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# Beyond Digital Access: Regional Technological Specialisations and Spatial Spillovers in E-Commerce Adoption Across Europe—A Spatial Panel Approach

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**Abstract**

E-commerce adoption varies substantially across European regions, raising the question of whether regional technological capabilities are associated with online purchasing behaviour beyond the effects of connectivity, economic development, human capital, and urbanisation. This study examines the relationship between regional technological specialisations and e-commerce adoption, with particular attention paid to spatial dependence and cross-regional effects. The analysis uses a balanced panel of 159 NUTS-2 regions across 23 EU countries over 2015–2024, comprising 1590 region–year observations. Two-way fixed-effects panel regressions and five spatial panel specifications (SAR, SEM, SARAR, SDM, and SDEM) are estimated using a five-nearest-neighbour spatial weights matrix. The results indicate a positive association between high-tech employment and regional e-commerce adoption, although its statistical significance depends on the specification and standard-error treatment. Strong positive spatial autocorrelation in e-commerce adoption is consistently observed. However, the estimated cross-regional relationships involving neighbouring regions' technological specialisations are specification-dependent and do not establish uniform positive technological spillovers. These findings suggest that regional digital-consumption patterns are spatially interconnected, while the benefits associated with technological specialisation may not automatically extend to neighbouring territories. Regional digitalisation policies should therefore combine connectivity and skills development with targeted measures that support inter-regional cooperation and the technological capabilities of less-developed regions.

**Keywords:** e-commerce adoption; regional technological specialisations; spatial dependence; spatial econometrics; European Union; NUTS-2 regions

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## 1. Introduction

At first, most people used the Internet solely for passive consumption (reading the news, sending emails or searching for information). Gradually, they began to buy products and services online, transforming the Internet into an active marketplace as more and more companies began to sell their products via websites and digital platforms [1].

In recent years, as Internet use has become widespread, e-commerce has experienced exponential growth, contributing substantially to European regional development and establishing e-commerce as the main driver of competitiveness, innovation and territorial cohesion.

Thus, in 2025, almost all EU citizens aged between 16 and 74 had used the Internet in the previous 12 months (95 per cent according to a survey), whilst 78 per cent had bought or ordered goods or services online [2]. On the supply side, too, e-commerce has made significant inroads among businesses, with 85.65 per cent of EU enterprises with online sales using their own websites or apps [3].

Initially, Internet access was viewed in very simple, binary terms, with the focus exclusively on infrastructure (cables, antennas, computers) [4,5]. Today, it is no longer just about access, but about how and how efficiently the technology is used, and the presence of an Internet cable or a 5G signal is no longer sufficient [6]. For a city or region to be truly digitally developed, a whole ecosystem is required, consisting mainly of: human capital (represented by people with the skills needed to use technology productively); private firms (capable of embracing digitalisation, automating processes or selling online); the institutional framework (comprising digitised public services, legislation and state support for technology); and, last but not least, innovation networks (universities, start-ups or research centres that create new solutions) [7].

The transition from mere connectivity to the active use of digital services can be explained by the Theory of the Diffusion of Innovations [8], which conceptualises the adoption of technology as a process of social change that spreads through networks of communication and interpersonal/inter-regional influence across time and space.

The shift towards a vibrant digital market (implicitly e-commerce) was initially driven by the development of physical telecommunications infrastructure and the level of Internet access penetration in households, these having been identified as the key factors without which e-commerce cannot reach consumers [9–11].

Subsequent research has shown that the level of education [12] and purchasing power, the latter measured by GDP per capita [13], are equally important determinants, whilst the presence of a workforce in high-tech sectors stimulates confidence and faster adoption of Information and Communication Technologies (ICT) [14]. Some studies [15–17] suggest that dense urban agglomerations provide the optimal logistical infrastructure for reducing 'last-mile delivery' costs, thereby stimulating the adoption of online transactions amongst the population.

However, the importance of these factors does not imply that their effects are identical across all regions or that they fully explain the differences in e-commerce adoption. For this reason, this study does not aim to be exhaustive or to provide a complete picture of e-commerce.

In this article, we use the percentage of employees in high-tech sectors as a means of assessing regional technological specialisation. We consider this variable to be a proxy indicator of a region's technological capabilities, as a region with a higher number of employees in the technology sector may reflect the presence of specialised skills, technology-intensive firms, and knowledge resources that create a favourable environment for the adoption of e-commerce. We investigate whether this regional technological specialisation is associated with e-commerce adoption, beyond traditional factors such as Internet access, educational attainment, and economic development.

Unlike existing studies, which analyse a region in isolation (assessing only what happens within it to explain its level of e-commerce), our article aims to analyse the spatial dimension of e-commerce adoption as well. Geographical regions are not isolated 'islands', and the economic activities within them do not take place in institutional or spatial isolation. Regions influence and are influenced by neighbouring territories through physical proximity, as well as through economic and technological links. What happens in a neighbouring region also matters for the region under analysis. According to Tobler's First Law of Geography, "all things are related, but nearby things are more related than distant things" [18].

Therefore, a region's ability to integrate e-commerce into its economy depends not only on its internal assets, but also on the technological dynamism and adoption rates of neighbouring territories. If a region has technologically advanced neighbours, we will seek to identify whether there is a spillover effect that will accelerate the adoption of e-commerce in that region as well.

By 'spillover effect' we mean the indirect, secondary or unintended impact that an event, decision, policy or activity in a particular field (in this case, commerce) has on other sectors, regions or individuals not directly involved [19].

Previous research has analysed the spatial distribution of e-commerce adoption, the regional determinants of digitalisation and the role of technological capabilities in regional development; however, such studies examined these topics separately, without directly linking them.

This study brings them together and conducts an analysis across three distinct dimensions:

- At the local level: Is there a link between how technologically specialised a region is and the extent to which e-commerce is used in that region?
- The digital neighbourhood effect (spatial dependence): If people in one region buy and sell a lot online, does this influence neighbouring regions to do the same?
- The technological effect of neighbours (inter-regional association): If neighbouring regions are highly technologically advanced, does this help the region in question to adopt e-commerce to a greater extent?

Using a panel of 159 European NUTS-2 regions over 2015–2024, the paper combines two-way fixed-effects panel regression and five spatial panel econometric models (SAR, SEM, SARAR, SDM and SDEM) to examine whether these relationships are positively correlated or whether they may differ in terms of direction and statistical robustness.

The remainder of this article is organised as follows: Section 2 reviews the theoretical background of digital ecosystems, spatial spillovers and the adoption of e-commerce. Section 3 presents the data, the construction of variables and the spatial econometric methodology. Section 4 presents and discusses the empirical findings, including the spatial dependence and spillover effects, whilst Section 5 concludes with policy implications and directions for future research.

## 2. Literature Review

Simply having access to technology (a mobile phone or an Internet connection) is only the first step. True digital development depends on how well prepared a region's society, economy and institutions are to use that technology for development. However, digital development was not an end in itself, but rather a means to achieve other socio-economic objectives.

### *2.1. Technological Specialisation and Other E-Commerce Drivers*

#### 2.1.1. Employment in High-Tech Sectors and the Adoption of E-Commerce

One aspect that has been less explored in traditional models of digital adoption is the role of regional technological specialisation, understood as the totality of technological capabilities and knowledge resources concentrated within a regional economy. From this perspective, the share of employment in high-tech sectors may indicate, albeit imperfectly, the extent to which a region possesses technical skills, knowledge-intensive activities and productive capacities associated with advanced technologies. These characteristics can help to create an environment conducive to the use of digital technologies and the adoption of online services.

Modern e-commerce is not just a website (which we consider to be the main prerequisite for the emergence and existence of e-commerce), but an entire infrastructure supported by high-tech specialists: cloud platforms, cyber security and smart payment systems, and artificial intelligence algorithms for recommendations [20].

In this study, we start from the premise that securing a job in high-tech sectors requires digital skills because high-tech knowledge-intensive services cannot employ staff without a high level of digital literacy and specific technical skills (programming, data analysis, cyber security, automation). As indicated in Ref. [21], basic computer skills have a significant positive impact on the development of e-commerce in European countries.

As advanced technologies (such as AI, cloud computing or the IoT) become mainstream in high-tech sectors, the skills required are becoming increasingly sophisticated, driving continuous reskilling and upskilling. Training and education programmes aimed at improving digital skills within the workforce can help reduce skills gaps and promote e-commerce growth [22].

A higher proportion of employees in IT, telecommunications and R&D is accelerating the creation of start-ups and local technology providers that help companies in the retail and manufacturing sectors make the transition to online commerce. IT education and skills are what underpin the development of e-commerce, and the IT sector and high-tech manufacturing are classified as primary industrial drivers for e-commerce [23].

Existing studies provide evidence supporting the importance of human capital and technological capabilities for the development of e-commerce. Thus, Ho et al.'s study emphasises that highly skilled human capital is an essential input for a country's Research and Development (R&D) sector—a sector that generates the new ideas and products associated with technological progress—and demonstrates that a high level of education amongst the population is a key endogenous determinant of e-commerce growth [24,25].

Another study [26] argues that, at the regional level, a high proportion of highly skilled employees is strongly and positively associated with the prevalence of company websites (an essential condition for digitalisation/e-commerce).

A lack of advanced digital skills amongst a workforce limits the exploitation of e-commerce's potential, and ICT training and skills development policies are needed in such cases to support the sector [22]. ICT skills and education represent fundamental investments in human capital that are necessary for the development of e-commerce. States could recognise that developing workforce skills is essential for the growth of e-commerce, rather than relying on technology transfer and knowledge spillovers [27].

Training in the field of e-commerce and the availability of IT/IS sector employees with relevant skills in this area have become key factors for the successful adoption of e-commerce systems by companies. Participation in continuing education and training has a more moderate influence (Beta = 0.274) and is associated with a higher rate of e-commerce adoption [28].

However, there are also studies which argue that the relationship between the level of education (secondary/tertiary education), ICT skills and final e-commerce turnover is limited or statistically insignificant [29].

