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PREFACE

This book delves into some of the most pressing and transformative issues facing the world today. In an era marked by rapid environmental, economic, and digital changes, it offers in-depth analyses of three interconnected topics: deforestation in Brazil, the Democratic Republic of the Congo, and Indonesia; competitiveness in the BSEC region; and the impact of mobile phone ownership on Kazakhstan's digital economy. Each of these topics, while distinct, represents critical concerns that demand thorough examination and thoughtful solutions.

The first chapter focuses on deforestation, one of the greatest threats to global environmental sustainability. By analyzing deforestation trends in Brazil, the Democratic Republic of the Congo, and Indonesia, this study provides an in-depth look at the environmental destruction in these countries and suggests future solutions.

The second chapter uses innovative methods to measure and analyze competitiveness through SITC (Standard International Trade Classification) technology classifications, providing insights into regional economic dynamics.

The third chapter examines the economic impact of mobile technology and how it contributes to Kazakhstan's economic transformation, especially in the context of a developing nation.

Through these three diverse yet interconnected topics, this book provides readers with a comprehensive perspective on some of the most critical global challenges of our time. Understanding the interactions between environmental, technological, and economic factors is not only an academic necessity but also a strategic requirement for shaping the future of global development.

The research presented in this book does more than describe the current state of affairs; it offers innovative methodologies and solutions to address these complex issues. In doing so, it provides valuable insights into how we can better navigate the challenges of today and tomorrow.

We hope that this book will offer its readers new perspectives on these important issues and encourage further inquiry into the solutions that can drive sustainable and equitable global progress.

Prof. Dr. Salih ÖZTÜRK

Dr. Mustafa Latif EMEK

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CHAPTER 1

ANALYZING DEFORESTATION IN BRAZIL, THE DEMOCRATIC REPUBLIC OF CONGO, AND INDONESIA: APPLICATION OF THE LMDI METHOD TO ANOTHER ENVIRONMENTAL CONCERN

Asst. Prof. Dr. Hasan RÜSTEMOĞLU

INTRODUCTION

Forests play a vital role in global ecosystems and they are crucial for all organisms[1]. Forests also contribute to human well-being through the various ecosystem services they provide. According to the Millennium Ecosystem Assessment (2005), Felipe-Lucia et al. (2018), and Temperli et al. (2020), and cited by Pichlerova et al. (2023), these services include wood production, habitat formation, nutrient fluxes, CO_2 sequestration, water infiltration, cooling and purification, flood control, climate regulation, recreation, aesthetic enjoyment, and scientific benefits. Forests also have some economic importance. Numerically, forest rents accounted for 0.2% of global real income in 2019, and in some regions of the world, the share of forest rents is even higher. Despite all the above mentioned benefits, forests remain under the threat of deforestation. In 2019, the total global forest area was 40.5 million sq. km whereas it was 42 million sq. km in 1992.

This corresponds to a 3.5% decrease during that period. As a result of deforestation, the overall share of global forest area in the land area decreased from 32.5% to 31.2% over the period from 1992-2019[2]. Deforestation is a widely discussed issue for the countries in the tropical

[1] The findings of this research were presented at the 7th International Economic Research and Financial Markets Congress which was held in April 2023, in Eskisehir, Turkey

[2] The available data for this study covers the period from 1992 to 2019.

belt of the world. However, deforestation is not only an environmental problem impacting the Amazon, south-east Asia, and central Africa, but also has also been widely observed in other regions of the world including Western Europe, North America, and China over the past several thousand years. National Geographic (2023) defines deforestation as the purposeful clearing of forest areas in order to make space for agriculture, grazing animals, obtaining wood for fuel, manufacturing, and construction (including not only buildings but also extensive road construction into regions that were once largely inaccessible). Other causes of deforestation are logging, cattle ranching, and oil palm and rubber tree plantations. Slash-and-burn agriculture is another reason for deforestation. Applying this agricultural method, farmers burn trees and use the ash produced as a fertilizer for their crops. However, this only enables the soil to become fertile in the short term. Potential consequences of deforestation are 1) increasing CO_2 emissions and accelerating global warming, 2) biodiversity loss, and 3) erosion risk (National Geographic, 2023).

When the literature on deforestation is examined, it is possible to observe that many different studies have been conducted using various different methods. One of the earliest studies was done by Allen and Barnes (1985) for the identification of the dynamics of deforestation in developing nations (39 countries in Africa, Latin America, and Asia) for the period between 1968 and 1978. This study utilized an econometric regression to estimate the short-term and long-term impacts of various determinants on deforestation. On the other hand, another early deforestation study employed historical data regarding deforestation in Costa Rica from 1940 to 1983 for the purpose of directing satellite monitoring to forest area changes (Sader & Joyce, 1988). In order to obtain a better understanding of the linkages between the spatial patterns of forest use, land use, and deforestation rate, Lorena and Lambin (2009) combined the time series of remote sensing data and household survey data and tested their hypothesis for the Amazon region. The spatial-temporal dynamics of deforestation have also gained the attention of many other scholars. For example, Villegas et al. (2021) performed an analysis to identify the effects of multiple deforestation drivers in different regions of Colombia. Rudel (2017) provided a comparison between dry and wet tropics' forests. The author reported that in order to curb the loss of dry forests, locally focused and administered policies are necessary. Joshi et al. (2015) conducted an analysis to identify the mapping dynamics of deforestation and forest degradation in Peru by employing radar satellite data. The researchers elucidated that 2.3% of the land in their study area had been disturbed during a period of only three years. One decomposition analysis was conducted by Franco-Solis and Montana (2021) for the period between 2000 and 2015. The authors applied structural decomposition analysis (SDA) to multiregional input output tables for three Latin American countries, namely Argentina, Brazil, and Paraguay. They compared the findings with the SDA results of the EU28, United States, and China.

Studies in which econometric regressions were employed for identifying the deforestation indicators have generally tested the validity of the environmental Kuznets curve (EKC) hypothesis (Hammig and Bhattarai, 2001; Ehrhardt-Martinez et al., 2002; Culas, 2007; Chiu, 2012; Esmaili and Nasrnia, 2014; Ahmed et al., 2015; Waluyo and Terawaki, 2016; Joshi and Beck, 2016; Zambrano-Monserrate et al., 2018; Murshed, 2020; Pablo-Romero, 2023). On the other hand, other scholars have provided a literature review or a meta-analysis on the deforestation studies in which the EKC hypothesis was utilized (Miah et al., 2011; Choumert et al., 2013). Hammig and Bhattarai (2001) focused on the dynamics of the deforestation problem including 66 countries in Latin America, Africa and Asia. The researchers examined the impact of factors such as GDP, political institution index, black market premium of foreign exchange, debt percentage, population growth rate, rural population density, and change in the cereal yield on deforestation. Ehrhardt-Martinez et al. (2002) tested the validity of the EKC hypothesis for deforestation in less developed countries over the period from 1980-1995. Other than real income, the authors investigated the impact of various factors on deforestation. They proved that the EKC hypothesis was strongly valid due to the urbanization level, rural-to-urban migration that partially reduced rural population pressure, the growth of urban economies (that were service dominated), and strong democratic states. Similar to Hammig and Bhattarai (2001), Culas (2007) also focused on the problem of deforestation in Latin America, Asia, and Africa. The researcher investigated the impacts of some explanatory variables including institutional variables, absolute forest area, and agricultural production index, proportion of forest area, population density, real income per capita, debt (% of GNP), export price index, and time trend on the deforestation rates of the three aforementioned regions. Chiu (2012) also examined different factors affecting deforestation by using panel estimation techniques. The researcher focused on the validity of the EKC hypothesis for 52 developing nations and the research period covered the period from 1972 to 2003. The results of Chiu's study provided strong evidence of the threshold effect between deforestation and real income for these developing nations. Another study utilizing panel estimation techniques was conducted by Joshi and Beck (2016) to test the validity of the EKC hypothesis in the OECD countries and non-OECD regions of Africa, Asia, and Latin America.

