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RELATIONSHIPS BETWEEN SOCIOLOGICAL, DEMOGRAPHIC AND MACROECONOMIC FACTORS AND E-COMMERCE MARKET TURNOVER

Wojciech MOLAS[1], Natalia NEHREBECKA[2*]

[1] Faculty of Economic Sciences, University of Warsaw; w.molas@uw.edu.pl, ORCID: 0009-0005-9751-1070
[2] Faculty of Economic Sciences, University of Warsaw; nnehrebecka@wne.uw.edu.pl, ORCID: 0000-0003-3870-7231
* Correspondence author

Purpose: The purpose of this article is to examine the relationship between the value of turnover in the booming e-commerce market and variables from economics, demographics and sociology.
Design/methodology/approach: The focus was on the analysis of panel data from 18 European economies over the period 2017-2022. Both static econometric models with fixed and random effects and dynamic models using the Blundell-Bond estimator were used.
Findings: The analysis conducted showed a significant and strong relationship between the value of e-commerce turnover per capita in the earlier period and its value in the later period. Furthermore, a positive relationship was found between the degree of urbanisation, the level of real GDP per capita and the increase in the percentage of internet users in the population and the value of e-commerce turnover per capita.
Research limitations/implications: The analysis focused mainly on panel data from 18 European economies, which limits the possibility to generalise the results to other regions or markets with different social and economic structures.
Practical implications: E-commerce enables companies to reach new markets and customers more easily, leading to increased sales and faster growth. Understanding the mechanisms of e-commerce growth in Europe can help companies optimise their strategy and expansion decisions.
Social implications: Analysis of demographic and sociological factors enables a better understanding of the purchasing preferences of different social groups, which provides valuable information for marketing and strategic planning.
Originality/value: The study's added value is its integrated approach to analysing the development of the e-commerce market in Europe, taking into account history, the evolution of consumer behaviour, business trends and econometric data analysis to understand the complexity of the phenomenon.
Keywords: e-commerce, e-commerce, internet, panel data, static and dynamic models.
Category of the paper: Research paper.

1. Introduction

Over the past decade or so, e-commerce has become an important part of the economy, representing a major sales channel for many companies. The growth of the e-commerce market is a result of technological advances, the increasing accessibility of the internet and, in recent years, the COVID-19 pandemic, which has accelerated the digital transformation of businesses (Zou, Cheshmehzangi, 2022). Personalisation of the shopping experience, digital marketing and social media have begun to play a key role in the development of this sector. Consumers are increasingly choosing to shop online, valuing convenience, a wide selection of products and the ability to quickly compare prices. In addition, the development of modern logistics technologies has improved delivery efficiency, increasing customer satisfaction. Younger generations, proficient in the use of the internet, are becoming an increasingly important target group for companies, prompting businesses to invest in e-commerce.

The development of e-commerce is a multidimensional phenomenon whose dynamics depends on a number of factors. The aim of this paper is to examine the relationship between the value of turnover in the rapidly growing e-commerce market and variables from economics, demography and sociology. The paper estimates both static models on panel data with fixed and random effects and selects the more appropriate of the two, as well as dynamic models with a systematic estimator of the Generalised Method of Moments (Arellano, Bover, 1995; Blundell, Bond, 1998). The models use annual panel data from 2017-2022 for eighteen European countries collected from Eurostat, World Bank and Statista.com databases.

The topic is relevant because of the growing role of e-commerce in business development and consumer behaviour. E-commerce enables companies to reach new markets and customers more easily, leading to increased sales and faster growth. Understanding the mechanisms of e-commerce growth in Europe can help optimise strategy and expansion. Analysis of demographic and sociological factors provides a better understanding of the purchasing preferences of social groups, which is valuable for marketing and strategic planning.

Based on the review of the related literature and the data analysis, research hypotheses were formulated and will be tested in the paper. Each hypothesis focuses on a different aspect related to the e-commerce market.

Hypothesis 1. There is a positive relationship between the value of e-commerce turnover per capita in the preceding period and the value of turnover in the following period. According to IMF research, countries with a higher share of online transactions before the pandemic experienced a greater increase in e-commerce turnover during the pandemic, while early-stage economies such as Brazil and Thailand had a smaller acceleration (Alcedo et al., 2022).