To summarise the studies analysed, the level of education reflects a broader dimension of the population's preparedness, whilst employment in high-tech sectors captures a more specific component of the regional productive structure. This distinction is important because the existence of a more educated population does not automatically imply the presence of a developed technological productive base. Furthermore, some of the studies mentioned analyse firms' adoption of websites, digital skills or the performance of the e-commerce sector, rather than the population's online purchasing behaviour directly. Consequently, their findings support the general relevance of technological capabilities and

human capital, but do not directly establish the relationship between regional technological specialisations and the adoption of e-commerce by consumers.

The share of employment in high-technology sectors provides an observable proxy for the technological specialisation of regional economies. However, it should not be interpreted as a direct measure of regional digital capabilities. In particular, it does not capture the digital skills of the population, the digital intensity of firms, the quality of digital infrastructure, or the extent to which households effectively use digital technologies. Its relevance lies in capturing the structural presence of technology-intensive economic activities, which may contribute to a more favourable environment for digital market development. Nevertheless, this proxy has limitations and should be interpreted accordingly.

#### 2.1.2. Household Internet Access and the Adoption of E-Commerce

Internet access forms the technical basis for participation in e-commerce [27]. However, access must be understood in terms of both the availability of infrastructure and its economic affordability. The existence of infrastructure does not automatically remove barriers to participation if connectivity services are too expensive or of insufficient quality [23].

Generally speaking, Internet access is a prerequisite without which online shopping cannot take place, although access in itself must be accompanied by demand and income factors to generate actual expenditure [24]. Waseem et al. even demonstrate that any country's e-commerce potential is critically dependent on the population's connectivity infrastructure [30].

Underdevelopment or a lack of Internet access amongst the population in developing countries acts as a critical barrier that limits the advancement of the digital economy and exacerbates the international digital divide.

One study identifies Internet penetration as a positive determinant of B2C e-commerce revenue in European countries [25], whilst another highlights the importance of Internet users for the growth of online retail sales [29]. Convergent findings are presented by [21,23,27,30,31], who emphasise the role of ICT infrastructure and the accessibility of digital services in the development of e-commerce. In economies where connectivity remains limited, particularly due to a lack of infrastructure, expanding access may be an essential condition for reducing the digital divide, including in rural areas, as suggested by some studies [22,32].

However, the relationship between infrastructure and technology adoption does not appear to be uniform across all geographical contexts. Thonipara et al. identify differences between rural, urban and semi-urban areas in the association between Internet availability and the presence of company websites [26]. In rural areas, the effect is significantly positive, but in urban and semi-urban areas, the effect is significantly negative. This finding suggests that the effects of connectivity also depend on the economic and territorial characteristics of the areas where the infrastructure is used. Also, Ref. [33] shows that e-commerce based on short videos and live streaming (SLE) generates an asymmetric pattern of spatial propagation: a negative direct local effect (caused by crowding-out and the concentration of resources on primary consumption) and a significantly positive indirect spatial spillover effect on neighbouring cities.

Consequently, Internet access should be treated as a distinct determinant of e-commerce adoption, rather than as a substitute for technological capabilities or the skills of the population. Furthermore, as connectivity becomes increasingly widespread, regional differences in adoption may also reflect other structural characteristics of local economies. This observation justifies the inclusion of Internet access as a control variable, so that the relationship between the regional technological specialisation and the adoption of e-commerce is not confused with the mere availability of digital infrastructure.

#### 2.1.3. Levels of Education and the Adoption of E-Commerce

The level of education amongst the population is not merely a social statistic; it directly measures individuals' intellectual capacity for innovation. Without an adequate level of training and skills amongst the workforce (on the supply/development side), a country cannot create or sustain modern and efficient digital businesses.

An educated population creates the necessary framework for generating innovation. It is not merely a question of using technology, but of the ability to build the infrastructure, tools and digital business models specific to e-commerce. The level of education amongst the adult population is a positive endogenous determinant, and one that is highly statistically significant, for the growth in per capita B2C e-commerce revenue [24].

Education can influence the adoption of e-commerce by developing the skills needed to use digital services, by enabling people to evaluate information available online, and by facilitating adaptation to new technologies. A lot of studies present findings that generally support a positive relationship between education and the development of e-commerce [21,23,25,27,30,31].

However, the empirical evidence is not consistent. One study highlights a surprising and counter-intuitive conclusion: structural macroeconomic variables, including tertiary education, have an extremely limited or statistically insignificant impact on e-commerce turnover in the EU-28 countries [29]. Another study shows that the relationship between education and firms' digital presence may vary depending on their location, finding that individuals with higher education are negatively correlated with website prevalence in urban areas (surprisingly) [26]. These differences may reflect both the specific characteristics of the samples and contexts analysed, and the fact that studies do not always measure the same economic outcome.

Although higher education (tertiary education) indicates a generally high level of educational attainment amongst the population, it does not automatically guarantee that these individuals possess the specific practical skills required to use advanced technologies or to set up digital businesses.

In the present study, tertiary education is included as a control variable (a key factor that must be taken into account to ensure the results are not distorted), whilst technological specialisation is approximated separately by the share of employment in high-tech sectors (a much more direct indicator of practical digital skills).

By separating these two factors, the study can accurately measure the actual impact of regional technological structure on e-commerce, whilst neutralising or isolating the influence of the population's general level of education.

#### 2.1.4. GDP per Capita and the Adoption of E-Commerce

GDP per capita is another frequently analysed determinant, as it reflects differences in economic development and, indirectly, in purchasing power. Higher income levels can facilitate purchases in general and online purchases in particular, whilst more developed economies may have more mature digital markets and more favourable conditions for the adoption of new technologies.

GDP per capita is conceptually identified in the literature as a determinant of e-commerce [24]. In the econometric model employed in [24], they utilise the 'GDP share of capital investment in telecommunications' and find that it is an endogenous growth factor, whilst high levels of GDP per capita in neighbouring countries generate positive regional spillover effects on trade.

Most studies present findings that generally support a positive association between the level of economic development or household income and the growth of e-commerce [21,23,27,31,34].

However, there are also studies that do not fully support this correlation. For example, Ref. [29] finds that GDP per capita (at purchasing power parity) has an extremely limited and statistically insignificant direct influence on the final share of e-commerce turnover in GDP within the EU-28. The authors show that some peripheral European economies exceed those of developed countries with a considerably higher GDP per capita in terms of online turnover.

The empirical results obtained for the districts in Germany show an unexpected negative correlation between regional GDP per capita and the prevalence of websites among small (craft-type) firms, an effect driven by the specific dynamics of urban districts [26]. GDP is only positively associated with website prevalence in rural areas. In urban areas, GDP is negatively associated with website prevalence. The authors explain this paradox by the fact that some cities have a lower-than-average GDP per capita and a very large number of small firms with websites, and the combination of these two factors has led to this result. In this study, GDP per capita is included to control for differences in economic development and purchasing power. Thus, the effect associated with the regional technological specialisation is estimated in relation to regions that may differ not only in terms of technological capabilities but also in terms of their overall level of development.

These seemingly divergent results must be interpreted whilst taking into account the differences between the dependent variables used. E-commerce revenue, the share of online sales in total retail trade, and the presence of a firm's website reflect distinct dimensions of digitalisation.

#### 2.1.5. Population Density and the Adoption of E-Commerce

It is generally considered that population density has a direct, positive and highly statistically significant effect on the growth of e-commerce revenue. However, recent studies suggest that population density may influence e-commerce through various mechanisms. On the one hand, population concentration may foster the development of infrastructure, logistics services and digital markets; on the other hand, in densely populated regions, the availability of physical shops and the accessibility of traditional retail may reduce the relative advantages of online shopping [23,35].

Some authors show that higher population density captures the effects of a larger market and advanced technological infrastructure (economies of scale in urban areas), enabling more efficient distribution and operation of B2C activities [25].

An econometric analysis at district level in Germany shows that high population density has a strong positive and highly statistically significant association ($p < 0.01$) with the probability that firms have a website (a proxy for the degree of digitalisation) [26]. Furthermore, ref. [36] notes that transactions carried out by people living in large cities (typically high-density areas) have the strongest positive impact on the development of e-commerce, followed by those in small towns/suburbs and then in rural areas. Similarly, in [30], urban population was found to be significantly associated with e-commerce. In the chapter devoted to the specialist literature, the authors [24] mention that the level of urbanisation is a potential determining factor in the development of e-commerce and state that in high-density regions, traditional retail is highly developed, efficient and accessible (e.g., local shops). Because physical retail networks are so close to consumers, the incentives to shop online (such as saving time or effort) decrease significantly. This results in an inversely proportional relationship between high population density (characteristic of heavily urbanised areas) and the adoption of e-commerce

In one study [27], the crude variable of population density proved to be statistically insignificant in the cross-national sample analysed. Consequently, population density cannot automatically be regarded as a positive determinant of e-commerce adoption. Its

effect depends on the balance between the advantages of urban agglomeration and the alternatives offered by traditional commerce, as well as on the characteristics of local markets and infrastructure. The inclusion of population density as a control variable allows for an examination of the relationship between the technological specialisation and the adoption of e-commerce without automatically attributing effects that might be associated with territorial structure.

### *2.2. Spatial Dependence, Diffusion and Spillover Effects in E-Commerce*

In this paper, in addition to analysing these traditional factors, we will go further and also provide an inter-regional perspective, as regions are interconnected and do not function as enclaves with protectionist policies. There are internal reasons why a region has a certain level of e-commerce, but that level cannot be explained solely by what happens within the region.

The recent literature has focused on analysing spillover effects between regions and, in general, considers that spillover occurs naturally and is influenced by the distance from the source [37]. Spatial proximity facilitates this unintended exchange of ideas, as the cost of transmitting knowledge increases with geographical distance. For this reason, firms in innovative sectors cluster spatially to capture these knowledge spillovers.

A study conducted across 31 provinces in China between 2012 and 2021 highlighted that the development of rural e-commerce generates a significant positive spatial spillover effect on the high-quality development of neighbouring rural regions [38]. Thus, a one-unit increase in e-commerce activity leads to a total rural economic growth of 0.0038 units, comprising a direct effect of 0.0011 units and a spillover effect of 0.0027 units. Consequently, the spatial spillover effect is greater than the direct effect, with e-commerce stimulating economic prosperity in adjacent towns and villages.