The authors investigated the impacts of factors such as economic growth, trade, agricultural land conversion, urbanization, population, and cereal yield on deforestation. Pablo-Romero et al. (2023) also highlighted the dilemma between deforestation and economic growth in their study. They focused on 19 Latin American nations and investigated the validity of the EKC hypothesis over the 1991-2014 period. Deforestation factors examined were real income per capita, rural population rate, energy use per capita, export volume index compared to the year 2000, and cereal yield.

All the aforementioned econometric regression studies utilized the panel estimation techniques. However, other scholars have tested the validity of the EKC hypothesis for a single country. For instance, Esmaeili and Nasrnia (2014) examined the validity of the EKC hypothesis in Iran by employing real income, property rights, the agricultural price index, forest area, export price index, wood price index, and urban population rate. Ahmed et al. (2015) studied the same topic for Pakistan by using the four factors of economic growth, energy use, trade openness, and population. Waluyo and Terawaki (2016) explored the validation of the EKC hypothesis for Indonesia by utilizing real income per capita, population growth, rural population, agricultural index, agricultural land area, roundwood production, and forest products exports. Murshed (2020) also focused on the same topic for Bangladesh by adding the quality of democracy to the research model as one of the determinants of deforestation. Lastly, Zambrano-Monserrate et al. (2018) provided a multinational deforestation analysis for five European countries (France, Germany, Greece, Portugal, and Turkey), but they did not use panel estimation methods.

The intended contributions of the present research to the literature are twofold:

1) This chapter aims to contribute to the literature by utilizing the logarithmic mean Divisia index (LMDI) method for deforestation for the first time. As previously discussed, various methodologies have been adopted for analyzing deforestation dynamics; however, to the best of our knowledge, no researchers have employed the LMDI method. The majority of the published studies in which the LMDI method was utilized have focused on the dynamics of CO_2 emissions, whereas several have examined the determinants of energy use. The LMDI method is based on the Kaya identity and the researcher strongly believes that by employing appropriate variables, it is possible to make a complete transformation and use this method for deforestation as well.
2) After the successful transformation of the LMDI calculations from the CO_2 decomposition analysis to the deforestation decomposition analysis, three case studies for the countries including Brazil, the Democratic Republic of Congo, and Indonesia will be provided since these countries are under the impact of severe deforestation. Between 1992 and 2019, the forest loss rates in Brazil, the DRC, and Indonesia were 14.6%, 15.5% and 19.4%, respectively. Therefore, identification of the factors that affect deforestation in these countries is significantly important. A comparison will also be provided for these countries according to the results of the decomposition

analysis and this will be the second contribution of the present chapter to the literature.

This chapter aims to provide a decomposition analysis for the deforestation problem in three countries - Brazil, the DRC, and Indonesia - by employing the LMDI approach[3]. Annual data covering the period from 1992 to 2019 will be used and five important determinants including deforestation intensity, biofuel intensity, energy supply intensity, income effect, and population effect will be considered. A comparison for these three different countries will be also done based on the empirical findings of the decomposition analysis.

The remainder of this study is planned as follows: Section 2 presents the transformation of the LMDI decomposition method from CO_2 emissions to deforestation.
Section 3 reports the results of this chapter based on the study aims and provides a comparison of the findings of each of the research countries. Lastly, Section 4 presents some concluding remarks and suggestions for the future studies.

2. Methodology

Lmdi Method

The Kaya identity shows the relationship between CO_2 emissions resulting from human activities and four driving forces, namely the carbon intensity of energy use (CO_2/EU), energy intensity of real income (EU/GDP), real income per capita (GDP/P), and population (P) (Kaya, 1989). That is,

[3] The deforestation, real income, population related datasets were extracted from the World Bank - World Development Indicators (WDI) database, whereas the datasets for total energy supply and biofuel production were sourced from the International Energy Agency (IEA) database.

$$CO_2 = \left(\frac{CO_2}{EU}\right)\left(\frac{EU}{GDP}\right)\left(\frac{GDP}{P}\right)(P) \quad (1)$$

The LMDI decomposition approach is a method widely employed for identifying the affecting factors of CO_2 emissions in different sectors (Akbostancı et al., 2009; Cai and Ma, 2018; Rüstemoğlu, 2021). Changes in energy-related CO_2 emissions can be decomposed into changes in carbon intensity, energy intensity, real income per capita, and population. The above-mentioned determining factors are computed by using the data of CO_2 emissions, energy use, total real income, and population. For transforming the LMDI analysis from the decomposition of CO_2 emissions to the decomposition of deforestation, we first need to change the proxy. Hence, the explained variable on the left side of equation will be set as deforestation. Deforestation is related with biofuel production, and therefore, it is added to the decomposition model. In addition to deforestation and biofuel production, other related variables such as total energy supply, real income, and population are also added. Then, the new version of the Kaya identity is as follows:

$$DEF = \left(\frac{DEF}{BIO}\right)\left(\frac{BIO}{TES}\right)\left(\frac{TES}{GDP}\right)\left(\frac{GDP}{POP}\right)(POP) \quad (2)$$

The second equation can be written in a simpler form:

$$DEF = (DI)(BI)(ESI)(IE)(P) \quad (3)$$

DI is the deforestation intensity of biofuel production (or deforestation intensity), BI is the biofuel share in total energy supply (or biofuel intensity), ESI is the energy supply intensity of per unit real income (or energy supply intensity), IE is the per capita real income (or income effect), and P is the population.

