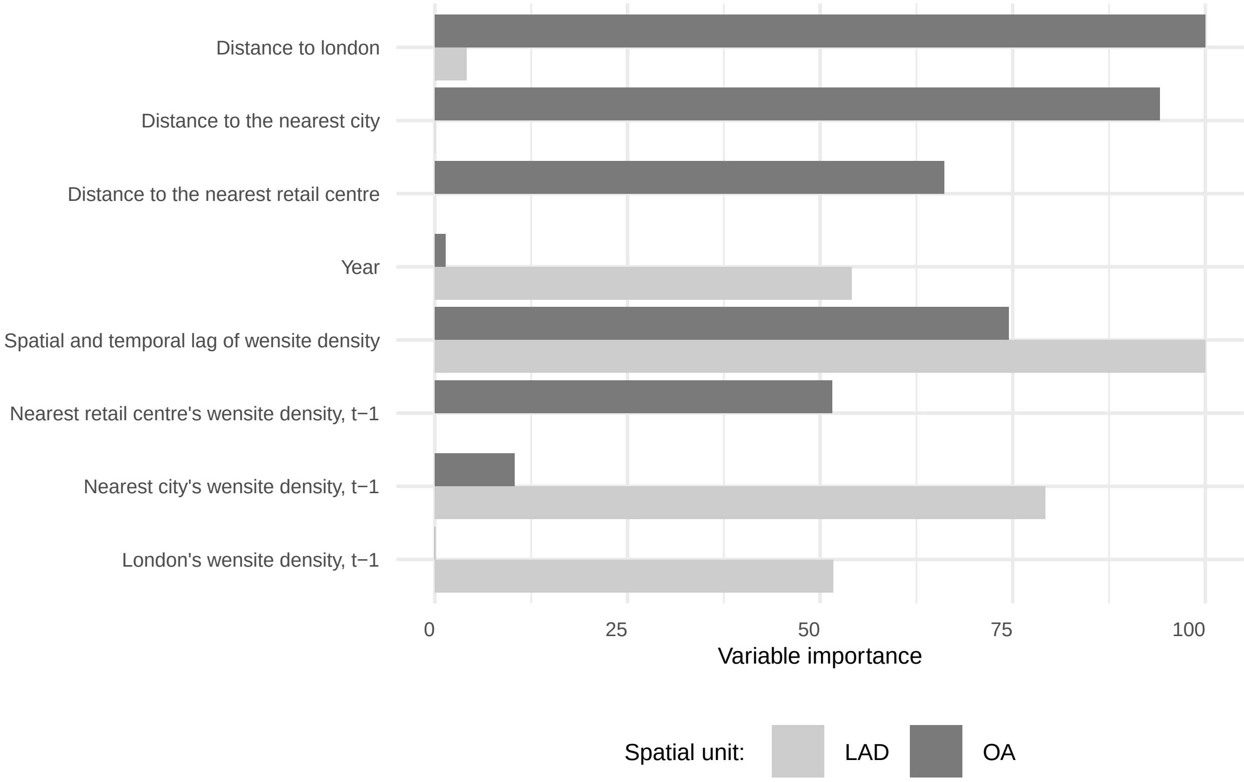

Figure 7: Variable importance

Table 5 presents the results of the recursive hold out models and allows to (i) highlight the regional heterogeneity of the spatial processes behind the diffusion of the Web, and (ii) compare this heterogeneity across the two different scales of analysis. It illustrates both regional similarities and differences. At the top of Table 5 the regions of South East and the West Midlands have the highest similarity with the rest of the country. In other words, the web density for the LAD of these regions can be very well predicted by models trained on data from the LAD from the rest of the country and, therefore, the spatial diffusion mechanisms for these regions represent quite well the UK's average. This should not come as a surprise as the spatial structure of both regions resembles the broader UK: both regions contain some highly urbanised LAD (South East is well integrated with the Greater London and West Midlands is the home of the city of Birmingham), but also smaller commuter towns as well as more rural settlements. At the other end of the spectrum, the spatial diffusion mechanisms for Northern Ireland, Scotland and North West diverge the most from the country average. Rurality and remoteness seem to be common attributes for these regions. This hierarchy though is not consistent across scales. For the more granular OA models, the spatial diffusion mechanisms for South West, Yorkshire and The Humber and North West regions are closer to the country average. Interestingly, these regions are well-known tourist destinations (Lake District, Peak District and Cornwall-Devon) and the exploratory analysis revealed clusters of high web density only visible at the OA scale (Figure 5). Then, Scotland, Northern Ireland and London have the lowest similarity with the country average. Again, rurality, peripherality, but also the highest level or urbanisation make the spatial diffusion mechanisms of these regions more distinct.

Table 5: Regional differences

Region	R^2 LAD	Rank LAD	R^2 OA	Rank OA
South East	0.952	1	0.122	6
West Midlands	0.926	2	0.126	4
Wales	0.909	3	0.122	8
Yorkshire and The Humber	0.908	4	0.160	2
East Midlands	0.904	5	0.122	7
South West	0.894	6	0.185	1
North East	0.887	7	0.124	5
London	0.880	8	0.090	11
East of England	0.876	9	0.106	9
North West	0.837	10	0.142	3
Scotland	0.774	11	0.059	12
Nortern Ireland	0.590	12	0.101	10

Comparing the above with Table A.2 in the Appendix, which presents the results for the the extended dataset with websites with up to 10 unique postcodes, the results do not differentiate much, signalling the robustness of the analysis. The most salient difference has to do with Northern Ireland. According to the extended sample at the granular OA level, Northern Ireland's spatial diffusion mechanisms are closer to the UK's average than the results based on the websites with a unique postcode. While the latter are websites and, consequently, economic activities solely based in Northern Ireland, websites with multiple postcodes also include websites with postcodes in Britain and, therefore, can be characterised by slightly different spatial diffusion processes.

4.2. Early adoption and latecomers

To test the second hypothesis (H_2), the spatial heterogeneity of Web adoption speeds is firstly analysed. As highlighted in the literature (Stuck and Walker, 2019), different agents have different perceptions about and levels of acceptance of the risks and the potential economic returns associated with the adoption of new technologies – see for instance the seminal work of Venkatesh and Davis (2000). To reveal such patterns, Figure 8 maps whether LAD reached their inflection point earlier or later than the UK in total and based on this are labelled as *fast* or *slow* accordingly. Inflection points have been used in the relevant literature to compare diffusion processes across different settings and technologies (Cherp et al., 2021; Woo and Magee, 2017) as they can enable more insightful comparisons than, for example, the average growth over the 1996-2012 study period.

The map illustrates a clear high concentration of fast adopting LAD in the South and East of England, as expected. There are also some concentrations in Wales, Scotland and the North West of England. At a more detailed level, there are some expected cases of LAD with relevant industrial backgrounds delineated as fast: the City of London, a world-renowned cluster of finance industries (Cook et al., 2007), and Reading, a town with high-tech service industries in proximity to London and its main airport, Heathrow (Pain and Walker, 2005). However, there are also LAD which were expected to appear as fast – e.g. Hackney in central London and Bristol, a well-established creative cluster (Oatley et al., 1999; Bassett et al., 2002) – but are delineated as slow. Similar to Beardsell and Henderson (1999), who analysed the spatial evolution of computer industry employment across 317 US metro areas, spatial heterogeneity is evident in the diffusion speed when the scale of analysis is as detailed as the LAD.

Importantly, there is obvious spatial clustering of fast and slow LAD. Out of the ten fastest LAD based on when they reached their inflection point (see detailed Table A.1 in the Appendix), nine were located in the South East of England and London and one in Cambridge. The above observations remain almost unchanged when the analysis includes websites with up to 10 unique postcodes – see Figure A.2 in the Appendix – demonstrating the robustness of the analysis. Given (i) the expectation that early adopters of new technologies are often rewarded (Rogers, 2010; Griliches, 1957; Ding et al., 2010), and (ii) the previous findings illustrating the long term and sustained productivity benefit for the early adopters of Web in the UK (Tranos et al., 2021), the observed spatial clustering of LAD with fast diffusion rates can further reinforce existing and rooted patterns of unequal economic productivity in the UK (McCann and Yuan, 2022).