Core cities or 'demonstration cities' develop advanced digital infrastructure, data analytics (big data), cloud computing and smart logistics [39]. This technological know-how does not remain confined locally, but 'spills over' to less developed regions, which absorb these technologies and best practices without having to reinvent them from scratch. This increases their production efficiency and enables them to grow at a faster rate, thereby closing the economic gap.

E-commerce facilitates cross-border trade, and countries that open up to imports from high-income economies benefit from an indirect transfer of technology, know-how and best practice [40]. The import of advanced digital products and services acts as a channel through which innovation from developed countries 'spills over' into developing economies, boosting their productivity.

In addition to these spatial spillovers, the specialist literature also identifies intra-sectoral spillovers [41], pecuniary spillovers [42,43], trade spillovers, and competitive inter-brand spillovers [43].

Spillover is sometimes defined as a mechanism for capturing or transferring value between platforms [44], showing that online content creation acts as a double-edged sword: it can be a positive spillover partnership (where content created on content platforms (e.g., reviews, videos) stimulates general interest in products and directs users to make purchases on the traditional platform) or a negative spillover war (building one's own online ecosystem that attracts customers away from traditional competitors).

These studies suggest that inter-regional relationships may be relevant to the development of e-commerce, digital infrastructure and economic performance. However, they do not directly answer the question of whether the technological specialisations of neighbouring regions are associated with the level of online shopping adoption in European regions.

A positive association between adoption levels in neighbouring regions may indicate spatial dependence, without proving the existence of positive spillover effects from technological capabilities. Similarly, the existence of spillover effects in other areas does not guarantee that they will manifest themselves with the same direction or intensity in the case of consumer behaviour.

From this perspective, spatial econometric models allow for the examination of different dimensions of inter-regional relationships. Models that include a spatial lag of the dependent variable investigate the association between the level of e-commerce adoption in a region and the levels observed in neighbouring regions. In contrast, models that include spatial lags of the explanatory variables allow us to examine the association between the characteristics of neighbouring regions—such as the technological specialisation or Internet access—and the adoption of e-commerce in the region under analysis.

Consequently, spatial analysis is not merely a technical extension of traditional models, but allows for the distinction between two research questions: whether e-commerce adoption exhibits spatial dependence, and whether this dependence is specifically associated with the technological characteristics of neighbouring regions.

### Research Gap and Research Hypotheses

In this article, technological specialisation refers to the relative concentration of employment in high-tech sectors and is used to capture the extent to which technology-intensive activities are integrated into a regional economic structure. This indicator reflects the presence and importance of technology-oriented economic activities, but it does not directly measure the population's digital capabilities, the digital intensity of firms across all sectors, or the quality of digital infrastructure.

Regional digitalization is a multidimensional process that involves more than just an increase in economic activities that adopt digital technologies. It also entails, in addition to the development of digital infrastructure, the availability of digital skills, the ability of firms and institutions to adopt technological innovations, and the extent to which individuals integrate digital technologies into their daily activities. These dimensions are interconnected and capture different aspects of the regional digital transformation process.

Regional digital capabilities constitute a broader concept, encompassing the resources and skills that enable economic agents to access, adopt, and effectively use digital technologies. It can be seen as the potential for the development of the digital economy. Technological specialisation can also contribute to the development of such capabilities, but it cannot be considered a comprehensive indicator of them.

Consumer adoption of e-commerce represents an additional, distinct dimension of regional digitization. Unlike technological specialisation, which describes the structure of regional economic activity by focusing on supply, the adoption of e-commerce captures an observable behavioural outcome on the demand side—namely, the extent to which individuals use online channels to purchase goods and services. This behaviour may be associated with the technological and socioeconomic characteristics of the region where consumers live, but it is not determined solely by the regional concentration of high-tech jobs. Differences in household income, education, Internet access, population characteristics, and other contextual conditions can also influence the volume of online purchases. Consequently, a region with relatively strong technological specialisation does not necessarily imply a correspondingly high level of e-commerce adoption among consumers.

This conceptual distinction provides the starting point for the present study. It does not assume that regional technological specialisation automatically translates into greater consumer participation in online markets, but rather examines whether the technological structure of regional economies is statistically associated with the adoption of e-commerce by

individuals. Consequently, the focus is on the relationship between a structural characteristic of regional economies and a specific form of consumer digital behaviour.

This study thus aims to contribute to the literature on the adoption of e-commerce by combining two complementary perspectives: one centred on local regional determinants and the other focused on spatial interdependencies. In this way, this research seeks to establish empirically whether the spatial effects of technological specialisations are positive and in what direction the results point. We thus obtain a clear distinction between the theoretical arguments regarding the possibility of the spread of technological advantages and the empirical evidence required to confirm them.

The central question is not only whether regions with more developed technological specialisations exhibit higher levels of e-commerce adoption, but also whether the observed spatial relationships can be linked to the technological specialisations of neighbouring territories.

The following research hypotheses have therefore been formulated:

**H1.** *Regional technological specialisation, proxied by high-technology employment share, is positively associated with e-commerce adoption.*

**H2.** *Regional e-commerce adoption exhibits significant positive spatial dependence across EU NUTS-2 regions.*

**H3.** *The technological specialisation of neighbouring regions has significant spillover effects on local e-commerce adoption.*

**H4.** *Economic development, human capital (education), connectivity (Internet access), and urbanisation (density) are positively associated with regional e-commerce adoption.*

## 3. Materials and Methods

### *3.1. Data*

The analysis is based on a balanced panel dataset covering 159 NUTS-2 regions from 23 EU countries over the period 2015–2024 (10 years). The final dataset used for empirical estimations contains 1590 region–year observations.

R software (version 4.2.2) was used to carry out the data analysis, and the map was generated using GeoDa (1.22.1).

The NUTS 2021 territorial classification was used throughout the sample to ensure spatial consistency over the entire period. Since some countries experienced changes in their NUTS-2 boundaries during the analysed period, a few adjustments were required. Portugal adopted a revised NUTS classification in 2024, increasing the number of NUTS-2 regions from seven to nine; thus, the 2024 observations were harmonised from NUTS 2024 to NUTS 2021 boundaries using approximate population-based weights, applied consistently across all variables. Specifically, Area Metropolitana de Lisboa (PT17) was reconstructed using 75% of Grande Lisboa (PT1A) and 25% of Peninsula de Setubal (PT1B). Centro (PT16) was reconstructed using 75% of Centro (PT19) and 25% of Oeste e Vale do Tejo (PT1D), while Alentejo (PT18) was reconstructed using 80% of Alentejo (PT1C) and 20% of Oeste e Vale do Tejo (PT1D). Although this approach may introduce some approximation errors, its application was limited to a single year of the ten-year study period (2015–2024), thereby limiting its potential impact on the overall results.

Similar harmonisation procedures were necessary for Ireland, Lithuania and Hungary, following the implementation of the 2016 NUTS revision which became effective in 2018. For these countries, observations for 2015–2017 concerning regional e-commerce adoption

and Internet access were harmonised to the NUTS 2021 classification using proportional adjustment factors derived from the first available regional data (2018). These factors were calculated from the relative differences between regional values in 2018 and applied retrospectively to reconstruct historical observations, assuming that relative regional patterns remained broadly stable over the three-year period. For all other variables, data were already available according to the NUTS 2021 classification, and no territorial reconstruction was required.

These adjustments allow the usage of a consistent geographical structure for the entire time span analysed.

A balanced panel structure was adopted to ensure consistency in the estimation of the regression models. Countries without available data for the dependent variable (Greece and Germany) were excluded. Poland was also excluded since data was reported only for 2023 and 2024, preventing reliable interpolation, while Croatia was excluded because of inconsistencies in territorial reporting. Linear interpolation was applied only to isolated missing observations for the e-commerce adoption and Internet access indicators. Specifically, missing values for France for 2020 were estimated using the average of the 2019 and 2021 observations, while missing values for Austria for 2015 were estimated using the corresponding values from 2014 and 2016. Unlike Poland, where data were available only for 2023–2024, these cases involved single-year gaps with observations available on both sides allowing for a reliable estimation.

The exclusions were primarily driven by data availability rather than sample selection. Nevertheless, the final sample covers 159 NUTS-2 regions across 23 of the 27 EU Member States, capturing considerable heterogeneity in economic development, technological specialisation and e-commerce adoption. The exclusion of Germany and Poland may underrepresent certain economic and technological structures, potentially affecting the estimated relationships and limiting their generalisability. Therefore, the findings should be interpreted as representative of the regions included in the analysis rather than the entire EU.

For spatial modelling purposes, geographically disconnected ultraperipheral regions were excluded from analysis to avoid distortions of the spatial weights matrix. These include: French overseas regions (Martinique, Guyana, Reunion, Mayotte and Guadeloupe), Portuguese autonomous regions (Madeira and Azores) and the Spanish Canary Islands. The Ceuta and Melilla regions were also excluded because of missing information. Similarly, the Aland region in Finland was excluded due to substantial data gaps across the variables included in the analysis.

The variables used in the empirical analysis, together with their definitions and table sources, are presented in Table 1. The entire dataset was retrieved from Eurostat.

The dependent variable is the percentage of individuals who ordered goods or services over the Internet in the last year. This indicator is a widely used measure of e-commerce adoption at the regional level, reflecting digital consumer behaviour [21,24,28].

The main explanatory variable is regional technological specialisation proxied by the share of employment in high-tech sectors. This indicator reflects the concentration of digitally skilled workers, technology-intensive economic activities, and specialised knowledge in the NUTS-2 region. It incorporates both advanced human capital and broader technological capabilities, such as innovation-oriented companies, digital expertise or knowledge networks. The concentration of high-technology activities contributes to local technological capabilities by creating an environment favourable to the adoption of digital practices [45]. Consequently, we expect that regions with stronger technological specialisations tend to exhibit higher levels of digital readiness and an increased openness to adopt digital services such as e-commerce. While high-tech employment cannot fully capture the multidimen-

sional nature of regional technological specialisations, it represents a comparable proxy available at the NUTS-2 level across most European countries and over a larger period of time.