Hypothesis 2. There is a relationship between the percentage of people with higher education and the size of the e-commerce market. Studies indicate that consumers with higher education are more likely to shop online, have higher incomes and better internet literacy

(Li et al., 1999; Swinyard, Smith, 2003). According to Eurostat's 2024 report, 88% of those with a university education have shopped online, compared to only 57% of those with primary or no education (Eurostat, 2023).

Hypothesis 3. There is a relationship between the level of urbanisation and the size of the e-commerce market. Although e-commerce reduces income inequality between urban and rural areas (Wang, 2023) and supports rural areas (OECD, 1999), a report by the World Bank and Alibaba Group (2019) indicates that cities drive e-commerce growth, as urban residents are more likely to shop online and more businesses operate in cities. A study by Wang, Liu (2015) on data from China confirms that urbanisation, GDP per capita and education level are important variables affecting e-commerce growth.

Hypothesis 4. There is a relationship between real GDP and e-commerce turnover. In European countries, the value of e-commerce turnover represents between 2% and 9% of GDP (PPRO, 2023). In developed countries, e-commerce has a higher value and better growth prospects due to access to ICT infrastructure and higher levels of consumption and income (Molla, Licker, 2005; Roszko-Wójtowicz et al., 2024). A study by Wang, Liu (2015) also confirms that GDP per capita influences the development of the e-commerce market.

Hypothesis 5. There is a positive relationship between the increase in the percentage of Internet users in society and the development of e-commerce. Internet access and the spread of ICT are key to the development of the e-commerce market. Cheba et al. (2021) identified internet access as one of the most important factors influencing the development of e-commerce, and Dumičić et al. (2018) and Wang, Liu (2015) confirmed this relationship in their analyses of Europe and China. The increase in the number of internet users may therefore be an important element to foster the development of the e-commerce market.

The added value of the article is the integrated approach to analysing the development of the e-commerce market in European countries, taking into account the history of development, the evolution of consumer behaviour and business trends, and econometric data analysis, which allows for a better understanding of the complexity of the phenomenon. The comprehensive analysis, compared to the existing literature (e.g. Wang, Liu, 2015; Cheba et al., 2021; Dumičić et al., 2018; Roszko-Wójtowicz et al., 2024), is based on data from a period of dynamic changes in the e-commerce market in many European economies, focusing on variables potentially related to the sector. The findings may be useful for e-commerce companies in terms of expansion decisions, strategy optimisation and forecasting.

The second section presents the literature on the e-commerce market, including early research, trends, barriers to growth, the relationship with the economy and the impact of the Covid-19 pandemic. The third section is the analysis, describing the econometric models, the survey methodology, the dataset and presenting the conclusions of the analysis.

2. Literature review

The first studies on the e-commerce market emerged in the late 1990s, when the sector was still young and internet access limited. Early research focused on understanding what motivated consumers to buy online and how e-commerce companies could enhance the shopping experience (Keeney et al., 1999). From the outset, e-commerce explored improving the shopping experience through product recommendation systems (Burke et al., 1997).

Efforts were also made to characterize consumers based on demographic factors and attitudes toward online shopping. Online shoppers tend to be younger, better educated, wealthier, and more knowledgeable about the internet compared to non-shoppers (Li et al., 1999; Swinyard, Smith, 2003). A lack of online experience is a characteristic of those who avoid shopping online (Novak et al., 2000; Miyazaki, Fernandez, 2001). Studies of Spanish consumers revealed that men are more likely to use e-commerce than women, and e-commerce is more popular among younger people. Higher education, digital skills, and income also increase the likelihood of using e-commerce. The study also identified e-banking and e-government as important predictors of consumer engagement in e-commerce (Pérez-Amaral et al., 2020).

