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E-Commerce and Factors Affecting Its Development: Empirical Evidence from Europe

Abstract

To investigate the factors that drive e-commerce growth in Europe, we performed a panel data analysis utilizing annual data from 32 European nations spanning a 12-year timeframe (2010 to 2021). By applying the advanced econometric technique Fully Modified Ordinary Least Squares (FMOLS) estimation we find that GDP per capita, internet usage for finding information about goods and services, level of education, computer skills, and internet access all positively and significantly affect e-commerce development. Conversely, the use of the internet for engaging with public authorities does not significantly affect e-commerce, while online banking usage shows a significant negative effect. Our study contributes to the existing literature by analyzing a larger and more representative panel over a broader time period, and by investigating some relatively under-explored variables. The findings are crucial for policymakers in developing strategies to boost e-commerce, focusing on economic growth and improving digital infrastructure and broadband internet access.

Keywords: e-commerce, online purchase, panel data analysis, fully modified ordinary least squares method, Europe.

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1. INTRODUCTION

In the past two decades, the rapid technological developments in the field of computer technology and internet, led to emergence of the "new economy" concept. One of the economic activities that was mostly affected by the fast growth and widespread use of internet is e-commerce. E-commerce has grown exponentially over the past two decades, with the largest increase in online shoppers especially during the COVID-19 pandemic. To fully harness the potential of e-commerce and increase its contribution to the post-pandemic recovery, it is necessary to understand which factors affect its adoption across countries. In addition, as part of the EU strategy to achieve a digital single market, a comparative analysis of e-commerce in European countries has become increasingly important.

Despite a growing body of literature on factors influencing e-commerce adoption, there is a lack of cross-country studies on this topic. To fill this gap, we conducted an econometric analysis of the aggregate-level factors influencing e-commerce adoption across 32 European countries in the period 2010-2021. Our results show that over the long term, GDP per capita, use of the internet for finding information about goods and services, access to internet, level of education and possession of basic computer skills have a positive and significant impact on online purchases, while using the internet for internet banking is found to have a negative effect. The results obtained can be further used by other researchers and are also of practical use to policy-makers for creating policies for promoting e-commerce.

Our paper presents a significant contribution to existing literature by developing a robust econometric model to assess the cross-country adoption of e-commerce. This model considers macro-level factors influencing e-commerce adoption, and explores less-researched drivers of e-commerce growth, such as using the internet for seeking information about products and services, as well as for interacting with government authorities. By utilizing a larger and more representative panel (32 countries in Europe, both developed and developing), analyzing a broader period (from 2010 to 2021) that encompasses periods of stability and economic shocks, and using balanced panel data, we enhance the generalizability of the results. Finally, the findings of this paper provide important implications for policymakers by highlighting areas that require more attention in advancing e-commerce adoption.

This paper is organized as follows. After the brief introduction, in Section 2 we provide a literature review. Section 3 describes econometric methods used in the research and explains variables used. Estimation of the econometric model, empirical results and possible implications for discussion are presented in Section 4. The final section concludes the paper and provides recommendations for further research.

2. LITERATURE REVIEW

A comprehensive review of the existing literature has shown that there is no consensus on the scope of e-commerce, and therefore there is no commonly accepted definition of e-commerce. While several researchers (Kauffman and Walden, 2001; Grandona and Pearson (2004); Poong et al., 2006) as well as OECD (2011) and EUROSTAT (2021) define e-commerce in the narrow sense as the exchange of products, services and/or information through computer networks other researchers define e-commerce in both a narrow and a broader sense. Turban et al. (2015, p.7) stated that e-commerce in the narrow sense is "the exchange of goods and services between (usually) independent organizations and/or individuals, through the extensive use of powerful ICT systems and a worldwide standardized network infrastructure.", and in the broader sense it includes not only the buying and selling of goods and services, but also the carrying out of other online activities such as servicing customers, collaborating with business partners and carrying out electronic transactions within the company. According to Stallmann and Wegner (2014), all digital commercial transactions between companies via the internet, especially the sale of goods and services, constitute e-commerce in the broader sense.

Clarke (1999) classified e-commerce into six categories: B2B (Business to Business), B2C

(Business to Customers), C2C (Customer to Customer), C2B (Customer to Business), B2A (Business to Administration), and C2A (Customers to Administration). In this paper, we use the definition of B2C e-commerce as given by Ho et al. (2007), that is, B2C electronic commerce is the use of the internet by companies and consumers for selling and buying goods and services, as well as for providing other business and after-sale customer services.

