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Investigating the digital convergence in European Union: an econometric analysis of pitfalls and pivots of digital economic transformation

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ABSTRACT
This study aims to investigate the convergence of digitalisation in the European Union (EU) in terms of DESI per capita in all EU countries during 2015–2020. The empirical results sustain the hypothesis of convergence of the degree of digital level in the European Union member countries. In evaluating the convergence process, we also aimed to investigate the role of economic development and education, measured by gross value added and education index. The analysis results, the use of sigma and beta convergence methods, showed that the role of economic development is likely to be decisive in resolving disparities, as opposed to that of educational development. The sigma convergence analysis showed that the gap between the EU-28 countries regarding digitalisation tends to decrease in the analysed period. Spatial data analysis, in turn, provides strong evidence for the presence of spatial autocorrelation in the DESI distribution. This result is based on a spatial lagged model that considers that DESI growth rates are related both to their initial levels of digitalisation and the growth rates of neighbouring regions.

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1. Introduction

The challenges posed by the health crisis have imposed digitalisation as one of the efficient and effective feedback solutions to respond to these causes, and the digital channels have proven to be sustainable and lucrative work solutions for both individuals and companies. Presenza and Petruzzelli (2019) referring to these aspects argued that global societies will become familiar with the phenomenon of globalisation and the new tools imposed by it, and the business environment will adapt and transform accordingly. From this perspective, digitalisation has allowed and encouraged the

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development of new, scalable business models, reducing the costs of trading, searching and identifying available resources, including market, automation of tasks and occupations, and the emergence of new specific industries. In a large approach, digitisation could be perceived as one of the most dynamic contemporary trends, presenting equally opportunities and risks for the development of society, generating the development and expansion of significant processes of change and restructuring in almost all economic sectors and society as a whole. In this sense, Gouvea et al. (2018) also remarked that digitalisation can be one of the most obvious and significant transformations in promoting the sustainability of society and production systems.

The company's digitalisation represents one of the major global trends, which determines transformations at the level of organisations from all sectors of activity and society. This reform involves adopting information and communication technology (ICT) solutions to optimise workouts and provide better services to customers or citizens as Lappi et al. (2019) argue. This has led researchers (Hagberg et al., 2016) to talk about a fundamental reform of digitalisation. It is increasingly affecting society on all fronts, with positive effects, by increasing access to information and the use of increasingly efficient technologies.

As it is highlighted in a large body of literature (Fernández-Portillo et al., 2020; Veeramacheneni et al., 2007) the digital dive started to become an issue concerning economic growth and productivity (Alfaro Cortés & Alfaro Navarro, 2011), and a matter of great importance for both domestic policymakers (Liu, 2022), also for the organisation success and its stakeholders and, not among the last, for the international organisations (World Economic Forum, 2018). Thus, digitalisation involves an innovative process in which research and the application of research results in real life is a necessary premise. These successive waves of innovation have led to unprecedented transformations of the economy and have reconfigured some sectors of the business models. There are also key technologies from the last two decades that have accelerated the process of digitalization, making it ubiquitous in the lives of individual users, such as the smartphone widely introduced in 2007, artificial intelligence (AI) and blockchain or distributed ledger technology (OECD, 2017).

According to Bughin et al. (2016), as of 2015, the European Union (EU) operated with only 12% of its digital potential. The digitalisation of Europe is uneven and still a long way from its full potential. There were also significant differences among European countries in digital intensity and between different sectors of activity. In 2015, the digital economy represented 5.0% of EU-28 GDP, the largest share being private consumption (53% of the digital economy), followed by private investment (15%). But, there were gaps in this regard as well (European Commission, Directorate-General for Research and Innovation, 2017). Northern European countries generally tend to have more digitalised economies than southern ones. Estimates show that Europe's digital transition is projected to have a significant economic impact. However, it has made progress in terms of digital infrastructure, a segment where, in 2015, only the United Kingdom surpassed the United States in the stock of digital capital. Bughin et al. (2016) showed that a plus of the member countries is given by the development of flourishing digital hubs, located mainly in the cities: Amsterdam, Berlin, Dublin, London, Paris and Stockholm. Highly successful

European companies, developed during the age of digital technology such as Spotify and Skype, have expanded globally. Other companies have successfully emerged by copying the model of digital businesses that already operated in other global markets

Avram (2020) showed that the predominantly same countries are in the first places in capitalising on the advantages offered by the digital market. Northern European countries generally tend to have more digitalised economies than southern ones. In the fields of e-administration, e-business and e-commerce, e-health or online security and confidentiality, Sweden, Denmark and Finland stand out, and Bulgaria, Romania and Italy are usually located at the opposite pole. In addition, there is a considerable gap in terms of digitalisation between EU Member States ranked first and last. This indicates the need for in-creased efforts, both at Union level as a whole and at the level of each Member State, in order to close or at least narrow the existing gaps. The data show (Avram, 2020) that the level of digitalisation in EU member states is well below their potential, with visible discrepancies from one state to another, requiring sustained efforts to close the gap between states and make progress across the European Union.

In this context, the European Commission launched the "Digital Package" on 19 February 2020, placing digitalisation at the heart of all its policies and priorities. Convergence trends between the EU members have been reached in economic and social dimensions in recent decades. The 2008–2011 crisis has stopped these trends. Thus, since 2008, the performance of the EU members has been marked by specific patterns of stagnation or deviation. The different performances of EU members and the deepening of inequalities have raised concerns about this issue. The primary concern concerns the feeling of injustice and social inequity among citizens, which fuels anti-European sentiment and undermines faith in the European project. In order to be able to formulate effective policies to achieve the upward convergence objective, decision-makers need information on the dynamics and divergent trends both between and within EU Member States.

This study started from the concern of the EU member states regarding their different performances. The gaps widened in the aftermath of the economic crisis of 2008. Maintaining disparities spreads feelings of injustice and social inequity, fuelling anti-European manifestations while contradicting the idea that deepening European integration leads to increased cohesion.

The situation generated by the Covid-19 crisis has accentuated the importance of digitalisation, demanding digital convergence, which would allow free access to information and communication. This implies for the countries at the bottom of the ranking, the recovery of gaps in the digital literacy of citizens, in the use of digital technologies in communication between individuals and institutions, in production processes and development of society as a whole, using integrated simplified electronic systems. This reduction of digital discrepancies can be achieved only by the large-scale implementation of digital technologies, which requires essential socio-economic transformations. The pandemic has also led to increased demand for digital public services and their use, accelerating the digital transformation of the contemporary societies. According to a study published by the European Investment Bank (2022), during the pandemic, the digital transformation has often become essential for the survival of companies. It has accelerated the transformation of the European economy.

Although remarkable progress has been made in reducing disparities among the Member States, especially after 2014, after the effects of the 2008–2011 economic crisis began to fade, the EU continues to face differences between countries, both economically, as well as socially, and also in the field of digitalisation. Thus, economic and social growth, accompanied by a high degree of convergence, is one of the main current challenges for decision-makers. The EU Member States continue to evolve differently, with gaps remaining. While Western and Central European countries concentrate most of their economic activity and investment, Eastern countries still face economic and social difficulties, experiencing low levels of investment and improper services. Reducing these gaps and ensuring coherent development are essential concerns for decision-makers in these countries. The European Commission is constantly developing regional development policies, tools and mechanisms. However, studies analysing regional economic convergence reveal the persistence of significant gaps, both economically and socially.

There is a constant "catching up" of economic development in modern history with overcoming the gaps. Our study aims to investigate whether this trend can be highlighted in the digitalisation of economies. The goal of this article is to investigate the degree of convergence at the level of EU member states, taking into account the defining elements of each economy, for the time period between the years 2015 and 2020. The study deals with the convergence of the digitalisation of EU countries, using the models used to assess economic growth by estimating the convergence σ and β of Digital Economy and Society Index (DESI) described in (European Commission, 2021). We also examine the role of economic and cultural development in the convergence process, using the gross value added (GVA) and the education index from the human development index. From this perspective, we appreciate that digital convergence should be a regional and national goal.

New developments in the socio-economic environment have raised concerns among policymakers. Therefore, economic development specialists have paid more attention to the phenomenon of convergence. They studied the evolution of the process of economic and social development in several countries, following the propagation effect of the various components of growth. In the dedicated literature, real convergence in the strict sense is most often analysed by two indicators: beta convergence (β) and sigma convergence (σ).

The concept of β convergence is related to Solow's neoclassical model, which assumes that the rate of economic growth depends fundamentally on the growth rates of two determinant factors, namely, capital stock and labour—the factors of production, whose connection is modelled by the production function. According to Solow, the marginal productivity of capital is decreasing, which means that economic growth will stop at some point. Thus, such an economy tends towards a stable status, the production function can regain an upward trend only under the influence of exogenous factors, such as, for example, technological progress or labour growth (Fischer & Dornbush, 1995 apud Dragulanescu & Dragulanescu, 2013). According to (Iancu, 2009), empirical research to validate the various convergence hypotheses attests that the situation of alignment of all countries to an absolute convergence cannot exist.