Wang, Liu (2015) discuss factors driving e-commerce growth in China, such as mobile service penetration, disposable income, number of computers per 100 households, and urbanization. Research on the impact of the Covid-19 pandemic highlights its significant effect on e-commerce growth, with a record 27% increase in 2020 (Cramer-Flood, 2021). Restrictions on traditional trade shifted demand to e-commerce, facilitating contactless transactions and reducing the risk of virus transmission (UNCTAD, 2021). The pandemic forced businesses to accelerate digital transformation, and e-commerce activity remained high in 2021. The proportion of internet users shopping online rose from 53% before the pandemic to 60% afterward across 66 countries. Notable increases were seen in the UAE (from 27% to 63%) and Bahrain (from 15% to 45%), while developed countries such as Greece, Ireland, Hungary, and Romania saw increases of 15-18 percentage points (UNCTAD, 2022). A PwC report (2021) indicates that the surge in online shopping in Poland during the pandemic represents a lasting shift in consumer behavior, with nearly 85% of Poles continuing to shop online to the same or greater extent after the pandemic.

E-commerce and the internet are vital to the economy, influencing GDP growth, productivity, and the labor market. Literature shows that online consumers are predominantly young, educated, and affluent. Key factors driving e-commerce growth include internet accessibility, urbanization, and high disposable income. Research on the Covid-19 pandemic underscores its role in accelerating e-commerce growth, shifting consumer behavior, and driving digital transformation in businesses.

3. Data description

A panel of data from 18 European countries for each year from 2017-2022 was used for the study. The countries analysed include: Bulgaria, Czech Republic, Germany, Estonia, Ireland, Spain, France, Italy, Cyprus, Lithuania, Hungary, Netherlands, Austria, Poland, Romania, Slovakia, Sweden, Norway. Data are taken from Eurostat, World Bank and Statista.com databases.

The research sample was selected taking into account countries with varying degrees of economic development and e-commerce market sophistication, focusing only on European countries. Countries for which data was not available for all periods analysed were not included in the study. The sample includes six countries where the e-commerce turnover per capita did not exceed €400, five where the value did not exceed €800 and seven where it was above €1000 per year.

Table 1 presents the variables used in the study, while Table 2 shows their descriptive statistics. The explanatory variable, **ECREVperCapita**, represents the total gross e-commerce turnover per capita in a country for a given year (in Euros) (see Figure 1), and was logarithmized in the study (e.g., Augustine, Rasp, 2023). The data includes only online sales of physical goods to private end consumers (B2C) and is derived from annual reports, national statistical offices, Google Trends, Alibaba.com, and industry knowledge. The statistics exclude sales of digital goods and services, as well as transactions between private individuals and businesses (B2B). The data was sourced from Statista.com, a German service specializing in data collection and visualization (Statista Market Insights, 2023).

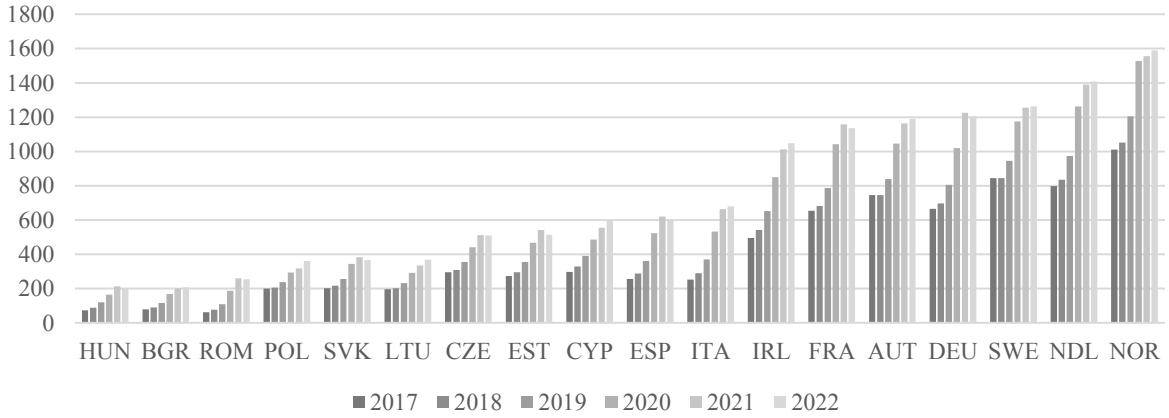

Figure 1. Value of annual e-commerce (B2C) market turnover per capita (in Euros).
Source: own elaboration.