**Table 1.** Variable definitions and data sources.

| Variable Name | Description | Eurostat Table |
|---|---|---|
| E-commerce | Individuals who ordered goods or services over the Internet for private use in the last year (percentage of individuals) | [tgs00052] |
| Technological specialisation | Employed persons in high-technology sectors (high-technology manufacturing and knowledge-intensive high-technology services) (percentage of total employment) | [tgs00039] |
| Internet access | Households that have Internet access at home by NUTS-2 region (percentage of households) | [tgs00047] |
| GDP/cap | Gross domestic product (GDP) at current market prices (Euros per inhabitant) | [nama_10r_2gdp] |
| Education | Population in private households by educational attainment level and NUTS-2 region tertiary education (levels 5–8) (percentage) | [edat_lfse_04] |
| Density | Population density by NUTS-2 region (persons per square kilometre) | [tgs00024] |

Several control variables are employed to better differentiate the impact of the technological-specialisation from other structural determinants of e-commerce adoption. The control variables cover several regional characteristics such as digital infrastructure, economic development, human capital, and urban structure. Internet access reflects the availability of the digital infrastructure required to participate in online activities, including e-commerce. It is expected that regions with higher Internet household connectivity will display higher levels of e-commerce adoption. However, since the Internet access in Europe almost reaches saturation, the differences in digital behaviour are likely to respond to other explanatory factors rather than simple connectivity. GDP per capita controls for the overall level of regional economic development, reflecting purchasing power and the resources available to households for digital consumption. Educational attainment, measured as the share of the population with tertiary education, reflects the human capital within each region. Higher education is usually associated with stronger digital skills, greater abilities to use online services and thus a higher share of e-commerce adoption. The education variable measures the general human capital stock, while the technological specialisation variable reflects the technological capabilities of the region. Finally, population density is included to account for urbanisation effects, since densely populated regions may benefit from better logistics infrastructure, availability of digital services and diffusion of innovation. Controlling for density ensures that the estimated effect of the technological specialisation is not simply reflecting differences associated with urban concentration.

Descriptive statistics for all variables are reported in Table 2, suggesting substantial heterogeneity across European regions. E-commerce adoption varies from 7.2% to 96.27%, with an average of 60.47%. Similarly, the technological-specialisation variable ranges from 0.8% to 14.1%, averaging 4.06%. The standard deviation at 2.29% reflects considerable regional heterogeneity in technological specialisation across Europe. GDP per capita and density report very large ranges, suggesting highly skewed distributions. Consequently, the logarithmic transformations of the GDP per capita and density variables are employed in

the regression analyses. As expected, Internet access exhibits lower variability, suggesting the widespread diffusion of digital infrastructure in the European countries.

**Table 2.** Descriptive statistics for the variables included in the dataset.

| | E-Commerce | Technological Specialisation | Internet Access | GDP/Capita | Education | Density |
|---|---|---|---|---|---|---|
| Min | 7.2 | 0.80 | 44.86 | 4000 | 11.50 | 3.40 |
| Q1 | 48.09 | 2.40 | 84.33 | 20,900 | 22.52 | 66.92 |
| Median | 63.36 | 3.60 | 90.10 | 30,300 | 32.70 | 103.90 |
| Mean | 60.47 | 4.06 | 88.50 | 32,206 | 32.54 | 310.46 |
| Q3 | 74.95 | 4.97 | 94.51 | 40,300 | 40.30 | 228.22 |
| Max | 96.27 | 14.10 | 100.00 | 127,000 | 63.60 | 7827.40 |
| Std Dev | 19.16 | 2.29 | 7.88 | 16,950 | 11.05 | 797.02 |

The correlation analysis suggests only moderate associations among the explanatory variables (Table 3). This result is also supported by the Variance Inflation Factors (VIFs), with values ranging from 1.34 for density to 2.43 for GDP per capita, well below conventional thresholds reported in the econometric literature [46]. Therefore, multicollinearity is not expected to affect the reliability of the estimated regression coefficients.

**Table 3.** Correlation matrix between the independent variables.

| | Technological Specialisation | Internet Access | GDP/Capita | Education | Density |
|---|---|---|---|---|---|
| Technological Specialisation | 1 | | | | |
| Internet Access | 0.3669 | 1 | | | |
| GDP/Capita | 0.5004 | 0.5797 | 1 | | |
| Education | 0.6272 | 0.5267 | 0.6442 | 1 | |
| Density | 0.3878 | 0.1345 | 0.3030 | 0.2817 | 1 |

### *3.2. Methods*

The empirical approach consists of three steps. First, baseline panel data regression models are estimated to identify the determinants of regional e-commerce adoption. Second, the spatial autocorrelation is assessed using Moran's I statistic. Finally, spatial panel regression models are estimated to account for potential spillover effects among neighbouring regions and to explicitly model spatial interactions.

The baseline panel data regression models include both the cross-sectional and temporal dimensions of the dataset. The two-way fixed-effects (FE) model was estimated to control for both unobserved region-characteristics and common time-specific shocks [46]. This type of model was preferred to the one-way fixed-effects specification since the inclusion of year fixed effects captures the common events affecting all European regions during the 2015–2024 period, such as the COVID-19 pandemic, post-pandemic recovery, inflationary pressures and accelerated digitalisation.

The equation of the estimated model is

$$Ecommerce_{it} = \alpha + \theta \cdot Technological\ specialisation_{it} + X_{it}\beta + \mu_i + \tau_t + \varepsilon_{it}$$

where $i$ is the region index, $t$ is the year index, and $X_{it}$ represents the vector of control variables: Internet access, the logarithm of GDP per capita, tertiary education attainment, and the logarithm of population density. Parameter $\theta$ shows the effect of regional technological

specialisation, whereas $\beta$ represents the coefficients associated with the control variables. $\mu_i$ represents the region fixed effects capturing the time-invariant regional characteristics, such as institutional quality, culture or geography, while $\tau_t$ is the year fixed effects absorbing common temporal shocks affecting all regions simultaneously. Finally, $\varepsilon_{it}$ is the idiosyncratic error term.

For comparison, the random-effects (RE) model is also estimated. The Hausman test is applied to determine the appropriate panel estimator. Rejection of the null hypothesis would indicate that the fixed-effects estimator is consistent and thus preferred [47].

Before estimating the spatial panel models, the presence of spatial dependence was assessed through Moran's I statistics. Spatial autocorrelation occurs when observations from neighbouring regions influence one another through various mechanisms, such as technological, economic or social interactions. If spatial autocorrelation is ignored in regression models, the assumption regarding independence between explanatory variables and the error term is violated, leading to biassed or inefficient parameter estimates [48,49].

Global spatial autocorrelation is evaluated using Moran's I statistic, defined as

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})\left(x_j - \overline{x}\right)}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

where $n$ is the number of spatial units (NUTS-2 regions in our case), $x_i$ and $x_j$ are values of the analysed variable in regions $i$ and $j$ respectively, $\overline{x}$ is the sample mean, and $w_{ij}$ represents the elements of a spatial weights matrix. Positive values for Moran's I indicate that similar values are clustered together, while negative values of the statistic indicate spatial dispersion. Values close to zero suggest the absence of global spatial dependence [48].

The spatial relationships are represented through a row-standardised five-nearest-neighbour (5-KNN) spatial weights matrix. In this type of matrix, each NUTS-2 region is connected to its five nearest geographical neighbours, based on centroid distances, while all remaining regions are weighted with zero. Row-standardisation ensures that weights associated with each region sum to one, facilitating comparability across observations [48]. The 5-KNN spatial matrix is suited for the European NUTS-2 regional system because it ensures that every region has the same number of neighbours, irrespective of differences in geographical size or shape. A distance-based matrix might have generated an unbalanced number of neighbours across regions, while contiguity-based matrices may produce isolated observations for islands. Consequently, the proposed 5-KNN spatial weights matrix provides a more balanced representation of the spatial interactions between European NUTS-2 regions [50]. Moran's I statistic was determined for all variables—dependent and explanatory—as a preliminary diagnostic. Evidence of statistically significant spatial autocorrelation justifies the extension from conventional panel regression to spatial panel econometrics.

To account for spatial autocorrelation in regional e-commerce adoption, various spatial panel specifications can be used. Following Refs. [48,50,51], these models identify the different mechanisms through which spatial interactions can occur.

First, the Spatial Autoregressive (SAR) Model assumes that the dependent variable is directly influenced by its neighbouring observations through a spatial lag of the dependent variable. The equation of the model is as follows:

$$y_{it} = \rho W y_{it} + X_{it}\beta + \alpha_i + \tau_t + \varepsilon_{it}$$

where $W$ denotes the spatial weights matrix and $\rho$ is the spatial autoregressive coefficient. The model entails global spillover effects: on average, the value of the dependent variable at time $t$ for region $i$ is explained not only by the explanatory variables for this observation, but also by those neighbouring region $i$. In our particular case, a significant and positive value

of $\rho$ would indicate that higher e-commerce adoption in neighbouring NUTS-2 regions is associated with higher adoption rates within the region itself.

The Spatial Error Model (SEM) assumes that spatial dependence arises from omitted variables or unobserved regional characteristics that are spatially correlated, which are all embedded in the error term. The model is expressed as

$$y_{it} = X_{it}\beta + \alpha_i + \tau_t + u_{it},\ u_{it} = \lambda W u_{it} + \varepsilon_{it}$$

where $\lambda$ is the spatial error coefficient. In this case, the spatial interaction is captured through the spatial autoregressive specification of the error term, suggesting that neighbouring regions share common unobserved characteristics influencing e-commerce adoption.

By simultaneously incorporating the spatial lag of the dependent variable and the spatially correlated disturbances, the SARAR Model is obtained [50]:

$$y_{it} = \rho W y_{it} + X_{it}\beta + \alpha_i + \tau_t + u_{it},\ u_{it} = \lambda W u_{it} + \varepsilon_{it}$$

This specification allows for spatial dependence to arise from the endogenous interactions among neighbouring regions, but also through omitted spatially correlated factors.