The equilibrium status is related, and often in a direct manner, to the specific economic characteristics, therefore convergence could be identified but not necessarily at the same long-term levels and values. In this situation, beta-convergence is conditioned. In the literature, Barro (1991) and Barro and Sala-I-Martin (1992) developed the conditional convergence concept, which assumes that the expected negative relationship between the initial level of per capita income and the growth rate is maintained only when structural differences between poor economies and rich economies remain constant. Along this line, Mankiw et al. (1992) deduced in their study that the conditional convergence model highlights the tendency to a systematically faster growth of the backward economies, detrimental to the developed economies, once the conditioning factors of this process are controlled.

Barro and Sala-I-Martín (1997) broadened the concept of capital in the neoclassical model from physical goods by including human capital and stressing the role of education. This approach has led to an impressive number of studies that have attempted to empirically measure the degree of beta convergence in different contexts.

Another concept of convergence, developed by Baumol (1986), is σ-convergence, as Barro and Sala-i-Martin (1990) called it. It refers to a reduction in disparities between regions over time. There were different opinions on convergence analysis in the literature, σ and β-convergence being the subject of debate. Chatterji (1992) and Quah (1996) pointed out that convergence clubs are formed endogenously, being associated with different initial conditions, and income distribution between economies is polarised, suggesting alternative empirics based on studying the dynamics of evolving distributions. Developing the topics addressed in these influential articles, the study of income convergence between countries continued to be a topic of interest, the number of studies growing continuously. To summarise, in the literature, two distinct generations of economic growth models emerged: the exogenous growth model, inspired by the neoclassical theory, and the endogenous growth model. Subsequently, the regional growth model takes shape. They take into account specific factors related to the level of development of a country or region (Williamson, 1965; Fujita et al., 1999; Brasili and Gutierrez, 2004; Dall'erba and Le Gallo, 2008). New economic geography models for interpreting regional disparities have managed to explain the lack of convergence. In our opinion, the concept of convergence can exceed the theory of economic growth, because the development of a country is a much more complex phenomenon, as Konya & Guisan (2008) showed. Thus, the dimensions of human life are becoming increasingly important (Bucur and Stangaciu, 2015).

As highlighted in some recent studies (Majumdar, 2020), the digitalisation of the economy is the way to recover economic gaps. In April 2019, The European Parliament and The Council published Directive (EU) 2019/790 on copyright and related rights in the Digital Single Market (DSM). Also, Gaftea et al. (2018) argued that the participation of EU member states in the DSM is strongly divided. Thus, EU countries with a degree of development below the European average are taking their own measures, leading to over-regulation and bureaucratic barriers. In this way, the Digital Single Market can become, at the same time, a support and a development mechanism, according to Gaftea et al. (2018).

Since 2014, the European Commission has monitored Member States' progress in the digital field and published annual reports on Digital Economy and Society Index

(DESI), which includes a broader content on the country's digital profile description, holistic analysis of European key digital policy areas, digitalisation status, and identifies priority areas in the field. (European Commission, 2021).

Empirical studies analysing digital convergence trends after the implementation of new regional development policies are minimal. In addition to the classical assessment of the convergence of digitalisation following the economic convergence model of Barro and Sala-i-Martin (1990, Barro and Sala-I-Martin, 1992, Barro and Sala-I-Martin, 1995, and 2004), this study incorporates spatial variables into the cross-sectional model, seeking to improve the model's explanatory power. Thus, this study will make a valuable contribution in explaining the regional convergence in terms of digitisation among the EU member states in a broader context of current economic developments.

This research extends the previous works in the field by considering three representative indicators, one for digital economy (DESI), another one for economic performance and growth (gross value added) and a third one for the level of education (education index), with the last two indicators acting also as control variables in this research. We are not only undertaking to design Spatial Econometric Models using the variables considered in the study, but also to determine whether there is a degree of convergence with regard to ICT development and use. This study additionally employs the traditional Sigma Convergence and Beta Convergence, that lead to a certain degree of divergence or convergence by using Spatial Econometric Data Models. Furthermore, this study creates patterns and models among countries considered for the study, based on the relation between digitalisation and economic development, and test the convergence degree. Section 2 addresses the methodological aspects, with the specification of the methods employed, describing the framework and investigation procedure, including a review of the variables. Section 3 describes the Results and articulates the Discussions, and the final section is dedicated to the conclusions and main findings of the research. This article closes by highlighting the limitations of and future directions for research.

2. Materials and methods

2.1. Data

This study analyses the potential of digitalisation convergence among the EU-28 countries from 2015 to 2020. The employed datasets are extracted from (European Commission, 2017; 2021; European Investment Bank, 2020; 2022; United Nations Development Programme, 2022) and covers the time interval mentioned above. The UK was also among the countries considered because Brexit took place in 2020. The Digital Economy and Society Index (DESI) (European Commission, 2017; 2021) was employed in order to measure digitalisation as the dependent variable. The log transformation was applied on order to reduce the variability of data. In terms of investigating the role of economic growth and the level of education, in the process of digital convergence, the gross value added Eurostat (2021) and education index (Human Development Report Office, 2022) were considered as control variables in this analysis. The dataset for the gross value added was extracted from Eurostat (2021). These are expressed in Current prices, million euros. The Education Index is a part imported from the Human Development Index (HDI) and it expresses the average of mean years of schooling (of adults) and expected years of schooling (of children), as considered by the Human Development Report Office (2022). For 2020, the values of the beginning of education were estimated using the forecast function.

2.2. Sigma convergence

Following the framework used by Kındap & Doğan (2019), we assessed sigma convergence and the evolution of the gap between countries using six indicators: (1) Maximum/minimum ratio, (2) Gini index, (3) Coefficient of variation, (4) Relative mean deviation, (5) Atkinson index and (6) Theil index. Sigma convergence occurs when the differentiation of the analysed features between economies decreases over time. In this sense, it can be said that its standard deviation between economies can measure the dispersion of the analysed variable. In addition, the coefficient of variation (CV) can be used in the convergence analysis, calculated according to the relation in Equation (1). In our analysis, we used the coefficient of variation of DESI.

$$CV = \frac{Standard\ Deviation}{Mean} \tag{1}$$

We verified the decrease in the digitalisation index dispersion over time by performing a regression of the trend line of the coefficient of variation for this index, following the procedure described by Gömleksiz et al. (2017). Thus, in Equation (2), we considered the evolution of the coefficient of variation of LnDESI levels in the EU-28 countries, as a dependent variable, for the period 2015–2020 (t = 1 … 6).

$$CV_{y,t} = \gamma_{0+} + \gamma_1 t + u_t \tag{2}$$

To test absolute or unconditional β convergence, we used the following regression equation:

$$\frac{1}{T} ln\left(\frac{y_{i,\ \ t}}{yi,\, t_0}\right) = \gamma_0 - \alpha_1 ln(y_{i,\,t_0}) + \varepsilon_i \tag{3}$$

Equation (3) is the result of a regression of the average rate of increase of the degree of digitisation of country i, based on cross-sectional data, in the period T ($T = t_{0\ \ldots\ t}$). Also, $y_{i,t0}$ is the initial year of period T, and γ_0 is a constant. We used a modified version of Equation (3) to test conditional β-convergence, considering the specific features of each country. In Equation (4), the $GVA_{i,t0}$ and $EI_{\mathrm{i,t0}}$ represent Gross Value Added and Education Index, respectively:

$$\frac{1}{T} ln\left(\frac{y_{i,\ \ t}}{yi,\, t_0}\right) = \gamma_0 + \alpha_1 ln(y_{i,\,t_0}) + \alpha_2 ln\left(yGVA_{i,\,t_0}\right) + \alpha_3 ln(EI_{i,\,t_0}) + \varepsilon_i \tag{4}$$

2.3. Beta convergence

Sigma Convergence is a tool designed to provide an instant picture of regional disparities and regional income dispersion. We aimed to extend this method to assess differences at the EU-28 level in the degree of digitalisation. This method is beneficial, but it does not provide enough data to completely reveal the presence of a convergence process. Instead, the beta convergence method highlights the evolution of the gap reduction between underdeveloped and prosperous countries, providing a tool to highlight and assess convergence.

According to Barro and Sala-I-Martin (1997), beta convergence is approached in two hypotheses: (i) absolute (unconditional) convergence, independent of the initial conditions in these countries, and (ii) conditional convergence, in which case convergence occurs only in countries structurally similar. As (Gömleksiz et al., 2017) argues, there are two reasons for the study of absolute regional convergence. The first refers to the fact that absolute convergence is much more relevant in the approach to regional policy. The study of the convergence of EU-28 countries in terms of digitalisation has, on the one hand, practical implications, in terms of specific policy definitions. On the other hand, the structural differences between countries within a development region are expected to be much smaller than those between these regions.