Table 1.
Inventory of variables used in the study

Variable name	Description of the variable	Source
ECREVperCapita	total e-commerce turnover per capita in the country in a given year	Statista.com
Sociological variables:		
INT	percentage of the population with access to the Internet	Eurostat
X3M	percentage of the population who have made an online purchase in a given year at least once in the last 3 months	Eurostat
EBANK	percentage of the population using internet banking	Eurostat
ECOM	percentage of businesses in the economy that sell online	Eurostat
Demographic variables:		
URB	percentage of population living in urban areas as defined by the UN	World Bank
AGE	median age of the population in a given year in a given country	Eurostat
EDU	percentage of population with tertiary education	Eurostat
Macroeconomic variables:		
UNEMP	unemployment rate	Eurostat
GDP	real GDP per capita in a given year in a given country	Eurostat
INFL	inflation rate	Eurostat
EX_IMP	the ratio of the value of exports to imports in a given country in a given year	Eurostat

Source: own elaboration.

Table 2.
Descriptive statistics of the variables used in the study

Variable	Number of observations	Average	Standard deviation	Min	Max
ECREVperCapita	108	582.86	400.34	62.43	1589.99
INT	108	89.22	6.22	67.33	99.01
X3M	108	49.57	18.79	11	83.26
EBANK	108	58.75	23.30	5.49	96.13
ECOM	108	17.87	7.82	4.30	44
URB	108	71.55	10.75	53.73	92.89
AGE	108	42.35	2.43	36.9	48
EDU	108	42.70	10.31	23.3	62.30
UNEMP	108	6.24	2.94	2.00	17.20
GDP	108	28100	17767.16	6120	77490
INFL	108	3.57	3.94	-1.10	19.40
EX_IMP	108	1.07	0.14	0.86	2.04

Source: own elaboration.

Due to the existence of a collinearity problem when variables such as median age, the percentage of consumers purchasing online in the population, and the extent to which e-banking is widespread in society, it was decided to exclude them from the model.

4. Methods

In the analysis of economic phenomena that require accounting for the heterogeneity of the groups under study (e.g., different countries), panel models with fixed or random effects are commonly used (Baltagi, 2005). This approach is also applied in studies of e-commerce market development (Ho et al., 2008; Roszko-Wójtowicz et al., 2024). In this paper, both fixed-effects (FE) and random-effects (RE) models are estimated, with appropriate tests conducted to

determine the more suitable model. However, it should be noted that static models do not account for dynamics or potential endogeneity issues, which can lead to inconsistent estimators. To address these concerns, dynamic models are used to control for endogeneity and improve estimator efficiency (Alzate et al., 2021; Shanmugalingam et al., 2023; Myovella et al., 2020). The Generalized Method of Moments (GMM) approach, proposed by Arellano, Bond (1991) and Blundell, Bond (1998), is commonly employed for this purpose.

5. Results

Table 4 shows the estimated values of two static models: fixed effects (Model 1 - general form and special forms) and random effects (Model 2 - general form and special forms), and two dynamic models: with a one-step and two-step GMM estimator (Model 3, Model 4). Spearman correlation coefficients were examined before proceeding to estimation (see Table 3).

Table 3.
Spearman correlation coefficients

	INT	Ln(GDP)	URB	EDU	EX_IMP	UNEMP	EBANK	ECOM	INFL
INT	1.00								
Ln(GDP)	**0.72**	1.00							
URB	0.52	0.44	1.00						
EDU	0.42	0.51	0.22	1.00					
EX_IMP	0.31	0.51	0.33	0.18	1.00				
UNEMP	-0.16	0.05	0.00	0.26	-0.26	1.00			
ECOM	0.33	0.44	0.23	0.17	0.34	-0.26	0.49	1.00	
INFL	0.13	-0.21	-0.04	-0.12	-0.26	-0.39	0.11	0.09	1.00

Source: own elaboration.