Finally, the Spatial Durbin Model (SDM), recommended by LeSage and Pace [51], contains a spatially lagged dependent variable and spatially lagged explanatory variables:

$$y_{it} = \rho W y_{it} + X_{it}\beta + WX_{it}\theta + \alpha_i + \tau_t + \varepsilon_{it} \quad (1)$$

where $WX_{it}$ represents the matrix of spatially lagged explanatory variables, while $\theta$ measures their associated effects. The SDM explicitly tests if the characteristics of neighbouring regions—for instance their technological specialisations, digital infrastructure or economic development—generate spatial spillover effects on e-commerce adoption.

The Spatial Durbin Error Model (SDEM) extends the spatial error specification by incorporating the spatially lagged explanatory variables:

$$y_{it} = X_{it}\beta + WX_{it}\theta + \alpha_i + \tau_t + u_{it},\ u_{it} = \lambda W u_{it} + \varepsilon_{it}$$

where $\lambda$ is the spatial error coefficient and $\theta$ measures the associations between neighbouring regions' explanatory characteristics and local e-commerce adoption. Unlike the SDM, the SDEM does not include the spatially lagged dependent variable, instead it accounts for spatially correlated unobserved factors through the error structure.

All spatial panel models are estimated using maximum likelihood estimation and under a two-way fixed-effects specification. The choice of fixed vs. random effects and the selection of the spatial model is done through diagnostic tests presented in the following section.

## 4. Results and Discussion

### *4.1. Baseline Panel Regression Results*

First, the conventional fixed- and random-effects (FE and RE) panel regression models are estimated (Table 4). The Hausman test strongly rejects the null hypothesis, indicating that the two-way fixed-effects model is appropriate for analysis. Additionally, the Wooldridge test suggests significant first-order serial correlation; thus, the interpretation of the results will be made primarily based on the FE model with region-clustered robust standard errors.

The estimated coefficients provide preliminary support for the proposed theoretical hypotheses. The regional technological specialisation, proxied by the share of employment in the high-technological sector, registers a positive coefficient across all models and remains statistically significant at the 10% level after correcting for serial correlation. Economically, the results show that a one-percentage-point increase in the share of high-tech employment is

associated with an increase of approximately 0.54 percentage points in regional e-commerce adoption. This result empirically supports the first research hypothesis (H1), suggesting that technologically specialised regions create a more favourable context for increased adoption of digital services.

**Table 4.** Results of the baseline panel regression models (fixed effects—FE and random effects—RE).

| Variable | FE Model | FE Model (Robust SE) | RE Model |
|---|---|---|---|
| Intercept | - | | −204.1999 (9.7680) |
| Technological specialisation | 0.5428 *** (0.2002) | 0.5428 * (0.3105) | 0.7737 *** (0.1937) |
| Internet access | 0.4483 *** (0.0351) | 0.4483 *** (0.0509) | 0.7395 *** (0.0309) |
| Ln (GDP/cap) | 25.0675 *** (1.5870) | 25.0675 *** (3.7495) | 19.4429 *** (1.1187) |
| Education | 0.1344 ** (0.0663) | 0.1344 (0.0874) | 0.4139 *** (0.0507) |
| Ln (density) | 0.9989 (3.9857) | 0.9989 (6.3221) | −3.3870 *** (0.6405) |
| R-Squared<br>F test | 0.3283<br>F test = 138.521 *** | | 0.6495<br>Chi-Square test = 2935.09 *** |
| Hausman test<br>Wooldridge test for serial correlation | Chi-Square test = 226.53 ***, df = 6<br>F = 143.62 *** | | |

Notes: standard errors are reported in parentheses. Significance levels: * at the 10% level, ** at the 5% level, *** at the 1% level.

Among the control variables, Internet access and GDP per capita are the strongest and most robust determinants of e-commerce adoption. The positive and highly significant coefficient of Internet access across all specifications suggests that, despite the relative saturation of Internet penetration across Europe, regional differences in connectivity still play an important role in explaining the variations in e-commerce adoption levels. In a similar way, GDP per capita registers a consistently positive and statistically significant coefficient, indicating that wealthier regions are more likely to benefit from higher purchasing power and more mature digital markets, and thus exhibit a greater readiness to adopt online purchasing behaviour.

The results for tertiary education attainment are less robust. Although statistically significant under conventional standard errors, the variable is no longer significant when cluster-robust standard errors are used ($p$-value = 0.12), suggesting that the estimated education effect may reflect regional characteristics rather than a systematic impact on e-commerce adoption. Population density is not significant in the fixed-effects specification, indicating that urbanisation does not influence regional e-commerce adoption.

Considering that digital technologies and digital behaviour may exhibit spatial diffusion across regions through knowledge transfer, labour mobility or market integration, in the next section we test the potential existence of spatial dependence.

### *4.2. Spatial Dependence Analysis*

Figure 1 illustrates the geographical distribution of e-commerce adoption across NUTS-2 European regions in 2024, revealing considerable regional heterogeneity in the diffusion of online purchasing. The highest levels of e-commerce adoption can be observed in Northern

and Western Europe, particularly in Sweden, Denmark, the Netherlands, and several regions of Ireland and France. In contrast, lower adoption rates are registered mainly in Southern and Eastern Europe, mainly in Romania, Bulgaria and Italy. The map provides preliminary visual evidence of positive spatial autocorrelation, suggesting that regions with similar levels of e-commerce adoption tend to cluster geographically rather than being randomly distributed across space.

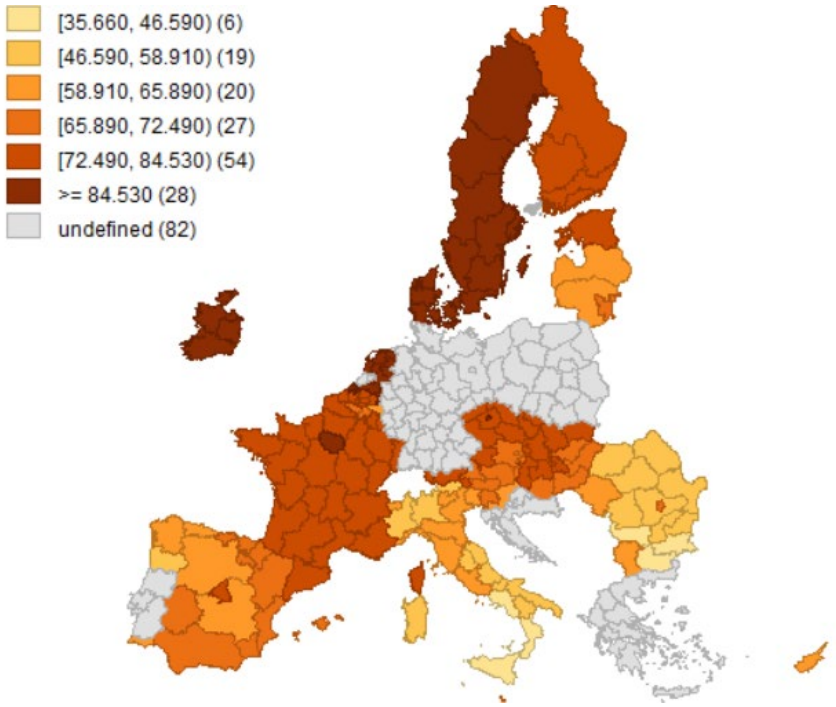



**Figure 1.** Spatial distribution of e-commerce adoption across European NUTS-2 regions (2024).

To assess the extent of spatial autocorrelation, Moran's I statistics were calculated, for both the dependent variable and the main explanatory variable (regional technological specialisation). The statistics were calculated for each year of the 2015–2024 period (Table 5). The results show strong and persistent positive spatial autocorrelation for regional e-commerce adoption throughout the entire sample period. Moran's I ranges between 0.803 and 0.859, remaining statistically significant at the 1% level in every year. This behaviour indicates that neighbouring regions consistently report similar levels of e-commerce adoption, confirming the existence of positive spatial clustering, as initially presumed from the visual representation.

Technological-specialisation also exhibits positive spatial autocorrelation, but with substantially lower Moran's I values; however, it remains statistically significant at a 10% level in all analysed years. We can conclude that regional technological capabilities appear to be more spatially dispersed, while digital consumer behaviour is much more spatially clustered.

The existence of statistically significant spatial autocorrelation is further confirmed by the spatial dependence diagnostic tests (Table 6). Both the Lagrange Multiplier (LM) test for spatial lag dependence and the LM test for spatial error dependence strongly suggest the presence of both types of spatial effects in the regression model. This finding is reinforced by the robust form of both LM tests, which remain highly statistically significant.

**Table 5.** Global Moran's I statistics for e-commerce adoption and technological-specialisation variables.

| Year | E-Commerce | Technological Specialisation |
|---|---|---|
| 2015 | 0.844 *** | 0.0887 * |
| 2016 | 0.851 *** | 0.0860 * |
| 2017 | 0.832 *** | 0.0797 * |
| 2018 | 0.832 *** | 0.101 ** |
| 2019 | 0.859 *** | 0.0867 ** |
| 2020 | 0.826 *** | 0.0960 ** |
| 2021 | 0.825 *** | 0.0955 ** |
| 2022 | 0.805 *** | 0.0812 * |
| 2023 | 0.813 *** | 0.0831 * |
| 2024 | 0.803 *** | 0.0888 * |

Significance levels: * at the 10% level, ** at the 5% level, *** at the 1% level.

**Table 6.** Spatial dependence diagnostic tests for the fixed-effects model.

| Test | Test Value | *p*-Value |
|---|---|---|
| LM test for spatial lag | 389.46 | 0.0000 |
| LM test for spatial error | 384.01 | 0.0000 |
| Robust LM test for spatial lag | 25.82 | 0.0000 |
| Robust LM test for spatial error | 20.375 | 0.0000 |

All these results provide the empirical evidence that conventional panel regression models fail to capture the geographical dimension of regional e-commerce adoption. In particular, standard panel models assume that outcomes are conditionally independent across regions and do not explicitly account for spatial interactions or spatially correlated disturbances. When such dependencies are present, conventional estimates may be inefficient, statistical inference may be unreliable, and the spatial transmission of regional characteristics remains unexplored.