For deforestation, the decomposition identity is expressed as:

$$DEF = \sum_i DEF_i = \sum_i X_1 X_2 \ldots X_n \quad (4)$$

For the additive form of the LMDI method, the difference is decomposed as:

$$\Delta DEF_{total} = DEF^{T} - DEF^{0} = \Delta DEF_{X1} + \Delta DEF_{X2} + \cdots + \Delta DEF_{Xn} \qquad (5)$$

In the above equation, the superscripts 0 and T represent the period 0 and period T, respectively.
The impact of the j[th] factor in Equation (5) in the LMDI method can be presented as:

$$\Delta V_{Xj} = \sum_i L\left(V_i^T, V_i^0\right) \ln\left(\frac{X_{ji}^T}{X_{ji}^0}\right) = \sum_i \frac{V_i^T - V_i^0}{\ln V_i^T - \ln V_i^0} \ln\left(\frac{X_{ji}^T}{X_{ji}^0}\right) \qquad (6)$$

As a result, the additive decomposition for deforestation takes the following form:

$$\Delta DEF_{total} = DEF^{T} - DEF^{0} = \Delta DEF_{DI} + \Delta DEF_{BI} + \Delta DEF_{ESI} + \Delta DEF_{IE} + \Delta DEF_{P} \qquad (7)$$

The right-hand side of Equation (7) consists of the subscripts DI, BI, ESI, IE, and P. These subscripts represent the impacts of deforestation intensity, biofuel intensity, energy supply intensity, income effect, and population, respectively. These components are computed as:

$$\Delta DEF_{DI} = \sum_i \frac{DEF_i^T - DEF_i^0}{\ln DEF_i^T - \ln DEF_i^0} \ln\left(\frac{DI_i^T}{DI_i^0}\right) \qquad (7a)$$

$$\Delta DEF_{BI} = \sum_i \frac{DEF_i^T - DEF_i^0}{\ln DEF_i^T - \ln DEF_i^0} \ln\left(\frac{BI_i^T}{BI_i^0}\right) \qquad (7b)$$

$$\Delta DEF_{ESI} = \sum_i \frac{DEF_i^T - DEF_i^0}{\ln DEF_i^T - \ln DEF_i^0} \ln\left(\frac{ESI_i^T}{ESI_i^0}\right) \qquad (7c)$$

$$\Delta DEF_{IE} = \sum_i \frac{DEF_i^T - DEF_i^0}{\ln DEF_i^T - \ln DEF_i^0} \ln\left(\frac{IE_i^T}{IE_i^0}\right) \quad (7d)$$

$$\Delta DEF_{P} = \sum_i \frac{DEF_i^T - DEF_i^0}{\ln DEF_i^T - \ln DEF_i^0} \ln\left(\frac{P_i^T}{P_i^0}\right) \quad (7e)$$

Using the LMDI method, a quantitative analysis is performed, not only to confirm the contributions of the various determinants of deforestation, but also to label the key factors for future studies.

3. Findings

Brazil

Noticeable economic growth performance was observed for Brazil in the study period. In 2019, Brazil's total real income was 97.4% higher compared to 1992. The country's per capita real income was $5974.6 in 1992 and increased to $8622.1 in 2019, which equates to a rise of 44.3%. Thus, the results of the LMDI decomposition analysis indicated that one of the main causes of the increase in deforestation rate in Brazil was the per capita real income. On average, it was found that the income effect raised the rate of deforestation in Brazil by 39705.8 sq. km per year. The cumulative share of the income effect was found to be 128.3% at the end of the study period. The cumulative effect of real income per capita on Brazil's deforestation was found to be 1072056.9 sq. km for the same year. As can be seen in Figure 1, the decline in economic activity reduced the rate of deforestation in some periods. These recessionary periods were identified by the researcher as 1997-98, 1998-99, 2002-03, 2008-09, 2013-14, 2014-15, and 2015-16. In the remaining 20 periods, however, Brazil's deforestation rate was substantially raised by the income effect.

The findings of the decomposition analysis indicate that population was another factor that raised Brazil's deforestation rate by a considerable amount. Brazil's population increased by 36.8%, from 154.3 million to 211 million, over the 1992-2019 period. Together with population growth, the urban population rate also rose substantially in Brazil. The high urbanization rate unfortunately resulted in the clearance of forest areas. Between 1992 and 2019, the urban population rate rose from 75.4% to 86.8%. Hence, the high population growth rate of the country increased the deforestation by 34397.6 sq. km on average, each year. Based on the LMDI decomposition analysis findings, the total impact of population on Brazil's deforestation was determined as 928735.5 sq. km and its share was equivalent to 111.2% for the 2018-19 period.

The study findings demonstrated that biofuel intensity was one of the minor determinants of Brazil's deforestation, mainly after 2007. Before that year, biofuel intensity was one of the prominent determinants of deforestation in the country. In 11 of 27 periods, the biofuel intensity decreased deforestation. However, in the remaining 16 periods, this factor increased the deforestation rate. According to the results, biofuel intensity consecutively raised deforestation between the periods 2000-2001 and 2008-2009, and between the periods 2014-2015 and 2018-2019. On the other hand, this factor consecutively reduced Brazil's deforestation, from the period 1994-1995 to 1997-1998 and from the period 2009-2010 to 2013-2014. LMDI findings revealed that biofuel intensity increased deforestation by 1406.8 sq. km, per year, on average. The cumulative effect of biofuel intensity was found to be 37984.2 sq. km at the end of the study period. Additionally, its cumulative share was computed as 4.5% at the end of the review period. The share of biofuels in total energy supply did not change significantly in the study period in Brazil. It was equivalent to 32.7% in 1992, declined to its minimum level of 25.4% in 2000, and after that year, it gradually increased to 32.2% until 2019. Therefore, the minor impact of biofuel intensity on Brazil's deforestation was not an unexpected outcome.

The results indicated that energy supply intensity was another minor factor in the changes of Brazil's deforestation during the period of examination. Brazil's total energy supply increased by 103.8% from 1992 and 2019. On the other hand, the countries' real income rose by 97.4%. In 13 of 27 periods, the energy supply intensity reduced Brazil's deforestation rate. However, in the remaining 14 periods, this factor raised the deforestation in Brazil. On average, the energy supply intensity caused an increase in the deforestation rate by 3819.4 sq. km annually. The LMDI analysis showed that the share of energy supply intensity was 12.3% in the 2018-19 period, whereas its cumulative impact was found to be 103124.1 sq. km.

The only factor that reduced Brazil's deforestation rate appeared to be the deforestation intensity for the studied period. Brazil's total forest area declined from 69.6% (in 1992) to 59.6% (in 2019). The deforestation intensity was calculated as 1.3 and 0.9 for the beginning and the end of the examined period. This decline explains why the deforestation intensity factor reduced the country's deforestation rate substantially. Based on the findings of the decomposition analysis, in 19 of 27 periods, deforestation intensity had a reducing impact on the rate of deforestation, whereas in the remaining 8 periods, it was raised by the factor. On average, this factor decreased Brazil's deforestation rate by 48389.8 sq. km each year, according to the LMDI computations. Lastly, the share of deforestation intensity was found to be -156.4%, whereas the cumulative contribution of the factor on deforestation was -1306524.5 sq. km in the 2018-2019 period. The factors that affected Brazil's deforestation are demonstrated in Figure 1.