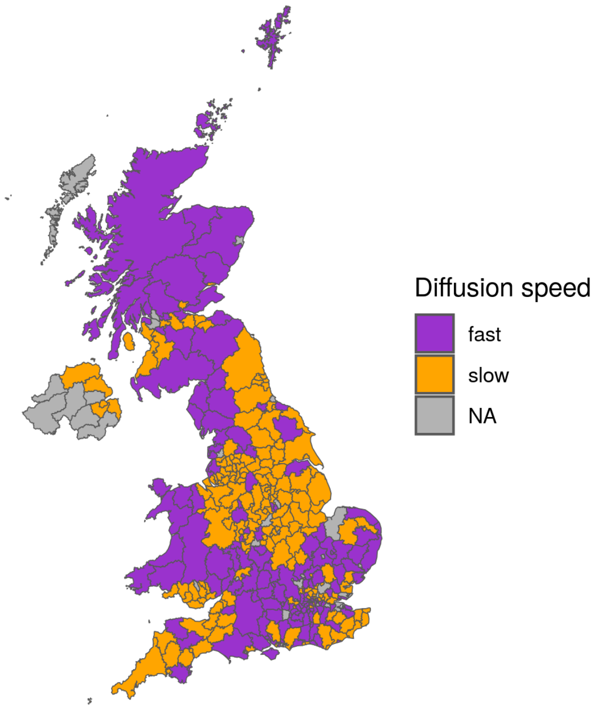

Figure 8: LAD Web diffusion speed, 1996-2012

To reveal patterns of early adoption and leapfrogging, the stability and volatility of the above patterns is analysed. Figure 9 plots the relative ranking of LAD based on website density at the beginning and the end of the study period. To decrease noise, the average ranking of 1996-1998 and 2010-2012 is plotted instead of the individual years. Each line represents a single LAD and the colours depict the 5th and 95th percentile of the absolute difference of the LAD ranking between 1996-1998 and 2010-2012. In other words, the 5th percentile includes the LAD, the relative position of which remained unchanged between the beginning and the end of the study period, both at the top and at the bottom of the hierarchy (small absolute difference in ranking). The 95th percentile includes LAD that either increased or decreased a lot their relative positions over time (high absolute difference in ranking). Thus, Figure 9 reveals cases of *leapfrogging* since the LAD at the top-right part of the figure managed to jump at the top of the hierarchy at the end of the study period.

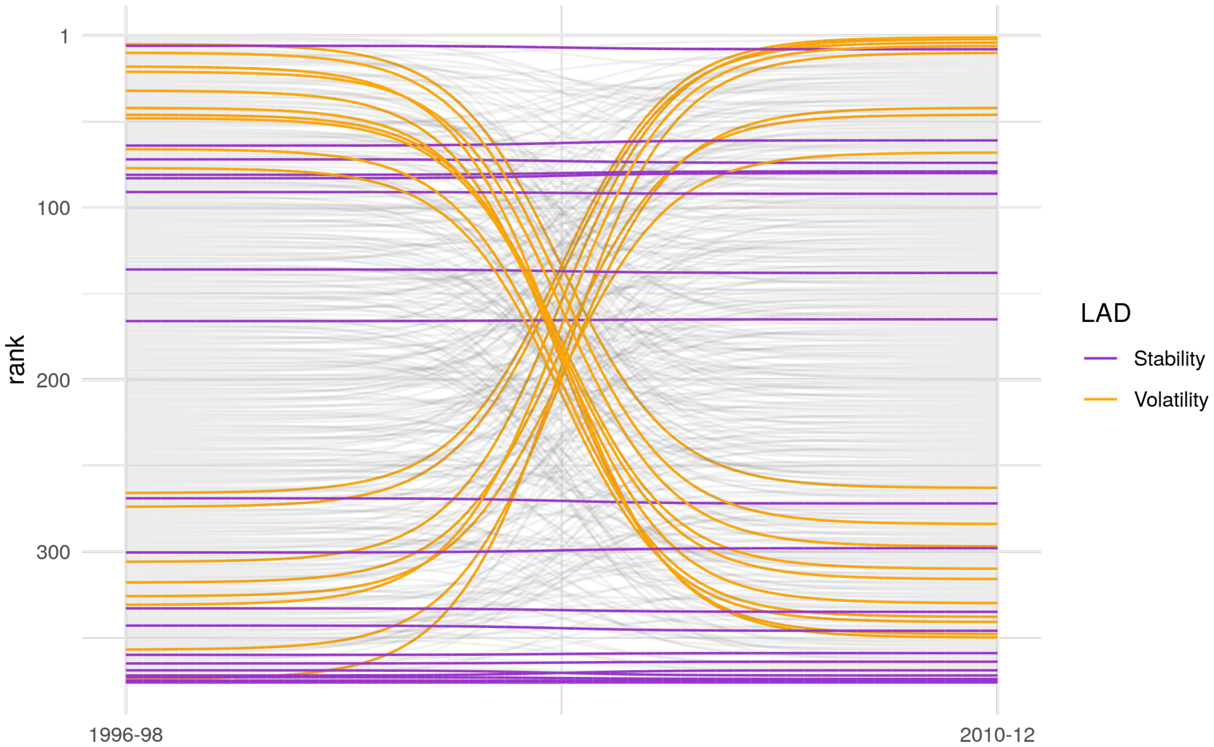

Figure 9: Dynamics of Web diffusion based on LAD rankings

To further analyse the above, Table 6 juxtaposes the volatility of the LAD Web diffusion against the early conditions as it reports the t_0 estimate (inflection point) for the leapfrogging LAD identified in Figure 9. Indeed, more than half of the LAD that drastically increased their relative position at the end of the study period reached the inflection point t_0 later than the country in total and, therefore, the Web diffusion speed has been relatively slow for them. The fact that these LAD experienced relatively faster diffusion rates at the end of the study period, which is aligned with the maturity period of the web, can lead to potential positive economic gains for these LAD. There is extensive literature describing the benefits of such technological leapfrogging and the underpinning argument is that latecomers can adopt and benefit from new technologies that have been developed elsewhere without incurring the hefty initial R&D costs (Teece, 2000).

Based on Figure 9 and Table 6, the opportunity to catch up that Perkins and Neumayer (2005) illustrated at the country level, is also visible at the much more detailed LAD scale. Although the relevant literature did not pay attention to cities and regions (Yu and Gibbs, 2018), the above finding advocates towards further exploring leapfrogging effects at such a granular scale. As previously, this is consistent with including websites with up to 10 postcodes (see Figure A.3).

All in all, the diffusion of the Web at the detailed scale of LAD is characterised by spatial heterogeneity, well-established spatial patterns and both stability and volatility. Although the relevant literature neglected local scales, the above findings illustrated that such local dynamics exists and worth further consideration and investigation especially regarding potential local economic effects.

Table 6: Late adopters

LAD	t_0 estimate	Diffusion speed
Halton	2007.1	slow
Blackpool	2002.4	fast
Rutland	2006.5	slow
Torbay	2002.2	fast
Isles of Scilly	2012.2	slow
North Devon	2002.9	fast
Gosport	2003.8	slow
Thanet	2004.0	slow
Na h-Eileanan Siar	NA	NA
Conwy	2002.6	fast

5. Conclusions

The paper offers an economic geography study of the diffusion of a new technology – the Web. Contrary to previous studies, it does so by adopting (i) a high level of spatial granularity, and (ii) a long study period that captures the very early stages of this technology until its maturity. This is the first time that the importance of granular spatial mechanisms for the diffusion of a new technology is exposed. Importantly, the empirical framework and the data employed here allows to observe the active engagement with the Web that is creating and maintaining a commercial website instead of the more passive action of browsing webpages and accessing the Internet.