Identifying the determinants of B2C e-commerce growth across countries is essential to evaluate the key factors affecting e-commerce development (Ho et al., 2007). The existing empirical literature on variables affecting e-commerce, lacks cross-country studies that focus on macro-level determinants of e-commerce adoption (Caselli & Coleman, 2001; Zhu et al., 2003; Mahmood et al., 2004), and the generalizability of their results is significantly limited by small samples or short sampling periods.). Moreover, the majority of studies used survey methods to analyze individual- and firm-level factors. Only a handful of cross-country studies have applied econometric methods to identify the factors influencing e-commerce growth at the aggregate level. To identify the factors driving B2C e-commerce growth across the European countries, we extensively reviewed the literature on cross-national analysis of e-commerce adoption, which employs econometric methods. A summary of the literature review is provided in Table 1.

Based on the literature review, we have chosen five independent variables that previous research has identified as the most significant determinants of e-commerce adoption across European countries. Below is a brief description of these factors.

Various studies stated that economic growth is one of the driving factors of e-commerce development in a country (Dumicic et al., 2017; Özekenci et al., 2019, Huterska and Huterski, 2022; Ğuz et al., 2022). In contrast to these findings, Novkovska and Dumicic (2019) found that the level of economic development does not have a significant impact on e-commerce adoption. To eliminate the effect of differences in price levels and to enable meaningful volume comparisons of GDP, we included GDP per capita adjusted for purchasing power as an independent variable in our model. We formulate the following hypothesis:

Hypothesis 1 (*H1*): *GDP per capita positively affects the development of e-commerce.*

Previous findings on the influence of educational attainment on e-commerce growth (Wang and Liu, 2015; Dumičić et al., 2017; Badîrcea et al. 2021; Ğuz et al., 2022) have empirically proved that the level of education is significantly and positively related to e-commerce. Therefore, we assume that higher levels of education make it easier for individuals to use the Internet for various purposes, including online shopping, and therefore test the following hypothesis:

Hypothesis 2 (*H2*): There is a positive relationship between e-commerce and level of education.

Previous empirical studies have highlighted the significance of internet access as a crucial factor for the development of e-commerce. (Novkovska and Dumicic, 2019; Huterska and Huterski, 2022). Based on this, we propose the following hypothesis:

Hypothesis 3 (*H3*): *Internet access has a positive effect on the growth of e-commerce at a country level.*

According to Ho et al. (2007), telecommunications investment intensity has a significant impact on a country's B2C e-commerce revenue growth. Wang and Liu (2015), Dumičić et al. (2017), and Ortiz et al. (2020) found a strong positive relationship between IT infrastructure and e-commerce growth. These findings lead to the formulation of the following hypothesis:

Hypothesis 4 (*H4*): A broadband internet connection contributes positively to the faster diffusion of e-commerce.

To fully benefit from digital infrastructure, society needs to have basic digital skills and be able to use digital services such as online banking and e-government. According to Eurostat

Table 1: Summary of the literature review

Author/ Year	Sample	Variables	Employed Methodology	Outcomes
Ho et al. (2007)	17 European countries, 2000-2004	The ratio of Internet users to total population, GDP share of capital investment in telecommunications, venture capital availability, credit card penetration, and adult literacy	Panel data analysis with robust error terms	Positive and significant effects of Internet user penetration, telecommunications investment intensity, and education levels on e-commerce in the endogenous growth model. Positive and significant effects of variables from a leading country on e-commerce in the exogenous growth model.
Simicevic et al. (2013)	EU-27 member states, 2009	Perceived barriers to buying/ordering over the internet,level of computer skills, level of Internet skills and level of Internet usage.	Multiple linear regression models	Positive effects of perceived barriers, level of computer skills and internet skills, and no effect of internet usage on e-commerce.
Wang & Liu (2015)	China, 2000-2012	Information infrastructure construction, economic level, educational level, urbanization level, technology level, living standards, human capital level and price index.	Factor model with partial least square regression.	Positive and significant effects of mobile phone penetration, per capita disposable income, number of computers per hundred households and urbanization rate on e-commerce. Positive, but not significant effect of real GDP per capita, knowledge index and Internet penetration on e-commerce.
Dumicic et al. (2017)	31 European countries (the EU-28 member states, Macedonia, Serbia and Turkey), 2015	GDP per capita in in PPS, government expenditure on education, Internet penetration rate and Internet skills level of individuals.	Regression analysis	Positive and significant effects of internet penetration rate, GDP level and education on e-commerce.
Özekenci et al. (2019)	31 European countries, 2004-2015	Internet user, inflation, GDP per capita, employment rate and population.	Panel data analysis	Positive effects of internet users, GDP per capita, and population, and negative effect of inflation on e-commerce.
Novkovska & Dumicic (2019)	31 European countries, 2017	GDP per capita in PPS, internet access for households and percentage of individuals aged 16–74, who have basic or above basic overall digital skills.	Multiple linear regression analysis	Positive and significant effects of internet access and digital skills level, and no effect of GDP per capita on e-commerce.