Therefore, we will further estimate the spatial panel models, including the SAR Model, SEM, SARAR Model and SDM, to account explicitly for cross-regional dependence and provide a more comprehensive understanding of the relationships between technological specialisations, socioeconomic characteristics and e-commerce adoption across European regions.

### *4.3. Spatial Panel Models*

Table 7 presents the estimation results of the spatial panel regression models considered in the study: the Spatial Autoregressive (SAR) Model, the Spatial Error Model (SEM), the Spatial Autoregressive with Autoregressive Disturbances (SARAR) Model, the Spatial Durbin Model (SDM), and the Spatial Durbin Error Model (SDEM). Overall, the coefficients remain consistent through all five specifications, indicating the robustness of the determinants for regional e-commerce.

Regional technological specialisation, proxied by the share of employment in high-tech sectors, has a positive and statistically significant coefficient across all spatial specifications. The variation in the coefficient is limited, ranging from 0.55 in the SDEM to 0.72 in the SEM, showing the stability of the positive relationship between technological specialisation and regional e-commerce adoption and the consistency of the estimated association after

accounting for alternative forms of spatial dependence. This result reinforces research hypothesis 1 (H1), suggesting that technological specialisation represents a significant dimension of regional digital development, beyond household Internet connectivity and regular socioeconomic characteristics.

**Table 7.** Results of the spatial panel regression models with two-way fixed effects.

| Variable | SAR | SEM | SARAR | SDM | SDEM |
|---|---|---|---|---|---|
| Technological Specialisation | 0.5982 *** (0.1668) | 0.7154 *** (0.1678) | 0.6458 *** (0.1695) | 0.6593 *** (0.1682) | 0.5486 *** (0.1784) |
| Internet Access | 0.3079 *** (0.0302) | 0.3965 *** (0.0360) | 0.3437 *** (0.0355) | 0.3570 *** (0.0379) | 0.3595 *** (0.0364) |
| Ln (GDP/cap) | 13.8633 *** (1.4297) | 19.8465 *** (1.9196) | 15.6979 *** (1.9763) | 12.9324 *** (2.3158) | 12.1475 *** (2.2430) |
| Education | 0.1671 *** (0.0553) | 0.1108 * (0.0596) | 0.1547 *** (0.0576) | 0.1333 ** (0.0594) | 0.1586 *** (0.0596) |
| Ln (Density) | 4.7150 (3.3226) | 3.3681 (3.6835) | 4.0411 (3.4988) | 3.6603 (3.6966) | 4.8102 (3.6604) |
| Spatial Lag Coefficient (Rho) | 0.5183 *** (0.0251) | | 0.4091 *** (0.0676) | 0.5338 *** (0.0267) | |
| Spatial Error Coefficient (Lambda) | | 0.5449 *** (0.0265) | 0.1844 ** (0.0897) | | 0.5460 *** (0.0264) |
| W. Technological Specialisation | | | | −0.8368 ** (0.3258) | −0.7575 * (0.4512) |
| W. Internet Access | | | | −0.1158 ** (0.0563) | 0.0852 (0.0750) |
| W. Ln (GDP/cap) | | | | 3.1895 (2.9693) | 22.8114 *** (3.6042) |
| W. Education | | | | 0.1395 (0.1034) | 0.2506 * (0.1433) |
| W. Ln (Density) | | | | 4.4372 (6.1315) | 9.7081 (8.8083) |
| Log Likelihood | −4145.82 | −7762.22 | −5973.486 | −4139.69 | −7738.186 |
| AIC | 8305.64 | | | 8303.38 | |

Notes: standard errors are reported in parentheses. Significance levels: * at the 10% level, ** at the 5% level, *** at the 1% level.

This result aligns with the literature arguing that a pool of highly skilled human capital and the IT/high-tech workforce are essential for the expansion of e-commerce [22,23,27]. Our results validate [21]'s argument that modern e-commerce is underpinned by a complex infrastructure of specialists (cloud, cyber security, AI), as well as the conclusions of [26], which show that a high proportion of skilled employees stimulates the adoption of digital technologies at the regional level. At the same time, our findings introduce an important nuance: whilst the general tertiary education variable loses its statistical significance in specifications with robust standard errors—in line with the counter-intuitive conclusions of [29] regarding the limited effect of general formal education on e-commerce turnover—the technological specialisation of the labour force (the high-tech ecosystem) exhibits a positive and statistically significant association in the reported specifications. This is consistent with the premise put forward by [22,27], according to which specific digital skills and the technical

training of the workforce are the key drivers of the digital market, rather than the general level of educational attainment.

The control variables also display stability across models. Internet access, GDP per capita and Education are positive and significant determinants of e-commerce adoption, providing partial support for research hypothesis 4 (H4). However, population density remains statistically insignificant, indicating that the hypothesised association between urbanisation and e-commerce adoption is not supported by the empirical results. The significance of Internet access indicates that despite a European context characterised by widespread Internet availability, the differences in connectivity still remain a relevant factor for online purchasing. GDP per capita highlights the economic dimension of e-commerce adoption, suggesting that purchasing power and regional development are strongly associated with participation in digital commerce. Thus, once technological specialisation, connectivity, economic development, human capital, and spatial dependence are taken into account, the results provide limited evidence of an association between urban concentration and online purchasing.

The results for the control variables largely confirm the traditional macroeconomic literature, but refute certain hypotheses in the context of regional fixed effects:

Internet access: The positive and highly significant coefficient confirms the findings of classic studies [9,11,21,23,27,30,31], demonstrating that connectivity infrastructure remains a fundamental prerequisite for e-commerce, even with Europe approaching digital saturation.

GDP per capita: The positive and robust coefficient confirms traditional hypotheses [21,23,24,27,31,34], showing that purchasing power and economic development stimulate the B2C market. This result contrasts with the conclusions of [29], who found an insignificant impact of GDP per capita within the EU-28, as well as the hypothesis of a negative relationship identified by [26].

Population density: The lack of statistical significance in the fixed-effects models (FE, SAR, SARAR, SDM) is consistent with the findings of [27], who found that gross density is insignificant at the cross-national level. This finding does not support the hypothesis of a direct effect of urbanisation put forward by [25,26,36]. As suggested by the literature [23,35], in very dense regions, the existence of a highly accessible and efficient traditional physical retail network can create a cross-channel substitution effect, thereby neutralising the logistical advantages of urbanisation in the equation of e-commerce adoption.

Regarding the spatial effects, an important finding refers to the spatial lag coefficient (rho), which is positive and highly significant in all three models including it (SAR, SARAR and SDM), with stable values ranging from 0.41 to 0.53. The robustness of these results provides strong empirical evidence that regional e-commerce adoption is influenced not only by local economic and social characteristics, but also by e-commerce adoption levels in neighbouring regions. The presence of positive spatial dependence in digital consumer behaviour is confirmed, since regions surrounded by neighbours with higher levels of e-commerce adoption also tend to exhibit higher local adoption rates. This finding not only supports research hypothesis 2 (H2) of the study, but offers an important methodological insight, that is, the importance of explicitly including spatial interaction terms when analysing regional digital development. The spatial association is in line with the geographical diffusion of digital practices and the integration of regional consumer markets. However, it is worth noting that the estimated models do not identify the mechanisms responsible for these patterns, since this is beyond the objectives of the empirical analysis. This finding is consistent with the Theory of the Diffusion of Innovations [8] and aligns with the recent empirical literature highlighting the spatially integrated nature of the digital economy [38–40], which demonstrates that digital expansion reduces transaction costs and

creates spatial interdependence across regions. Rather than being an isolated choice, online consumption reflects positive spatial dependence across adjacent territories. While this pattern aligns with theoretical expectations regarding shared market conditions and regional interactions, our macro-level spatial design captures the resulting spatial interdependence rather than the specific underlying channels.

To account for alternative forms of spatial dependence, the analysis extends the SAR Model and SEM specifications by estimating the Spatial Autoregressive with Autoregressive Disturbances (SARAR) Model, the Spatial Durbin Model (SDM), and the Spatial Durbin Error Model (SDEM). As mentioned in the methodology, the SARAR Model incorporates spatial dependence in e-commerce adoption and spatially correlated disturbances, while the SDM and SDEM introduce spatially lagged explanatory variables to observe the association between neighbouring regions' characteristics and local adoption and to investigate the potential spillover effects generated by the explanatory variables.

The SARAR estimates indicate a positive and statistically significant spatial coefficient, with the spatial error coefficient also being significant, but only at a the 5% level. Accordingly, the Wald test for model reduction (Table 8) rejects the reduction of SARAR to SAR or to SEM, which also offers weak evidence for preferring SARAR to SAR. The two Durbin specifications show that only some of the spatially lagged explanatory variables are statistically significant across the models. Specifically, while spatially lagged technological specialisation displays a negative point estimate in both the SDM and SDEM specifications, these raw coefficients cannot be directly interpreted as marginal spillover effects. Therefore, the direct, indirect and total impacts are assessed to examine the magnitude and statistical significance of cross-regional effects and thus evaluate research hypothesis 3 (**H3**).

**Table 8.** Wald tests for spatial model restrictions.

| Reduction Test | Wald Chi Square | *p*-Value |
|---|---|---|
| SARAR → SAR | 4.2250 | 0.0398 |
| SARAR → SEM | 36.6011 | <0.001 |
| SDM → SAR | 12.6055 | 0.0274 |

Note: The arrow (→) indicates the proposed reduction from the general model to the restricted specification.

This surprising negative result theoretically contrasts with the hypothesis of spontaneous and uniform technological spillovers [37], which assumed that investment in R&D and knowledge naturally and beneficially spills over into neighbouring regions. Because the SDM impact decomposition reveals that the indirect technological-specialisation effect is not statistically significant, this finding cannot be interpreted as empirical evidence of spatial polarisation, competitive displacement, or regional brain drain. While theories of economic agglomeration [42,52] suggest that digital infrastructure and e-commerce development may trigger concentration forces, our impact decomposition reveals no statistically significant evidence of cross-regional technological spillovers in this context.