Specifically, two hypotheses are tested. Firstly, whether the three diffusion mechanisms namely distance, urban hierarchy and the S-shaped pattern of the cumulative level of adoption shaped the diffusion of the commercial Web in the UK at granular geographical scales. The analysis firstly illustrates how well the S-pattern of cumulative adoption fits at the local scale and offers some descriptive insights about the importance of the distance and hierarchical diffusion mechanisms. Then, the modelling exercise reveals the remarkably good predictive capacity of these mechanisms at granular geographical scales. The modelling framework exposes that the relative importance of these spatial mechanisms differ across different scales. It also reveals spatial heterogeneity. While for some UK regions the importance of the spatial diffusion mechanisms are very similar to the rest of the country, other regions diverge significantly from the country average.

To do the above, a robust and novel ML modelling framework was designed to predict website diffusion over space and time using as predictors the spatial diffusion mechanisms. Space- and time-sensitive CV was designed for the model to avoid overfitting. Importantly, the results are robust against different specifications and subsets of the data. This is the first time that the power of these mechanisms in predicting the diffusion of a new technology was empirically tested, importantly, at very fine scales.

The second hypothesis assessed whether the diffusion of the web is shaped by both early adoption and latecomer effects. On the one hand, the analysis highlighted the heterogeneity of adoption rates between LAD as well as the spatial clustering of LAD with similar adoption rates. Importantly, the observed spatial clustering of LAD with fast diffusion rates can reinforce existing and rooted patterns of unequal economic productivity in the UK (McCann and Yuan, 2022). Previous research had already indicated the long-term productivity gains of the early adoption of such technologies (Tranos et al., 2021). On the other hand, the analysis also exposed instances of remarkable stability as well as volatility of the Web adoption, with the latter being indicative of leapfrogging. While the literature had discussed the benefits of technological leapfrogging at the national scale (Teece, 2000; Perkins and Neumayer, 2005), local scales had escaped such studies (Yu and Gibbs, 2018). Thus the leapfrogging evidence presented here advocate towards further exploring such effects at granular scales.

The paper offers a number of different contributions. Firstly, it assesses, for the first time, the role of these spatial diffusion mechanisms at such granular spatial scales. While previous studies had highlighted these mechanisms (Hägerstrand et al., 1968; Rogers, 2010; Grubler, 1990), their role had never been tested before at such granular scale. The findings talk directly to this literature (e.g. Beardsell and Henderson, 1999; Haller and Siedschlag, 2011; Lengyel et al., 2020). More broadly, the paper offers a robust methodological framework, which utilises novel data and modern ML algorithms and techniques to model the diffusion of a new technology across space and time. It directly addresses the data problem which prevented economic geographers in engaging with diffusion studies (Neumayer and Perkins, 2005; Kemeny, 2011; Zook and McCanless, 2022). Thus, the paper seeks to renew economic geography's interest in the diffusion of new technologies. Current data science advances including the availability of granular enough data and adequate methods can enable economic geographers to reveal interesting spatial patterns of diffusion of new technologies as this paper has demonstrated. This is important as (i) various stakeholders are interested in predicting localised demand for new technologies for planning purposes, for example 5G networks (Leibowicz et al., 2016; Meade and Islam, 2021), and (ii) the adoption of such digital technologies is associated with local economic gains (Solow, 1957; Aghion, 1990; Kemeny, 2011; Tranos et al., 2021; Capello et al., 2024). Importantly, although the geographical focus of this paper is the UK, the empirical framework developed here is easily transferable to other geographical contexts.

