Technological Forecasting & Social Change 184 (2022) 121959

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Going online: Forecasting the impact of websites on productivity and market structure

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A R T I C L E I N F O

JEL codes:
D21
D22
L10
L22
O33

Keywords:
Internet
Website
ICT
TFP
Productivity
Market concentration
Forecasting

A B S T R A C T

We develop a unifying framework to investigate the effects of firms' internet presence on productivity and market structure. Using information on website adoption as an indicator of online trading, we treat the decision of entering an e-commerce market equivalent to the decision of entering a foreign market. Our theoretical framework draws from a dynamic model of international trade, which accounts for firms' heterogeneity in productivity levels and in the returns to productivity enhancing investments. We test the predictions of our model using UK and Spanish company account data, over the 1995–2010 period merged with information of companies' online status. The period analysed is associated with the early stage of internet diffusion and our sample countries represent fast (the UK) and slow (Spain) diffusion. Our results show that website adoption is associated with higher productivity growth and with a reduction in market concentration in both countries. The increase in competition operates via a negative selection mechanism, whereby productivity growth is inversely related to the pre-entry productivity levels. We also find that productivity gains decline over time.

1. Introduction

The advent of the internet and the adoption and diffusion of Information and Communication Technology (ICT) have profoundly changed both firms' and consumers' behaviour. The declining costs of purchasing and using the new technology, next to the relaxation of regulatory constraints, have allowed a fast adoption of a whole range of ICT related applications, among which firms' websites are some of the most important examples (Porter, 2001). Websites are the first sign of a company's presence on the internet and mark the beginning of a process that can lead to online advertising and trading. Adoption of websites, particularly in the initial phase of diffusion of the technology, is also an indicator of innovative behaviour that can affect companies' performance and market shares. Hence registering a website can be considered an indicator of adoption of a new business model and analysing the economic consequences of 'going online' is important to further our understanding of the economic implications of the digital revolution.

Compared to 'bricks and mortar' businesses, operating online implies lower set up costs and allows a variety of firms to enter the market, increasing competitive pressure. This process may lead firms to revise their price policies more regularly, which may ultimately reduce their profit margins (Litan and Rivlin, 2001; Porter, 2001; Brown and Goolsbee, 2002; Goldmanis et al., 2010). This should push the least competitive firms out of the market, contributing to a more efficient environment. Hence, a first effect of trading online would be to increase productivity. A rich literature has widely documented the ICT and productivity nexus, considering several ICT applications such as e-commerce and the internet (Stanley et al., 2018; Vu et al., 2020). However, two issues remain unresolved: first, there is no formal analysis of the productivity enhancing effects of operating online in a dynamic setting; second, except for Koch et al. (2021), the majority of studies implicitly assume firms' homogeneity in terms of productivity performance. Further firm-level analysis is thus needed to address these issues.

Next to a productivity effect, trading online can also have an impact on market structure. As discussed in Autor et al. (2017) with reference to the US economy, highly innovative and efficient firms, taking advantage

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https://doi.org/10.1016/j.techfore.2022.121959
Received 17 February 2022; Received in revised form 17 June 2022; Accepted 9 August 2022
Available online 23 August 2022

of network effects, can gain a dominant position (or 'superstar' status) in the market, leading to increasing concentration. However, the low costs of setting up a website and entering an online market, may facilitate entry and lead to a decrease in concentration, as hypothesised in Litan and Rivlin (2001). There is an ongoing debate on whether markets are becoming more concentrated across OECD countries. The empirical evidence is mainly confined to the US (OECD, 2018), where results point towards increasing concentration. However, little is known about what is happening in other countries and what theoretical mechanism relate online businesses with productivity and market concentration.

The main aim of this paper is to provide a unifying theoretical framework for the analysis of how website adoption can affect both productivity and market structure. More specifically, our analysis will address the following research questions:

RQ1: is trading online via the adoption of websites contributing to firms' productivity performance?
RQ2: is the adoption of online trading leading to more competitive markets?

To address these questions, we first develop a theoretical framework, which draws from the trade literature (Helpman, 2006; Lileeva and Trefler, 2010). In our context, a firm setting up a website and entering an e-commerce market is comparable to a firm entering a foreign market.[1] In international trade, firms must undergo a certain amount of initial costs before trading with a foreign country. In our framework, these are represented by the costs related to setting up a website, a necessary condition for future trading to happen. Similar to entering a foreign market, entering a digital market will expand firms' sales and increase productivity (Bustos, 2011). Our framework allows for heterogeneity in firms' productivity performance and investments in productivity-enhancing technological innovations. The main feature of our theoretical set up is that it provides a mechanism of firm entry into the e-commerce market which can result in reallocation of market shares and ultimately affect market structure.

We put our theoretical framework to the empirical test using large samples of UK and Spanish firms, observed over the 1995–2010 period. We link company accounts data with information on companies' online presence, identified from the date they registered their web domain. Specifically, we construct measures of firm process innovation behaviour[2] associated with the adoption of a website by using an intelligent system to automatically extract a set of indicators from a given corporate website (Domenech et al., 2012). Hence, our study provides an instructive example of how data retrieved from the internet can complement standard data sources, such as firm financial statements, and enrich the set of information available for economic analysis.

Our empirical analysis develops in two parts: in the first part we estimate firm level productivity (TFP) and test for the presence of significant differences in productivity growth between website adopters and non-adopters, using a difference-in-difference approach, and accounting for firms' heterogeneity in productivity performance. In the second part, we assess the link between online presence via a website and market structure by constructing a measure of market concentration at the 2-digit industry level. Following Geroski and Pomroy (1990), we express concentration as a function of the number of companies with a website within each industry, technological conditions, and market size. Our results show that website adoption is associated with higher productivity growth, although productivity gains decline over time. Market concentration, measured by the Herfindahl-Hirschman Index (HHI), has declined in the UK and, to a lesser extent, in Spain. The number of companies with website presence is associated with reduced market concentration and thus increased competition in both countries. We also find that technology more widely defined, captured by capital intensity and Total Factor Productivity (TFP), contributes to an increase in market concentration. In the UK this effect is observed in the overall sample and within manufacturing; in Spain it mainly emerges in manufacturing.

Our study contributes to bridging the gap between two economic literatures: the literature on the relationship between digital technologies and productivity and the literature on innovation and market structure. While the first has seen a blossoming of contributions in recent years, to our knowledge there has not been any attempt at investigating how the effect of new technologies on productivity leads to changes in market structure. Existing work on the relationship between innovation and market structure have mainly addressed the question of which market structure is best to foster innovation (e.g., Sutton, 1991; Aghion et al., 2005; Vives, 2008; Hashmi, 2013), while leaving the question of how innovations can affect market structure in the background. As such, our work provides an important extension to the seminal work of Blair (1972), Geroski et al. (1987), and Geroski and Pomroy (1990). Our work uses data for two European countries and hence widens the current discussion on whether markets are becoming more concentrated which has so far primarily focused on the US. In addition, these two countries differ in terms of adoption and diffusion of new technologies, innovation policy and regulatory regimes, and as such they provide interesting settings for analysing the effects of website adoption. Our work also contributes to the understanding of the wider role of the internet on the economy, a role that is still debated in the literature. For example, Stanley et al. (2018) in their meta-analysis of the impact of ICT on growth find that all types of ICT contribute to growth, except for the internet. Our study shows that going online positively influences productivity, although this effect declines over time.

The paper is organised in five sections. In the next section we review the relevant literature, develop a theoretical framework and formulate our hypotheses. In Section 3 we discuss the main features of our data while in Section 4 we present a firm-level analysis of the relationship between website adoption and productivity. In Section 5 we focus on the relationship between website adoption and market structure. Section 6 concludes the paper.

2. Theoretical framework

2.1. Background

The advent of the internet and increasing investments in ICT and complementary intangible assets have played a major role in the US' 1990s productivity revival and, despite some initial scepticism about the importance of the new technological revolution compared to the discoveries of the past (Cowen, 2011), it is undeniable that ICT and its countless applications, including websites, have had a profound impact on the economy. The empirical analysis has extensively focused on the effects of ICT on productivity performance and the evidence shows that productivity gains are substantial, both at the country and regional level (O'Mahony and Vecchi, 2005; Iammarino and Jona-Lasinio, 2015; Shao and Lin, 2016; Marsh et al., 2017). An early review of the empirical

[1] *E*-commerce, also known as electronic commerce or internet commerce, refers to the buying and selling of goods or services using the internet, and the transfer of money and data to execute these transactions. *E*-commerce is often used to refer to the sale of physical products online, but it can also describe any kind of commercial transaction that is facilitated through the internet. The website is the key type of application in e-commerce trade. While a website might overstate online presence it might well also underrepresent it as firms can trade online by other means such as apps or internet platforms and host websites, for example.