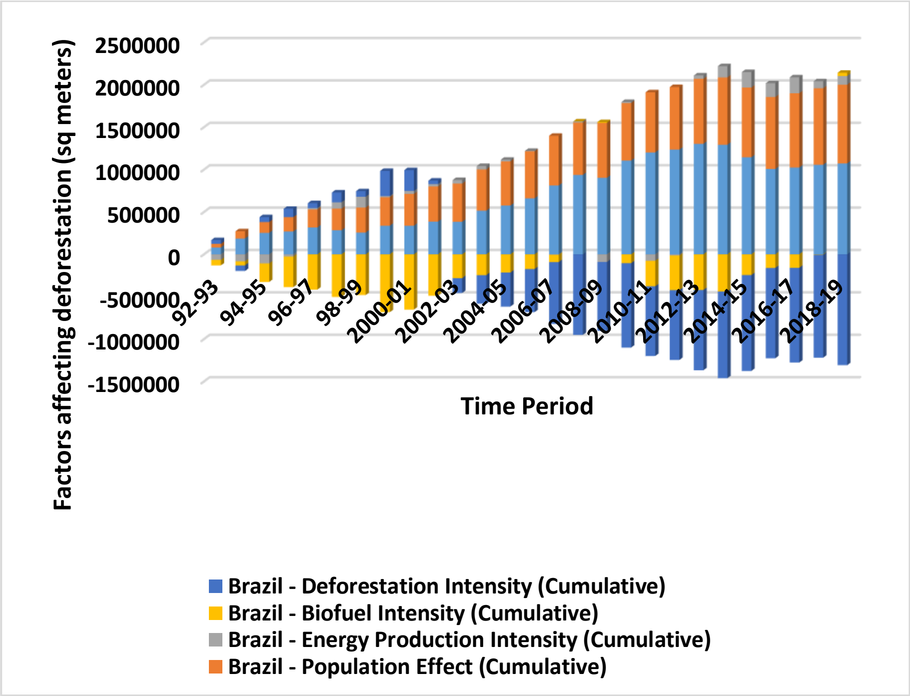

Figure 1. Factors affecting Brazil's deforestation over 1992-2019 (Source: Author's computations)

The Democratic Republic of Congo

The population effect was the major determinant of the changes in the deforestation rate in the DRC. The DRC's population numerically increased by 132.5%, from 37.3 million to 86.8 million. Hence, the high population growth resulted in high deforestation. On average, the population effect raised deforestation in the DRC by 27296.9 sq. km, per year. The share of the population effect was calculated as 334.6%, whereas its cumulative impact on deforestation was 737016.3 sq. km for the period 2018-2019.

Energy supply intensity was another factor that led to an increase in the deforestation rate of the DRC. This can be explained by the significant rise in the country's energy supply, which was greater than the increase in real income. Over the period 1992-2019, energy supply in the DRC increased by 151.4%, whereas real income increased by 84.6%. In 14 of 27 periods, the energy supply intensity caused an increase in the DRC's deforestation rate; however, in the remaining 13 periods, this factor caused it to decrease. It is notable that the energy supply intensity reduced the deforestation rate in the DRC for some consecutive periods from 2002-2003 to 2007-2008, 2012-2013 to 2014-2015, and 2016-2017 to 2018-2019.

However, the results also revealed that there were other consecutive periods (from 1992-1993 to 2001-2002) where the factor raised deforestation in the country. The annual average impact of energy supply intensity on the DRC's deforestation was computed as 8054.4 sq. km. Additionally, the cumulative share of the factor was calculated as 98.7%, and its total impact on deforestation was found to be 217467.8 sq. km for the period 2018-2019.

The biofuel intensity effect had a minor accelerating impact on the deforestation rate of the DRC. The results indicated that the biofuel intensity factor raised the deforestation rate in 12 periods and reduced it 15 periods between 1992 and 2019. It was observed that there were consecutive periods (from 1994-95 to 1995-96, 2001-2002 to 2006-2007, 2009-2010 to 2010-2011, 2012-2013 to 2013-2014, and 2016-2017 to 2018-2019) in which the biofuel intensity decreased the deforestation rate of the country.

The biofuel intensity effect increased the DRC's deforestation by 2163.8 sq. km per year, on average. Its cumulative share in deforestation was found to be 26.5%, and the total effect was 58422.7 sq. km at the end of the review period. In general, biofuels are vital in the energy production matrix in the Democratic Republic of Congo and this was important was also determined to be valid for the period from 1992-2019 included in the scope of the research. The share of biofuels in total energy supply was 87.9% in 1992 and it rose to 94.5% in 2019. Therefore, the finding that the biofuel intensity factor increased deforestation in the country was not a surprising result.

The real income effect had a decreasing impact on the deforestation rate of the DRC. The DRC's real income per capita declined from $645.6 to $512.6 between 1992 and 2019. The decrease in the country's real income per capita was 20.6% over the examined period. As a result, real income per capita reduced the deforestation rate in 12 periods between 1992 and 2019.

There were some consecutive periods in which per capita real income increased deforestation (from 2002-2003 to 2007-2008, 2009-2010 to 2014-2015, and 2016-2017 to 2018-2019); however, the cumulative impact of the determinant was negative. It was found that, on average, the real income effect decreased deforestation in the country by 5213 sq. km, annually. The cumulative share of this determinant was computed as -63.9%, whereas the total effect was -140750.5 sq. km for the period 2018-2019.

Similar to Brazil, the deforestation intensity factor reduced deforestation in the Democratic Republic of Congo. In the country, the deforestation intensity declined from 1.7 (in 1992) to 0.8 (in 2019). Therefore, the deforestation intensity factor decreased the rate of deforestation in the DRC and this was not a surprising outcome.

Based on the LMDI decomposition results, the deforestation intensity factor decreased the DRC's deforestation rate in 26 of 27 periods. The annual average contribution of this factor on the DRC’s deforestation was calculated as -24144.2 sq. km. Its cumulative impact was found to be -651892.4 sq. km and its share in the total deforestation of the country was computed as -296% for the period 2018-2019.

It is possible to state that the deforestation intensity factor was more dominant than real income in reducing the DRC's deforestation rate. The determinants that affected the DRC's deforestation are depicted in Figure 2.

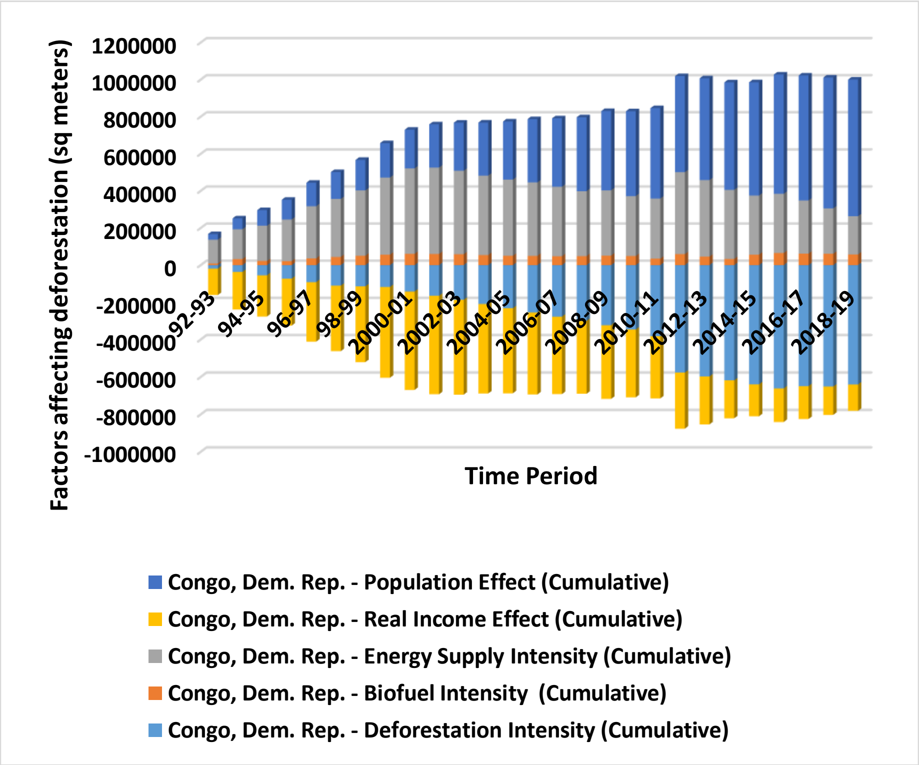

Figure 2. Factors affecting the DRC's deforestation over 1992-2019 (Source: Author's computations)

Indonesia

For Indonesia, the research findings emphasized that the real income effect, deforestation intensity, and population appeared to be of the factors that increased deforestation over the period 1992-2019. On the other hand, biofuel intensity and energy supply intensity were the two factors that decreased the rate of deforestation.