A. Appendix

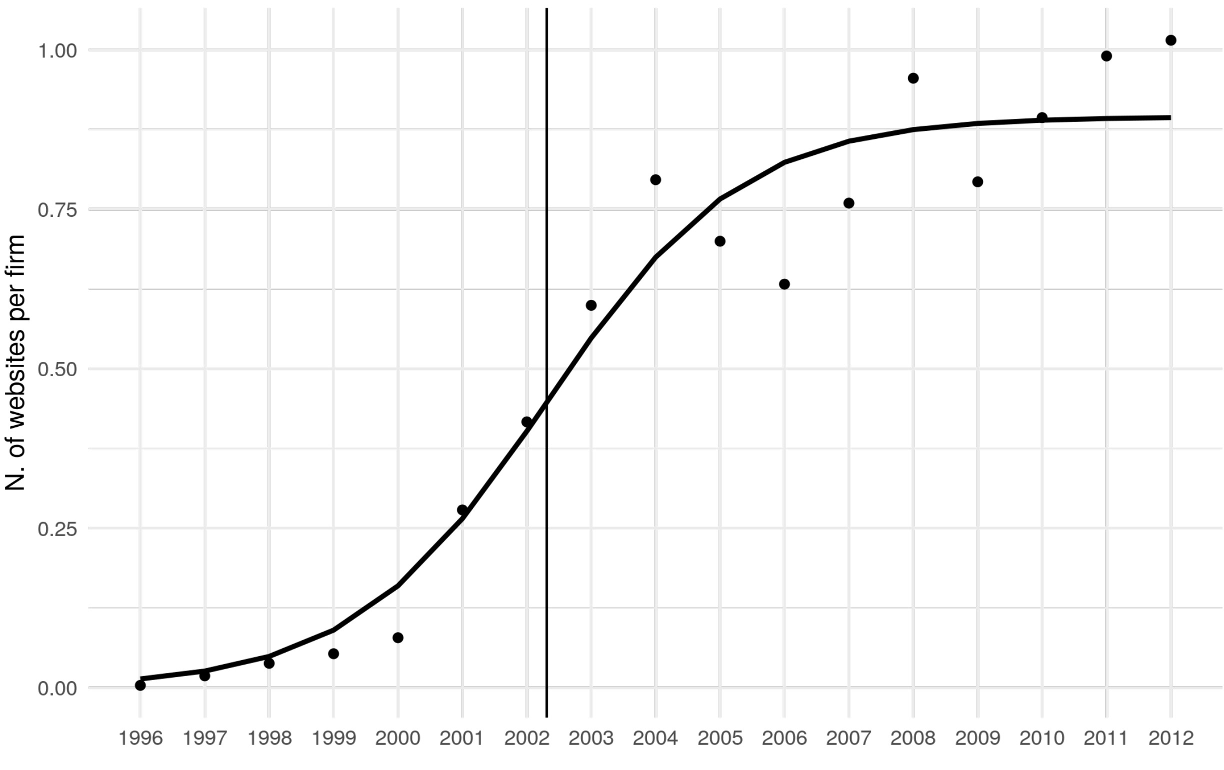

Figure A.1: Cumulative adoption of the Web, UK; up to 10 postcodes per website

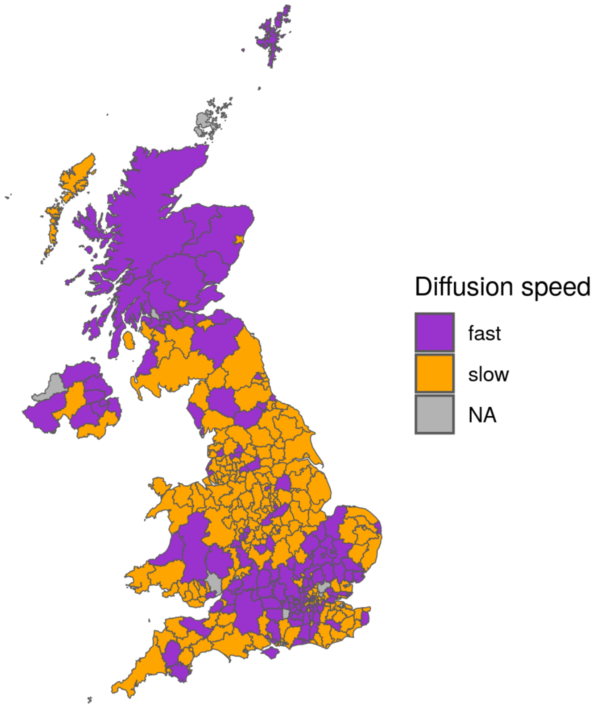

Figure A.2: LAD Web diffusion speed, 1996-2012; up to 10 postcodes per website

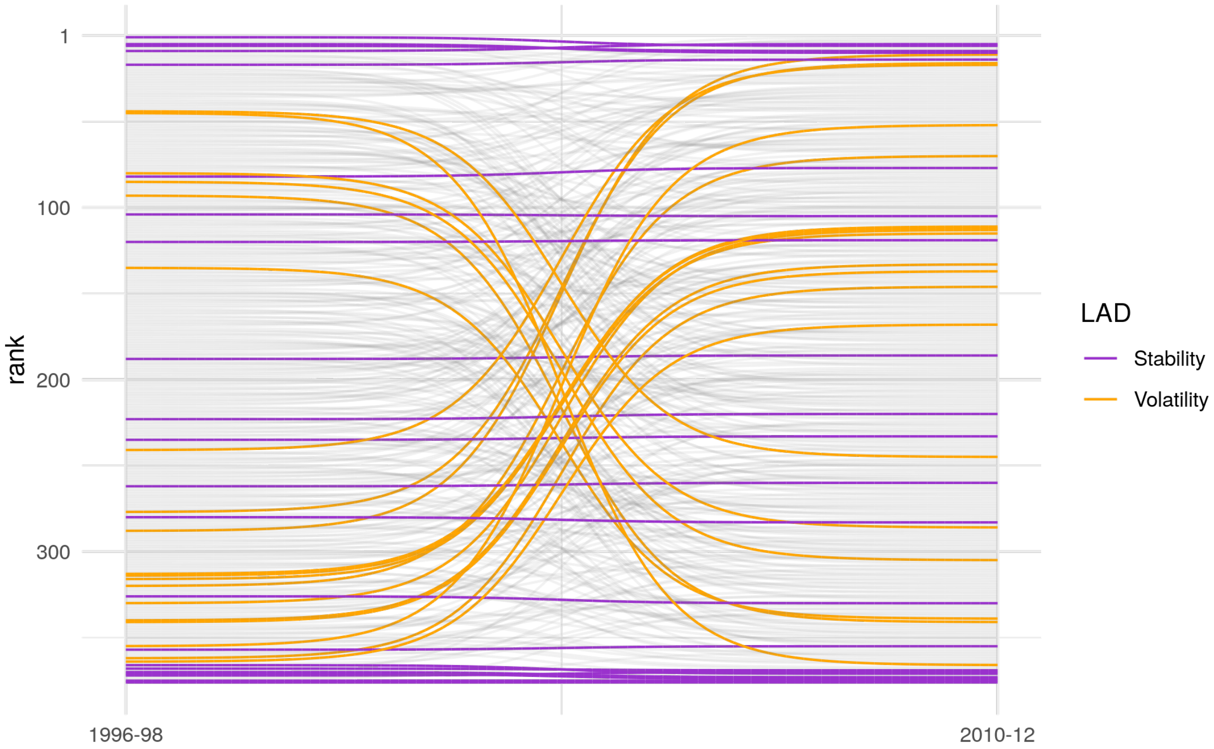

Figure A.3: Dynamics of Web diffusion based on LAD rankings; up to 10 postcodes per website