[2] Process innovation is the implementation of new production or delivery methods. It includes significant changes in technique, equipment and software (OECD, 2005). Registering a website online can therefore be considered as an indicator of process innovation because it involves the use of new software and new ways of interacting with customers. Relevant examples come from a growing number of studies on omni-channels, arising with the adoption of websites and entry into e-commerce often manifested in the 'buy-online-pick-in-store' (BOPS) model (e.g., Sopadjieva et al., 2017).

evidence by Kretschmer (2012) concludes that a 10 % increase in ICT increases productivity growth by approximately 0.5 %. Looking at both developed and developing countries and considering different types of ICT, such as landlines, cell phones and internet access, Stanley et al. (2018) confirm previous results of a positive contribution of ICT on growth, except for the internet.

Firm level studies of the productivity effects of different ICT applications, such as broadband, enterprise software, and e-commerce (Rincon et al., 2005; Sánchez et al., 2006; Engelstätter, 2009; Czernich et al., 2011; Grimes et al., 2012) broadly provide evidence of a positive but heterogeneous impact on firm performance. These results confirm the review of the literature by Draca et al. (2007), which mainly focuses on US-based studies. However, the evidence of a positive effect is sometimes weak. For example, Sánchez et al. (2006) find that internet usage has a positive impact on productivity in a sample of 400 Spanish firms observed in 2002. The squared term of this variable, however, has a negative and significant effect, suggesting that the returns to internet usage diminish beyond a certain threshold. Bertscheck et al. (2013) find a positive impact of broadband on firms' productivity performance in Germany; however, such effect loses significance when they account for the endogeneity of the decision to use broadband. Haller and Lyons (2015) do not find any significant effect of broadband adoption on the productivity of Irish manufacturing firms. In addition, existing studies mostly rely on the estimation of a static Cobb-Douglas production function and, except for a broad distinction between services and manufacturing, firms' heterogeneity is largely unaccounted for. This means that the extant literature does not provide insights on how different firms benefit from investing in various types of ICT applications, nor of whether the effects on productivity are longstanding.

The role of ICT is not only confined to productivity gains. Litan and Rivlin (2001) in an early discussion of the possible consequences of the internet on the economy put forward the view that markets will become closer to the economists' notion of perfect competition, characterised by large numbers of buyers and sellers, bidding in a market with perfect information. This initial view has been challenged in recent years (Autor et al., 2017) but research on the relationship between ICT and market structure is very limited. Since the early 2000s, the internet and its applications have evolved. Websites have become ubiquitous and internet platforms have acted as intermediaries bringing together different types of users and enabling economic and/or social interactions through online and multiple (omni-) channels (e.g., Bahn and Fischer, 2003; Sopadjieva et al., 2017). Assembling users - buyers and sellers, consumers and advertisers - involves network effects and switching costs. The value users assign to internet platforms and websites depends on the number of users. The larger the number, the lower the cost and the more extensive the benefits.[3]

One of the consequences of network effects and internet platforms is that internet firms often have relatively low costs of serving additional customers because the underlying engineering is scalable; thus, individual firms may easily expand the markets they serve through the internet (Varian, 2010). This implies that, if the internet and its applications such as websites have the potential of increasing competition, they will also favour the most productive firms, which can gain higher market shares in a disproportionate way compared to previous innovative waves (Autor et al., 2017). The market dominance of Apple, Google, Amazon and Facebook provides examples of this phenomenon, and it has raised concerns about the increasing market concentration in high-tech sectors, particularly in the US (Autor et al., 2017; Bessen, 2017). An important question is whether these are 'outliers' operating in a market that still provides ample opportunities for other firms to enter, or whether we are indeed facing a generalised trend of increasing market concentration.

Recent evidence for the US shows increasing concentration in over 75 % of industries (Grullon et al., 2019). Lax enforcement of antitrust laws and technological innovation, including the adoption of the internet in the late 1990s, are the two main explanations for this trend. Initial evidence discussed in Valletti et al. (2017) shows that, in contrast to the US, there has been no increase in concentration in most European countries after the 2007 financial crisis. This is further supported by the analysis in Gutiérrez and Philippon (2018), who find that concentration ratios have remained stable in Europe. Bajgar et al. (2019) challenge this conclusion showing that industry concentration has increased in both Europe and the US over the 2001–2012 period, although the increase is stronger in the US. The study, however, is based on aggregate data for selected EU countries, thus, it does not offer any insights on individual countries' experiences. In addition, the analysis is of descriptive nature, hence, it does not provide any evidence on the mechanisms that might drive concentration. These important limitations of the extant literature require further evidence.

2.2. Theory and hypotheses

Our theoretical framework for the analysis of the relationship between e-commerce and market structure (and productivity) draws from the trade literature. In this context, we treat the decision of a firm to set up a website and enter an e-commerce market as equivalent to the decision of a firm to enter a foreign market. Entering a foreign market incurs initial fixed costs and operating abroad involves additional variable costs. The entry increases the effective size of the market, promotes investments and raises firm-level productivity.[4] In the case of e-commerce, there are initial fixed (sunk) costs associated with setting up a website. These sunk costs are incurred independently of the firm's decision to trade on the internet, and they are generally considered to be small compared to bricks-and-mortar business costs (Latcovich and Smith, 2001). Trading on the internet increases the size of the market as firms no longer need to rely on geographical proximity to its customers. Similar to trading with a foreign country, there is complementarity between expanding sales and undertaking productivity enhancing investments.[5]

In formalising our framework, we follow ideas in Helpman (2006) and an application by Lileeva and Trefler (2010) by considering a traditional market with an emerging and expanding e-commerce segment. Demand consists of consumers with CES ($\sigma > 1$) preferences, and the market structure is monopolistic competition. Firm demand is determined by original market size A; A^* is the gain in effective demand from entry into the e-commerce market segment. The firm productivity is defined as in Lileeva and Trefler (2010) as the output φ_0 from a standardised bundle of inputs, including sales costs. In entering the e-commerce market, the firm will incur fixed cost of F^W where $W = 1$ indicates that the firm has a website and $W = 0$ that it does not. At the time of entry, the firm will also incur proportional (*ad valorem*) costs at a

[3] De Stefano et al. (2016) argue that the effects of internet are heterogeneous and consistent with the idea that ADSL broadband allowed firms to create websites and develop e-commerce sales for the first time extending the market reach for these firms. That is it lowered communication costs with customers. They are also able to show that these effects are strongest when the firm makes complementary investments and has high absorptive capacity.

[4] Via the internet a firm can serve not only its existing customers, who might simply switch from buying using traditional methods to buying online, but it can also expand into new markets that were previously out of reach due, for example, geographical distance and high entry and communication costs (De Stefano et al., 2016).

[5] The idea of complementarity between expanding sales and investing in productivity is not new; it appears in Atkeson and Burstein (2010), Lileeva and Trefler (2010), and Bustos (2011) all of whom provide conditions under which a cost reduction due to sales expansion induces firms to simultaneously invest in productivity. Verhoogen (2008) describes a related complementarity between exporting and investing in quality.

rate τ-1, for example, for using and maintaining its website, and operating in the e-commerce market.[6]

Considering firm's (static) optimisation problem, firm's maximum profit as a function of the entry decision is:

$$\pi_0(W) = \varphi_0[A + W\tau^{-\sigma}A^*] - WF^W. \quad (1)$$

From Eq. (1), the firm will adopt a website and enter the e-commerce market when productivity is larger than the ratio between the fixed costs of setting up a website (F^W) and the variable costs of trading on a wider market ($\tau^{-\sigma}A^*$), i.e.$\varphi_0 > \frac{F^W}{\tau^{-\sigma}A^*}$. This is known at the Melitz cut-off in the trade literature (Melitz, 2003).