The first studies on beta convergence between economies were performed by Barro and Sala-i-Martin (1990), Barro et al. (1991), and Barro and Sala-I-Martin (1992), who formulated a general estimation relationship. Following the framework used by Kındap & Doğan (2019), we adapted this general relation, considering that y represents the level of digitalisation of a country, evaluated by the DESI indicator, in logarithmic expression, using the following equation:

$$\frac{1}{T} ln\left(\frac{y_{i,\ \ t+T}}{yi, t}\right) = \alpha - \left(\frac{1 - e^{-\beta T}}{T}\right) ln(y_{i,t}) + u_{i,t} \tag{5}$$

where i expresses the country, t indexes time, T is the length of the observation interval, namely 2015–2020, the coefficient β is the rate of convergence, and u is an error term. In order to detect the existence of convergence, we rearranged Equation (5) as follows:

$$ln\left(\frac{y_{i,\ \ t+T}}{yi, t}\right) = \alpha + \gamma ln(y_{i,t}) + u_{i,t} \tag{6}$$

where a negative value of the coefficient γ indicates convergence.

Relation (7) is used to calculate the convergence rate/speed, according to the methodology given by Barro and Sala-I-Martin (2004).

$$\gamma = -(1 - e^{-T\beta})$$

$$\text{Convergence speed: } \beta = -\frac{ln(1+\gamma)}{T} \tag{7}$$

According to Equation (7), if convergence occurs ($\gamma < 0$), then higher initial levels of the degree of digitalisation have a negative effect on the final increase. Thus, β could express the annual convergence rate of an economy to its equilibrium level of digitalisation. In the convergence analysis, it is also essential to estimate the half-life (τ), defined as the period required for half of the initial inequalities of the digitalisation level to disappear. To evaluate this indicator, the relation (8) is used

$$\tau = \frac{ln(2)}{\beta} \tag{8}$$

2.4. Spatial autocorrelation

In recent years, spatial effects have been considered in beta convergence analyses as it is described in (Gömleksiz et al., 2017). Looking to assess regional convergence from a spatial perspective, Rey and Montouri (1999) showed that spatial externalities and propagation effects are significant in analysing growth patterns. Thus, they demonstrated that this approach offers more perspectives for analysing the phenomenon of convergence and the trend of economic growth at a regional level. These results justify the consideration, in regional analyses, of spatial autocorrelation, as Kındap & Doğan (2019) argued. They are based on the definition that Griffith (2003) gives to spatial autocorrelation. He showed that spatial autocorrelation is a measure of grouping global data, and reflects the degree to which objects or activities located in a given geographical unit are similar to other objects and activities located in neighbouring or nearby geographical units, demonstrating an interdependence between neighbouring regions. Following the framework used by Kındap & Doğan (2019), we used the Moran index to test whether the DESI index distribution is random or whether a distribution model can be identified. Moran (1950) introduced this index for measuring spatial dependence, an indicator sensitive to extreme values, as stated by Cliff and Ord (1975). According to Celebioğlu and Dall'erba (2010), Moran's I statistics provide tools for testing and highlighting both global spatial autocorrelation and local spatial autocorrelation. To measure global spatial autocorrelation, following the procedure described by Kındap & Doğan (2019), we used Moran's I, defined by Anselin (1988), and Anselin (2005), using an adapted relation (9), as follows:

$$I = \frac{N}{\sum_{i,j=1}^{N} w_{i,j}} \frac{\sum_{i,j=1}^{N} w_{i,j}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{9}$$

where N is the number of countries, y_i is the DESI (in logarithmic expression) of country i, y_j is the DESI of country j, $\bar{y}$ is the average DESI for all countries, and w_{ij} is an element of the standardised matrix of spatial weights (W). To estimate the spatial matrix, following the procedure described in (Kındap & Doğan, 2019) we constructed the queen contiguity neighbourhood structure.

As described by Kındap & Doğan (2019), local spatial autocorrelation analysis allows highlighting of those regions with a significant local spatial autocorrelation. The method involves calculating the significance of local statistics for each country, allowing the identification of the location of spatial clusters. According to Anselin (2005), a spatial cluster is signalled by a positive and significant local spatial autocorrelation relationship: (1) High-High (HH), showing a high-income region, with high-income neighbours, and (2) Low-Low (LL), showing a low-income region with low-income neighbours.

A spatial aberration is signalled by a negative and significant local spatial autocorrelation relationship: (1) High-Low (HL), showing a high-income region, with low-income neighbours, and (2) Low-High (LH), showing a low-income region with high-income neighbours. To assess spatial dependence, we used the local Moran's I statistic, calculated as follows:

$$I_i = \frac{(y_i - \overline{y})}{\frac{1}{N}\sum_{i=1}^{N}(y_i - \overline{y})^2} \sum_{i,j=1}^{N} w_{i,j}(y_i - \overline{y}) \tag{10}$$

In the case of a significant spatial autocorrelation, testing the beta convergence hypothesis regarding spatial parameters and the interaction between locations is necessary.

2.5. Spatial econometric models

According to Elhorst (2014), three different types of interaction effects can be used to explain why a variable measured in one location can be influenced by values measured at other sites: (i) endogenous interaction effects among the dependent variables, or (ii) exogenous interaction effects among the independent variables and (iii) interaction effects among the error terms. This approach has led to the development of a comprehensive model of spatial grouping, as shown by Kındap & Doğan (2019):

$$Y = \alpha + \delta WY + X\beta + WX\theta + \mu \tag{11}$$

$$\mu = \tau W\mu + \varepsilon$$

where WY expresses the endogenous interaction effects, WX expresses the exogenous interaction effects, Wμ expresses the interaction effects among the values of the disturbing variable of the different units, and ε is the independent and identically distributed error term. Introducing the model from relation (11) into the beta convergence model, a customised model resulted, as follows:

$$ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \delta Wln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) + \gamma ln(y_{i,t}) + \theta Wln(y_{i,t}) + u_{i,t} \tag{12}$$

$$u_{i,t} = \tau W u_{i,t} + \varepsilon_{i,t}$$

As it is described in the literature by LeSage (2015) imposing restrictions on one or more parameters (δ, θ, λ) of the general spatial grouping model, three linear spatial econometric models can be obtained as: (i) Spatial Error Model (SEM), (ii) Spatial Lag Model (SLM) or (iii) Spatial Autoregressive Combined Model (SACM).

The SEM assumes that only the error terms in the regression are correlated. According to (Rey and Montouri, 1999), it can be expressed as

$$ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \gamma ln(y_{i,t}) + u_{i,t} \tag{13}$$

The SLM examines how countries' DESI growth rates depend on their own initial level of digitisation, but also on growth rates in the corresponding neighbouring countries. The SLM can be expressed as:

$$ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \gamma ln(y_{i,t}) + \delta W ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) + u_{i,t} \tag{14}$$

The SACM includes both a self-correlated dependent variable and an auto-correlated disturbance.

$$ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \delta W ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) + \gamma ln(y_{i,t}) + u_{i,t} \tag{15}$$

For data processing, GeoDa software has been applied, which is designed as a tool that facilitates the exploration and analysis of geospatial data (Anselin, 2005).

3. Results and discussion

3.1. Empirical analysis

The latest regional statistics show that disparities in digitalisation between EU-28 countries are still high (Figure 1a) and suggest the presence of the convergence phenomenon. While the DESI level of the most digitalised country is almost 2.18 times higher than that of the least digitalised country in 2015, the ratio dropped to 1.85 in 2020. As Figure 1b shows, the less digitalised regions in 2015 had better performance in increasing the degree of digitalisation during 2015–2020.

The authors note that, during the period under review, due to the harmonisation efforts of the governments of the European Union's member states, they improved digitalisation policies, creating the premises for Europe's Digital Decade (https://ec.europa.eu/info/strategy/priorities-2019-2024/europe-fit-digital-age/europes-digital-decade-digital-targets-2030_en). Figure 2 shows the relative positions of EU-28 countries on digitalization between 2015 and 2020 and highlights that the less digitalised countries converge to the EU average. Looking at the absolute values, we see that in

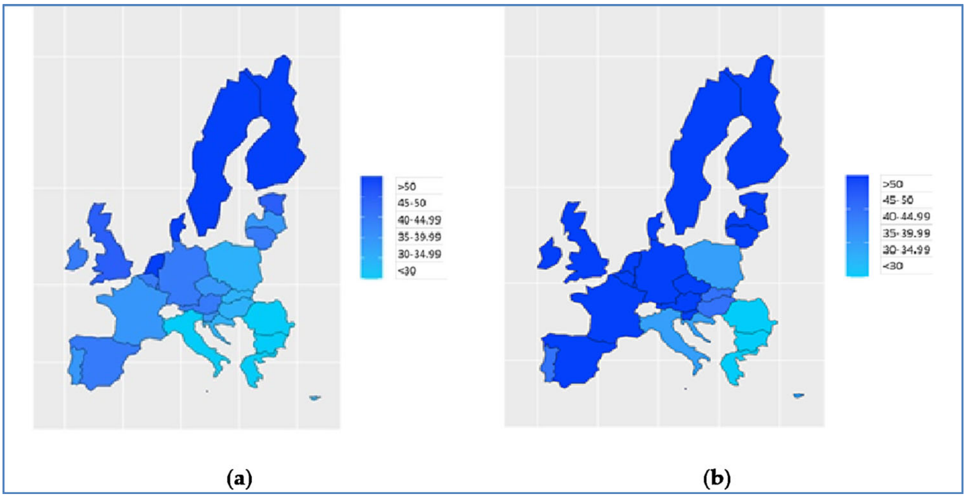

Figure 1. DESI by EU-28 countries: (a) 2015 and (b) 2020.
Source: authors̀ based European Commission (2021)