Among the factors that raised the deforestation rates, real income was the leading one in Indonesia. The country's real income per capita rose by 136.9%, from $1637 (in 1992) to $3877.4 (in 2019) and it became an upper middle income nation as a result. Consequently, Indonesia's deforestation rate was increased in 25 of 27 periods. The periods 1997-1998 and 1998-1999 were the only two periods in which the rate of deforestation in Indonesia was decreased by the real income effect. Real income caused an annual increase of 27463.4 sq. km in the deforestation rate of Indonesia, on average. Overall, the cumulative increase in Indonesia's deforestation that was caused by the real income effect was 741511.1 sq. km. and its share in total deforestation was computed as 256.2% for the period 2018-2019.

Deforestation intensity was detected as the second accelerating factor of Indonesia's deforestation in the period of examination. Indonesia's deforestation intensity was 0.4 (in 1992) and it increased to 0.7 (in 2019). Consequently, deforestation intensity raised the rate of deforestation in 22 of 27 periods. The periods 2001-2002, 2002-2003, 2005-2006, 2006-2007, and 2017-2018 were the only times in which the deforestation rate in Indonesia was reduced. The yearly increase in Indonesia's deforestation due to the deforestation intensity effect was computed as 21777.5 sq. km, on average. Utilizing the LMDI formula, the cumulative impact of deforestation intensity on Indonesia's deforestation rate was computed as 587993.3 sq. km. Its share in total deforestation was identified as 203.1% for the 2018-2019 period.

Population was the third and last factor that increased the deforestation rate in Indonesia. The country's population rose by 44.1%, from 187.7 million (in 1992) to 270.6 million (in 2019). As a consequence, the population effect continuously raised the rate of deforestation. On average, Indonesia's deforestation rate was raised by the population effect by an amount of 11379.4 sq. km, per year. The population effect was responsible for a cumulative impact of 307242.4 sq. km. in the 2018-2019 period. The share of the factor was calculated as 106.1% at the end of the studied period.

For Indonesia, energy supply intensity and biofuel intensity were the two factors that decreased the rate of deforestation during the period 1992-2019. Among these two factors, the impact of biofuel intensity was major, whereas the energy supply intensity played a minor role in reducing deforestation. From 1992 to 2019, Indonesia's total energy supply increased by 126%, whereas the country's real income increased by 241.4%. Thus, the energy supply intensity declined from

14.7 to 9.7 in the same period. Using the LMDI formula, it was found that the energy supply intensity factor reduced the rate of deforestation in 19 of 27 periods. However, in the remaining 8 periods, the energy supply intensity factor raised Indonesia's deforestation. The annual average impact of energy supply intensity on Indonesia's deforestation was found to be -13967.5 sq. km. The cumulative impact of the energy supply intensity factor was computed as -377123 sq. km. for the 2018-19 period. In that period, the factor's share was equal to -130.3% in total deforestation.

In Indonesia, the energy supply from biofuels decreased remarkably by 26.6%, from 1.9 million TJ to 1.4 million TJ over the 1992-2019 period. Hence, the share of biofuels in total energy supply dropped to 13.6% from 41.9% in the aforementioned period. The sharp decline in in the share of biofuel in the total energy supply affected the biofuel intensity factor in Indonesia's deforestation. In 23 of 27 periods, the factor decreased the deforestation rate substantially. Biofuel intensity caused an annual decrease of -35931.2 sq. km in Indonesia's deforestation, on average. Its cumulative impact was calculated as -970142.4 sq. km. and the share was found to be -335.1% for the last year of the examined period. The factors that determined Indonesia's deforestation are presented in Figure 3.

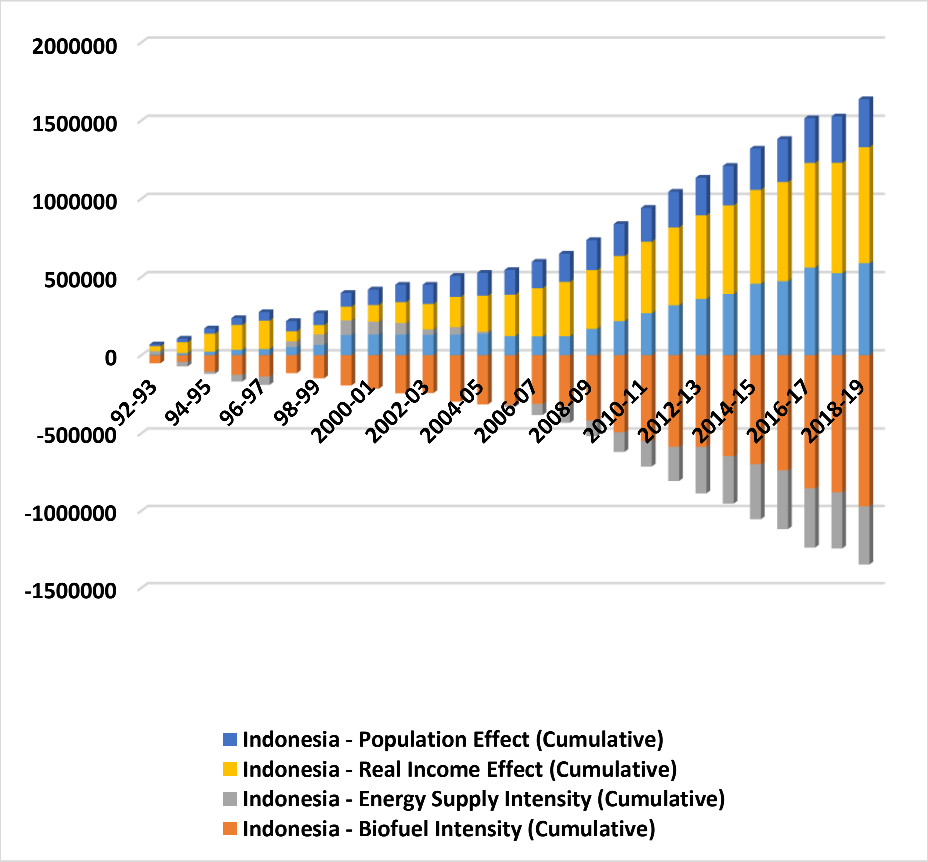

Figure 3. Factors affecting Indonesia's deforestation over 1992-2019 (Source: Author's computations)

Comparison of the empirical results

The findings of the LMDI calculations for the three research countries are presented in Table 1 below.