Besides the entry decision, the firm makes an investment decision that can raise its productivity from φ_0 to φ_1 for a fixed cost F^I. The key implication here is that entering the e-commerce market and investing are complements in the sense of Milgrom and Roberts (1990). The firm's maximum profit with investing in productivity is

$$\pi_1(W) = \varphi_1[A + W\tau^{-\sigma}A^*] - WF^W - F^I. \quad (2)$$

The difference between profit from both entering e-commerce and investing and neither entering nor investing is the difference between profits in the two states. From Eqs. (1) and (2) it follows that

$$\pi_1(1) - \pi_0(0) = \left[\varphi_0\tau^{-\sigma}A^* - F^W\right] + \left[(\varphi_1 - \varphi_0)A - F^I\right] + \left[(\varphi_1 - \varphi_0)\tau^{-\sigma}A^*\right]. \quad (3)$$

The first term in parentheses captures the increase in profit from e-commerce without investing in productivity. The second term in parentheses captures the increase in profit from investing in productivity without e-commerce. The third term represents the increase in profits from e-commerce and investing in productivity. This term is always positive because productivity gains raise profits on all units sold in both traditional and e-commerce market segments.

If the first two terms in Eq. (3) are negative, the firm will not enter the e-commerce market without investing and will not invest without entering the e-commerce market. At this margin the complementarity between e-commerce and investing may (or may not) make it worthwhile for the firm to enter the e-commerce market and invest at the same time. Thus, the firm will be indifferent at the margin if $\pi_1(1) = \pi_0(0)$. From this indifference condition and Eq. (3) we can derive a downward-slopping function

$$\varphi_1 - \varphi_0 = -\varphi_0\frac{\tau^{-\sigma}A^*}{A + \tau^{-\sigma}A^*} + \frac{F^I + F^W}{A + \tau^{-\sigma}A^*}, \quad (4)$$

which represents a wedge above which the firm prefers to enter e-commerce and invest.

If a firm has already set a website and entered e-commerce, it will invest if and only if $\pi_1(1) > \pi_0(1)$. This condition defines a threshold of productivity gains

$$\varphi_1 - \varphi_0 = \frac{F^I}{A + \tau^{-\sigma}A^*}, \quad (5)$$

above which incumbent firms in the e-commerce market invest.

The model implies that the effect of entering an e-commerce market on firm productivity depends on two sources of heterogeneity: differences in initial firm productivity and in the returns to productivity enhancing investment. New entrants usually have faster productivity growth than non-entrants. This productivity gain is inversely related to initial productivity, i.e., it is higher for firms that are less productive before entry.[7] This market dynamic (negative selection) could result in reallocation of market shares from larger to smaller firms and lead to a decline in market concentration. This would be consistent with the initial view of the internet as a force increasing competition (Litan and Rivlin, 2001). The incumbent firms that have already set up a website and operate in the e-commerce market are characterised by (sufficiently) high productivity.

Considering the implications of our conceptual framework for the evolution of the market structure we hypothesise that:

H1. Firms adopting websites and entering e-commerce subsequently exhibit higher productivity growth compared to the non-entrants.

H2. The increase in productivity is inversely related to the initial (pre-entry) productivity level.

According to H2, we should observe a reallocation of market shares from initially more productive to less productive firms, which have successfully invested in new technologies and gained in relative productivity.

As a corollary to H1 and H2, we hypothesise that:

H3. The mechanism outlined can lead to an equilibrium where website adoption is negatively associated with market concentration, at least, in the early stage of website adoption.

With time, due to the expansion of e-commerce activities, trading costs may drop and the marginal firms, which were indifferent between entering and not entering, would enter the e-commerce market. However, the concurrent generation of network effects by incumbent firms may start acting as a barrier to entry; an associated outcome is the emergence of internet platforms and other 'superstar' companies. Thus, we need to point out that our conceptual framework is primarily concerned with the early stage of website adoption in an economy.

3. Data and descriptive statistics

The sources of our UK and Spanish firm data are the FAME and SABI databases respectively, covering the period 1995–2010. We draw a 1 % non-stratified random sample from each database, from the set of manufacturing and services firms with ten or more employees at the beginning of our period. The total number of firms in our UK sample is 3668 and our Spanish sample has 3879 firms. Comparing our samples with aggregates from the EUKLEMS database (O'Mahony and Timmer, 2009), we find that our samples represent about 1 % of both value added and employment. To further verify the representativeness of our samples we compare the sample distributions of value added and employment with the respective source dataset distributions using Kolmogorov-Smirnov tests, the results from which are reported in Appendix A, Table A1. The tests provide evidence that the distributions of our samples are not statistically different from the distributions of the original datasets.

Both country samples contain information on value added, physical assets, number of employees, turnover and cost of materials used. Monetary values are deflated using 2-digit industry deflators, extracted from the EUKLEMS database. The data includes companies operating in manufacturing and in services; industries are classified following NACE Rev. 1. Summary statistics are presented in Appendix A, Table A2. Spanish firms are on average smaller than UK firms, a well-known fact of the industry structure differences in the two countries (Pagano and Schivardi, 2003; Eurostat, 2011).

[6] Even though it is argued that internet firms have relatively low (marginal) cost of serving additional users, there is also evidence that in the context of e-commerce there are various 'new' costs (e.g., of online payments and of shipping) that need to be taken into account when considering an e-business being sustainable (Hackl et al., 2014; Corporate Finance Institute (CFI), 2022).

[7] For the context of exporting see Fig. 1 and the Appendix in Lileeva and Trefler (2010) who provide more detail and graphical presentation of the firm's optimal choices.

Data regarding the online status of firms in both countries were retrieved from the WHOIS database, containing information about the internet domain names, which are part of the URL of a corporate website (e.g., *microsoft.com*). Since one of the first steps to set up a website is to register a domain name, we use the registration date as a proxy for the decision to set up a website and start operating online.[8] A limitation of this proxy is that websites can be used just as marketing devises. However, a new advertising tool can attract new customers, increase sales, and affect firm behaviour and market concentration.

We find usable information for the online status of 3263 UK firms and 3750 Spanish firms.[9] From these data we construct two main indicators: the firm online decision (*online*), and the total number of firms with online presence (*n_online*). The first indicator is a dummy variable equal 1 when the firm has registered its domain name and zero otherwise. We find that the decision of going online is irreversible, i.e., once a firm decides to launch a website this remains operational for the duration of our sample period. Consistent with our theoretical framework, we assume that having a website indicates that the firm will start trading online or via a multitude of channels. The total number of firms with a website in each year (*n_online*) provides a measure of technology diffusion; this is created at the 2-digit industry classification and at the whole economy level.

Table 1 presents the distribution of firms across broad industrial sectors and the number of firms with a website in 1995 and in 2010. We have 856 manufacturing firms in Spain and 621 in the UK. Consistent with the industry structure of both economies, services cover a much larger number of firms than manufacturing. Among services, the wholesale and retail industry is highly represented in Spain (862) while finance, insurance, real estate, and business services dominate the UK industry structure (1142). We also observe a larger number of firms operating in the construction and hotel and restaurant sectors in Spain (with 585 and 291 firms respectively), compared to the UK (103 and 108 firms respectively).

Large differences in the two countries can be seen in the proportion of online firms at the beginning and at the end of our sample period. In 1995 only a handful of Spanish firms had their own website. The technology diffuses over time so that by 2010 the number of firms with a website increases substantially. However, the proportion of online firms in Spain reaches at most 56 % in manufacturing in 2010 and it is still quite low in services, particularly when compared with the UK. The UK has a low percentage of firms online in 1995 but their number increases rapidly and by 2010 most firms are represented on the internet by their own website. Nearly 100 % of manufacturing firms are online, compared to 8.7 % in 1995, while the proportion of firms online in the finance, insurance, real estate, and business services rises from 11 % to 82 %. Hence, the uptake of the technology has been more pervasive in the UK compared to Spain which is consistent with the view that countries may adopt and use technologies differently.

Our figures indicate that the UK was ahead of Spain in the technology adoption process. Innovation and technology adoption depend on many factors, such as skill endowments and regulatory structure (Acemoglu, 1998; Lewis, 2011). The UK has been the EU country that most resembles the US in terms of flexible business regulatory framework, both in the product and labour market, and this might have facilitated the adoption of ICT and the use of related applications, such as websites (Becker et al., 2016). The UK also has a higher proportion of medium and large firms compared to Spain and the empirical evidence shows that larger firms are more successful innovators (Pagano and Schivardi, 2003; Davies et al., 2007).

4. Firm level analysis of productivity and website adoption

Following our theoretical framework, we begin our empirical analysis with the investigation of the relationship between productivity and firms' adoption of websites. Productivity is measured in terms of total factor productivity (TFP), derived using the Levinsohn and Petrin (2003) method (LP).[10] Details of the method are presented in Appendix B.