Based on the tests conducted, the preferred static model is a special version of the random effects model with a robust stratified estimator. In contrast, the preferred dynamic model is the one with the two-step systematic estimator of the generalized method of moments (GMM), due to its ability to account for the true variance-covariance structure of moments and its higher estimation efficiency compared to the one-step systematic GMM estimator (cf. Roodman, 2009; Windmeijer, 2005).

The research hypotheses presented in the introduction were verified based on the estimation results. The first hypothesis posited a positive relationship between e-commerce market turnover per capita in the preceding period and turnover in the following period. In the dynamic models, the lagged variable was significant at the 1% level with positive estimates, confirming that turnover in the previous period can shape future turnover. This aligns with predictions based on International Monetary Fund research (Alcedo et al., 2022).

The second hypothesis explored the relationship between the percentage of the population with higher education and e-commerce turnover per capita. In the RE model, the EDU variable was insignificant, suggesting that higher education does not significantly affect e-commerce turnover. Although the literature suggests that consumers with higher education are more likely to shop online (Eurostat, 2023; Li et al., 1999; Swinyard, Smith, 2003), the observed relationship was not strong enough for statistical significance. In the dynamic models, EDU showed a negative parameter significant at the 10% level, indicating that higher education may reduce e-commerce turnover. This could be due to better-educated consumers prioritizing other spending over online shopping. Thus, hypothesis 2 is rejected. Further research is needed to explore this relationship in more depth.

Table 4.
Parameter estimates for static and dynamic models

Explanatory variables	Model 1 Fixed effects			Model 2 Random effects			Model 3 One-step system GMM	Model 4 Two-step system GMM
	General form*	Specific form*		General form*	Specific form*			
Ln(ECREVperCapita) at t-1	-	-	-	-	-	-	0.783*** (0.052)	0.823*** (0.059)
Ln(GDP)	0.651## (0.404)	0.642## (0.398)	-	1.012*** (0.206)	1.012*** (0.196)	-	0.217*** (0.056)	0.162** (0.061)
INT			0.020*** (0.0055)			0.0278 *** (0.0066)		
ECOM	0.002 (0.004)	-	-	0.001 (0.005)	-	-	-0.003** (0.001)	-0.0016 (0.0011)
URB	0.123* (0.070)	0.127* (0.068)	0.106 ## (0.0659)	0.013** (0.007)	0.013** (0.006)	0.0274 ** (0.011)	0.00146* (0.0008)	0.0017** (0.0007)
EX_IMP	-0.204* (0.098)	-0.203** (0.087)	-0.229*** (0.076)	-0.269** (0.108)	-0.256** (0.104)	-0.2552 *** (0.069)	-	-
UNEMP	-0.042## (0.025)	-0.042## (0.024)	-	-0.029# (0.021)	-0.282# (0.020)	-	-	-
EDU	-0.023## (0.014)	-0.023## (0.014)	-0.0097 (0.0128)	0.006 (0.010)	0.005 (0.009)	0.0087 (0.0088)	-0.00176** (0.00083)	-0.0018* (0.001)
INFL	-0.002 (0.007)	-	-0.0045 (0.0056)	-0.004 (0.007)	-	-0.0073 # (0.0056)	-	-
Time effects								
2018	0.012 (0.035)	0.011 (0.032)	0.024 (0.025)	0.215 (0.026)	0.020 (0.024)	0.012 (0.014)	-0.1865*** (0.037)	-0.1516*** (0.037)
2019	0.14** (0.058)	0.140** (0.056)	0.149 *** (0.049)	0.161*** (0.044)	0.160*** (0.042)	0.128 *** (0.026)	-0.0679** (0.032)	-0.0408 (0.033)
2020	0.473*** (0.083)	0.476*** (0.086)	0.386 *** (0.077)	0.509*** (0.058)	0.511*** (0.058)	0.356 *** (0.037)	0.0861*** (0.012)	0.0936*** (0.016)
2021	0.585*** (0.116)	0.583*** (0.112)	0.493 *** (0.115)	0.610*** (0.077)	0.603*** (0.074)	0.448 *** (0.064)	-	-
2022	0.540*** (0.167)	0.520*** (0.127)	0.514 *** (0.144)	0.591*** (0.113)	0.553*** (0.079)	0.494 *** (0.084)	-0.1125*** (0.022)	-0.0919*** (0.02)
Const	-8.137## (5.264)	-8.239## (5.081)	-2.909 (4.818)	-4.603*** (1.625)	-4.637*** (1.530)	1.337 * (0.791)	-0.6454** (0.242)	-0.3948 (0.244)
R^2 *between*	0.4076	0.3986	0.2756	0.8777	0.8787	0.5437	-	-
R^2 *within*	0.9197	0.9195	0.9262	0.9116	0.9112	0.9201	-	-