Table1. Summary of LMDI findings for the deforestation rates in three research countries (Source: Author's computations)

	Brazil	The DRC	Indonesia
Real Income Effect	1072056.9 (128.3%)	-140750.5 (-63.9%)	741511.1 (256.2%)
Population Effect	928735.5 (111.2%)	737016.3 (334.6%)	307242.4 (106.1%)
Energy Supply Intensity	103124.1 (12.3%)	217467.8 (98.7%)	-377122.8 (-130.3%)
Biofuel Intensity	37984.2 (4.5%)	58422.7 (26.5%)	-970142.4 (-335.1%)
Deforestation Intensity	-1306524.5 (-156.4%)	-651892.4 (-296%)	587993.3 (203.1%)
Total Deforestation	835376.2 (100%)	220264.3 (100%)	289481.7 (100%)

The real income effect was the leading determinant of Brazil's and Indonesia's deforestation rates among the increasing factors. On the other hand, this factor reduced the deforestation rate of the DRC, since the country's economy contracted in many years of the research period. Fundamentally, it is an expected result that real income increased the rate of deforestation, especially in the earlier phases of economic growth in the developing nations. Therefore, one can conclude that the situation of the DRC is temporary.

The population effect played a significant role in increasing the rate of deforestation in all three countries. It was the most affecting factor in the DRC's deforestation, second leading determinant of Brazil's deforestation and third major accelerating factor of Indonesia's deforestation. Brazil's annual population growth rate was 1.7% in 1992 and it dropped to 0.8% in 2019. The average annual growth rate of Brazil's population was 1.2% in that period and this value is very close to the world average of 1.3%. As the population increases, its destructive impact on forests will be more visible. The DRC's annual average population growth rate was equal to 3.2% for the period 1992-2019 and this number was 2.5 times higher than the world average. The sharp population increase has clearly reduced the forest areas of the

DRC, and therefore, the country should decrease the population growth rate. Indonesia's annual average population growth rate was found to be 1.4% and this measure was slightly higher than the world average. Therefore, the significant increase in the population of Indonesia also raised the rate of deforestation. It can also be recommended that the population growth of both the DRC and Indonesia be controlled in order to preserve the forests and increase the per capita well-being.

Energy supply intensity exhibited different trends in the deforestation of each research country based on the LMDI computations. Energy supply intensity played a minor accelerating role in Brazil's deforestation, whereas it caused a considerable increasing impact in the DRC's deforestation. However, in Indonesia, the energy supply intensity factor reduced the rate of deforestation. Furthermore, it is possible to conclude that the declining impact of energy supply intensity compensated for the increasing impact of the population effect in Indonesia's deforestation.

Biofuel intensity represents the impact of biofuel share in total energy supply on deforestation. The research results showed that the biofuel intensity effect increased the deforestation rates in Brazil and the DRC by a minimal amount. However, the biofuel intensity decreased Indonesia's deforestation rate by a large amount. The share of biofuels in Indonesia's energy supply decreased substantially; however, coal was the main source that replaced biofuels in this regard. Therefore, although the biofuel intensity reduced Indonesia's deforestation, other environmental risks occurred since coal became the major source in the country's total energy production. Overall, it is notable that the biofuel intensity factor decreased Indonesia's rate of deforestation by a large amount and it successfully offset the harmful impact of the real income factor.

Deforestation intensity was the fifth and last factor included in the decomposition analysis. The results of the LMDI approach for the three countries showed heterogeneity regarding the impact of deforestation intensity. The deforestation intensity factor caused a major decline in the rates of deforestation in Brazil and the DRC.

However, it increased the deforestation in Indonesia. For Brazil, the deforestation intensity factor compensated for the total accelerating impact of the factors such as real income, energy supply intensity, and biofuel intensity. For the DRC, the deforestation intensity factor successfully decreased the total increasing impact of energy supply intensity and biofuel intensity.

4. CONCLUSION

This chapter applied a well-known method (LMDI decomposition analysis) for a different environmental concern for the first time, namely deforestation. Five determining factors including real income, population, deforestation intensity, biofuel intensity, and energy supply intensity were identified and three countries that heavily experienced deforestation, namely Brazil, the DRC, and Indonesia, were considered.

Different findings were observed regarding the decomposition analysis. The real income effect increased the deforestation rate of Brazil and Indonesia, whereas it followed an opposite trend in the DRC's deforestation. Population was the factor that increased the deforestation in all research countries. Energy supply intensity also impacted the deforestation rates differently in each research country. This factor had a major increasing impact on the DRC's deforestation, and a minor increasing impact on Brazil's. However, energy supply intensity had a significant reducing impact on Indonesia's rate of deforestation. According to the results of the decomposition analysis, the biofuel intensity effect also indicated different results for the research countries. While this factor slightly increased the rate of deforestation in Brazil and the DRC, it significantly reduced deforestation in Indonesia. In the decomposition analysis, different results were also revealed for the deforestation intensity factor for the research countries. While this factor greatly reduced deforestation in Brazil and the DRC, it caused a significant increase in Indonesia.

The research findings revealed that population increased deforestation in all three countries and it is important to reduce the population growth rate. Among all the research countries, the highest increase in the deforestation rate was observed in Indonesia (43.8%) followed by Brazil (32.8%) and the DRC (28.4%). There was a considerable decline in the deforestation rate of Brazil, mainly starting in 2010. As highlighted by Tacconi et al. (2019), Indonesia can implement an aggressive and strategic law enforcement policy to decrease the deforestation rates, as observed in Brazil. There was a remarkable decline in the replacement of primary forests by palm oil plantations in Indonesia. However, further improvements are possible if the Crude Palm Oil (CPO) fund is used more extensively. As elucidated by Nurfatriani et al. (2019), the costs for replanting assistance could be increased from 40% to 60%. For the DRC, as suggested by Kipute et al (2023), a sufficient budget allocation is crucial for the conservation of forest areas. The researcher of the present study also supports this idea since the forests are both environmentally and economically important in the DRC. Forest rents constituted 8.7% of the DRC's GDP, in 2019, which was significantly higher than Brazil's (0.7%) and Indonesia's (0.4%) forest rent share in total economic activity.

This chapter showed that deforestation dynamics could be analyzed by utilizing the LMDI approach, which has been widely applied for the decomposition of CO_2 emissions and energy consumption in the scientific literature. Further studies could be conducted by using different variables including urbanization and/or logging amounts to examine the important accelerators of deforestation.

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CHAPTER 2

MEASURING COMPETITIVENESS THROUGH SITC TECHNOLOGY CLASSIFICATION: THE CASE OF BSEC

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Prof. Dr. Kenan ÇELİK

INTRODUCTION

In today's global landscape the share of products from different industrial sectors in the export portfolios of countries with increasing foreign trade activities has increased significantly. Countries are striving to improve their effectiveness and competitiveness in the international arena by diversifying their exports and focusing on products with high added value. In particular, products from technology-intensive industries and high-quality services have proven to be competitive advantages in international trade and thus contribute to an increase in added value. International cooperation initiatives, regional alliances and organizational integration have played an important role in increasing export competitiveness. Reducing trade barriers and strengthening cooperation facilitates the creation of an international trade environment that is oriented towards value creation. This ongoing process not only contributes to increasing economic growth but also promotes sustainable development by increasing competitiveness in international trade. Therefore, countries need to identify the economic sectors in which they have a high level of competitiveness. This enables countries to optimize their gains from foreign trade and improve social welfare.