Testing H1 and H2 implies testing for differences in productivity growth between website adopters and non-adopters. We carry out this test using a difference-in-difference analysis, based on the following regression model:

$$\Delta TFP_{it} = \alpha + \beta \, online_{it} + e_{it}, \tag{6}$$

where the estimated beta coefficient represents the difference between ΔTFP of (new) website adopters and ΔTFP of non-adopters. Eq. (6) is estimated using Ordinary Least Squares (OLS), under the assumption that the error term, e_{it} is uncorrelated with the decision to operate online. To account for firms' heterogeneity in initial productivity levels, we estimate Eq. (6) by quintiles, considering firms belonging to the 25th, 50th and 75th percentiles of the TFP distribution.

We start our analysis from the year 2000, our benchmark, as this provides a larger samples of website adopters both in the UK and in Spain. We then estimate Eq. (6) for two periods: 2001–2003 and 2004–2006 to examine changes in the effect of website adoption on productivity over time.[11] Table 2 presents our results.

Results in row (a) show that new entrants in the online market who have invested in new technology (new adopters of websites) have higher productivity growth compared to non-adopters, consistent with H1. Productivity gaps between adopters and non-adopters are higher for least productive firms. For example, in Spain the productivity gap for firms in the 25th percentile is nearly three times larger than the median firm (0.068 vs 0.023), while the productivity gap for the median firm is nearly twice as large as for firms in the 75th percentile (0.023 vs 0.012). These differences are statistically significant at conventional significance level. A similar pattern of results is observed for the UK, although productivity gaps between new adopters and non-adopters are generally smaller.

In row (b) we focus on new adopters, and we report differences in TFP growth over the 2001–2003 period. This shows that, consistent with H2, the productivity growth of new adopters (ΔTFP of new website adopters) is inversely related to their initial TFP level. In fact, for both countries our results show declining productivity gains as we move from the least to the most productive firm in the benchmark year.

[8] Some other studies have used the domain creation date in the WHOIS database as a proxy for the date in which the companies go online (e.g., Weltevreden et al., 2008; Blazquez and Domenech, 2014). Nevertheless, this data source is not free from limitations. On the one hand, the *whois* creation date could overestimate the online presence if the domain is just parked. On the other hand, it could underestimate the online presence if the firms begin to develop their site in a subdomain or in a free website service. In any case, the risk that the analysed website does not correspond to the firm of interest is little. URLs are provided by the firms in their financial statements and recorded by the SABI and FAME databases which we were able to verify.

[9] There are several reasons why the online information is not available for all companies: the *whois* service of some domains does not disclose the creation date (e.g. subdomains); the *whois* service of some domains does not allow the automatic retrieval of information; the *whois* service of the domain was down in all trials; the URL present in FAME or SABI was not correct. The omission of firms due to lack of internet status information did not affect the representativeness of our samples as verified by *t*-tests of sample means for key variables.

[10] As a robustness check we compute two additional measures: one based on the residuals of a production function estimated using the Fixed Effects estimator and a second one defined as labour productivity (Value added/Total number of workers). All measures are highly correlated as evident from Appendix A, Table A3. Therefore, we use TFP(LP) in the analyses that follow.

[11] Later years are not included in this part of the analysis as in the UK most companies have a website then, hence, it is not possible to compare adopters and non-adopters. Besides, our goal is to compare new and incumbent (old) adopters over two three-year equal periods.

Table 1
Distribution of firms across industrial sectors and online status.

	Industry	Number of firms	Firms online Spain (*n_online*)		Number of firms	Firms online UK (*n_online*)	
		Spain	1995	2010	UK	1995	2010
1	Agriculture, mining and quarrying (AtC)	100	0 (0 %)	17 (17 %)	61	5 (8.2 %)	50 (82 %)
2	**Manufacturing (D)**	856	5 (0.6 %)	483 (56 %)	621	54 (8.7 %)	589 (96 %)
3	Electricity, gas and water supply (E)	15	0 (0 %)	6 (40 %)	10	1 (10 %)	6 (60 %)
4	Construction (F)	585	1 (0.2 %)	127 (22 %)	103	5 (8.9 %)	92 (89 %)
5	Wholesale and retail trade (G)	862	6 (0.7 %)	416 (48 %)	535	35 (6.5 %)	471 (88 %)
6	Hotels and restaurants (H)	291	0 (0 %)	83 (29 %)	108	5 (4.6 %)	80 (74 %)
7	Transport, storage and communications (I)	254	1 (0.4 %)	94 (37 %)	190	20 (10.5 %)	166 (87 %)
8	Finance, real estate and business services (JtK)	498	1 (0.2 %)	208 (42 %)	1142	127 (11.1 %)	942 (82 %)
9	Community, social and personal services (LtQ)	289	0 (0 %)	72 (25 %)	493	20 (4.1 %)	390 (79 %)
	Total services (5–9)	2194	8 (0.4 %)	873(40 %)	2468	207 (8.4 %)	2049 (83 %)
	Total sample (1–9)	3750	14 (0.37 %)	1506 (40.16 %)	3263	272 (8.34 %)	2786 (85.38 %)

Bold indicates major/aggregate category.
Data sources: FAME (UK), SABI (Spain); the industry classification follows the NACE, Rev. 1.; information on online status is derived from WHOIS records.

Table 2
Productivity (TFP) growth and website adoption: difference-in-difference estimates.

		Initial TFP quantiles (at 2000)					
		(p-25)	(p-50)	(p-75)	(p-25)	(p-50)	(p-75)
		Spain			United Kingdom		
(a)	ΔTFP new website adopters - ΔTFP non-adopters (2001−2003)	0.068	0.023	0.012	0.032	0.016	0.009
		(0.026)	(0.012)	(0.005)	(0.012)	(0.007)	(0.004)
			[−3.404]	[−2.192]		[−2.467]	[−1.808]
(b)	ΔTFP new website adopters (2001–2003)	0.093	0.043	0.030	0.081	0.048	0.040
			[−2.365]	[−1.769]		[−2.130]	[−1.588]
(c)	ΔTFP incumbents - ΔTFP non-adopters (2004–2006)	0.041	0.013	0.000	0.013	0.008	0.000
		(0.018)	(0.006)	(0.001)	(0.005)	(0.004)	(0.002)
			[−3.911]	[−2.552]		[−1.761]	[−2.047]
	Average number of employees	22	32	55	145	176	396
	Average real value added	486	728	2069	2865	5130	14,895

Notes: The reported TFP growth rate (ΔTFP) is per annum. Value added is in thousands of Euros for both countries; both the Average number of employees and Average real value added are computed for the period prior to entry into the e-commerce market (at 2000). In rows a and c coefficients from OLS regressions, by quantile, are reported with the standard errors in round brackets. In square brackets, we report the t-values from two-sample *t*-tests for the difference in means of (p-50)-(p-25) and (p-75)-(p-50) respectively.

Finally, in row c, we report results from the estimation of Eq. (6) for the second period (2004–2006). In this period the initial cohort of entrants becomes the incumbents, hence the estimated beta coefficient represents the difference between ΔTFP of incumbents and ΔTFP of non-adopters. Comparing incumbents' change in TFP against non-adopters, we find that the initial negative relationship between TFP level and TFP growth weakens in both countries. This indicates that, over time, productivity gains decline.

The analysis of productivity provides evidence in support of H1 and H2 concerning firm heterogeneous responses to the entry into the e-commerce market, as indicated by the adoption of a website. Furthermore, the implication of our theoretical framework is that the (new) entrants create a competitive turbulence where successful productivity enhancing investments allow the possibility of re-ordering of firms in terms of their productivity positions. This mechanism underlines our H3, concerning the deconcentrating effect of website adoption on market structure which we test in the next section.

5. Industry analysis: the link between websites and concentration

5.1. Modelling the relationship between concentration and website adoption

To investigate the relationship between website adoption and market concentration we follow Geroski and Pomroy (1990) in assuming that changes in market concentration are a function of the deviations between actual and equilibrium levels of concentration. The presence of adjustment costs implies that we will observe a partial adjustment of actual concentration levels towards the long-run equilibrium in any given period, hence the relationship can be represented by the following partial adjustment model:

$$C_t - C_{t-1} = \gamma_0 \left[C_t^* - C_{t-1}\right], \tag{7}$$

where C_t is the actual level of market concentration, C_t* is the long run equilibrium level of concentration, and γ_0 is speed of adjustment.[12] Although C_t* is unobservable, it can be expressed as a function of innovation (τ), market size (S) and technological conditions (K) (Geroski and Pomroy, 1990):

$$C_t^* = \gamma_1 \tau_t + \gamma_2 S_t + \gamma_3 K_t. \tag{8}$$

Substituting (8) into (7) we obtain:

$$C_t = \beta_1 C_{t-1} + \beta_2 \tau_t + \beta_3 S_t + \beta_4 K_t, \tag{9}$$

where $\beta_1 = (1 - \gamma_0)$, $\beta_2 = \gamma_0\gamma_1$, $\beta_3 = \gamma_0\gamma_2$ and $\beta_4 = \gamma_0\gamma_3$.