Author/ Year	Sample	Variables	Employed Methodology	Outcomes
Ortiz et al. (2020)	13 European countries, 2003-2017	Mobile phone penetration, research and development, and per capita disposable income.	Panel data analysis	Positive effects of mobile phone penetration, research and development, and per capita disposable income on e-commerce.
Badîrcea et al. (2021)	EU-27 member states, 2011-2020	Education level, consumer's residence, consumer's labour market status, internet banking and mobile and non-mobile users.	VECM model	Positive and significant effects of the individual's education level, place of residence and employment status, use of the internet for internet banking, and ownership of a mobile device on e-commerce.
Ğuz et al. (2022)	29 countries, (EU-28 member countries and Turkey), 2007-2019	Internet use, employment by education level and GDP per capita.	Panel data analysis	Positive and significant effects of GDP per capita, internet usage rate and education level on e-commerce.
Huterska & Huterski (2022)	EU-27 member states, 2010–2021	Broadband access to internet, internet use preferences, ageing, GDP per capita, and human resources in science and technology	Panel data analysis	Positive and significant effects of broadband internet access, internet use preferences, ageing, GDP per capita, and human resources in science and technology on e-commerce.

Source: Compiled by authors

(2023), "basic skills" refers to having at least one basic skill, but not necessarily possessing skills in all four domains (information, communication, problem-solving, and software skills). Simicevic et al. (2013) and Dumičić et al. (2017) found a strong and positive correlation between the percentage of people who make online purchases and their level of computer skills. Based on this, we are testing the following hypothesis:

Hypothesis 5 (H5): There is a positive relationship between e-commerce and basic computer skills level.

In addition to the main drivers of e-commerce that were previously analyzed, we have included some less-examined variables in the model, such as the utilization of the internet for e-banking and e-government services (Garín-Muñoz et al.,2019; Badîrcea et al. 2021). This has led to the formulation of the following hypotheses:

Hypothesis 6 (*H6*). There is a positive relationship between finding information about goods and services on internet and e-commerce.

Hypothesis 7 (*H7*). Using the internet for internet banking positively influences e-commerce.

Hypothesis 8 (*H8*). The use of the internet to interact with e-government has a positive impact on e-commerce development at the macro level.

The frequency of individuals' internet use plays a significant role in the development of e-commerce. Several studies have shown that more regular and diverse internet use is associated with a higher likelihood of online shopping (Özekenci et al., 2019; Huterska and Huterski, 2022; Ğuz et al.,2022). However, Simicevic et al.(2013) found that internet usage did not have a statistically significant influence on online sales. As a result, we propose the following hypothesis:

Hypothesis 9(H9). The frequency of internet use is driving the development of e-commerce at the country level.

Based on the nine postulated hypotheses, our research question is: What factors influence the development of e-commerce in Europe at an aggregate level, and which of them are the critical drivers of e-commerce growth?

3. DATA AND METHODOLOGY

To test the nine hypotheses that have been formulated, panel data analysis will be employed. We collected annual data on online purchases by individuals in 32 European countries with different levels of economic development, as the dependent variable and data on nine explanatory variables and analyze these data over a period of 12 years (from 2010 to 2021). We chose this specific timeframe as it encompasses periods of economic stability and growth, as well as periods of severe economic shocks (such as the COVID-19 pandemic crisis, Russia's invasion of Ukraine, and the cost-of-living crisis). The data needed for our research were obtained from a single source - the Eurostat database, ensuring that the data is comparable. All estimations were conducted using EViews 9 statistical software.

Panel data estimation was chosen as the most adequate econometric method because of its numerous advantages. An obvious advantage is a larger data set with more variability, and less collinearity among the variables than pure time series data or cross-sectional data (Hsiao, 2022; Baltagi, 2022; Brooks, 2019). In addition, large panel data sets contain more information on the dynamics of many cross-sectional units over long periods. Unlike time series models, panel data analysis accounts for individual heterogeneity and can control heterogeneity by allowing for individual-specific variables. Not controlling for the unobserved individuals' specific effects leads to bias in the estimates. Other advantages of panel data analysis are improved estimation efficiency, more degrees of freedom, and reduced multicollinearity (Hsiao, 2022). In particular, panel data are a valuable tool for studying the dynamics of change in the variables (Baltagi, 2022). Unlike pure time series or cross-sectional data, panel data can detect and measure statistical effects. The method also allows all sample countries to be viewed as one unit (a group of European countries).