This study aims to determine Turkey's export competitiveness in the Black Sea Economic Cooperation (BSEC) market based on technology intensity using the Revealed Comparative Advantage (RCA) index. Given Turkey's geographical proximity to the BSEC region and its potential for cooperation with countries in the region. It is necessary to assess Turkey's relative competitive advantage in export by technology intensity and analyze this advantage comparatively. The analysis aims to show Turkey's trade relations with these regional countries and evaluate their competitiveness in terms of technology intensity.

As far as we know, there is no study in the literature that measures Turkey's competitiveness in the export industry based on technology intensity in Turkey's foreign trade with BSEC countries. However, Turkey's foreign trade relations with BSEC countries are very highly important and the impact of these relations on technological competitiveness should not be ignored. The available literature also contains numerous studies in which competitiveness is measured at sector and country level using various indices and comparative analyses of different countries are carried out. However, no study analyses the export competitiveness of BSEC countries using Lall's (2000) Standard International Trade Classification Revision 3 (SITC Rev.3) technology classification. In this regard, this paper makes an important contribution to the literature by differentiating from other studies and determining whether Turkey has a comparative advantage in the export industry by technology intensity in the BSEC market. The initial section of the study presents fundamental introductory information regarding the establishment of the BSEC. The second section addresses the foreign trade of the countries in question with Turkey. The third section provides an overview of the existing literature on the subject. In the fourth section, the data and methodology used are explained in detail, and the competitiveness of Turkey exports in the BSEC market is calculated based on technology intensity. This calculation is based on Lall's standard SITC Rev.3 classification of international trade for seven different product groups. Based on these product groups, Turkey's level of competition is analysed and the results are presented comparatively. The final section evaluates the results of the study.

1. BSEC

BSEC is the result of a political and economic reconstruction that emerged after the collapse of the Soviet Union as a consequence of globalization at the world level and international integration at the regional level. It emerged as a regional economic cooperation initiative led by Turkey in the late 1980s. At a time when Eastern Europe was transitioning economically to a free market economy and politically to multi-democracy the BSEC, was founded in 1992 with an agreement signed by the member states in Istanbul. The founding members include located in the Black Sea basin. These countries are Albania, Azerbaijan, Bulgaria, Armenia, Georgia, Moldova, Romania, the Russian Federation, Turkey, Ukraine and Greece. With the accession of Serbia in 2004, the number of BSEC members rose to 12. In addition, North Macedonia was admitted as the 13th member of the BSEC in 2020 (Çeştepe et al., 2017; BSEC, 1992).

2. TURKEY'S TRADE WITH BSEC

Turkey's trade with the world and with the BSEC region, and the shares Turkey exports and imports in this region's trade, are shown in Table 1.

Table 1. Turkey's Foreign Trade Values With The BSEC (Billion $)

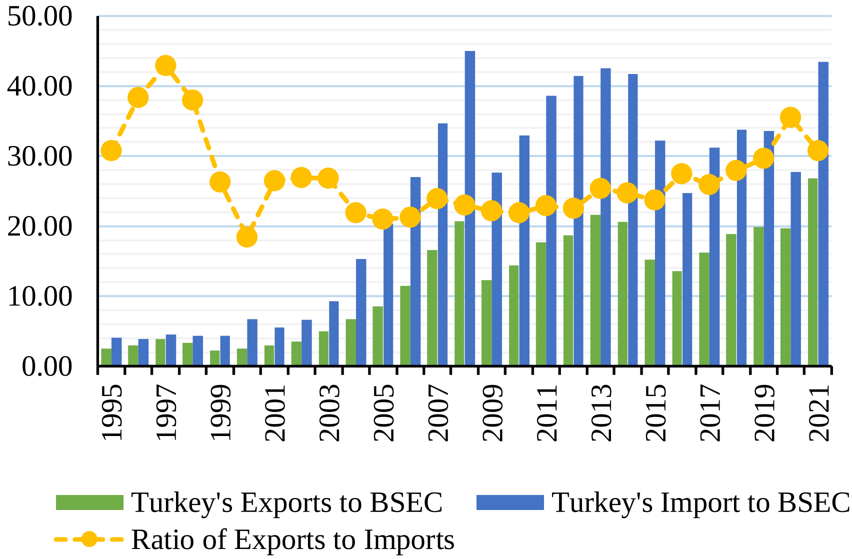
Year	Turkey's total exports	Turkey's exports to BSEC	Turkey's share of BSEC in total exports (%)	Turkey's total imports	Turkey's imports from BSEC	Turkey's share of BSEC in total imports (%)
1995	21.60	2.49	11.5	35.71	4.05	11.3
1996	23.05	2.95	12.8	42.93	3.85	9.0
1997	26.24	3.86	14.7	48.59	4.50	9.3
1998	26.88	3.30	12.3	45.91	4.34	9.5
1999	26.59	2.26	8.5	40.69	4.30	10.6
2000	27.77	2.48	8.9	54.50	6.71	12.3
2001	31.33	2.94	9.4	41.40	5.55	13.4
2002	35.76	3.55	9.9	51.55	6.59	12.8
2003	47.25	4.98	10.5	69.34	9.29	13.4
2004	63.12	6.72	10.6	97.54	15.33	15.7
2005	73.48	8.52	11.6	116.77	20.36	17.4
2006	85.53	11.48	13.4	139.57	26.98	19.3
2007	107.27	16.58	15.5	170.06	34.65	20.4
2008	132.03	20.71	15.7	201.96	45.03	22.3
2009	102.14	12.25	12.0	140.93	27.67	19.6
2010	113.88	14.41	12.7	185.54	32.92	17.7
2011	134.91	17.71	13.1	240.84	38.65	16.1
2012	152.46	18.68	12.3	236.55	41.41	17.5
2013	161.48	21.57	13.4	260.82	42.54	16.3
2014	166.50	20.63	12.4	251.14	41.75	16.6
2015	150.98	15.25	10.1	213.62	32.17	15.1

2016	149.25	13.58	9.1	202.19	24.74	12.2
2017	164.49	16.20	9.9	238.72	31.23	13.1
2018	177.17	18.89	10.7	231.15	33.80	14.6
2019	180.83	19.90	11.0	210.35	33.55	16.0
2020	169.66	19.70	11.6	219.51	27.74	12.6
2021	225.22	26.78	11.9	271.43	43.49	16.0

Source: UN Comtrade; UNCTADstat (2024).