In our study we measure market concentration using the Herfindahl-Hirschman Index (HHI), which is defined as follows:

[12] Nickell (1985) provides an excellent exposition of the general idea and underlying theory which leads to a solution of a dynamic problem by minimising a loss function, which is static in nature. Eq. (7) nests several of the models of market structure which have been used in the literature (e.g., Ornstein et al., 1973; Caves and Porter, 1980; Levy, 1985; Geroski et al., 1987); for a survey, see Curry and George (1983).

$$HHI = \sum_{j=1}^{n} (MS_j)^2, \tag{10}$$

where MS is the firm's j market share, computed as the ratio between the firm's turnover and the 2-digit industry turnover, derived from our firm data.[13] A more precise estimation of the HHI index requires information on the market shares of all firms in the industry; nevertheless, Bresnahan and Reiss (1991) find that in concentrated industries almost all variation in competitive conduct occurs with the entry of the second or third firm. Perhaps surprisingly, once there are three to five firms in a market, the next entrant has little effect on competitive conduct.

As discussed in the introduction, the adoption of a website can be considered a proxy for companies' innovative behaviour, hence we use the number of companies with a website within each industry (*n_online*) as a proxy for innovation.[14] Market size is industry turnover computed by aggregating companies' turnover at the 2-digit industry level. We use two alternative measures of technological conditions: industry capital intensity, defined as capital-output ratio, and TFP. Hence, the empirical counterpart of Eq. (9), expressed in log-linear form, is as follows:

$$\begin{aligned} ln(HHI_{it}) &= \sum \alpha_i + \beta_1 ln(HHI_{it-1}) + + \beta_2 ln(n\_online_{it}) + \beta_3 ln(Size_{it}) \\ &+ \beta_4 ln(Technology_{it}) + \sum d_t + \varepsilon_{it}. \end{aligned} \tag{11}$$

Eq. (11) also includes a set of time dummies d_t in order to capture variations in concentration over time; industry fixed effects are represented by $\Sigma\alpha_i$ and ε_{it} is a zero mean, normally distributed error term.[15] Eq. (11) provides a direct test of our H3 concerning the effect of website adoption on market concentration. If websites are having a decentralizing effect hence promoting competition, we expect the coefficient on the number of companies online (β_2) to be negatively signed. A similar negative effect is expected for the coefficient on market size (β_3), while technological conditions, as captured by the capital-output ratio, are expected to have a positive impact on concentration. The effect of TFP is more difficult to predict as this more general proxy for technological conditions might also include innovations that have a decentralizing effect. Summary statistics for all regression variables, showing mean values by industry, are reported in Appendix A, Table A4.

Fig. 1 shows variations over time in the weighted average HHI for the manufacturing and service sectors. In both countries we observe lower concentration in services than in manufacturing. In the UK concentration declines over time in both sectors, a result consistent with the analysis in Valletti et al. (2017) which shows a decline in the HHI index in the UK, after the financial crisis. In Spain we observe some decrease in market concentration in services while in the manufacturing sector there is a declining trend from 1995 to 2003, followed by increasing concentration in later years. Given that these trends are observed during a period of fast website adoption, there may be a relationship between changes in market concentration and the number of firms online.

In Fig. 2 we plot HHI against the number of firms online (in logarithm) using data for the year 2005, when there is a sufficiently large number of online companies in both countries. The figure shows a negative correlation between HHI and the number of firms online, suggesting that website adoption might have contributed to a decrease in market concentration, hence increasing the degree of competition. Similar trends can be observed using different years or an average over the sample period.

5.2. Econometric results

The estimation of Eq. (11) requires us to address two possible sources of endogeneity. First, the inclusion of the lagged dependent variable implies that standard OLS methods will lead to seriously biased coefficients (Nickell, 1981). Second, although there are some doubts on the positive impact of competition on innovation (Pagano and Schivardi, 2003), there is a general agreement that the connection between market structure and innovation is not a one-way causal relationship (Symeonidis, 1996).[16] In the presence of simultaneity, estimates based on OLS would be biased, even when controlling for industry and time fixed effects.

To address these endogeneity issues, we implement a System GMM estimator (Blundell and Bond, 1998, 2000) which is based on the estimation of a system of equations in first differences and in levels. Lagged levels are used as instrument for the equation estimated in first differences and lagged first differences are used as instruments for the equation in levels.[17] We minimize the problem related to instruments proliferation, that can potentially overfit endogenous variables, by limiting our lag structure to one lagged level of the endogenous variables for the equation in first differences, and one first difference for the levels equation (Roodman, 2006, 2009).

Results for the UK are presented in Tables 3a (total sample) and Table 3b (manufacturing and services). Column (1) presents a benchmark specification, which only includes our proxy for innovation, the number of companies with websites. The remaining columns include additional controls for market size and technological conditions. Time dummies are included in all specifications while fixed effects are controlled for through the first difference transformation in the GMM estimator.

In the UK the impact of online presence is negative and statistically significant, in all samples, supporting our hypotheses that increasing online presence reduces market concentration. Across all industries, our coefficient estimates indicate that a 1 % increase in the number of firms with websites decreases market concentration by 0.18 % in the benchmark model (Column 1 in Table 3a).[18] The effect declines slightly when we include proxies for technological conditions and market size

[13] We also calculated HHI using the underlying datasets and found that this series and the sample HHI series are highly correlated and exhibit very similar trends over time. Alternative to HHI, a measure of concentration often used in the literature is the top four-firm concentration ratio (C4), which is measured as the combined production share of the four largest firms in an industry. The measures are found highly correlated so that results are not too sensitive to the indicator used in empirical analyses as shown by Davies and Lyons (1996).

[14] Geroski and Pomroy (1990) argue that it is far easier to observe innovation (changes in technology) than it is to observe or to measure the "level of technology" itself. They build-up an index of innovation by examining the history of technical change while we use a directly observed measure of website adoption.

[15] Entry is treated by Geroski and Pomroy (1990) as a mechanism by which changes in market structure occur than a determinant of C_t*. To the extent that entry depends on the determinants of C_t* and on differential (C_t - C_t*), then its workings are implicitly captured in Eq. (11).

[16] Pagano and Schivardi (2003) find that firm size is positively associated with productivity growth and R&D investments and that favouring the development of small sized firms, for example by supporting small firms with tax breaks and less binding employment protection legislation, can have detrimental effects on the rate of innovation and on a country's productivity performance.

[17] Besides the fact that we use GMM instrumental variables approach, the endogeneity issue between innovation and market structure could be less sever in our dataset because our measure of innovation (internet) is very different from what is used in related studies, which often rely on R&D expenditure or patenting behaviour. While R&D and patents are mainly carried out by large firms and require substantial investments, having a website is relatively inexpensive and a website can be adopted by a whole variety of firms operating across all industries, and not being related to those that are traditionally classified as R&D intensive. The figures in Table 1 confirm this by showing that, by the year 2010, the difference in the percentage of firms online in manufacturing, where most of the R&D investments are concentrated, and in services is rather small in both countries (56 % in manufacturing versus 40 % in services in Spain, and 96 % versus 83 % in the UK).

[18] The speed of adjustment from equation (7) is $\gamma_0 = 1 - \beta_1$; thus, β_2 represents the short run effect of *n_online* on market concentration, while the long run effect is β_2/γ_0.