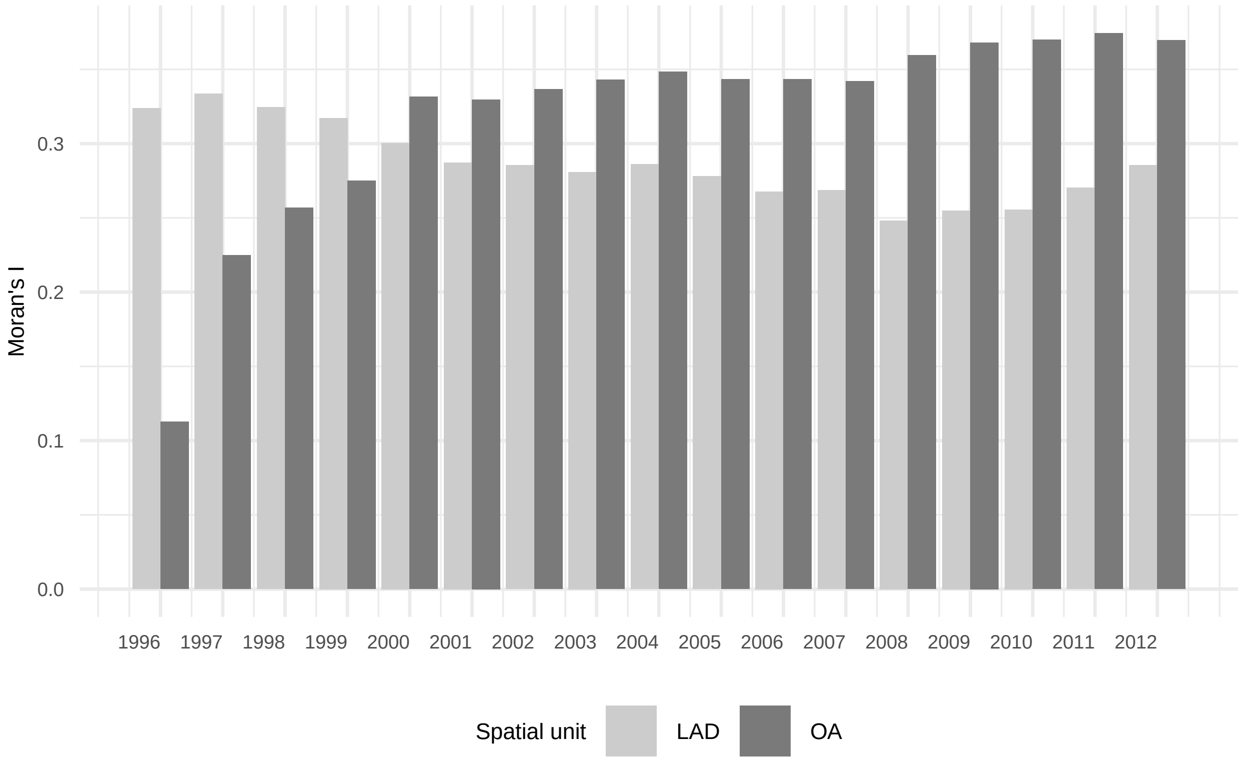

Figure A.4: Website density Moran's I; up to 10 postcodes per website

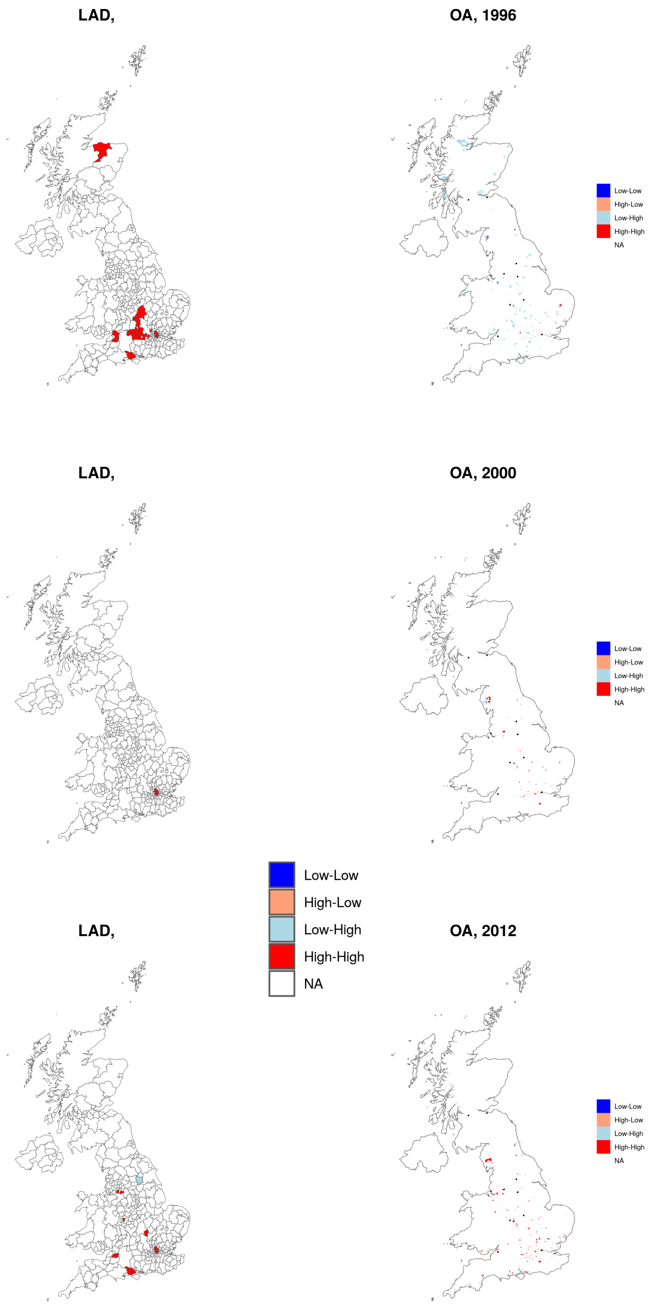

Figure A.5: Website density LISA maps; up to 10 postcodes per website

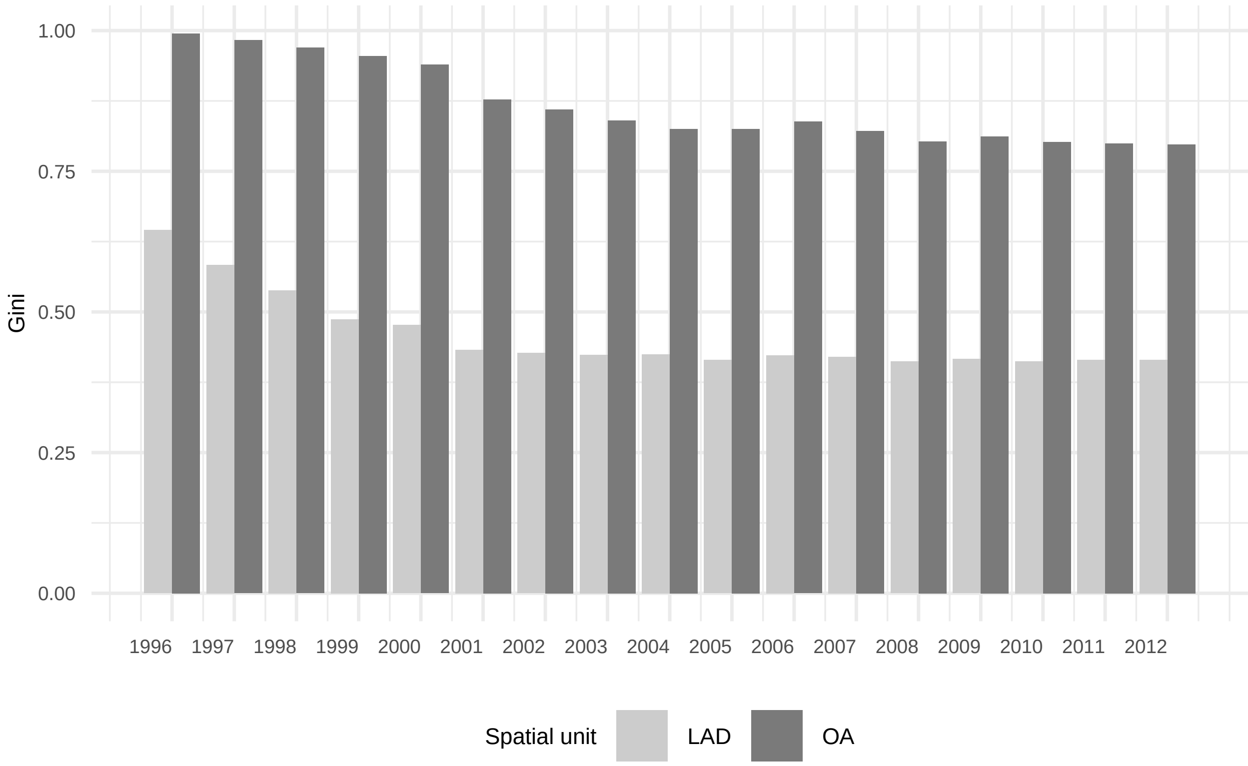

Figure A.6: Website density Gini coefficient; up to 10 postcodes per website

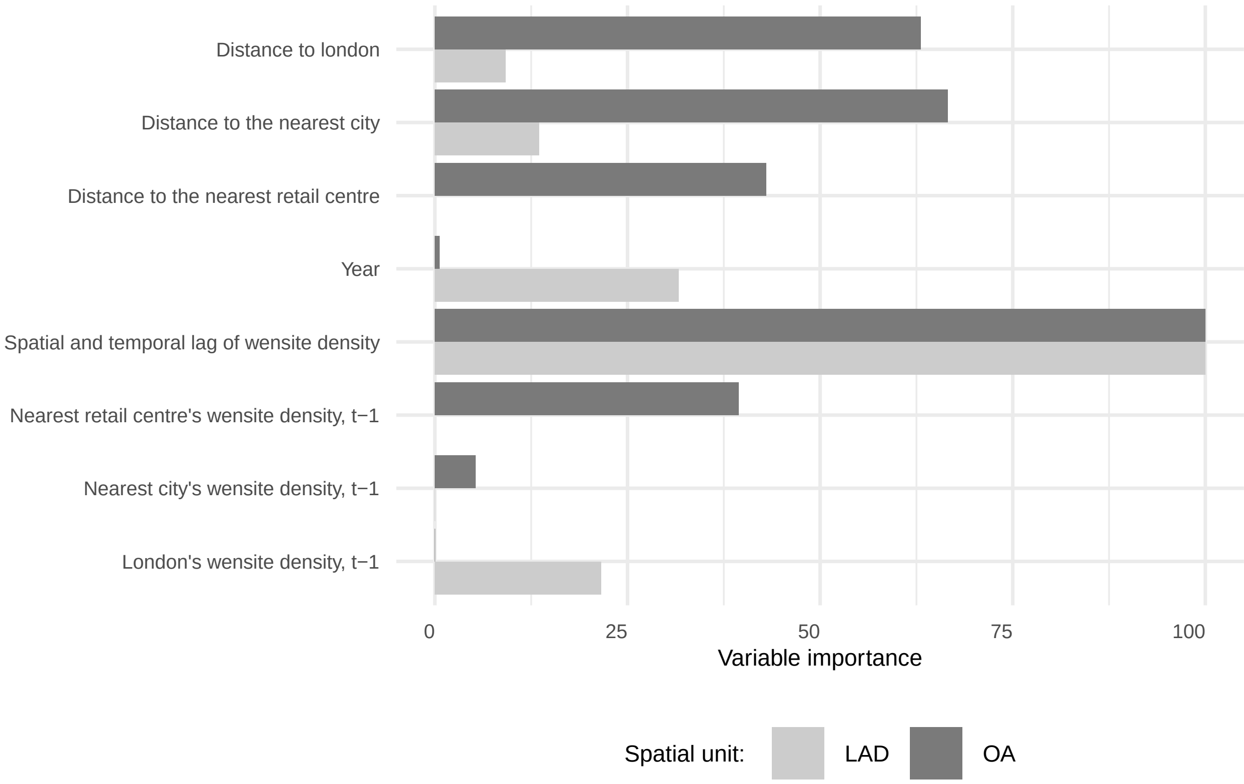

Figure A.7: Variable importance; up to 10 postcodes per website

Table A.1: S-curve estiamtes for LAD

LAD	Region	t_0 estimate	Std. error	R^2	Diffusion speed
Horsham	South East	2001.423	0.254	0.950	fast
Fareham	South East	2001.443	0.346	0.925	fast
Kingston upon Thames	London	2001.513	0.354	0.933	fast
Kensington and Chelsea	London	2001.581	0.341	0.943	fast
Runnymede	South East	2001.582	0.266	0.943	fast
Bracknell Forest	South East	2001.586	0.324	0.928	fast
Elmbridge	South East	2001.656	0.333	0.932	fast
Reigate and Banstead	South East	2001.665	0.253	0.964	fast
South Cambridgeshire	East of England	2001.680	0.433	0.905	fast
Walsall	West Midlands	2001.715	0.413	0.901	fast
Surrey Heath	South East	2001.718	0.333	0.933	fast
Woking	South East	2001.759	0.292	0.951	fast
South Norfolk	East of England	2001.874	0.358	0.931	fast
City of London	London	2001.874	0.499	0.930	fast
Wokingham	South East	2001.891	0.287	0.958	fast
Reading	South East	2001.900	0.318	0.948	fast
Sevenoaks	South East	2001.904	0.407	0.926	fast
Huntingdonshire	East of England	2001.912	0.402	0.925	fast
Pendle	North West	2001.924	0.407	0.923	fast
St Albans	East of England	2001.933	0.396	0.927	fast