The starting point of our econometric analysis is the following panel model:

$$Y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j X_{itj} + u_{it} \tag{1}$$

where i = 1,...,32 and t = 2010,...,2021, Y_{it} represents the dependent variable (individuals who purchased online as percentage of all individuals), X_{itj} are the independent variables, β_j is the parameter that summarizes the *j* factor contribution to the dependent variable, and u_{it} is the error term with zero mean and constant variance.

To test the nine hypotheses formulated above, we suggest the following panel data regression model:

$$\begin{aligned} ECOM_{it} = \beta_0 + \beta_1 GDPPC_{it} + \beta_2 EDU_{it} + \beta_3 COMSKILLS_{it} + \beta_4 ACC_{it} + \\ + \beta_5 BB_{it} + \beta_6 USE_{it} + \beta_7 INFO_{it} + \beta_8 EBANK_{it} + \beta_9 EGOV_{it} + u_{it} \end{aligned} \tag{2}$$

where the dependent variable *ECOM* refers to the individuals who purchased online in the last 12 months as a percentage of all individuals, β_0 represents the constant term (or intercept), β_1 to β_9 are the coefficients of the explanatory variables, *GDPPC* stands for GDP per capita expressed in purchasing power parities (PPS), *EDU* is a level of education as the share of individuals with high formal education in all individuals, *COMSKILLS* stands for individuals possessing basic computer skills and is expressed as a percentage of all individuals, *ACC* is the internet access expressed as a percentage of households with internet access, *BB* refers to individuals living in a household with broadband access to internet as percentage of all individuals, *USE* stands for frequency of

Table 2: Descriptive analysis

	BB	INFO	ACC	COMSKILLS	USE	EBANK	EGOV	EDU	GDPPC	LOG(ECOM)
Mean	54.876	64.354	80.821	63.861	68.360	50.087	51.724	68.417	34153.29	3.728
Median	56.000	66.000	82.800	65.230	69.000	50.000	51.000	73.000	30367.00	3.892
Maximum	93.000	94.000	99.180	86.770	98.000	96.000	94.000	98.000	89557.00	4.522
Minimum	6.00	21.00	40.00	20.000	21.000	2.000	5.000	12.000	11029.00	1.386
Std. Dev.	21.625	16.619	12.917	12.680	16.533	25.909	21.578	20.321	14737.00	0.644
Skewness	-0.3024	-0.4478	-0.8337	-0.971	-0.406	-0.062	0.052	-0.766	1.763	-1.330
Kurtosis	2.031	2.477	3.136	4.262	2.601	2.010	2.196	2.695	6.792	4.693
Jarque-Bera	20.704	17.069	44.431	85.171	12.992	15.804	10.425	38.758	425.559	157.77
Probability	0.0000	0.0001	0.0000	0.0000	0.0015	0.0003	0.0054	0.0000	0.0000	0.0000

Source: Author's own calculations

internet use and is expressed as share of individuals using the internet every day during the 12 months prior to the Eurostat survey, *INFO* stands for the percentage of individuals using the internet for finding information about goods and services, *EBANK* represents the share of individuals using the internet for internet banking, *EGOV* is the percentage of individuals using the internet for interacting with public authorities via websites (e-government services), and u_{it} is the error term with zero mean and constant variance. In the model above, i indexes the cross-sectional dimension, and t the time series dimension.

4. EMPIRICAL ANALYSIS AND DISCUSSION

To understand the basic features of the data in the sample and make general inferences about them, first we conducted a descriptive statistical analysis. Through descriptive statistics, we can get familiar with the measures of central tendency as well as the measures of variability of the dataset. The empirical results are presented in Table 2.

On average, online purchases in countries of interest account for 3.728%, with internet access of 80.82%, GDP of 10.362%, broadband connection of 54.876%, using the internet for finding information about goods and services for 64.354%, and basic computer skills of 63.861%. The maximum values of online purchases, internet access, broadband connection, computer skills and GDP are respectively 4.52, 99.18, 93.00, 94.000, 86.770 and 11.04%.

Based on measures of central tendency, we can see that the data show a left-skewed distribution, as the median values for eight of the ten variables are greater than the mean values. In addition, the measure of skewness is negative for all variables except for the use of the internet in interaction with public authorities. Therefore, a priori information was obtained that the data did not show a symmetrical distribution.