The choice of spatial specification considers both statistical evidence and model complexity. Although SAR provides a parsimonious representation of spatial dependence in regional e-commerce adoption, the Wald tests reject the restrictions of reducing both SDM and SARAR to SAR (Table 8). Moreover, SDM achieves a slightly lower AIC than SAR (8303.38 versus 8305.64), indicating a modest improvement in model fit. These results suggest that the more general specifications capture additional spatial dependencies that should not be disregarded. Consequently, SAR is retained as a parsimonious benchmark rather than the statistically preferred specification, while SDM provides complementary evidence of spatial dependence. The direct, indirect and total effects of SAR and SDM are

examined below, while the robustness of the results to alternative spatial weights matrices is assessed in Section 4.4.

Table 9 reports the decomposition of direct, indirect and total impacts from the SDM. The share of high-tech employment indicates a positive and statistically significant direct impact, suggesting that a one-percentage-point increase in the regional share of high-tech employment is associated with an average increase of approximately 0.6 percentage points in local e-commerce adoption. However, the negative indirect and total impacts are not statistically significant. Thus, although the coefficient of spatially lagged technological specialisation is statistically significant in the SDM specification, the impact decomposition does not reveal a significant negative cross-regional effect. Therefore, research hypothesis 3 (H3), stating that technological specialisation of neighbouring regions has significant spillover effects on local e-commerce adoption, is not supported by the SDM results, considering the estimated indirect effect is not statistically significant.

**Table 9.** Direct, indirect and total effects of the Spatial Durbin Model (SDM).

| Variable | Direct | Indirect | Total |
|---|---|---|---|
| Technological Specialisation | 0.5982 *** | −0.9790 | −0.3808 |
| Internet Access | 0.3664 *** | 0.1509 | 0.5173 *** |
| Ln (GDP/cap) | 14.2042 *** | 20.3790 *** | 34.5832 *** |
| Education | 0.1599 *** | 0.4254 ** | 0.5853 *** |
| Ln (Density) | 4.4657 | 12.9045 | 17.3702 |

Significance levels: ** at the 5% level, *** at the 1% level.

Regarding the remaining explanatory variables, the association between Internet access and e-commerce adoption is also local, as shown by the lack of significance of indirect effects. By contrast, GDP per capita and education generate positive and statistically significant direct and indirect impacts, suggesting that e-commerce adoption is associated not only with a region's own economic development and human capital, but also with the corresponding characteristics of spatially connected regions. More precisely, higher GDP per capita and educational attainment in neighbouring regions are associated with greater local participation in e-commerce. These results suggest that economic prosperity and human capital of surrounding regional economies may contribute to the increase in digital consumer adoption, consistent with the geographical interconnectedness of regional markets. Population density remains statistically insignificant across all impact measures, as expected from initial SDM estimates.

The SAR impact decomposition (Table 10) indicates statistically significant positive indirect impacts for the share of high-tech employment, Internet access, GDP per capita and education, suggesting the propagation of the regional explanatory variables through endogenous spatial dependence in e-commerce adoption. It is worth mentioning that in the SAR Model, the indirect impacts arise from the spatial autoregressive mechanism, since the estimated effects of neighbouring regions' explanatory characteristics are not included separately as in the SDM specification. In this case, a one-percentage-point increase in high-tech employment in one region is associated with an average increase of approximately 0.64 percentage points in local e-commerce adoption and an aggregate increase of approximately 0.61 percentage points across other regions, albeit transmitted through the spatially lagged dependent variable. Therefore, the SAR results remain mainly consistent with H2, indicating spatial dependence in regional e-commerce adoption.

**Table 10.** Direct, indirect and total effects of the Spatial Autoregressive (SAR) Model.

| Variable | Direct | Indirect | Total |
|---|---|---|---|
| Technological Specialisation | 0.6354 *** | 0.6066 *** | 1.2420 *** |
| Internet Access | 0.3271 *** | 0.3122 *** | 0.6393 *** |
| Ln (GDP/cap) | 14.7254 *** | 14.0570 *** | 28.7824 *** |
| Education | 0.1775 *** | 0.1694 *** | 0.3469 *** |
| Ln (Density) | 5.0082 | 4.7809 | 9.7891 |

Significance levels: *** at the 1% level.

### *4.4. Robustness Check*

To assess the robustness of the spatial panel results to the definition of spatial connectivity, the Spatial Autoregressive (SAR) Model and the Spatial Durbin Model (SDM) were re-estimated using alternative row-standardised spatial weights matrices based on the four- and six-nearest-neighbours (4 KNN, 6 KNN) specifications, in addition to the baseline 5 KNN specification (Appendix A). The same sample and model specifications were used. The results indicate that the spatial autoregressive coefficient remains positive and statistically significant at 1% across all specifications, ranging from 0.486 to 0.533 in the SAR Model and from 0.488 to 0.56 in the SDM. Technological specialisation, Internet access, GDP per capita, and education report positive and statistically significant coefficients across all three spatial weights specifications in both models. Population density remains statistically insignificant in all cases, except for a weak significance at 10% reported in the SDM 4-KNN specification. These findings confirm that the main estimated relationships and the spatial dependence are robust to alternative spatial weights matrices.

The comparison between SAR and SDM further highlights the importance of model specification. Although SAR achieves a marginally lower AIC under the 4-KNN matrix, SDM exhibits lower AIC values under the 5-KNN and 6-KNN specifications. Furthermore, the Wald tests (Table A3) reject the reduction of the SDM to SAR for the 5-KNN and 6-KNN specifications, but not for the 4-KNN one. These findings suggest retaining SAR as a parsimonious benchmark; however, we cannot argue its statistical superiority compared to the SDM. Thus, the SDM is retained as an important complementary specification.

The robustness analysis of SDM spatial impacts (Table A4) confirms that the direct effects of technological specialisation, Internet access, GDP per capita, and education remain positive and statistically significant across alternative spatial weights matrices. Among indirect effects, only GDP per capita consistently exhibits positive and significant spillovers. Technological specialisation shows negative but statistically insignificant spillovers, while those of Internet access and education vary in significance across specifications. Overall, the main direct effects are robust, but the indirect effects are more sensitive to the spatial weights specification.

The Wooldridge test indicates serial correlation in the baseline fixed-effects specification, motivating the use of region-clustered robust standard errors for that model. However, the spatial panel estimates rely on conventional maximum-likelihood standard errors, which are not explicitly adjusted for potential residual temporal autocorrelation. Consequently, although the sensitivity analysis demonstrates relative stability of the main coefficient estimates across alternative spatial weights matrices, it does not establish the robustness of their statistical significance to temporal dependence. The inferential results of the spatial models should therefore be interpreted with caution.

To further assess the adequacy of the spatial specifications and the robustness of the empirical findings, we conducted additional diagnostics for residual spatial autocorrelation and serial correlation.

First, residual spatial autocorrelation was tested in the SAR Model and SDM estimated with the 5-KNN spatial weights matrix. Moran's I tests were performed for each year of the 2015–2024 period. For both specifications, all annual Moran's I tests report $p$-values above 0.05, indicating that the residual spatial autocorrelation is not statistically significant at the 5% level. These results suggest that the models adequately capture the main patterns of spatial dependence in the data (Table A5, Appendix A).

Second, we investigated first-order serial correlation in the residuals of the 5-KNN SAR Model and SDM. Serial dependence was assessed through auxiliary regressions of model residuals on their one-period temporal lag, with standard errors clustered at the regional level. The estimated coefficients were positive and statistically significant for both the SAR Model (0.163, $p$-value $< 0.001$) and SDM (0.153, $p$-value $< 0.001$), indicating modest but significant temporal persistence in the disturbances. These findings motivated an additional robustness analysis incorporating a first-order autoregressive error structure.

Accordingly, both models were re-estimated by explicitly incorporating an AR(1) process in the error term, allowing disturbances within each region to be correlated across consecutive years, while maintaining the spatial autoregressive structure and two-way fixed effects. The estimated AR(1) coefficients were positive and statistically significant for both SAR and SDM, providing further evidence of first-order serial dependence. An important result is that accounting for serial correlation did not modify the main findings—the key explanatory variables retained their signs and statistical significance, while population density remained insignificant. Furthermore, the spatial autoregressive parameters remained positive and highly significant in both models (Table A6, Appendix A). These results support the robustness of the main empirical conclusions to first-order serial correlation.

## 5. Conclusions

The empirical findings across the sampled EU regions have several implications for regional digitalisation policies.

The positive and statistically significant direct association between regional high-tech employment and e-commerce adoption across spatial regression models highlights local technological specialisation as a key dimension of regional digital development. This finding suggests that policies relying solely on expanding Internet connectivity may be insufficient to address regional disparities in online purchasing behaviour, as fostering e-commerce adoption depends on the local digital ecosystem. In this regard, regional policies could adapt key principles from successful technology cluster models, such as Silicon Valley, by encouraging strategic partnerships between universities and the business sector. Such collaborations can accelerate digital skills development, facilitate technology transfer to SMEs, and support local innovation hubs associated with broader regional digitalisation.

Because a region's urbanisation level does not show a statistically significant association with its e-commerce adoption rate, policy priorities should shift to factors showing robust positive associations, such as digital infrastructure, income levels, and digital skills. Regional cohesion policies and national digitalization programmes should focus their resources on directly strengthening these core determinants. Regarding infrastructure, actionable steps include ensuring universal access to high-speed Internet and supporting local businesses in adopting essential digital technologies, such as cloud computing, cybersecurity solutions, and inter-regional payment systems. Regarding educational and digital skills factors, regional programmes should prioritise reskilling and upskilling initiatives focused on applied digital competencies and e-commerce skills for both the general public and SMEs, rather than relying solely on general formal education. Similarly, addressing economic factors requires targeted policies to boost disposable income and foster financial inclusion (such as

access to banking services and digital payments), thereby translating consumption potential into actual online purchasing behaviour.

In alignment with the EU's Cohesion Policy and the targets of the Digital Decade 2030 [53], national and regional authorities should directly invest in building local technology ecosystems, including advanced digital skills training, support for innovative start-ups, and regional digital innovation hubs. Passive technology adoption or relying on assumed spillover effects from neighbouring metropolitan regions is insufficient to bridge regional divides [54].