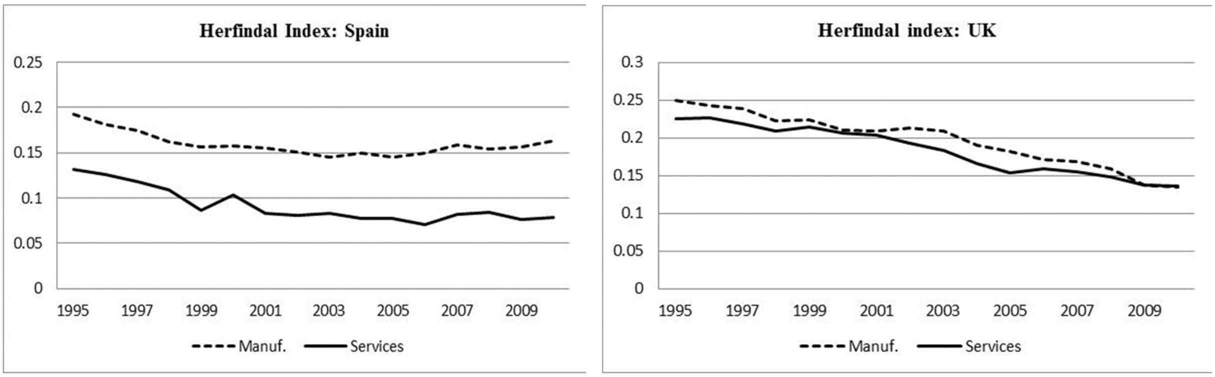
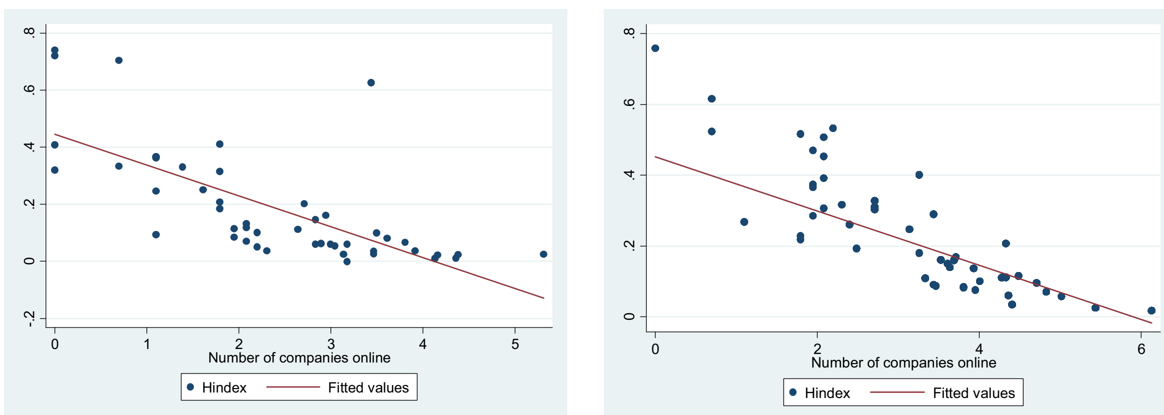


Fig. 1. Market concentration in Spain and in the UK: 1995–2010.



(a) Spain (b) UK

Fig. 2. Relationship between market concentration and website diffusion (number of companies online): 2005.

(Columns 3 and 4) but coefficient estimates for the online presence are always statistically significant.

Consistent with the analysis in Geroski and Pomroy (1990) market size is negatively related to market concentration while technological conditions have a positive impact. Hence, although a particular application of new technology (websites) increases competition, we also find evidence that technology more generally defined leads to an increase in market concentration. This effect is also found in the subset of manufacturing industries (Table 3b, columns 1–4). In the services sector (Table 3b, columns 5–8), on the other hand, the impact of online presence is larger, with coefficients ranging between −0.25 (benchmark specification) and − 0.16, while the additional controls for technological conditions are never statistically significant. This suggests that in these industries the competition inducing effect of the internet prevails.

Results for Spain show a similar patter to that observed in the UK. In the total sample of companies (Table 4a) coefficient estimates imply that a 1 % increase in the number of companies online contributes to a decline in market concentration between 0.12 % (Column 1) and 0.20 % (Columns 3 and 4). We also find a positive effect of one of our proxies for technological conditions (TFP), indicating that a 1 % increase in TFP is associated with a 0.11 % increase in market concentration. When distinguishing between manufacturing and services (Table 4b), we obtain the same results we discussed for the UK: the number of companies online reduces concentration in both sectors, while technology more generally defined increases concentration only in manufacturing.[19]

The difference in the impact of technology in the two sectors can be explained by the nature of the production process. As discussed in Dunne et al. (2013), some service industries are characterised by a one-to-one relationship between service provider and client and therefore there is a constraint on how much output can be produced by a single company. In manufacturing scaling up production is relatively easier, particularly with the adoption of robotization and Artificial Intelligence (AI). Indeed, coefficient estimates for capital intensity, which also measures scale effects (Ornstein et al., 1973), are never statistically significant in the service sector. Overall, our results are consistent with the assumption that online access is a form of technological development that leads to lower barriers to entry (Litan and Rivlin, 2001) in any industry. However, while in manufacturing this effect is partly offset by the increase in the scale of production facilitated by new technologies, in services the role of the internet in promoting competition remains unchallenged.

6. Conclusion

In this paper we present a new theoretical framework that brings together two phenomena that are typically treated separately in the extant literature: the productivity effect of the adoption of a new technology, here represented by website adoption, and how this new technology affects market structure. We believe our approach provides a

[19] As a robustness check we have also used HHI calculated from the underlying datasets and found results qualitatively very similar to the ones reported for both countries.

Table 3a
Internet and market concentration, UK, all sectors, 1995–2010. Dependent variable: Herfindahl Index (HHI).

	(1)	(2)	(3)	(4)
Ln(*HHI*)$_{t-1}$	0.729***	0.700***	0.631***	0.700***
	(0.079)	(0.072)	(0.080)	(0.069)
Ln(n_online)	−0.178***	−0.201***	−0.142***	−0.130***
	(0.049)	(0.045)	(0.043)	(0.038)
Ln(Capital intensity)		0.083**	0.103**	
		(0.039)	(0.042)	
Ln(Sales)			−0.112***	−0.070
			(0.041)	(0.046)
Ln(TFP)				0.065*
				(0.033)
Constant	0.013	−0.745**	0.077	0.395
	(0.054)	(0.369)	(0.356)	(0.425)
Observations	750	750	750	745
R^2	0.939	0.935	0.934	0.934
Number of IV	58	87	116	116
Number of industries	54	54	54	54
Hansen J test	36.76	34.79	34.47	42.49
Difference-in-Hansen test	33.81	31.22	32.15	39.79
e(ar1)	0.001	0.001	0.001	0.001
e(ar2)	0.194	0.187	0.194	0.197

Notes: System GMM estimates. Robust standard errors, clustered by industry, are reported in parentheses. A set of year dummies is added in every specification. Variables in levels dated (t-1) are used as instruments for the equation in first differences and the contemporaneous first differences are used as instruments for the levels equation. The Hansen J and Difference-in-Hansen (excluding group) tests do not reject the nulls in any specification estimated.
*** Significant at 1 %.
** Significant at 5 %.
* Significant at 10 %.

Table 4a
Internet and market concentration, Spain, total sample. Dependent variable: Herfindahl Index (HHI).

	(1)	(2)	(3)	(4)
Ln(*HHI*)$_{t-1}$	0.850***	0.749***	0.742***	0.765***
	(0.074)	(0.160)	(0.072)	(0.060)
Ln(n_online)	−0.119*	−0.030	−0.180***	−0.224***
	(0.059)	(0.222)	(0.056)	(0.051)
Ln(Capital intensity)		0.094	0.094	
		(0.074)	(0.072)	
Ln(Sales)			−0.026	0.035
			(0.082)	(0.057)
Ln(TFP)				0.109**
				(0.054)
Constant	−0.031	−1.123	−0.442	−0.520
	(0.048)	(0.696)	(0.517)	(0.490)
Observations	724	711	711	709
R^2	0.925	0.924	0.918	0.920
No of IVs	58	87	116	116
Number of industries	53	53	53	53
Hansen J test	30.21	15.91	26.86	26.07
Difference-in-Hansen test	28.78	13.48	23.39	23.15
e(ar1)	0.004	0.009	0.005	0.003
e(ar2)	0.896	0.848	0.853	0.775

Notes: System GMM estimates. Robust standard errors, clustered by industry, are reported in parentheses. A set of year dummies is added in every specification. Variables in levels dated (t-1) are used as instruments for the equation in first differences and the contemporaneous first differences are used as instruments for the levels equation. The Hansen J and Difference-in-Hansen (excluding group) tests do not reject the nulls in any specification estimated.
*** Significant at 1 %.
** Significant at 5 %.
* Significant at 10 %.

better understanding of the complex role in which the digital revolution is shaping the economy.