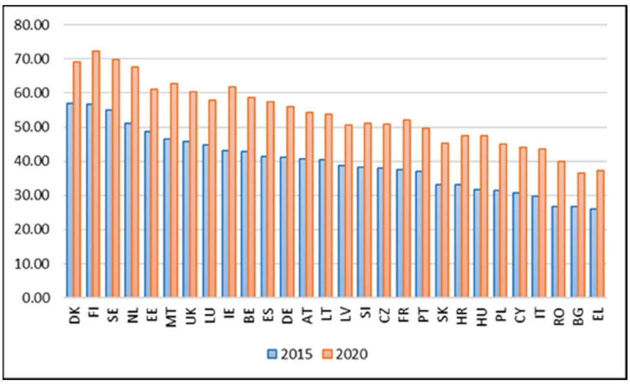

Figure 2. DESI by EU-28 countries: (a) 2015 and (b) 2020.
Source: authors̀ based European Commission (2021)

2015–2020, the Digital Economy and Society Index increased in all countries (Figure 2).

Thus, the relative convergence in Figure 3 occurred because countries with relatively low DESI performed better in growth and contributed to the increase in digitalisation at the EU level relatively more than in the past.

Although the results presented in the reports of European and national bodies to some extent support the existence of a regional convergence of the degree of digitalisation, we considered that an additional analysis is appropriate to obtain a clear conclusion. Thus, this study aims to verify whether the EU Member States converge using the new approaches in the literature, trying to answer whether regional disparities have narrowed in 2015–2020. In this regard, Figures 1 and 2 show that countries that are close to each other have similar DESI levels and growth rates. Next, we considered testing the statistically significant effect of geographical proximity on the growth rates of the digitalisation of countries.

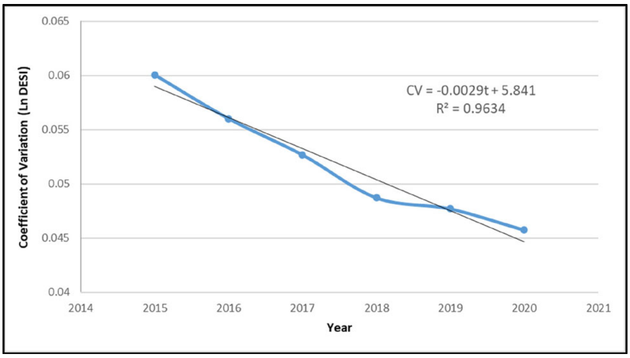

Figure 3. σ-Convergence of DESI in EU-28 countries.
Source: authors 'computation based European Commission (2021)

Table 1. The results of the σ convergence analysis of DESI for the EU-28.

Year	Mean	Standard deviation	Coefficient of variation
2015	3.6593	0.2197	0.0600
2016	3.7227	0.2085	0.0560
2017	3.7813	0.1992	0.0527
2018	3.8427	0.1872	0.0487
2019	3.9020	0.1861	0.0477
2020	3.9677	0.1815	0.0457

Source: authors' own computations.

3.2. Sigma convergence of digitalisation of EU countries

Analysing the data presented in Table 1, obtained from the convergence analysis σ for the studied countries, we observed that the coefficients of variation and the standard deviation tend to decrease as DESI grows, pointing out that, over time, DESI tends to equalise among economies and the variation between their DESI levels decreases. This result argues that σ-convergence exists between EU member states for 2015–2020, in terms of digitalisation. The data show that the standard deviation of the DESI of EU member states was almost 0.22 in 2015 and decreased to 0.18 in 2020. At the same time, the coefficient of variation decreased from 0.06 to a value less than 0.05. Thus, it is possible to conclude that, in 2015–2020, the evolution of the DESI growth rate shows a decreasing dispersion of digitalisation in the European Union, also supporting the hypothesis of the existence of σ-convergence.

Figure 3 shows the evolution of the DESI coefficients of variation for the analysed countries, together with the trend line over the analysed period. It reveals a σ-convergence during 2015–2020, when the countries' CV continuously decreases during the period, from 0.0600 in 2015 to 0.0457 in 2020. During this period, DESI in the EU-28 area increased by about 35%. In addition, Figure 3 depicts the regression of the trend line of the regions in which the coefficient of variation in the DESI level between countries is the dependent variable, and the time variable is the $t = 1 \ldots 6$. The coefficient of the time variable (t) has a negative and statistically significant value. This signals the phenomenon of σ-convergence.

Figure 4 shows that the Digital Economy and Society Index increased in all countries, and that their regional variation decreased from 2015 to 2020. When we check

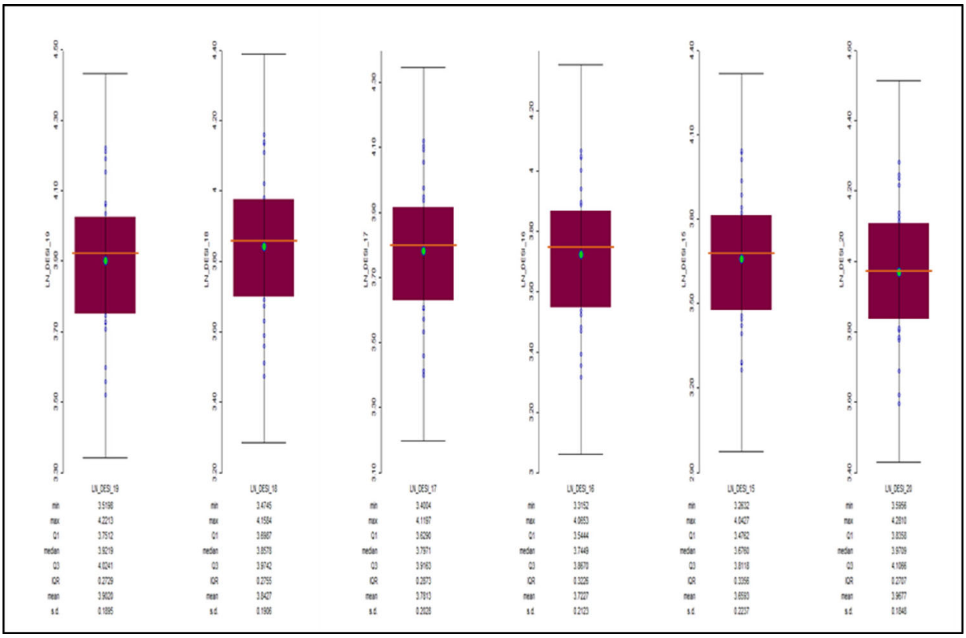

Figure 4. Dispersion of DESI in EU-28 countries.
Source: authors̀ based European Commission (2021)

the DESI growth rates of EU-28 in those years, we notice that the developed Nordic countries show subunit DESI growth rates, and well-developed economies have recorded values between 1 and 1.5. In contrast, the former communist countries and, also, Italy and Greece, relatively poorer regions, have reached growth rates above 1.5. This evolutionary model is the main element that argues for sigma convergence in 2015–2020. In addition, it has been found that since 2015, the dispersion has increased. At the same time, the EU member states' development level has increased. Thus, the results of our study on sigma convergence in the case of digitalisation are in line with the literature on economic convergence.

Figure 5 shows the evolutions of the indicators, and it is observed that similar trends follow largely, which is an argument in favour of sigma convergence. Inequality decreased continuously until 2018 and increased in 2019 for all analysed indicators: MMR, Gini Index, Atkinson Index, and Theil Index. We are beginning to see a reduction in equality again in 2020. These results are in line with the evolution of the CV, shown above in Figure 3. These results support the sigma convergence hypothesis in terms of digitisation between EU-28 countries in 2015–2020.