To strengthen local capabilities, less developed regions require targeted incentives designed to foster ICT skills and support small and medium-sized enterprises (SMEs) in adopting advanced technologies, such as artificial intelligence, cybersecurity, and cloud computing. Furthermore, EU-level policy-making should incorporate explicit mechanisms for inter-regional cooperation, through the funding of:

- Partnerships between technology hubs and SMEs in less developed regions, focused on joint training and skills-transfer programmes;
- Inter-regional networks of digital service providers, logistics, and e-commerce platforms;
- Joint initiatives for innovation and market-access programmes for enterprises in neighbouring territories.

Finally, given the strong positive spatial dependence observed in digital consumption across adjacent regions, regional policies may explore closer logistics coordination and interoperable cross-border or inter-regional payment infrastructures. Such measures could help support shared market integration across neighbouring territories, while remaining tailored to local structural conditions. Stated separately, policy-makers should design economic policies that avoid concentration of resources in highly developed regions and actively stimulate the capacity of lagging areas. The empirical evidence suggests that technological spillovers do not automatically diffuse across regional boundaries on their own (spontaneous spillovers). Therefore, regional policy cannot rely on passive technological diffusion; rather, targeted support is required to build local technological capabilities in less-developed regions.

Cooperation should aim for concrete outcomes—such as the effective use of digital tools by partner firms—rather than focusing solely on the number of partnerships formed. Economic policies need to be designed strategically to build the tech capacity of left-behind regions and transform regional structural asymmetries into effective mechanisms for knowledge transfer and innovation absorption. Spatially neutral policies that risk unintentionally reinforcing existing regional disparities should thus be carefully evaluated, ensuring that lagging regions receive targeted support for digital adoption.

*Limitations and Future Research*

Several limitations of this study should be acknowledged. First, the geographical coverage of the analysis is limited by data availability and consistency, resulting in the exclusion of certain EU countries and territories. Although the balanced panel provides substantial regional and temporal coverage, the exclusion of four EU Member States due to data limitations, particularly Germany and Poland, may affect the representativeness of the sample and limit the generalisability of the findings to the entire European Union. Second, high-tech employment captures only one dimension of regional technological ecosystems. Other characteristics, including innovation capacity, digital entrepreneurship, and firm-level technological adoption, may also contribute to regional digitalisation. However, these dimensions are not available at the NUTS-2 level for European countries. Finally, although the spatial panel models account for regional and temporal fixed effects and spatial dependence, their conventional maximum-likelihood standard errors are not explicitly adjusted

for residual temporal autocorrelation. Given the evidence of serial correlation in the baseline panel specification, this may affect the reliability of statistical inference in the spatial models.

Furthermore, the observational nature of the data limits causal interpretation, as potential endogeneity arising from reverse causality and omitted time-varying factors cannot be entirely excluded. Although regional and temporal fixed effects account for time-invariant regional heterogeneity and common temporal shocks, the estimated relationships should be interpreted as associations rather than causal effects.

Future research could address these limitations by expanding geographical coverage, incorporating additional indicators of regional technological capabilities, and employing estimation and inference procedures that jointly accommodate spatial and temporal error dependence.

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## Appendix A

**Table A1.** Robustness of SAR estimates across alternative KNN spatial weights matrices.

| Variable | SAR 4 KNN | SAR 5 KNN | SAR 6 KNN |
|---|---|---|---|
| Technological Specialisation | 0.5471 *** (0.1672) | 0.5982 *** (0.1668) | 0.6015 *** (0.1678) |
| Internet Access | 0.3135 *** (0.0303) | 0.3079 *** (0.0302) | 0.2987 *** (0.0304) |
| Ln (GDP/cap) | 14.3446 *** (1.4311) | 13.8633 *** (1.4297) | 13.5057 *** (1.4389) |
| Education | 0.1531 *** (0.0554) | 0.1671 *** (0.0553) | 0.1775 *** (0.0556) |
| Ln (Density) | 5.0498 (3.3298) | 4.7150 (3.3226) | 4.5483 (3.3435) |
| Spatial Lag Coefficient (Rho) | 0.4855 *** (0.0245) | 0.5183 *** (0.0251) | 0.5329 *** (0.0260) |
| Log Likelihood | −4151.5 | −4145.82 | −4151.99 |
| AIC | 8317 | 8305.64 | 8318 |

Notes: standard errors are reported in parentheses. Significance levels: *** at the 1% level.

**Table A2.** Robustness of SDM estimates across alternative KNN spatial weights matrices.

| Variable | SDM 4 KNN | SDM 5 KNN | SDM 6 KNN |
|---|---|---|---|
| Technological Specialisation | 0.5808 *** (0.1687) | 0.6593 *** (0.1682) | 0.6808 *** (0.1694) |
| Internet Access | 0.3372 *** (0.0379) | 0.3570 *** (0.0379) | 0.3425 *** (0.0381) |
| Ln (GDP/cap) | 10.9735 *** (2.4657) | 12.9324 *** (2.3158) | 15.1109 *** (2.3157) |
| Education | 0.1372 ** (0.0600) | 0.1333 ** (0.0594) | 0.1547 *** (0.0597) |
| Ln (Density) | 6.2391 * (3.7447) | 3.6603 (3.6966) | 1.9688 (3.6812) |
| Spatial Lag Coefficient (Rho) | 0.4880 *** (0.0261) | 0.5338 *** (0.0267) | 0.5598 *** (0.0274) |
| W. Technological Specialisation | −0.6532 ** (0.3036) | −0.8368 ** (0.3258) | −1.0322 *** (0.3517) |
| W. Internet Access | −0.0739 (0.0540) | −0.1158 ** (0.0563) | −0.1072 * (0.0586) |
| W. Ln (GDP/cap) | 5.8304 * (3.0780) | 3.1895 (2.9693) | −0.4527 (3.0607) |
| W. Education | 0.0975 (0.0969) | 0.1395 (0.1034) | 0.0575 (0.1120) |
| W. Ln (Density) | −1.4281 (5.8417) | 4.4372 (6.1315) | 9.8544 (6.5794) |
| Log Likelihood | −4146.95 | −4139.69 | −4144.94 |
| AIC | 8317.89 | 8303.38 | 8313.88 |

Notes: standard errors are reported in parentheses. Significance levels: * at the 10% level, ** at the 5% level, *** at the 1% level.

**Table A3.** Wald tests for the reduction of SDM to SAR across alternative KNN spatial weights matrices.

| Reduction Test | Wald Chi Square | *p*-Value |
|---|---|---|
| SDM → SAR (4 KNN) | 9.0904 | 0.1055 |
| SDM → SAR (5 KNN) | 12.6055 | 0.0274 |
| SDM → SAR (6 KNN) | 14.7498 | 0.0115 |

Note: The arrow (→) indicates the proposed reduction from the general model to the restricted specification.

**Table A4.** Robustness of direct, indirect and total effects under the 4-KNN and 6-KNN spatial weights matrices.

| | 4 KNN | | | 6 KNN | | |
|---|---|---|---|---|---|---|
| **Variable** | **Direct** | **Indirect** | **Total** | **Direct** | **Indirect** | **Total** |
| Technological Specialisation | 0.5320 *** | −0.6734 | −0.1414 | 0.6037 *** | −1.4018 * | −0.7981 |
| Internet Access | 0.3491 *** | 0.1650 * | 0.5142 *** | 0.3525 *** | 0.1819 | 0.5344 *** |
| Ln (GDP/cap) | 12.4493 *** | 20.3728 *** | 32.8220 *** | 16.0593 *** | 17.2364 *** | 33.2957 *** |
| Education | 0.1589 *** | 0.2995 * | 0.4584 ** | 0.1718 *** | 0.3102 | 0.4819 * |
| Ln (Density) | 6.4523 * | 2.9445 | 9.3968 | 3.2668 | 23.5894 * | 26.8562 * |

Significance levels: * at the 10% level, ** at the 5% level, *** at the 1% level.

**Table A5.** Residual spatial autocorrelation in SAR Model and SDM (5-KNN).

| Year | SAR—Moran's I | SDM—Moran's I |
|---|---|---|
| 2015 | −0.0874 (0.079) | −0.0769 (0.126) |
| 2016 | −0.0268 (0.657) | −0.0213 (0.746) |
| 2017 | 0.0744 (0.0797) | 0.0828 (0.053) |
| 2018 | −0.0506 (0.339) | −0.0494 (0.352) |
| 2019 | −0.0074 (0.982) | −0.015 (0.852) |
| 2020 | −0.0769 (0.126) | −0.0824 (0.0993) |
| 2021 | 0.0393 (0.317) | 0.0394 (0.315) |
| 2022 | 0.0234 (0.520) | 0.0219 (0.542) |
| 2023 | −0.0354 (0.529) | −0.0292 (0.620) |
| 2024 | −0.0588 (0.257) | −0.0563 (0.280) |

Note: *p*-values are reported in parentheses.

**Table A6.** Robustness analysis: 5-KNN SAR and SDM estimated with AR(1) errors.

| Variable | SAR | SDM |
|---|---|---|
| Technological Specialisation | 0.5595 *** (0.1710) | 0.6008 *** (0.1726) |
| Internet Access | 0.3034 *** (0.0302) | 0.3428 *** (0.0377) |
| Ln (GDP/cap) | 13.6960 *** (1.4106) | 11.9790 *** (2.4485) |
| Education | 0.1569 *** (0.0567) | 0.1292 ** (0.0605) |
| Ln (Density) | 4.1541 (3.5121) | 3.6064 (3.9099) |
| Spatial Lag Coefficient (Rho) | 0.5032 *** (0.0263) | 0.5132 *** (0.0277) |
| W. Technological Specialisation | | −0.6993 ** (0.3371) |
| W. Internet Access | | −0.1040 * (0.0560) |
| W. Ln (GDP/cap) | | 4.2827 (3.0193) |
| W. Education | | 0.1389 (0.1072) |
| W. Ln (Density) | | 2.7021 (6.4772) |
| Temporal autoregressive coefficient (Phi) | 0.1511 *** (0.0186) | 0.1490 *** (0.0187) |

Notes: standard errors are reported in parentheses. Significance levels: * at the 10% level, ** at the 5% level, *** at the 1% level.

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