Skewness is clearly a measure of a distribution's asymmetry. The Kurtosis values disclose that

Table 3: Correlation matrix

VARIABLES	BB	INFO	ACC	COMSKILLS	USE	EBANK	EGOV	EDU	LOG(GDPPC)
BB	1.0000	0.8845	0.8620	0.5305	0.8658	0.8657	0.8436	0.9487	0.7202
INFO	0.8845	1.0000	0.8376	0.5808	0.8805	0.8994	0.8827	0.8222	0.6837
ACC	0.8620	0.8376	1.0000	0.4238	0.9493	0.8165	0.7804	0.8835	0.6824
COMSKILLS	0.5305	0.5808	0.4238	1.0000	0.4188	0.5350	0.5194	0.4321	0.4595
USE	0.8658	0.8805	0.9493	0.4188	1.0000	0.8687	0.8446	0.8408	0.6771
EBANK	0.8657	0.8994	0.8165	0.5350	0.8687	1.0000	0.9253	0.7869	0.6967
EGOV	0.8436	0.8827	0.7804	0.5194	0.8446	0.9253	1.0000	0.7676	0.6720
EDU	0.9487	0.8222	0.8835	0.4321	0.8408	0.7869	0.7676	1.0000	0.7018
LOG (GDPPC)	0.7202	0.6837	0.6824	0.4595	0.6771	0.6967	0.6720	0.7018	1.0000

Source: Author's own calculations

the variables *BB, EDU, COMSKILLS, USE, INFO, EBANK* and *EGOV* are platykurtic distributions, i.e., they have less kurtosis than the normal distribution (mesokurtic).

In contrast, the variables *ACC, GDPPC* and *ECOM* have a leptokurtic distribution, with kurtosis greater than 3 which is the value for the normal distribution. Furthermore, the Jarque-Bera test is a goodness-of-fit test that analyzes if skewness and kurtosis in a sample dataset match the normal distribution. In general, platykurtic distributions have fewer outliers and thinner tails than normal distributions, while leptokurtic distributions have more outliers and fatter tails than normal distributions. The Jarque-Bera statistic test always yields a positive result, and if it is far from zero, it shows that the sample data do not follow a normal distribution. The Jarque-Bera test statistic indicates that none of the observed variables in this study has a normal distribution.

There are large divergences between the values of the variables used. This is especially true for GDP per capita in purchasing power parity. Since our sample consists of countries with different levels of economic development, we assume the existence of heterogeneity in the estimation of GDP per capita. Therefore, to eliminate the heteroskedasticity effect, we will continue to estimate the relationship using natural logarithms of GDP.

Table 4: Variance Inflation Factors

VARIABLE	VARIANCE INFLATION FACTORS CENTERED (VIF)
C	NA
INFO	7.789947
LOG(GDPPC)	2.270529
ACC	5.843053
COMSKILLS	1.583004
EBANK	9.464135
EGOV	7.716282
EDU	5.365953

Source: Author's own calculations

The correlation coefficients between the variables are given in Table 3. As we can see from Table 2, all the variables are positively correlated, with the highest correlation coefficient between the variables *USE* and *ACC* and *BB* and *EDU* of 0.949. After dropping the variable *BB*, since it explains almost the same effect as the variable *ACC* and the variable *USE* because it is highly correlated with *ACC*, we have again tested for the presence of multicollinearity, this time by estimating the variance inflation factors (VIF) and the results are given in Table 3.

The values of all VIF in Table 4 are all less than 10, indicating that now there is no problem of multicollinearity.

The next step in our analysis is testing for cross-sectional dependence (CD). This is an essential step before testing for stationarity of the variables, since the result of this test determines which generation of unit root test will be applied. One of the problems that panel data are facing is the inherent presence of cross-sectional dependence, which means that error terms or disturbances in panel data are dependent between cross-sections. It basically arises when the countries that are subject of interest are associated regionally or globally and is a result of some common factors that affect all the countries, such as energy prices, inflation rate, technological innovation, etc. If the common factors, which are omitted from the model, are correlated with the regressors, which is usually the case, both the standard homogeneous estimators for panel data (FE, RE, or FD) and the heterogeneous MG estimator are inconsistent. In this case, Pesaran (2006) suggested to approximate the unobserved common factors by cross-sectional averages of the regressand and regressors, augmenting the model with the latter to obtain unbiased estimates. The null hypothesis is that there is no cross-section dependence (correlation) in residuals. For testing this hypothesis, we have implemented three tests: Breusch-Pagan Lagrange Multiplier (LM), Pesaran scaled LM, and Pesaran CD as a summary for all variables used in analysis.

Table 5 shows that based on the *p* values of the cross-dependence tests of all the variables used in the study in the period 2010-2021, the null hypothesis is rejected, which means that the variables have influence across countries in the long run and that any unexpected change in social, environmental and economic phenomena in one of the analyzed European countries appears to spread to other countries. Therefore, we can proceed with tests and estimation techniques that can account for cross-sectional dependence.