3.3. Beta convergence of digitalisation of EU countries

3.3.1. The OLS model estimation

Testing the beta convergence hypothesis requires analysing the evolution of digitalisation levels for the countries studied. In this regard, we used Equation (8) to regress the growth rate of DESI compared to the initial level of the period considered, namely that of 2015. We also included two other control variables, namely the

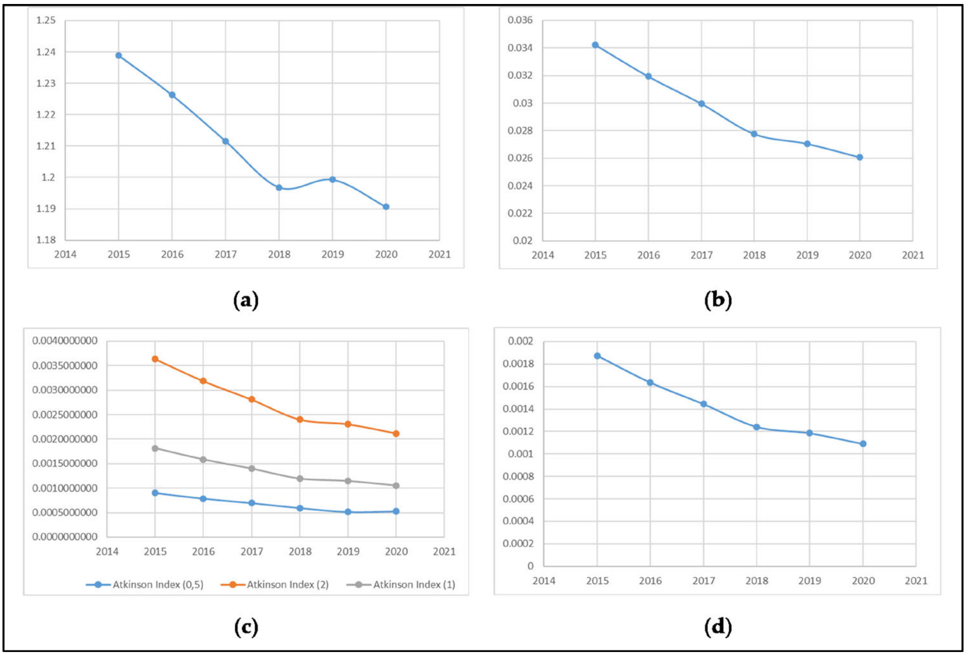

Figure 5. Static measures of digitalization disparities in EU-28 countries. (a) Maximum to minimum ratio; (b) Gini index; (c) Theil index; and (d) Atkinson index.
Source: authors̀ own computations

education index and the gross value added. If the beta convergence hypothesis is maintained, a negative correlation between the DESI rate and the initial DESI levels in EU countries is predictable.

We first estimated the OLS model. Table 2 shows the summary of the OLS cross-sectional model. The DESI coefficient of the initial year is negative and statistically significant, which confirms the existence of unconditional β convergence between countries in this estimation hypothesis.

The accuracy of the model adjustment is 62.5%, and the value of the F statistic verifies the null hypothesis, which supports the validation of the model. In addition, the convergence rate (β), given the slope of the regression line, shows that EU-28 countries reduce the distance to equilibrium by 4.86% per year, which means just over 14 years to reach equilibrium. This value represents a much higher convergence rate than the overall economic convergence rate estimated by Barro and Sala-I-Martin (1997). In this respect, it should be noted that the EU-28 countries are experiencing a relatively high recovery process in terms of digitalisation for this period.

3.3.2. The OLS model diagnostics

The multicollinearity condition number has a value of 40.99, greater than 30, suggesting multicollinearity problems. To test the normality of the residue, we used the Jarque-Bera test. The probability associated with the test has a value of 65.69%, showing that we cannot reject the null hypothesis, which ensures the robustness of our results. To detect heteroskedasticity, we used the Breusch-Pagan and Koenker-Bassett tests calculated with GeoDa. Both statistical tests support the acceptance of the null

Table 2. Cross-sectional estimation of absolute β-convergence of DESI in EU-28.

	OLS method		
	Coefficient	Std. error	Prob.
Constant	2.289413987	0.140893221	0.00000000*
Log of initial year DESI	−0.253148269	0.038433979	0.00000055*
R-square		0.62526825	
F-statistic		43.38296533	
Prob. (F-statistic)		0.00000055*	
Speed of convergence (β)		0.0486481 (14.24818609 years)	
Multicollinearity condition number		40.989190	
Jarque-Bera test		0.8403 (0.65695)	
Breusch-Pagan test		2.7837 (0.24861)	
Koenker-Bassett test		2.5867(0.27435)	
White test		3.9661 (0.55431)	

*[1] 5% significance level.
Source: authors' own computations.

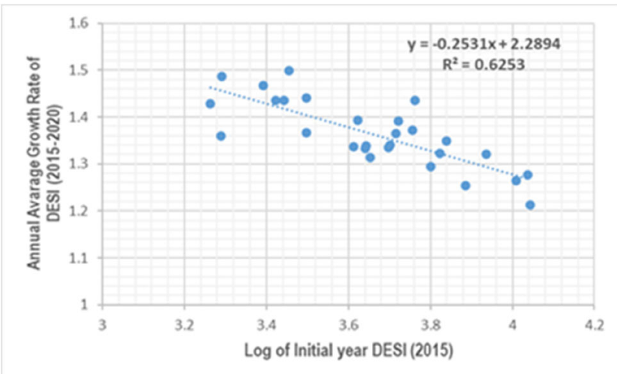

Figure 6. Absolute β-convergence of DESI in the EU-28 countries.
Source: authors 'computation based European Commission (2021)

hypothesis. The results of the White test are consistent with the other two tests, which allows us to accept the homoscedasticity hypothesis of the regression model so that we can continue to interpret the result of the OLS model.

3.3.3. The absolute β convergence

The results of the absolute β convergence of the EU-28 countries digitalisation are presented in Figure 6, where the annual growth rate of DESI in 2015–2020 is represented on the abscissa, and the value of DESI log in 2015, on the ordinate. Figure 6 depicts a negative slope of the regression line. The p regression value in Figure 6 is 0.000, which confirms the validation of the model. The figure also allows the comparison among the EU-28 countries for the β convergence hypothesis.

Barro and Sala-I-Martin (1992) showed that strictly, only differences in technology do not affect β when the determinants of technology and preferences are essentially similar, but other parameters differ. We tried to extrapolate this idea in terms of digitalisation considering the outputs of the economies, expressed as GVA and their level of education. Thus, the assumption that the value of the stable level and the progress of digitalisation does not essentially differ between countries implies that less

Table 3. Cross-sectional estimation of conditional β-convergence of DESI in EU-28.

Model with control variable: the education index			
	Coefficient	Std. Error	Prob.
Constant	2.28403	0.156194	0.00000
Log of initial year DESI	−0.256322	0.0533244	0.00006
Educational index	0.0199726	0.227562	0.93076
R-square		0.625384	
F-statistic		20.8675	
Prob. (F-statistic)		0.00000	
Speed of convergence (β)		0.04596287 (15.08 years)	
Model with control variable: the gross value added			
	Coefficient	Std. error	Prob.
Constant	2.21095	0.142542	0.00000
Log of initial year DESI	−0.261947	0.0372856	0.00000
Log of GVA	0.00924796	0.00522961	0.08920
R-square		0.682498	
F-statistic		25.795	
Prob. (F-statistic)		0.000005	
Speed of convergence (β)		0.050623274 (13.69 years)	
Model with control variables: the education index and the gross value added			
	Coefficient	Std. error	Prob.
Constant	2.23362	0.152174	0.00000
Log of initial year DESI	−0.245103	0.051446	0.00008
Educational index	−0.111123	0.229724	0.63297
Log of GVA	0.0101044	0.00559891	0.08369
R-square		0.670147	
F-statistic		16.2532	
Prob. (F-statistic)		0.000006	
Speed of convergence (β)		0.046862327 (14.79 years)	

*[1] 5% significance level.
Source: authors' own computations.

digitalised economies tend to grow unconditionally faster than those in which the IT sector is more robust. In 2015–2020, regions with a lower initial DESI (e.g. Greece, Romania, Italy) recorded relatively higher average growth rates. In contrast, more digitalised countries, such as Denmark, Sweden, Finland, and Estonia, grew relatively slowly.

Table 3 presents the results of estimating conditional β convergence based on cross-sectional data for 2015–2020. Three variants were analysed, namely:

1. A model considering the annual growth rate of DESI as a dependent variable and DESI as an explanatory variable, to which we added the education index as a control variable;
2. A model considering the annual growth rate of DESI as a dependent variable and DESI as an explanatory variable, to which we added the gross added value as a control variable;
3. A model considering the annual growth rate of DESI as a dependent variable and DESI as an explanatory variable, to which we added both control variables simultaneously.