Model verification								
Name of the test	**Test statistic [p-value]**							
F test / Wald test: joint insignificance of variables	163.79 [0.000]	164.54 [0.000]	444,78 [0,000]	1629.90 [0.000]	1498.08 [0.000]	3798,84 [0,000]	-	-
F test/Wald test: joint insignificance of *year*	24.75 [0.000]	27.46 [0.000]	50,93 [0,000]	393.94 [0.000]	438.86 [0.000]	392,54 [0,00]	-	-
Hausman test	9.80 [0.4584]						-	-
Breusch-Pagan test: random effects	-		-	169.18 [0.000]	173.55 [0.000]	142,01 [0,000]	-	-
Test F: fixed effects	32.49 [0.000]	36.31 [0.000]	92,81 [0,00]	-	-	-	-	-
RESET test	1.79 [0.199]	1.80 [0.197]	2,06 [0,113]	2.61 [0.056]	2.06 [0.113]	2,06 [0,113]	-	-
Jarque-Bera test	52.97 [0.000]	53.15 [0.000]	52,55 [0,000]	29.50 [0.000]	28.13 [0.000]	54,59 [0,000]	-	-
Wald test: gr. heteroskedasticity	12170.96 [0.000]	11074.02 [0.000]	2763,61 [0,000]	565.67 [0.000]	483.21 [0.000]	507,34 [0,000]	-	-
Wooldridge test	412.02 [0.000]	668.31 [0.000]	44,585 [0,000]	412.02 [0.000]	668.30 [0.000]	44,585 [0,000]	-	-
Pesaran CD test	-0.54 [0.590]	-0.45 [0.656]	-1,46 [0,144]	1.52 [0.129]	1.52 [0.128]	-0,628 [0,53]	-	-
Sargan test	-	-	-	-	-	-	1.88 [0.390]	1.89 [0.389]
Hansen test	-	-	-	-	-	-	4.16 [0.125]	4.16 [0.125]
Arellano-Bonda AR(2) test	-	-	-	-	-	-	-1.33 [0.183]	-1.12 [0.261]

Note: *Models estimated with robust cluster estimator.
Significance level # 0.20 ## 0.15 * 0.10 ** 0.05 *** 0.01.

Source: own elaboration.

The third hypothesis, concerning the relationship between urbanization and e-commerce turnover, found that the URB variable in the RE model was significant at the 5% level. An increase in urbanization is associated with higher e-commerce turnover per capita, consistent with the findings of the World Bank and Alibaba Group (2019) and other studies (Wang, Liu, 2015). Urbanization promotes economic development, better internet access, and a higher standard of living, facilitating e-commerce growth. Both static and dynamic models support this conclusion, allowing us to accept hypothesis 3.

The fourth hypothesis concerned the link between real GDP per capita and e-commerce turnover per capita. The ln(GDP) variable was significant at the 1% level in the RE model. Dynamic models also showed a significant positive relationship. As GDP per capita increases, so does e-commerce turnover. This aligns with previous studies (Roszko-Wójtowicz et al., 2024; Molla, Licker, 2005; Wang, Liu, 2015). Higher GDP supports purchasing power and online shopping, while also fostering investment in ICT and logistics infrastructure, further boosting e-commerce.

The fifth hypothesis examined the relationship between internet accessibility and e-commerce turnover. The INT variable in the RE model was significant, showing that increased internet access leads to higher e-commerce turnover, consistent with prior research (Wang, Liu, 2015; Dumičić et al., 2018; Cheba et al., 2021). Expanding internet access allows

businesses to reach more consumers and reduces transaction costs, fostering e-commerce growth. Therefore, hypothesis 5 is confirmed.