Table 5: Cross-sectional dependence test

Null hypothesis: No cross-section dependence (correlation) in residuals			
Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	1063.097	496	0.0000
Pesaran scaled LM	18.00536		0.0000
Pesaran CD	4.446943		0.0000

Source: Author's own calculations

Before estimation, we test the stationarity properties of these panel data using panel unit root tests. The existing empirical literature suggests a range of panel unit root tests. However, almost all available tests are subject to some statistical shortcomings regarding: (1) the power of the test and (2) the properties of sample size. The idea of incorporating the averages to the regressions per country is also used by Pesaran (2007) to immunize the Im Pesaran and Shin unit-root test against the presence of unobservable factors. These unit-root tests that control for the cross-sectional dependence and are known as second-generation tests. (Burdisso and Sangiacomo, 2016). Based on the results we obtained from the CD test and considering the differences between countries in the sample, and to generate consistent results in the presence of such cross-section dependence, we believe that the Im, Pesaran and Shin (IPS) test is a more realistic assumption and decided to apply the second generation of panel unit root tests, such as the Im, Pesaran and Shin (IPS) test proposed by Pesaran (2007) because it relaxes the assumption of cross-sectional independence and allows for cross-sectional dependence. The results are presented in Table 6.

Table 6: Unit root test

	Im, Pesaran and Shin (IPS) unit root test			
Variable	**Null Hypothesis: Unit root (individual unit root process)**			
	Level	Probability	First Difference	Probability
ACC	0.64288	0.7398	-5.56926	0.0000
EBANK	8.59027	1.0000	-1.95608	0.0252
BB	9.67400	1.0000	-2.94965	0.0016
COMSKILLS	0.75342	0.7744	-3.70886	0.0001
USE	3.80109	0.9999	-3.56073	0.0002
EDU	5.17363	1.0000	-5.67038	0.0000
INFO	2.89928	0.9981	-4.75427	0.0000
Log(GDP)	2.46540	0.9932	-2.15303	0.0157
EGOV	5.81057	1.0000	-4.45310	0.0000
ECOM	-3.71312	0.9999	-4.78728	0.0000

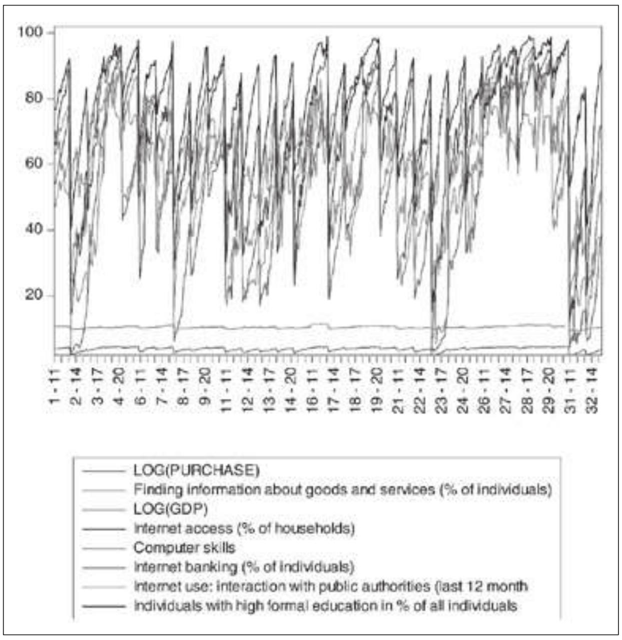
Source: Author's own calculations

Table 7: Cointegration tests

Type of test	**Null Hypothesis: No cointegration**			
Kao Residual Cointegration Test	**t statistic**	**P value**		
	-8.297429	0.0000		
Johansen cointegration test	Model: Linear deterministic trend: Intercept (no trend) in cointegration equation and VAR			
Number of Cointegrating equations	Trace statistic	Probability	Maximum eigenvalue	Probability
None *	395.3937	0.0000	189.0107	0.0001
At most 1 *	206.3830	0.0000	71.80309	0.0000
At most 2 *	134.5799	0.0000	52.83452	0.0003
At most 3 *	81.74540	0.0003	36.62925	0.0075
At most 4*	45.11616	0.0147	22.54933	0.0813
At most 5	22.56682	0.0809		
	Model: No deterministic trend: No intercept or trend in cointegration equation and VAR			
Number of cointegrating equations	Trace statistic	Probability	Maximum eigenvalue	Probablity
None *	400.5425	0.0000	221.8256	0.0001
At most 1 *	178.7170	0.0000	60.88975	0.0008
At most 2 *	117.8272	0.0007	51.78312	0.0016
At most 3	66.04412	0.0964	31.02040	0.1056

Source: Author's own calculations

Figure 1: Movement of the variables in the period 2010-2021



Source: Author's own calculations

As we can see from the results of the IPS unit root test in Table 6, all the variables are nonstationary in level and stationary in the first difference, i.e., I(1). When the data used in the panel model are non-stationary, i.e., integrated of first order, estimation using OLS will cause a spurious problem. To solve this problem, it is necessary to test if there is a cointegration relationship among the nonstationary variables. Therefore, we continue our analysis with testing for the presence of cointegration among the variables by applying the Kao (1999) cointegration test.