Analysing the model that considered the education index as a control variable, the sign of the DESI coefficient is negative, unlike the sign of the education index, which is positive, and this suggests that the growth rate of DESI and the education index

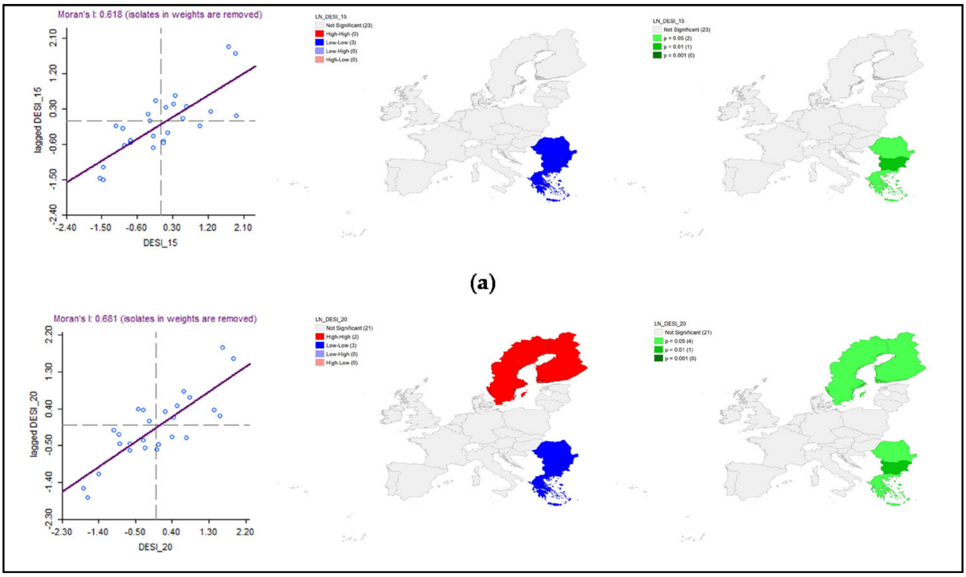

Figure 7. Moran's I statistics for DESI in EU-28. (a) 2015 and (b) 2020.
Source: authors' own computations

vary in the same direction. However, as the p value of the coefficient of the control variable indicates, that is not significant. The second model, with gross value added as the control variable, shows the variation of the growth rate of the digitalisation index in the same sense as that of the gross value added. Also, in this case, the p-value of the coefficient of the control variable shows that it is not significant at a 5% significance level, but significant at a 10% significance level. The situation is maintained even when both control variables have been considered simultaneously. But, in this case, the growth rate of DESI varies in the opposite direction to the education index. This behaviour could mean that digitalisation changes the landscape of the national education systems. The coefficient of determination (R-square) is between 62.5% and 68.2%, being slightly higher than the values given by the absolute convergence model. Finally, the estimated convergence rate is between 4.59% and 5.10%, being close to the absolute convergence model. The conclusion is that, although the p values at a significance level of 0.5% confirm the significance of all models, the control variables are not statistically significant. According to the results presented in Table 3, for a p-value of 10%, the gross value added slightly increased the convergence rate of digitalisation between countries during the analysed period. Therefore, we considered this variable in spatial analysis.

3.4. Spatial dependence in EU-28 countries

3.4.1. Preliminaries

Figure 7 depicts the results of the spatial autocorrelation diagnosis for DESI for 2015 and 2020, by Moran scatter plots. It depicts the connection between the degree of digitalisation of a country, expressed by DESI, and its spatial gap (DESI of neighbouring countries). Moran's I is similar to the correlation coefficient but its value depends

Table 4. Global Moran's I for digitalization in EU countries.

Growth rate/Periods	Weighted MORAN's I	E(I)
2015	0.6816	−0.40
2016	0.6982	−0.40
2017	0.7004	−0.40
2018	0.6675	−0.40
2019	0.7357	−0.40
2020	0.7221	−0.40

Moran's I: Malta and Cyprus were removed because they are island states and they were considered to have no neighbours.
Source: authors' own computations.

on the weighted matrix. The slope of the regression line represents the value of Moran I's statistics obtained after 999 permutations, the values over 0.6 supporting a significant positive spatial autocorrelation. This shows that the DESI value in a country depends positively on its values in the neighbouring areas. The maps show the spatial clusters obtained. These maps show different situations at the beginning and the end of the analysed period. Thus, at the beginning of the analysed period, HH clusters are not identified, while the LL cluster is located mainly in the southeastern region (less digitalised area), grouping countries with the lowest DESI values, namely, Greece, Bulgaria and Romania. At the end of the analysed period, the HH cluster is located in the northern part of the EU (the Nordic countries, namely, Sweden and Finland, which remain at the top of digitalisation, their pace of digitalisation remaining behind the EU area), while the LL cluster is, also, located in the south-eastern part (the less digitalised area).

The annual values of the Moran's I indexes, presented in Table 4, confirm the existence of a statistically significant positive spatial autocorrelation for DESI in EU-28 countries, because Moran I shows an upward trend over the analysed period, with the exception of 2018, the values showing very different figures from those expected (E(I)), where:

$$E(I) = -\frac{1}{n-1} \quad (15),$$

where n is the number of observations.

We have extended the OLS model by including spatial effects to assess spatial dependence, customising the Equation (14). The variable in the analysed models was the growth rate of DESI in EU-28 countries for the period 2015–2020, the same as in the OLS model. Thus, three models considered spatial dependence:

1. The first model considers interaction effects between the DESI growth rates of EU-28 countries (SAR model).
2. The second model added interaction effects between error terms (SEM model).
3. The third model included both endogenous effects (SAC model).

3.4.2. Spatial regression model selection

We wanted to see how the scatter plots of the variables considered in the analysis relate to each other. For this, we created a scatter plot matrix (Figure 8). Figure 8

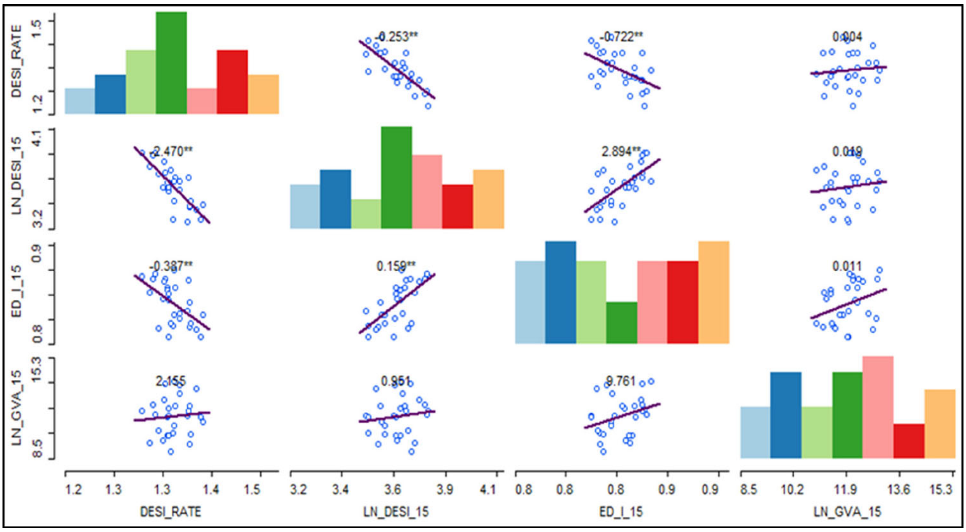

Figure 8. Scatter plot matrix.
Source: authors̀ own computations

Table 5. Diagnostics for spatial autocorrelation of the OLS Model.

	Value	Prob
Moran's I (error)	0.5470	0.58437
Lagrange multiplier (lag)	3.6186	0.05714
Robust LM (lag)	3.7262	0.05356
Lagrange multiplier (error)	0.0127	0.91040
Robust LM (error)	0.1203	0.72869
Lagrange multiplier (SARMA)	3.7389	0.15421

Source: authors' own computations.

depicts a weak negative correlation between the rate of increase in the degree of digitalisation and its initial level, as we expect. The correlation with the growth rate of added value is very weak.

To identify the appropriate spatial autocorrelation model, we used the classical selection procedure presented in Anselin (2005), which provides ways to discriminate between an SLM model and an SEM model, based on the tests proposed by Baltagi et al., 2003 and Baltagi et al., 2007. For this, we first analysed an OLS model. Table 5 shows the results of the diagnostics for spatial dependence of this model. It is important to note that Moran's statistic is not significant as the p-value of 0.58 shows, meaning that it is possible that the spatial distribution of the characteristics could be the result of random spatial processes.

The process began with consideration of the standard LM-Error and standard LM-Lag test statistics. Since the p-value of the LM-lag test (0.05714) did not confirm the null hypothesis unlike LM-error (0.91040), at a 10% significance level, we preferred to define a spatial regression lag model, customising Equation (14). This decision is in line with the robustness of the LM test statistics. Thus, in the case of the spatial convergence analysis of the degree of digitalisation of the EU-28 countries, only Robust LM (lag) is significant ($p = 0.05$) compared to Robust LM (error) ($p = 0.73$), as described by Anselin (2005). The spatial lag model assumes that there are

Table 6. Summary of the spatial lag model—maximum likelihood estimation.