Our analysis relies on the assumption that the adoption of a website is an indicator of the firm's decision to invest in a new technology and to enter an e-commerce market. Using company accounts data for the UK and Spain, merged with unique information on the firms' presence on the internet via their websites, our results show that firms adopting a website and entering an e-commerce market subsequently exhibit higher productivity growth compared to non-entrants; further, this productivity growth is inversely related to the pre-entry productivity level. This *negative selection* is the key element in our model that leads to a decline in market concentration as it can result in the reallocation of

Table 3b
Internet and market concentration in manufacturing and services, UK. Dependent variable: Herfindahl Index (HHI).

	Manufacturing				Services			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(*HHI*)$_{t-1}$	0.820***	0.774***	0.768***	0.839***	0.664***	0.684***	0.653***	0.736***
	(0.108)	(0.074)	(0.079)	(0.058)	(0.091)	(0.080)	(0.091)	(0.096)
Ln(n_online)	−0.100	−0.148***	−0.117**	−0.154***	−0.251***	−0.232***	−0.166**	−0.161**
	(0.060)	(0.051)	(0.052)	(0.048)	(0.069)	(0.059)	(0.060)	(0.058)
Ln(Capital intensity)		0.087*	0.100*			0.051	0.067	
		(0.047)	(0.053)			(0.046)	(0.051)	
Ln(Sales)			−0.035	0.052*			−0.088**	−0.053
			(0.043)	(0.028)			(0.031)	(0.052)
Ln(TFP)				0.037				0.039
				(0.025)				(0.038)
Constant	−0.001	−0.750*	−0.514	−0.641**	−0.084	−0.593	0.157	0.647
	(0.054)	(0.420)	(0.309)	(0.290)	(0.085)	(0.492)	(0.430)	(0.508)
Observations	298	298	298	298	339	339	339	337
R^2	0.941	0.935	0.936	0.937	0.932	0.935	0.935	0.937
Number of IVs	58	87	116	116	58	87	116	116
Number of industries	21	21	21	21	23	23	23	23
Hansen J test	4.86	1.60	0.16	1.27	11.60	4.13	1.65	6.07
Difference-in-Hansen test	4.15	1.23	0.12	1.08	10.05	3.71	1.19	5.66
e(ar1)	0.023	0.022	0.021	0.028	0.002	0.002	0.001	0.002
e(ar2)	0.182	0.180	0.181	0.193	0.129	0.121	0.121	0.301

Notes: System GMM estimates. Robust standard errors, clustered by industry, are reported in parentheses. A set of year dummies is added in every specification. Variables in levels dated (t-1) are used as instruments for the equation in first differences and the contemporaneous first differences are used as instruments for the levels equation. The Hansen J and Difference-in-Hansen (excluding group) tests do not reject the nulls in any specification estimated.
*** Significant at 1 %.
** Significant at 5 %.
* Significant at 10 %.

Table 4b
Internet and market concentration in manufacturing and services, Spain. Dependent variable: Herfindahl Index (HHI).

	Manufacturing				Services			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(*HHI*)$_{t-1}$	0.881***	0.870***	0.850***	0.824***	0.837***	0.821***	0.818***	0.798***
	(0.052)	(0.048)	(0.048)	(0.045)	(0.060)	(0.054)	(0.047)	(0.065)
Ln(n_online)	−0.113**	−0.106**	−0.130**	−0.169***	−0.128**	−0.147***	−0.158	−0.157*
	(0.049)	(0.038)	(0.050)	(0.045)	(0.047)	(0.042)	(0.096)	(0.084)
Ln(Capital intensity)		0.108***	0.098**			−0.065	−0.061	
		(0.038)	(0.046)			(0.050)	(0.059)	
Ln(Sales)			0.007	0.020			0.003	0.001
			(0.051)	(0.035)			(0.086)	(0.094)
Ln(TFP)				0.138**				0.067
				(0.050)				(0.048)
Constant	0.072	−0.964***	−1.005*	−0.639*	−0.017	0.405	0.371	−0.183
	(0.080)	(0.323)	(0.488)	(0.366)	(0.072)	(0.377)	(0.483)	(0.763)
Observations	315	315	315	315	281	281	281	281
R^2	0.925	0.922	0.922	0.923	0.921	0.917	0.916	0.922
Number of IVs	58	86	116	116	58	87	116	116
Number of industries	21	21	21	21	22	22	22	22
Hansen J test	8.43	0.18	0.76	0.83	7.44	1.46	0.39	4.16
Difference-in-Hansen test	6.12	0.12	0.72	0.78	7.02	1.30	0.33	3.51
e(ar1)	0.001	0.001	0.001	0.001	0.046	0.047	0.046	0.048
e(ar2)	0.211	0.238	0.242	0.276	0.802	0.786	0.778	0.756

Notes: System GMM estimates. Robust standard errors, clustered by industry, are reported in parentheses. A set of year dummies is added in every specification. Variables in levels dated (t-1) are used as instruments for the equation in first differences and the contemporaneous first differences are used as instruments for the levels equation. The Hansen J and Difference-in-Hansen (excluding group) tests do not reject the nulls in any specification estimated.
*** Significant at 1 %.
** Significant at 5 %.
* Significant at 10 %.

market shares from larger to smaller firms.

Our results show that in both the UK and Spain the adoption of websites has contributed to a decline in market concentration. However, a wider definition of technology, measured by capital intensity and TFP, has a positive effect on market concentration, particularly in manufacturing, therefore partially offsetting the competition enhancing effect of the internet. In services, the more general technology effect is not statistically significant, which suggests that service industries are moving towards a more competitive market structure.

Our analysis supports existing studies showing that European markets are becoming more competitive than US markets, as discussed in Gutiérrez and Philippon (2018). In this study, the mechanism leading to lower concentration rests on the higher degree of political independence of European supra-national institutions, compared to national and US regulators. Although our model does not account for institutional factors, it provides a consistent evidence based on microeconomic theoretical foundations and detailed firm and industry level data. Furthermore, the comparative aspects of our analyses can nevertheless be linked to institutional factors. From a policy perspective, our results supports measures directed at facilitating firms' internet access and e-commerce as these can promote higher levels of competitions.

The difference in market concentration in the US and Europe can also be a consequence of the late technology adoption in European countries. Whether concentration trends in Europe will converge to the US level in the future is hard to forecast. Our analysis focuses on the early years of website adoption and our data stops in 2010; it cannot therefore account for the fast technological developments of the next decade. To address this important question, future analysis should be based on more recent data, and utilise different (direct) measures of companies' online operations and technology adoption. Finally, our industry-level analysis of concentration cannot account for a more granular industry classification due to data constraints. These are particularly relevant when investigating concentration trends in manufacturing and services. Further research, utilising even larger datasets, is thus needed to expand our knowledge of the relationship between technology adoption, productivity, and market structure.

CRediT authorship contribution statement

Marian Rizov: Conceptualization, Methodology, Formal Analysis, Investigation, Writing – Original Draft, Review and Editing, Visualization, Project Administration; **Michela Vecchi**: Conceptualization, Software, Investigation, Validation, Writing – Original Draft, Review and Editing, Visualization, Supervision; **Josep Domenech**: Conceptualization, Resources, Data Curation.

Acknowledgement

Josep Domènech acknowledges that this research was partially funded by MCIN/AEI/10.13039/501100011033 under grant PID2019-107765RB-I00.

Appendix A. Tables

Table A1
Kolmogorov–Smirnov tests of sample representativeness.

Variables	Manufacturing	Services	Total sample
Panel A: Spain			
Value added	0.031 (0.084)	0.025 (0.103)	0.022 (0.065)
Number of employees	0.029 (0.107)	0.026 (0.090)	0.021 (0.079)

(*continued on next page*)

Table A1 (*continued*)

Variables	Manufacturing	Services	Total sample
Number of observations	1556	2194	3750
Panel B: UK			
Value added	0.041 (0.101)	0.023 (0.125)	0.020 (0.131)
Number of employees	0.038 (0.151)	0.024 (0.103)	0.022 (0.088)
Number of observations	795	2468	3263

Note: The Kolmogorov–Smirnov test verifies whether a data sample comes from the same original distribution (SABI and FAME dataset respectively). The maximum absolute distance (D_{KS}) and significance level (*p*-value) in parentheses are reported for each pair of the respective variable distributions. The null of no difference is not rejected if $p > 0.05$.

Table A2
Summary statistics for productivity analysis.