The results of this test are shown in Table 7. The Kao ADF statistic is statistically significant which is clear evidence of the existence of a long-term relationship among the variables. To check the robustness of the test, we also conducted the Johansen test and applied two models. According to the first model, trace statistic reveals that there are 5 cointegrating equations while maximum eigenvalue shows existence of 4 cointegration equations. By implementing the second model, both statistics indicate the existence of 3 cointegrating equations at 5% level of significance.

In Figure 1, we have shown the movement of all the variables in the period 2010-2021. By analyzing the graph, we can conclude that the series individually are not stationary, but there is an evidence of existence of cointegration, since they are following each other.

According to Im, Pesaran, and Shin test of the unit root on the variables, we found that all the variables used in our study are integrated of the same order, i.e. I(1). We have also found that these variables are cointegrated. It is well known that estimation of a model with non-stationary variables using OLS could lead to spurious regression. On the other hand, both cointegration tests, Kao and Fisher-Johansen revealed the existence of a long-term relationship. If we use OLS method to estimate the long-run relationship in cointegrated panels, the estimators will suffer from heteroscedasticity, and the distribution of OLS estimations is not standard, which disables us to use standard inference procedures. Having all these facts in mind, we will proceed with Fully Modified Ordinary Least Squares (FMOLS). FMOLS is a non-parametric approach which was originally designed first time by Philips and Hansen (1990) and Philips and Moon (1999) and developed by Pedroni (2001a) and Pedroni (2001b), to provide optimal estimates of cointegration regressions. This technique takes into account the possible correlation between the error term and the first differences of the regressors and the presence of a constant term in order to deal with corrections for serial correlation (Maeso-Fernandez et al., 2006).

Table 8 shows the results of the panel cointegration relationship derived from FMOLS pooled estimation methods. It examines the validity of long-term linear cointegration relations between observed variables of the analyzed 32 European countries. The analysis takes natural logarithm of the online purchases as the dependent variable, with an adjusted sample range from 2010 to 2021. The panel FMOLS long-run estimation results of the 32 European countries indicate that almost all the coefficients of the observed variables are statistically significant at 1% and 5% levels, except for the variable *EGOV*. This finding can be explained by the fact that, as a result of growing investment in e-government, all European countries have already achieved a satisfactory level of e-government development. Today, overall, 84 percent of government

Table 8: Fully modified OLS estimation

Variable	Coefficient	Std. Error	t-statistic	Prob.
FINDINGINFO	0.002814	0.001398	2.012591	0.0450
LOG(GDP)	0.254548	0.100462	2.53378	0.0118
ACCESS	0.017528	0.001669	10.4999	0.0000
COMPUTER_SKILLS	0.003357	0.000924	3.632262	0.0003
BANKING	-0.010498	0.001544	-6.798451	0.0000
INTERNET_USE__INTERACTION_ WITH_PUBLIC_AUTHORITIES_ _LAST_12_MONTH	-0.001498	0.001143	-1.310123	0.1911
EDU	0.021834	0.001165	18.74719	0.0000
R-squared	0.98408	Mean dependent var		3.775446
Adjusted R-squared	0.982128	S.D. dependent var		0.598604
S.E. of regression	0.080025	Sum squared resid		1.985225
Long-run variance	0.008778			

Source: Author's own calculations

services across the European countries can be completed fully online, meaning that citizens of these countries can obtain these services fully digitally, without the need for a physical visit to the local city office (Farooq and Embacher-Köhle, 2023). Thus, hypothesis *H9* is rejected.

The FMOLS estimation results reveal a significant long-term correlation between *ECOM* and the independent variables *INFO, ACC, EDU, GDPPC*, and *COMSKILLS*. Specifically, a 1% increase in *GDPPC* results in a 0.2545% rise in *ECOM*, indicating that higher economic development positively impacts e-commerce growth (hypothesis *H1*). Additionally, a 1% increase in *INFO* leads to a 0.00028% rise in *ECOM*, suggesting that the more the internet is used for finding information about goods and services, the more likely it is to make an online purchase (hypothesis *H6*).