	Value
Mean dependent var	1.36308
S.D. dependent var	0.0703365
Lag coef. (Rho)	−0.0463339
R-squared	0.710986
Sigma-square	0.00109162
S.E of regression	0.0330397
Log likelihood	51.96
Akaike info criterion	−95.92
Schwarz criterion	−90.5912
W_LOG of growth rate of DESI	−0.0463339
	(0.03872)
Constant	2.2379
	(0.00000)
Log of DESI	−0.268917
	(0.00000)
Log of GVA	0.0140482
	(0.00631)

Source: authors' own computations.

dependencies directly between the levels of the dependent variable. That is, the scan level at a location is affected by the scan level at nearby places. The term 'lag', which is a specification of digitisation from nearby places, is included in the regression, and the coefficient and p-value are interpreted as independent variables.

3.4.3. Spatial lag model

Table 6 shows the results of this model. Because the analysis of R-squared (R2) is not adequate in a spatial regression model, following the procedure described in (Anselin, 2005), we studied Log- Likelihood, Akaike Info Criterion (AIC) and Schwarz Criterion (SC). Comparing the Log-Likelihood values for OLS (49.99) and SLM (51.96), a higher value is observed in the case of SLM. Balancing for the worsened fit for the added variable (spatial delay-dependent variable), AIC (-93.97 to −95.92) and SC (-89.98 to −90.59) both increased relative to OLS, [demonstrating] once again a worsening of matching to the spatial delay specification.

The spatial autoregressive coefficient is estimated at −0.046, significant at a p-value of 0.03872. The spatial delay model and the classic LOG model of DESI differ in terms of the significance of the other regression coefficients. Thus, LOG of DESI remains as significant as in the OLS model (p-value is 0.0000), but the significance of LOG of GVA changes, the p-value decreasing from 0.089 to 0.006.

The size of all the estimated coefficients is also affected, with an evident increase in the absolute value. It can be considered that the explanatory power of these variables, attributed to their value in each country, was due to the values in neighbouring countries. This is contained in the coefficient of the spatially delayed dependent variable.

The estimated convergence rate (β) is 5.22%, slightly higher than that of the absolute convergence model (5.06%), which also means a duration of 13.3 years to reach equilibrium, slightly less than that of the absolute convergence model (13.7 years).

The tests provided by GeoDa were analysed to diagnose the SLM model, according to the framework described in (Anselin, 2005). The p-value for the error terms

(0.31510) in the case of the Breusch-Pagan test for heteroscedasticity is not significant. This result shows that heteroskedasticity is not a problem. The second test mentioned by Anselin (2005) is the probability ratio test, a classical specification test that compares the null model (classical regression specification) with the alternative model of spatial delay. The value of 3.9472 (p-value 0.04695) demonstrates the significance of the autoregressive spatial coefficient.

The three classical tests, namely, Wald test (W), Likelihood Ratio test (LR), and [LM-Lag test?] are asymptotically equivalent, but in the finite samples, the order should be the following: W > LR > LM. In our example, the Wald test is (-2.07)2 = 4.28, the LR test is 3.95, and the LM-Lag test was 3.62 which is compatible with the expected order. This validates the asymptotic properties of Maximum Likelihood estimates and test statistics. The fairly good fit of the model, the low degree of non-normality and the fulfilment of the condition of heteroskedasticitysupport this variant of the SLM model.

The three classical tests mentioned by Anselin (2005), namely the Wald (W) test, the probability ratio test (LR), and the Lagrange Multiplier (LM), are asymptotically equivalent. Still, the order to be followed in the finite samples should be W > LR > LM. The results of our study are in the expected order. Thus, the Wald test is (-2.07) 2 = 4.28, the LR test is 3.95, and the LM-Lag test is 3.62. Given the acceptable fit of the model, the low degree of abnormality and the fulfilment of the heteroskedasticity condition, these results support this variant of the SLM model.

4. Conclusions

The COVID-19 pandemic has clarified the need for digital connectivity and access to digital services. The global pandemic has accelerated long-standing processes that progressed slowly before the crisis, such as automation, digitalisation or remote work implementation. Still, fiscal uncertainty and lack of transparency persist and will continue to affect the business environment. The COVID-19 pandemic has shown that digitalisation can radically change society, starting with the means of communication and continuing with the labour market. On the one hand, there has been a sharp increase in the use of the Internet, businesses have become increasingly digital, e-commerce has grown, and on the other hand, there is a growing trend in the use of digital public services. Thus, digitalisation drives economic recovery and increases the resilience of the health sector, becoming a significant issue for European countries. In this regard, the European Commission has adopted three work programs for the "Digital Europe" program, which will benefit from total funding of almost 2 billion euros. This network will be essential in EU policies, especially in industrial and small and medium-sized enterprises and start-ups. It will provide access to both technology development and testing, support in the digital transformation of domestic economy, shaping the private and public organisations structure and management across Europe, including the transformation of administrations. To reduce the feeling of mistrust, the EU is committed to creating a secure digital space for citizens and businesses in a way that is inclusive and accessible to all.

The results of this study on the dynamics and trends of digitalisation support the implementation of these programs aimed at achieving the convergence objective. This study focussed on the convergence of EU Member States' results and performance on digitalisation, looking at DESI and considering the education index and the gross added value as control variables. Understanding the determinants of the trends of these indicators represented the economic involvement of the objective of the analysis

The idea of regional convergence is supported in all models presented because the growth rate of DESI is negatively and significantly associated with the initial DESI in all cases. The estimated rate of convergence varies from 4.68% to 5.22%, which implies a period of equilibrium of 13.3 to 14.8 years. Our findings are consistent with the economic convergence model of Barro et al. (1991), Barro and Sala-I-Martin (1992), and Barro and Sala-I-Martin (1995), the difference being the almost double convergence rate. In addition, we observed that by adding spatial variables into the cross-sectional model, the estimated results for the convergence velocity support the idea of convergence.

Furthermore, considering spatial dependence, according to the methodology described in (Kındap & Doğan, 2019), the resulting model could better explain the convergence than the basic OLS model, providing a better match for test statistics (R-sq, Log-Likelihood, AIC, SC). It was also proved that the spatial dependency coefficients are statistically significant and could be considered for analysis. The model selection tests presented in Table 5 indicate statistically significant results and support the spatial dependence hypothesis. These results mean that cross-sectional estimates support the existence of spatial dependence on digitalisation between the countries analysed and show the SLM as the correct specification. An EIB study published in April 2020 (European Investment Bank, 2020) shows that the EU is still lagging behind the US in digitalisation, with only four member states ahead of the US in this area: Denmark, the Netherlands, the Czech Republic and Finland. These results are consistent with the results of our study, showing that countries with a higher level of economic development, in which the number of large firms is higher, tend to digitalise faster.

Limitations and future recommendations

Investigating the digital convergence in European Union using the econometric analysis of pitfalls and pivots of digital economic transformation represents an important challenge for understanding the major causes of the digital gap widening among European digital economies development. The most significant limitation of this article is that because the number of observations contained in cross-sectional regressions is limited to 28 variables, the models designed during this research display fewer statistical variations among the cross-section in which the spatial dependence effect is different from zero. Thus, for further research, we intend a panel data analysis to consider the variation of time series. The novelty of the research lies in applying the method of convergence analysis to the level of digitalisation extension of EU-28 countries, in order to identify both the strengths and weaknesses of the digital economy strategies for development and implementation.

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Author contributions

All authors were involved in the documentation phase, in choosing the research methodology, in records' selection and analysis, as well as in results analysis and discussions. All authors participated in the manuscript preparation and approved the submitted manuscript.

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Data availability statement

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Disclosure statement

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References

Alfaro Cortés, E., & Alfaro Navarro, J. L. (2011). Do ICT influence economic growth and human development in European Union countries? *International Advances in Economic Research*, *17*(1), 28–44. https://doi.org/10.1007/s11294-010-9289-5

Anselin, L. (1988). Spatial econometrics: Methods and models. *Dordrecht*. Kluwer Academic Publishers.

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Anselin, L. (2005). *Exploring spatial data with GeoDaTM: a workbook*. Center for spatially integrated social science.

Avram, A. C. (2020). Digitalisation of services in the European Union. *The Journal of Global Economics*, *12*(1), 49–68. https://www.researchgate.net/publication/344237271

Baltagi, B., Song, S., & Koh, W. (2003). Testing panel data regression models with spatial error correlation. *Journal of Econometrics*, *117*(1), 123–150. https://doi.org/10.1016/S0304-4076(03)00120-9

Baltagi, B., Song, S., Jung, B., & Koh, W. (2007). Testing for serial correlation, spatial autocorrelation and random effects using panel data. *Journal of Econometrics*, *140*(1), 5–51. https://doi.org/10.1016/j.jeconom.2006.09.001

Barro, R. J. (1991). Economic growth in a cross section of countries. *The Quarterly Journal of Economics*, *106*(2), 407–443. https://doi.org/10.2307/2937943

Barro, R. J., & Sala-I-Martin, X. (1992). Convergence. *Journal of Political Economy*, *100*(2), 223–251. https://doi.org/10.1086/261816

Barro, R. J., & Sala-I-Martin, X. X. (1990). Economic growth and convergence across the United States. *National Bureau of Economic Research Working Paper Series*, 3419. Retrieved 6 September, 2021, from https://www.nber.org/system/files/working_papers/w3419/w3419.pdf

Barro, R. J., & Sala-I-Martin, X. X. (2004). *Economic growth* (2nd ed.). The MIT Press.