Variable	Obs.	Mean	Std.	Min	Max
Panel A: Spain					
Real VA (Y)	24,884	985.189	1488.689	15.547	22,034.600
Number of employees (N)	24,884	33.133	34.5168	2	268
Real capital stock (K)	24,884	1452.508	3100.843	0.819	31,969.253
Panel B: UK					
Real VA (Y)	18,368	9290.666	20,174.236	109.574	376,280.159
Number of employees (N)	18,368	221.5609	402.8826	4	3369
Real capital stock (K)	18,368	18,717.833	68,436.446	4.674	999,125.127

Note: For comparison purposes we have converted the UK Pound values into Euros using the average annual exchange rate over the period. Monetary values are in thousands.

Table A3
Correlations of productivity measures.

	TFP_OLS 1	TFP_OLS 2	TFP_LP 1	TFP_LP 2	LAB_PROD
Panel A: Spain					
TFP_OLS 1	1				
TFP_OLS 2	0.999	1			
TFP_LP 1	0.989	0.988	1		
TFP_LP 2	0.989	0.988	1.000	1	
LAB_PROD	0.890	0.889	0.921	0.918	1
Panel B: UK					
TFP_OLS 1	1				
TFP_OLS 2	1.000	1			
TFP_LP 1	0.940	0.939	1		
TFP_LP 2	0.950	0.950	0.996	1	
LAB_PROD	0.902	0.902	0.832	0.861	1

Note: TFP measures indexed by 1 are from specification which does not control for firm's online presence; TFP measures indexed by 2 are from specification which includes online presence.

Table A4
Summary statistics over industrial sectors.

	Industry	No of firms	HHI	n_online	Capital intensity	Sales	TFP
	Spain						
1	Agriculture, mining and quarrying (AtC)	100	0.48	0.90	27.52	16,980.63	2.56
			(0.35)	(1.99)	(84.14)	(35,478.29)	(2.94)
2	Manufacturing (D)	856	0.26	10.66	1.29	125,070.50	4.55
			(0.26)	(13.91)	(13.84)	(148,088.90)	(2.92)
3	Electricity, gas and water supply (E)	15	0.61	1.34	1.04	16,159.94	8.38
			(0.26)	(1.12)	(1.85)	(9267.25)	(4.54)
4	Construction (F)	585	0.01	52.56	0.26	918,671.90	3.34
			(0.01)	(46.49)	(1.14)	(466,692.80)	(1.43)
5	Wholesale and retail trade (G)	862	0.03	66.02	0.57	1,294,960.00	3.81
			(0.01)	(75.30)	(1.60)	(1,169,675.00)	(1.58)
6	Hotels and restaurants (H)	291	0.02	39.69	5.89	94,231.93	2.39
			(0.01)	(29.87)	(12.79)	(80,460.00)	(0.79)
7	Transport, storage and communications (I)	254	0.34	8.89	0.72	108,863.00	4.71
			(0.37)	(10.68)	(0.82)	(121,570.00)	(3.08)
8	Finance, real estate and business services (JtK)	498	0.35	12.27	2.14	99,388.32	5.39
			(0.31)	(22.83)	(5.45)	(148,851.90)	(4.92)

(*continued on next page*)

Table A4 (*continued*)

	Industry	No of firms	HHI	n_online	Capital intensity	Sales	TFP
9	Community, social and personal services (LtQ)	289	0.25	4.80	1.14	38,264.99	2.92
			(0.31)	(6.70)	(2.08)	(51,526.14)	(3.15)
	Total services (5–9)	2194	0.26	17.26(	1.53	238,806.00	4.20
			(0.32)	36.46)	(4.46)	(584,612.10)	(3.79)
	Total sample (1–9)	3750	0.31	12.19	4.32	159,598.70	4.06
			(0.32)	(26.53)	(62.81)	(406,551.60)	(3.54)
	UK						
1	Agriculture, mining and quarrying (AtC)	61	0.40	4.05	4.97	147,256.20	1.93
			(0.31)	(5.10)	(21.33)	(210,563.50)	(2.13)
2	Manufacturing (D)	621	0.28	17.03	1.51	616,749.30	3.93
			(0.19)	(26.73)	(10.52)	(833,735.80)	(3.27)
3	Electricity, gas and water supply (E)	10	0.24	3.09	0.91	411,745.80	6.90
			(0.27)	(2.16)	(0.29)	(381,696.50)	(10.82)
4	Construction (F)	103	0.10	50.00	0.38	718,875.40	2.91
			(0.06)	(31.55)	(0.24)	(363,044.70)	(1.79)
5	Wholesale and retail trade (G)	535	0.06	92.68	1.62	3,859,694.00	6.46
			(0.04)	(77.84)	(8.85)	(2,787,974.00)	(3.55)
6	Hotels and restaurants (H)	108	0.10	47.12	37.57	844,588.80	3.84
			(0.02)	(26.96)	(41.27)	(383,830.10)	(1.64)
7	Transport, storage and communications (I)	190	0.27	20.11	0.63	828,250.40	8.36
			(0.21)	(18.70)	(0.43)	(604,841.90)	(7.91)
8	Finance, real estate and business services (JtK)	1142	0.17	71.30	2.38	1,934,674.00	5.48
			(0.12)	(110.85)	(10.26)	(3,129,107.00)	(4.50)
9	Community, social and personal services (LtQ)	493	0.28	31.11	1.62	430,037.80	1.79
			(0.20)	(30.03)	(3.74)	(488,765.50)	(1.62)
	Total services (5–9)	2468	0.20	50.78	3.18	1,471,371.00	5.09
			(0.18)	(76.81)	(29.89)	(2,366,905.00)	(5.28)
	Total sample (1–9)	3263	0.25	30.35	2.20	924,776.00	4.46
			(0.22)	(57.11)	(21.58)	(1,731,968.00)	(5.82)

Notes: Mean and (Standard Deviation) is reported for each variable over the composite 2-digit NACE Rev. 1 industry values. Total number of 2-digit NACE industries is 53 for Spain and 54 for the UK. *Sales* is measured as the mean in '000 Euro over the composite 2-digit NACE industry sales. *No of firms* represents the total number of sample firms by industry category.

Appendix B. A model of productivity and estimation algorithm

As common in the productivity literature (e.g., Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Rizov and Walsh, 2009) we specify a log-linear (Cobb-Douglas) production function:

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \beta_i i_{jt} + \omega_{jt} + \eta_{jt}, \tag{B1}$$

where the log of output of firm j at time t (y_{jt}) is modelled as a function of the logs of the firm's state variable at t, capital (k_{jt}), and a variable input, labour (l_{jt}). In the model there is a second freely variable input (i_{jt}) which denotes intermediate inputs such as materials and energy. The error structure comprises of a stochastic component (η_{jt}), with zero expected mean, and a component that represents unobserved productivity (ω_{jt}). Both ω_{jt} and η_{jt} are unobserved, but ω_{jt} is a state variable, and thus affects firm's equilibrium choices – input demands, while η_{jt} has zero expected mean given current information, and hence does not affect decisions.

Because productivity is an unobservable, estimating the production function is affected by simultaneity bias. To address this simultaneity we estimate Eq. (1) using the Levinsohn and Petrin (2003) estimator. This method expresses unobserved productivity as a function of observable variables, intermediate materials and capital stock, $\omega_{jt} = f(i_{jt}, k_{jt})$. Under the assumption of common input and output prices across firms and no measurement errors in the input demand, the use of this productivity *proxy function* helps to address endogeneity issues related to the estimation of the production function coefficients. In our analysis, we extend the specification of the proxy function by adding the firm's choice regarding the online decision, λ_{jt}. This is a dummy variable equal to one for a firm with online presence and zero otherwise. This extension controls for the fact that firms that have and use a website possibly face different input and output demand conditions compared to firms that do not have online presence. The modified proxy function becomes $\omega_{jt} = f(i_{jt}, k_{jt}, \lambda_{jt})$.

From the estimation of Eq. (B1) using the Levinsohn and Petrin (2003) estimator we can derive a measure of Total Factor Productivity (TFP), as follows:

$$TFP_{jt} = \omega_{jt} + \eta_{jt} = y_{jt} - \widehat{\beta}_k k_{jt} - \widehat{\beta}_l l_{jt} - \widehat{\beta}_i i_{jt}. \tag{B2}$$

This measure will be used to investigate the impact of the internet on productivity, which is then regressed on different measures of companies' online behaviour, as well as additional controls. Results from the estimation of the production function are available from the authors upon request.

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