Other variables were also tested. The ECOM variable was insignificant in the dynamic model with a two-step system estimator, possibly because large market players dominate e-commerce turnover (Soava et al., 2022). The EX_IMP variable showed a significant negative relationship with e-commerce turnover, suggesting that economies with a higher export-to-import ratio may have lower per capita e-commerce turnover. However, this finding contradicts other studies (Noroozi et al., 2010; Wang et al., 2021; Terzi, 2011), and further research is needed to clarify this relationship.

The UNEMP variable showed a negative coefficient significant at the 20% level. E-commerce's relationship with unemployment appears neutral (Biagi, Falk, 2017). While e-commerce may support labor market activity in developed economies (Banescu et al., 2022), no direct link between e-commerce turnover and unemployment was found.

The INFL variable was insignificant, suggesting that the e-commerce market is more resilient to inflation than traditional trade (Goolsbee, Klenow, 2018). However, high inflation may still limit e-commerce growth by reducing purchasing power and creating a challenging business environment (Beyrouthy, 2024).

Finally, the time effect estimates for 2020 indicate that it was the year in which e-commerce growth was the most significant.

6. Discussion

The findings highlight not only the complexity of the e-commerce landscape but also the need to view it through the lens of broader socio-economic structures. While factors such as urbanisation and GDP per capita appear to support market growth, their impact is likely mediated by deeper systemic elements like infrastructure development, logistics networks, and consumer trust in digital services. The lack of a link between education and e-commerce turnover challenges assumptions about digital literacy and suggests that access and usability may outweigh formal education levels in driving online shopping behavior.

The strong influence of internet penetration and the pandemic's acceleration of digital adoption also point toward a growing digital divide — where participation in e-commerce is increasingly shaped by access rather than traditional socio-economic status. These observations raise further questions about equity in digital economies and the long-term sustainability of e-commerce growth across different social groups. As the market evolves, especially with the rise of mobile commerce and AI-driven platforms, future research should aim to capture these nuances and shifts in user behavior more granularly.

7. Summary

The study of the e-commerce market is complex due to its dynamic nature, rapidly changing trends, and the variety of factors influencing its development. Nevertheless, the analysis conducted provides important insights into this sector and the variables associated with it. This study investigates the existence of correlations between sociological, demographic, and macroeconomic factors and e-commerce turnover, aiming to show how changing socio-economic conditions affect the dynamics and development of the e-commerce market.

In recent decades, technological advances have contributed to the rapid growth and transformation of e-commerce. The study found a strong relationship between per capita e-commerce turnover across different periods, suggesting no grounds to reject Hypothesis 1 concerning the positive relationship between the lag of the explanatory variable and its current value. Similarly, there were no grounds to reject Hypotheses 3 and 4, which suggested that urbanisation and higher GDP per capita positively influence the development of the e-commerce market. Urbanisation facilitates better consumer access, and, when combined with higher GDP per capita, supports more efficient logistics and investment in digital technologies. However, Hypothesis 2 was rejected, as no significant relationship was found between education level and e-commerce turnover. Additionally, the study found no grounds to reject Hypothesis 5, which posited a positive correlation between the percentage of internet users and the value of e-commerce turnover. The COVID-19 pandemic further accelerated digitalisation, acting as a key factor that contributed to the rapid transformation of the e-commerce sector and its record growth.

Despite the valuable results, the study has certain limitations. The analysis is based mainly on panel data from 18 European economies, which may limit the generalisability of the findings to other regions with different socio-economic structures. Future research could focus on a deeper understanding of differences in consumer behaviour, especially in the context of technology adoption in various social groups. Moreover, given the growing popularity of m-commerce, it would be valuable to further explore this segment, particularly aspects such as user engagement, mobile device usage, and the adaptation of logistics to the mobile-first model—areas that may offer important avenues for future exploration.

The findings of this study can support strategic decision-making by e-commerce companies and provide valuable insights for researchers in this field. However, continuous monitoring and analysis of developments in this area are essential for businesses to remain competitive in the evolving digital economy.

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