Barro, R. J., & Sala-I-Martin, X. (1995). *Economic growth*. McGraw-Hill.

Barro, R. J., & Sala-I-Martin, X. (1997). Technological diffusion, convergence, and growth. *Journal of Economic Growth*, *2*(1), 1–26. https://doi.org/10.1023/A:1009746629269

Barro, R. J., Sala-I-Martin, X., Blanchard, O. J., & Hall, R. E. (1991). Convergence across states and regions. *Brookings Papers on Economic Activity*, *1991*(1), 107–182. https://doi.org/10.2307/2534639

Baumol, W. J. (1986). Productivity growth, convergence, and welfare: What the long-run data show. *American Economic Review*, *76*, 1072–1085.

Brasili, C., & Gutierrez, L. (2004). *Regional convergence across European Union*. Development and Comp Systems. https://www.researchgate.net/publication/23742220/.

Bucur, I. A., & Stangaciu, O. A. (2015). The European Union convergence in terms of economic and human development. *CES Working Papers*, *7*(2), 256.

Bughin, J., Hazan, E., Labaye, E., Manyika, J., Dahlström, P., Ramaswamy, S., & Cochin de Billy, C. (2016). *Digital Europe: Pushing the frontier, capturing the benefits*. McKinsey & Company. https://www.mckinsey.com/∼/media/mckinsey/business%20functions/mckinsey%20digital/our%20insights/digital%20europe%20pushing%20the%20frontier%20capturing%20the%20benefits/digital-europe-full-report-june-2016.ashx.

Celebioglu, F., & Dall'erba, S. (2010). Spatial disparities across the regions of Turkey: An exploratory spatial data analysis. *The Annals of Regional Science*, *45*(2), 379–400. https://doi.org/10.1007/s00168-009-0313-8

Chatterji, M. (1992). Convergence clubs and endogenous growth. *Oxford Review of Economic Policy*, *8*(4), 57–69. https://doi.org/10.1093/oxrep/8.4.57

Cliff, A., & Ord, J. (1975). The choice of a test for spatial autocorrelation. In J. Davies, & M. and McCullagh (Eds.), *Display and Analysis of Spatial Data* (pp. 54–77). John Wiley and Sons.

Dall'erba, S., & Le Gallo, J. (2008). Regional convergence and the impact of European structural funds over 1989–1999: A spatial econometric analysis. *Papers in Regional Science*, *87*(2), 219–244. https://doi.org/10.1111/j.1435-5957.2008.00184

Elhorst, J. P. (2014). *Spatial econometrics from cross-sectional data to spatial panels*. Springer.

European Commission. (2021). The Digital Economy and Society Index (DESI). https://digital-strategy.ec.europa.eu/en/policies/desi.

European Commission, Directorate-General for Research and Innovation. (2017). *Digitisation research and innovation: Transforming European industry and services*. Publications Office. https://doi.org/10.2777/890905

European Investment Bank. (2020). *Who is prepared for the new digital age? Evidence from the EIB Investment Survey*. https://www.eib.org/attachments/efs/eibis_2019_report_on_digitalisation_en.pdf.

European Investment Bank. (2022). *Digitalisation in Europe 2021–2022: Evidence from the EIB Investment Survey*. https://www.eib.org/attachments/publications/digitalisation_in_europe_2021_2022_en.pdf.

Eurostat. (2021). Gross value added and income by A*10 industry breakdowns [nama_10_a10]. http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a10 (accessed 12th October, 2021).
Fernández-Portillo, A., Almodóvar-González, M., & Hernández-Mogollón, R. (2020). Impact of ICT development on economic growth. A study of OECD European union countries. *Technology in Society*, *63*, 101420. https://doi.org/10.1016/j.techsoc.2020.101420
Fischer, S., & Dornbush, R. (1995). Macroeconomia, Il Mulino, Bologna. In Dragulanescu, I. V., & Dragulanescu, N. (2013), *Some theories of environmental sustainability. Romanian Statistical Review* (Vol. *12*; pp. 14–22). https://doi.org/10.7551/mitpress/6389.001.0001
Fujita, M., Krugman, P. R., & Venables, A. (1999). *The spatial economy: Cities, regions, and international trade*. MIT Press.
Gaftea, V. N., Ioniiă, A., NiīU, I., & Popa, I. F. (2018). România şi Piaţa Unică Digitală a Uniunii Europene. Institutul European din România.
Gömleksiz, M., Şahbaz, A., & Mercan, B. (2017). Regional economic convergence in Turkey: Does the government really matter for? *Economies*, *5*(3), 27. https://doi.org/10.3390/economies5030027
Gouvea, R., Kapelianis, D., & Kassicieh, S. (2018). Assessing the nexus of sustainability and information & communications technology. *Technological Forecasting and Social Change*, *130*, 39–44. https://doi.org/10.1016/j.techfore.2017.07.023
Griffith, D. A. (2003). Spatial filtering. *Spatial Autocorrelation and Spatial Filtering* (pp. 91–130). Springer Berlin Heidelberg.
Hagberg, J., Malin, S., & Egels-Zandén, N. (2016). The digitalization of retailing: An exploratory framework. *International Journal of Retail & Distribution Management*, *44*(7), 694–712. https://doi.org/10.1108/IJRDM-09-2015-0140
Human Development Report Office. (2022). Human development index (HDI). United Nations development programme. https://hdr.undp.org/data-center/human-development-index#/indicies/HDI (accessed 12th October, 2021)
Iancu, A. (2009). *Convergenta Reala si Integrarea in UE*. National Institute of Economic Research.
Kındap, A., & Doğan, T. (2019). Regional economic convergence and spatial spillovers in Turkey. *International Econometric Review (IER)*, *11*(1), 1–23.
Konya, L., & Guisan, M.-C. (2008). What does the human development index tell us about convergence? *Applied Econometrics and International Development*, *8*(1), 19–40. https://ssrn.com/abstract=1307751.
Lappi, T. M., Aaltonen, K., & Kujala, J. (2019). Project governance and portfolio management in government digitalization. *Transforming Government: People, Process and Policy*, *13*(2), 159–196. https://doi.org/10.1108/TG-11-2018-0068
LeSage, J. (2015). Spatial econometrics. *Handbook of research methods and applications in economic geography* (pp. 23–40). Edward Elgar Publishing.
Liu, T. C. (2022). Digital policy in European countries from the perspective of the digital economy and society index. *Policy & Internet*, *14*(1), 202–218. https://doi.org/10.1002/poi3.274
Majumdar, S. (2020). Directive (EU) 2019/790 of the European Parliament and of the Council: Overhaul of European Union's copyright rules: A study. Library Hi Tech News. https://eur-lex.europa.eu/eli/dir/2019/790/oj.
Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, *107*(2), 407–437. https://doi.org/10.2307/2118477
Moran, P. A. (1950). Notes on continuous stochastic phenomena. *Biometrika*, *37*(1–2), 17–23. https://doi.org/10.1093/biomet/37.1-2.17
OECD (2017). Going digital: Making the transformation work for growth and well-being. https://www.oecd.org/mcm/documents/C-MIN-2017-4%20EN.pdf.
Presenza, A., & Petruzzelli, A. M. (2019). Investigating business model innovation in Haute Cuisine. Role and behavior of chef-entrepreneurs. *International Journal of Hospitality Management*, *82*, 101–111. https://doi.org/10.1016/j.ijhm.2019.03.027

Quah, D. T. (1996). Empirics for economic growth and convergence. *European Economic Review*, *40*(6), 1353–1375. https://doi.org/10.1016/0014-2921(95)00051-8

Rey, S. J., & Montouri, B. D. (1999). US regional income convergence: A spatial econometric perspective. *Regional Studies*, *33*(2), 143–156. https://doi.org/10.1080/00343409950122945

UNDP (United Nations Development Programme). (2022). *Human Development Report 2021-22: Uncertain Times, Unsettled Lives: Shaping our Future in a Transforming World*. New York. Retrieved 21 September, 2021, from https://hdr.undp.org/data-center/human-developmentindex#/indicies/HDI

Veeramacheneni, B., Ekanayake, E. M., & Vogel, R. (2007). Information technology and economic growth: A causal analysis. *Southwestern Economic Review*, *34*, 75–88.

Williamson, J. G. (1965). Regional inequality and the process of national development: A description of the patterns. *Economic Development and Cultural Change*, *13*(4, Part 2), 1–84. https://doi.org/10.1086/450136

World Economic Forum. (2018). Digitial transformation inititative. Executive summary. http://reports.weforum.org/digital-transformation/wp-content/blogs.dir/94/mp/files/pages/files/dti-executive-summary-20180510.pdf (Accessed 11th March, 2021).