LAD	Region	t_0 estimate	Std. error	R^2	Diffusion speed
Perth and Kinross	NA	2001.943	0.228	0.970	fast
Bromley	London	2001.945	0.396	0.919	fast
Rushmoor	South East	2001.962	0.518	0.912	fast
Powys	NA	2001.969	0.278	0.963	fast
Swindon	South West	2001.996	0.390	0.916	fast
Chelmsford	East of England	2002.008	0.545	0.911	fast
Crawley	South East	2002.008	0.379	0.949	fast
Dumfries and Galloway	NA	2002.012	0.251	0.967	fast
Inverclyde	NA	2002.030	0.330	0.915	fast
North Hertfordshire	East of England	2002.031	0.475	0.920	fast
Moray	NA	2002.050	0.358	0.947	fast
Orkney Islands	NA	2002.070	0.283	0.958	fast
Fife	NA	2002.070	0.363	0.945	fast
Mole Valley	South East	2002.071	0.460	0.925	fast
Guildford	South East	2002.113	0.413	0.941	fast
Buckinghamshire	South East	2002.114	0.390	0.942	fast
Cotswold	South West	2002.116	0.375	0.946	fast
Shetland Islands	NA	2002.120	0.332	0.949	fast
South Oxfordshire	South East	2002.146	0.367	0.950	fast
Watford	East of England	2002.157	0.451	0.929	fast
Aberdeenshire	NA	2002.168	0.416	0.931	fast
Southampton	South East	2002.189	0.472	0.922	fast
Mid Suffolk	East of England	2002.196	0.442	0.922	fast
Eden	North West	2002.196	0.334	0.949	fast
South Lakeland	North West	2002.197	0.238	0.974	fast
Stoke-on-Trent	West Midlands	2002.203	0.419	0.927	fast
Babergh	East of England	2002.209	0.449	0.927	fast
Bexley	London	2002.213	0.493	0.909	fast
Torbay	South West	2002.215	0.374	0.942	fast
Brentwood	East of England	2002.219	0.336	0.936	fast
Ceredigion	NA	2002.227	0.241	0.971	fast
Spelthorne	South East	2002.232	0.451	0.933	fast
Bath and North East Somerset	South West	2002.238	0.402	0.941	fast
Falkirk	NA	2002.245	0.367	0.938	fast
Broxtowe	East Midlands	2002.258	0.435	0.932	fast
East Hertfordshire	East of England	2002.261	0.453	0.928	fast
Stirling	NA	2002.268	0.251	0.975	fast
Ealing	London	2002.294	0.523	0.922	fast
Mid Sussex	South East	2002.295	0.453	0.936	fast
Barrow-in-Furness	North West	2002.303	0.284	0.959	fast
West Oxfordshire	South East	2002.322	0.467	0.929	fast
Sutton	London	2002.326	0.544	0.911	fast
Portsmouth	South East	2002.356	0.479	0.921	fast
Great Yarmouth	East of England	2002.369	0.265	0.968	fast
East Hampshire	South East	2002.370	0.474	0.931	fast
Wyre Forest	West Midlands	2002.376	0.561	0.916	fast
Angus	NA	2002.378	0.396	0.939	fast
Argyll and Bute	NA	2002.427	0.321	0.962	fast

LAD	Region	t_0 estimate	Std. error	R^2	Diffusion speed
Scottish Borders	NA	2002.428	0.298	0.962	fast
East Suffolk	East of England	2002.431	0.533	0.919	fast
Blackpool	North West	2002.443	0.294	0.962	fast
Cherwell	South East	2002.448	0.533	0.923	fast
Wandsworth	London	2002.449	0.570	0.921	fast
Tendring	East of England	2002.456	0.456	0.935	fast
Westminster	London	2002.459	0.437	0.952	fast
Richmond upon Thames	London	2002.462	0.389	0.956	fast
Test Valley	South East	2002.463	0.553	0.920	fast
Isle of Wight	South East	2002.478	0.377	0.953	fast
Vale of White Horse	South East	2002.496	0.408	0.949	fast
Croydon	London	2002.510	0.504	0.927	fast
Hounslow	London	2002.521	0.426	0.952	fast
Copeland	North West	2002.524	0.237	0.971	fast
Wiltshire	South West	2002.528	0.450	0.940	fast
Gwynedd	NA	2002.536	0.372	0.954	fast
Hillingdon	London	2002.560	0.470	0.940	fast
Conwy	NA	2002.564	0.372	0.954	fast
Highland	NA	2002.566	0.270	0.972	fast
Basingstoke and Deane	South East	2002.572	0.461	0.947	fast
Harrow	London	2002.587	0.509	0.936	fast
West Berkshire	South East	2002.595	0.696	0.902	fast
North Lincolnshire	Yorkshire and The Humber	2002.596	0.501	0.933	fast
East Dunbartonshire	NA	2002.598	0.528	0.925	fast
Bradford	Yorkshire and The Humber	2002.598	0.613	0.916	fast
Waverley	South East	2002.606	0.512	0.928	fast
Stroud	South West	2002.608	0.559	0.916	fast
Herefordshire, County of	West Midlands	2002.622	0.388	0.956	fast
North Norfolk	East of England	2002.624	0.422	0.945	fast
Nottingham	East Midlands	2002.630	0.531	0.936	fast
Castle Point	East of England	2002.645	0.470	0.936	fast
North Warwickshire	West Midlands	2002.657	0.380	0.955	fast
Gravesham	South East	2002.680	0.473	0.933	fast
Lancaster	North West	2002.692	0.336	0.963	fast
West Suffolk	East of England	2002.699	0.536	0.930	fast
Stafford	West Midlands	2002.719	0.499	0.933	fast
Tunbridge Wells	South East	2002.720	0.401	0.958	fast
Oxford	South East	2002.723	0.583	0.934	fast
East Lothian	NA	2002.731	0.537	0.927	fast
Redcar and Cleveland	North East	2002.750	0.509	0.929	fast
Tamworth	West Midlands	2002.755	0.551	0.929	fast
South Hams	South West	2002.773	0.422	0.952	fast
Allerdale	North West	2002.784	0.376	0.958	fast
Central Bedfordshire	East of England	2002.825	0.620	0.921	fast
East Cambridgeshire	East of England	2002.843	0.636	0.927	fast
Havant	South East	2002.853	0.541	0.932	fast
South Lanarkshire	NA	2002.874	0.486	0.938	fast