The research findings indicate that access to the internet, level of education, and computer skills have a positive impact on the growth of e-commerce in the long term. A 1% increase in internet access is linked to a 0.018% rise in e-commerce activity ((hypothesis *H3*). Additionally, higher levels of education and basic computer skills contribute to this expansion, with a 1% increase in basic skills resulting in a 0.0034% increase in e-commerce (hypothesis *H5*), and a 1% increase in higher education leading to a 0.022% rise in online purchases (hypothesis *H2*). Therefore, hypotheses *H1, H2, H3, H5*, and *H6* are accepted. These findings align with previous studies on e-commerce determinants (Simicevic et al, 2013; Dumičić et al., 2017; Özekenci et al., 2019, Ğuz et al. 2022 and Huterska and Huterski, 2022).

In contrast to previous findings (Badîrcea et al., 2021), our estimates suggest that the use of internet for online banking has a significant negative impact on the growth of e-commerce in the long run. Specifically, an increase in the variable *EBANK* results in a 0.001% decrease in online purchases. These results can be explained by the fact that in today's digital era, mobile banking is rapidly becoming the preferred digital channel for many customers, replacing traditional online banking. It is anticipated that in the long run, the number of mobile banking users will surpass that of online banking. Therefore, the hypothesis *H7* is rejected.

Given that the R-squared and FMOLS-adjusted R-squared values are both above 98%, we can conclude that the independent variables explain 98% of the variation in the dependent variable, and less than 2% of the variation is attributable to other factors.

5. CONCLUSION

In our paper, we examined the impact of nine factors (macroeconomic, social, and technological factors) on the growth of e-commerce in Europe. To achieve this objective, we employed panel data analysis as it is the most suitable econometric method, to analyze yearly data for 32 European countries over a 12-year period (2010-2021).

The results of our study indicate that all the independent variables we investigated, except for one variable (use of the internet for interacting with public authorities), have significant effects on the development of e-commerce in the European countries over the long term. Nearly all the variables we examined (use of the internet for finding information about goods and services, internet access, level of education, GDP per capita, and basic computer skills), except one (use of the internet for internet banking), have a positive impact on the growth of e-commerce.

Our research contributes to the existing body of literature on endogenous growth theory, which suggests that the main factors driving e-commerce growth originate from within a country. We have enhanced previous econometric studies by analyzing a larger and more representative panel (32 countries with different levels of economic development). Our analysis covers a broader period (from 2010 to 2021) and utilizes balanced panel data. Furthermore, our paper investigates the impact of various macro-level endogenous variables, including macroeconomic, social, and technological factors. Some of these variables, such as the use of the internet to access information about goods and services and to engage with government agencies, have not been adequately explored in previous research.

The results obtained are also of practical use for policymakers and business in European countries. Higher GDP per capita leads to an increase in online shopping. Therefore, economic growth should be the focus of the development policies of European countries. It is necessary to improve ICT infrastructure and provide broadband internet access to facilitate the faster expansion of e-commerce. Efforts to deliver high-quality digital infrastructure must be accompanied by increased investment in education and computer skills.

Like any research, this study is not without limitations. Due to data unavailability for the EU non-member countries, we could not include all European countries in our panel data analysis. One direction for future research is to extend our sample to all European countries, and introduce new variables in the model (age, gender, m-banking), thus generating new insights.

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E-trgovina i faktori koji utječu na njezin razvoj: empirijski dokazi iz Europe

Sažetak

Kako bismo istražili faktore koji pokreću rast e-trgovine u Europi, proveli smo analizu panel podataka koristeći godišnje podatke iz 32 europske zemlje u razdoblju od 12 godina (2010. do 2021.) Primjenom napredne ekonometrijske tehnike procjene potpuno modificiranih običnih najmanjih kvadrata (FMOLS) nalazimo da BDP po glavi stanovnika, korištenje interneta za traženje informacija o robi i uslugama, razina obrazovanja, računalne vještine i pristup internetu pozitivno i značajno utječu na razvoj e-trgovine. Nasuprot tome, korištenje interneta za suradnju s tijelima javne vlasti ne utječe značajno na e-trgovinu, dok korištenje internet bankarstva pokazuje značajan negativan učinak. Naša studija doprinosi postojećoj literaturi analizom većeg i reprezentativnijeg panela tijekom šireg vremenskog razdoblja i istraživanjem nekih relativno nedovoljno istraženih varijabli. Nalazi su ključni za kreatore politike kada razvijaju politike za promicanje e-trgovine kroz inicijative kao što su poboljšanje digitalne infrastrukture i osiguravanje širokopojasnog pristupa internetu.

Ključne riječi: e-trgovina, online kupnja, analiza panel podataka, metoda potpuno modificiranih običnih najmanjih kvadrata, Europa.