LAD	Region	t_0 estimate	Std. error	R^2	Diffusion speed
Stratford-on-Avon	West Midlands	2002.879	0.470	0.945	fast
Arun	South East	2002.882	0.526	0.938	fast
Fenland	East of England	2002.891	0.632	0.918	fast
Monmouthshire	NA	2002.893	0.501	0.935	fast
Denbighshire	NA	2002.901	0.457	0.947	fast
Southend-on-Sea	East of England	2002.903	0.551	0.932	fast
High Peak	East Midlands	2002.903	0.488	0.946	fast
Pembrokeshire	NA	2002.905	0.387	0.958	fast
Malvern Hills	West Midlands	2002.907	0.524	0.940	fast
Camden	London	2002.915	0.599	0.941	fast
North Devon	South West	2002.926	0.426	0.950	fast
Wyre	North West	2002.927	0.553	0.927	fast
Darlington	North East	2002.933	0.615	0.929	fast
Swale	South East	2002.940	0.447	0.948	fast
Welwyn Hatfield	East of England	2002.951	0.628	0.922	fast
Mid Devon	South West	2002.960	0.485	0.946	fast
Lewes	South East	2002.964	0.507	0.945	fast
Dorset	South West	2002.968	0.407	0.958	fast
Brighton and Hove	South East	2002.976	0.578	0.934	fast
Braintree	East of England	2002.978	0.534	0.938	fast
Epsom and Ewell	South East	2002.979	0.746	0.908	fast
Sefton	North West	2002.980	0.616	0.928	fast
Eastleigh	South East	2002.992	0.595	0.929	fast
Craven	Yorkshire and The Humber	2002.993	0.379	0.965	fast
Hammersmith and Fulham	London	2002.997	0.585	0.944	fast
Greenwich	London	2003.014	0.571	0.930	slow
Cheltenham	South West	2003.025	0.602	0.937	slow
Worcester	West Midlands	2003.041	0.659	0.920	slow
Tower Hamlets	London	2003.043	0.660	0.926	slow
New Forest	South East	2003.046	0.554	0.941	slow
East Renfrewshire	NA	2003.046	0.739	0.900	slow
Fylde	North West	2003.056	0.501	0.946	slow
Carmarthenshire	NA	2003.067	0.390	0.958	slow
West Lancashire	North West	2003.076	0.547	0.937	slow
Hastings	South East	2003.086	0.685	0.911	slow
Carlisle	North West	2003.111	0.541	0.934	slow
Wychavon	West Midlands	2003.115	0.570	0.935	slow
Isle of Anglesey	NA	2003.144	0.403	0.960	slow
Dudley	West Midlands	2003.150	0.678	0.925	slow
Ryedale	Yorkshire and The Humber	2003.152	0.380	0.961	slow
Rother	South East	2003.162	0.366	0.966	slow
Leicester	East Midlands	2003.167	0.686	0.924	slow
Breckland	East of England	2003.182	0.567	0.938	slow
Tandridge	South East	2003.190	0.747	0.918	slow
Shropshire	West Midlands	2003.206	0.621	0.928	slow
West Devon	South West	2003.228	0.489	0.949	slow
Milton Keynes	South East	2003.231	0.700	0.929	slow

LAD	Region	t_0 estimate	Std. error	R^2	Diffusion speed
Sandwell	West Midlands	2003.234	0.760	0.916	slow
Winchester	South East	2003.234	0.443	0.956	slow
Redditch	West Midlands	2003.238	0.706	0.923	slow
Rugby	West Midlands	2003.265	0.709	0.922	slow
North Somerset	South West	2003.278	0.558	0.939	slow
West Lindsey	East Midlands	2003.285	0.674	0.924	slow
Richmondshire	Yorkshire and The Humber	2003.286	0.425	0.958	slow
Melton	East Midlands	2003.292	0.534	0.946	slow
Chichester	South East	2003.295	0.582	0.942	slow
Torridge	South West	2003.301	0.532	0.942	slow
Dundee City	NA	2003.303	0.568	0.939	slow
South Ayrshire	NA	2003.303	0.626	0.931	slow
East Devon	South West	2003.308	0.492	0.947	slow
Bolton	North West	2003.323	0.774	0.913	slow
Hertsmere	East of England	2003.326	0.726	0.924	slow
Bournemouth, Christchurch and Poole	South West	2003.347	0.662	0.936	slow
Maldon	East of England	2003.349	0.495	0.951	slow
Barnet	London	2003.352	0.766	0.919	slow
Brent	London	2003.389	0.762	0.925	slow
Midlothian	NA	2003.413	0.732	0.921	slow
Boston	East Midlands	2003.416	0.593	0.933	slow
Scarborough	Yorkshire and The Humber	2003.421	0.431	0.963	slow
Kirklees	Yorkshire and The Humber	2003.435	0.725	0.925	slow
Tameside	North West	2003.441	0.819	0.907	slow
Newport	NA	2003.449	0.635	0.930	slow
Glasgow City	NA	2003.451	0.759	0.922	slow
Clackmannanshire	NA	2003.454	0.585	0.936	slow
Three Rivers	East of England	2003.458	0.628	0.947	slow
Harborough	East Midlands	2003.488	0.549	0.950	slow
Rochdale	North West	2003.496	0.685	0.937	slow
Tonbridge and Malling	South East	2003.497	0.710	0.927	slow
Somerset West and Taunton	South West	2003.502	0.491	0.955	slow
Wrexham	NA	2003.512	0.553	0.942	slow
Worthing	South East	2003.522	0.622	0.938	slow
Tewkesbury	South West	2003.540	0.580	0.946	slow
City of Edinburgh	NA	2003.541	0.685	0.941	slow
Coventry	West Midlands	2003.592	0.564	0.948	slow
Northumberland	North East	2003.607	0.508	0.954	slow
Mid and East Antrim	NA	2003.609	0.893	0.900	slow
Wigan	North West	2003.617	0.755	0.929	slow
Lichfield	West Midlands	2003.629	0.625	0.939	slow
Ashford	South East	2003.633	0.535	0.944	slow
Cornwall	South West	2003.638	0.443	0.963	slow
Mendip	South West	2003.652	0.505	0.955	slow
Stevenage	East of England	2003.665	0.525	0.958	slow

LAD	Region	t_0 estimate	Std. error	R^2	Diffusion speed
Blaenau Gwent	NA	2003.666	0.643	0.933	slow
Lincoln	East Midlands	2003.666	0.634	0.940	slow
South Somerset	South West	2003.676	0.553	0.948	slow
Charnwood	East Midlands	2003.677	0.699	0.934	slow
North Ayrshire	NA	2003.682	0.607	0.942	slow
Folkestone and Hythe	South East	2003.684	0.792	0.905	slow
Eastbourne	South East	2003.684	0.697	0.930	slow
Blackburn with Darwen	North West	2003.685	0.680	0.938	slow
Dover	South East	2003.699	0.574	0.948	slow
Adur	South East	2003.735	0.551	0.954	slow
Haringey	London	2003.739	0.667	0.943	slow
Gosport	South East	2003.751	0.600	0.934	slow
Trafford	North West	2003.752	0.640	0.949	slow
Norwich	East of England	2003.756	0.742	0.939	slow
West Lothian	NA	2003.758	0.652	0.943	slow
North East Lincolnshire	Yorkshire and The Humber	2003.811	0.858	0.920	slow
Bristol, City of	South West	2003.828	0.831	0.928	slow
Rushcliffe	East Midlands	2003.839	0.591	0.954	slow
Hinckley and Bosworth	East Midlands	2003.857	0.749	0.934	slow
Torfaen	NA	2003.861	0.841	0.922	slow
Swansea	NA	2003.875	0.650	0.947	slow
Wolverhampton	West Midlands	2003.882	0.793	0.931	slow
Kingston upon Hull, City of	Yorkshire and The Humber	2003.885	0.757	0.936	slow
Calderdale	Yorkshire and The Humber	2003.889	0.714	0.939	slow
North Northamptonshire	East Midlands	2003.902	0.746	0.935	slow
Stockton-on-Tees	North East	2003.902	0.955	0.916	slow
Wealden	South East	2003.906	0.736	0.938	slow
Thanet	South East	2003.953	0.667	0.947	slow
Broadland	East of England	2003.962	0.727	0.938	slow
West Northamptonshire	East Midlands	2003.972	0.736	0.940	slow
North Kesteven	East Midlands	2003.976	0.633	0.942	slow
Neath Port Talbot	NA	2003.981	0.767	0.933	slow
Rhondda Cynon Taf	NA	2003.991	0.769	0.925	slow
Enfield	London	2003.992	0.588	0.954	slow
East Lindsey	East Midlands	2004.010	0.577	0.952	slow
Teignbridge	South West	2004.015	0.681	0.941	slow
York	Yorkshire and The Humber	2004.025	0.739	0.944	slow
Harlow	East of England	2004.030	0.803	0.936	slow
Vale of Glamorgan	NA	2004.033	0.592	0.951	slow
Newark and Sherwood	East Midlands	2004.034	0.668	0.946	slow
Merton	London	2004.041	0.932	0.922	slow
Hambleton	Yorkshire and The Humber	2004.065	0.636	0.953	slow
Bedford	East of England	2004.068	0.852	0.933	slow
Stockport	North West	2004.075	0.757	0.942	slow

LAD	Region	t_0 estimate	Std. error	R^2	Diffusion speed
South Ribble	North West	2004.126	0.674	0.948	slow
Uttlesford	East of England	2004.144	0.905	0.926	slow
Rossendale	North West	2004.160	0.976	0.923	slow
Oldham	North West	2004.162	0.801	0.938	slow
Sheffield	Yorkshire and The Humber	2004.189	0.770	0.944	slow
Ribble Valley	North West	2004.204	0.718	0.945	slow
Maidstone	South East	2004.222	0.854	0.932	slow
Cheshire West and Chester	North West	2004.234	0.742	0.947	slow
Thurrock	East of England	2004.241	0.841	0.924	slow
Telford and Wrekin	West Midlands	2004.241	1.024	0.917	slow
Cardiff	NA	2004.246	0.823	0.937	slow
County Durham	North East	2004.250	0.626	0.953	slow
Plymouth	South West	2004.252	0.785	0.934	slow
Bridgend	NA	2004.256	0.547	0.956	slow
Rotherham	Yorkshire and The Humber	2004.273	0.722	0.938	slow
Hyndburn	North West	2004.298	0.881	0.932	slow
Newcastle upon Tyne	North East	2004.305	0.906	0.932	slow
Wakefield	Yorkshire and The Humber	2004.314	0.905	0.923	slow
Havering	London	2004.345	0.822	0.938	slow
South Kesteven	East Midlands	2004.353	1.026	0.915	slow
Canterbury	South East	2004.354	0.602	0.960	slow
Broxbourne	East of England	2004.363	0.817	0.944	slow
Peterborough	East of England	2004.382	0.937	0.932	slow
Redbridge	London	2004.411	1.028	0.925	slow
Bury	North West	2004.431	0.735	0.953	slow
Harrogate	Yorkshire and The Humber	2004.433	0.971	0.927	slow
Birmingham	West Midlands	2004.435	1.182	0.912	slow
South Tyneside	North East	2004.446	0.636	0.948	slow
Chorley	North West	2004.462	1.093	0.913	slow
North East Derbyshire	East Midlands	2004.483	0.703	0.953	slow
Lambeth	London	2004.485	0.958	0.937	slow
Doncaster	Yorkshire and The Humber	2004.496	0.672	0.953	slow
South Gloucestershire	South West	2004.499	0.881	0.937	slow
Caerphilly	NA	2004.499	0.819	0.938	slow
East Staffordshire	West Midlands	2004.501	1.132	0.910	slow
North Tyneside	North East	2004.509	0.864	0.933	slow
South Holland	East Midlands	2004.534	0.851	0.941	slow
Gateshead	North East	2004.535	0.869	0.934	slow
St. Helens	North West	2004.542	1.097	0.923	slow
Flintshire	NA	2004.549	0.764	0.951	slow
Selby	Yorkshire and The Humber	2004.549	0.716	0.947	slow
Belfast	NA	2004.556	1.332	0.906	slow
Sedgemoor	South West	2004.613	0.540	0.966	slow

LAD	Region	t_0 estimate	Std. error	R^2	Diffusion speed
Exeter	South West	2004.617	0.964	0.936	slow
South Derbyshire	East Midlands	2004.629	0.934	0.938	slow
Derbyshire Dales	East Midlands	2004.668	0.648	0.963	slow
East Riding of Yorkshire	Yorkshire and The Humber	2004.683	0.728	0.955	slow
Basildon	East of England	2004.691	1.067	0.925	slow
Barking and Dagenham	London	2004.800	1.198	0.916	slow
Causeway Coast and Glens	NA	2004.834	1.024	0.928	slow
North Lanarkshire	NA	2004.839	0.878	0.945	slow
Chesterfield	East Midlands	2004.887	1.173	0.927	slow
Newcastle-under-Lyme	West Midlands	2004.933	1.172	0.925	slow
East Ayrshire	NA	2004.934	1.280	0.903	slow
Nuneaton and Bedworth	West Midlands	2004.956	0.950	0.941	slow
Blaby	East Midlands	2004.959	1.059	0.929	slow
Leeds	Yorkshire and The Humber	2004.979	0.836	0.956	slow
Erewash	East Midlands	2004.987	0.939	0.944	slow
Bassetlaw	East Midlands	2004.998	0.982	0.944	slow
Hackney	London	2005.026	1.157	0.934	slow
Barnsley	Yorkshire and The Humber	2005.055	0.912	0.942	slow
Amber Valley	East Midlands	2005.105	1.017	0.941	slow
Colchester	East of England	2005.144	1.250	0.927	slow
Ashfield	East Midlands	2005.176	1.073	0.942	slow
Wirral	North West	2005.184	1.084	0.939	slow
Knowsley	North West	2005.186	1.160	0.923	slow
Windsor and Maidenhead	South East	2005.195	1.746	0.902	slow
Bromsgrove	West Midlands	2005.494	1.144	0.941	slow
Liverpool	North West	2005.526	1.276	0.936	slow
Staffordshire Moorlands	West Midlands	2005.583	1.426	0.924	slow
Islington	London	2005.970	1.223	0.955	slow
Warrington	North West	2006.015	1.387	0.942	slow
Newham	London	2006.078	1.908	0.907	slow
Bolsover	East Midlands	2006.188	1.143	0.957	slow
Lisburn and Castlereagh	NA	2006.193	1.970	0.903	slow
Manchester	North West	2006.449	1.434	0.950	slow
Sunderland	North East	2006.479	1.679	0.928	slow
South Staffordshire	West Midlands	2006.490	1.837	0.922	slow
Rutland	East Midlands	2006.529	0.986	0.967	slow
Cannock Chase	West Midlands	2006.700	2.231	0.917	slow
Mansfield	East Midlands	2006.889	1.579	0.946	slow
Ards and North Down	NA	2006.947	2.485	0.907	slow
Halton	North West	2007.069	0.932	0.967	slow
Burnley	North West	2007.372	2.286	0.919	slow
Middlesbrough	North East	2010.074	5.297	0.900	slow
Isles of Scilly	South West	2012.163	4.257	0.953	slow

Table A.2: Regional differences; up to 10 postcodes per website

Region	R^2 LAD	Rank LAD	R^2 OA	Rank OA
Yorkshire and The Humber	0.864	1	0.191	5
West Midlands	0.860	2	0.148	8
South East	0.848	3	0.171	7
North West	0.827	4	0.221	1
London	0.826	5	0.118	9
South West	0.801	6	0.194	4
Wales	0.746	7	0.114	11
East Midlands	0.732	8	0.117	10
East of England	0.731	9	0.178	6
North East	0.695	10	0.215	2
Scotland	0.588	11	0.052	12
Nortern Ireland	0.488	12	0.197	3

Table A.3: Model metrics for growth model

	$RMSE$	R^2	MAE
Local Authorities	0.286	0.506	0.223

Table A.3 presents the results of a Random Forest model that was trained based on Equation 7 using all LAD data points. In essence, this is a model similar to the one estimated based on Equation 3 and presented in Table 2, with the main difference being the dependent variable which is the year growth rate of website density for each LAD. To avoid cases with LAD have no websites, $t \in [2000, 2012]$. The high predictive capability of the model reflects the robustness of the modelling approach.

$$\begin{aligned} Website\,Density\,Growth_t \sim Distance\,London + Website\,density\,London_{t-1} + \\ Distance\,Nearest\,City + Website\,density\,Nearest\,City_{t-1} + \\ Distance\,Nearest\,Retail_i + Website\,density\,Nearest\,Retail_{t-1} + \\ W * Website\,density_{t-1} + \\ year_t \end{aligned} \tag{7}$$

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