Table 1 provides an insight into the foreign trade values between Turkey and the BSEC from 1995 to 2021. During this period, Turkey's total exports and imports increased continuously, with total imports often exceeding total exports. While Turkey's exports to the BSEC countries were occasionally subject to fluctuations, there was an overall upward trend. For example, Turkey's exports, which were around US $ 2.5 billion in 1995, increased to US $ 21 billion in 2008 and reached US $ 27 billion in 2021. Similarly, Turkey's imports from BSEC countries have generally increased, although there have declined in some years. Analyzing the share of BSEC countries in Turkey's total exports and imports, it can be seen that the contribution of BSEC countries to Turkey's export industry increased from 1995 to 1997, followed by a subsequent decline. It increased again from 2001 to 2013, but this share has been declining since 2013. BSEC shares in Turkey's total exports peaked at 15.5% in 2007 and 15.7% in 2008, 14.7% in 1997 and around 13.4% in 2006 and 2013. In recent years, the share of BSEC in Turkey's total exports was around 10.7% in 2018, 11% in 2019, 11.6% in 2020 and around 11.9% in 2021. On the other hand, the share of BSEC in Turkey's total imports has generally increased. While the share of BSEC in Turkey's total imports was 11.34% in 1995, it increased to 16% in 2021. Based on these results, it is clear that the share of BSEC in Turkey's foreign trade is significant in the period 1995-2021.

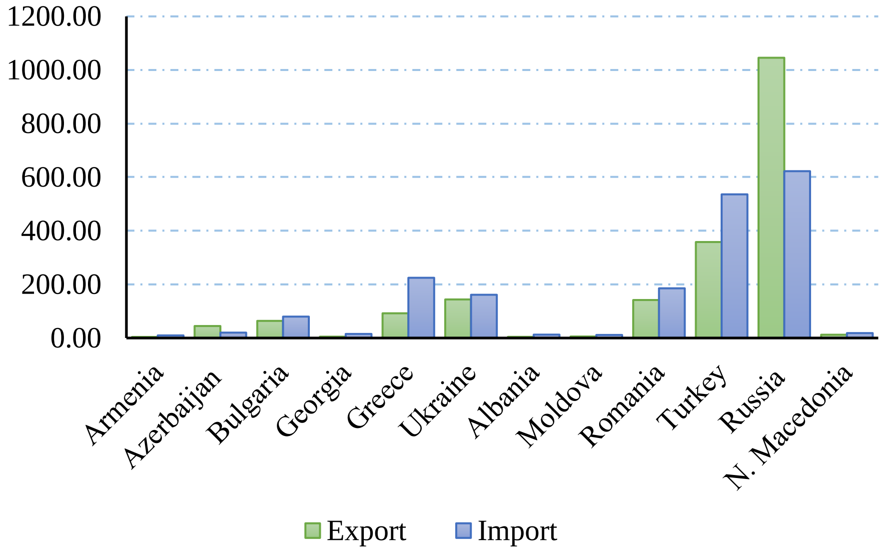
Graph 1. BSEC Foreign Trade With Turkey ($)



Source: UN Comtrade; UNCTADstat (2024).

Graph 1 shows trade between Turkey and the BSEC in the form of a bar graph. From this data, it can be seen that Turkey's trade with BSEC shows changes in certain periods. While trade increased continuously in the period 1995-2008, it declined with the global crisis of 2008-2009. An increase was observed again in the period 2009-2014, Although there was a decline in 2015 and 2016, trade tended to increase in the following years. The ratio of exports to imports fluctuates between the periods. The highest values were recorded at 71% in 2020, 56% in 2018 and 55% in 2016.

Graph 2. Average Percentage Of World Trade Accounted For By BSEC Countries (%, 1995-2021)



Source: UN Comtrade; UNCTADstat (2024).

Graph 2 shows the average percentage share of the BSEC countries in world trade in the period 1995-2021. The average of the percentage shares of Turkey and the other BSEC countries in total exports and total imports is calculated. Looking at the average percentage share of BSEC countries in world trade, it can be seen that Russia has the largest share. At the same time, other BSEC countries such as Turkey, Greece, Romania and Ukraine also have significant shares in world trade. Armenia, Moldova and Albania stand out among the BSEC countries with a smaller share of world trade.

3. LITERATURE REVIEW

Balassa and Noland (1989) analyzed the comparative advantages of the USA and Japan in 57 primary goods, 167 manufacturing products. and 20 high-tech product groups using data from 1967-1983. calculating the Balassa index and the net trade index. The authors found that the USA performs better in skilled labor-intensive goods than Japan. It is also noted that both countries have increased their comparative advantage in the high-technology group.

The work of Fertö and Hubbard (2003) examined the development of Hungary's competitiveness in the European Union (EU) market from 1992-1998. The authors calculated the RCA index using a 4-digit product classification to represent the agricultural industry. The calculations showed that Hungary has a comparative advantage in product groups such as live animals, meat, cereals, vegetables and fruit, sugar, beverages, oilseeds, mushrooms, wood, animal and vegetable substances, oils and fats.

Utkulu and Seymen (2004) analyzed Turkey's competitiveness in the EU market using seven different RCA indices for the period 1990-2003. and found that Turkey has a comparative advantage in 7 out of 63 product groups in the EU market. These product groups include clothing and clothing accessories, vegetables and fruit, sugar, sugar preparations, honey, tobacco, oilseeds, oleaginous fruits, rubber products textile yarns, fabrics, and related products.

Batra and Khan (2005) systematically analyzed the similarities between the comparative advantage models revealed by India and China in the world market and calculated the Balassa RCA index based on HS2 commodity classification with export data from 2000-2003. The analysis shows that there are great similarities in the structure of comparative advantage for India and China. It is highlighted that both India and China have comparative advantages in labor and resource-intensive industries in the global market. India has the largest comparative advantage in organic chemical products such as cotton, garments, nuclear reactors, and iron and steel industry products. On the other hand, China has the biggest highest comparative advantage in electronic products and is also strong in organic and inorganic chemical products.

Shen and Gu (2007) calculated the Balassa RCA index based on the 4-digit SITC from 1995 to 2006 to determine the comparative advantage of manufactured goods exported from China to the USA. The authors found that most of the trade between the two countries is inter-industry trade and a small portion is vertical trade between industries. They also found that trade between the USA and China is complementary rather than competitive and that the USA trade deficit with China is generally due to China's comparative advantage in these product groups.

Erkan (2011) analyzed the RCA coefficients of N-11 countries by SITC technology classification from 1993-2009, and the results of the analysis show that the highest RCA coefficients in products exported by N-11 countries are found in exports of raw materials and labor-intensive goods. It was also found that the Philippines ranks first in exports of research-based products which are high value-added and value and difficult to imitate and that South Korea and Mexico follow the Philippines in this area.

Sandalcılar (2011) analyzed the competitiveness between Turkey and Syria. The BEC and SITC classifications were used for the period from 2000 to 2009. According to the SITC Rev.3 classification, the RCA index was calculated for 1- and 2-digit products. The results showed that Turkey has a comparative advantage in the Syrian market in all product groups except 2-digit products.

Kalaycı (2013) analyzed the trade relations between Turkey and Russia using the RCA index. Grubel Lloyd and export similarity ındex from 2005-2010. In the analysis results, the author found that Turkey has a comparative advantage in sectors such as coffee, tea, cocoa, spices and related products, travel goods, handbags and similar carrier products, footwear and accessories, fruits and vegetables, and apparel. On the other hand, The author noted that disadvantages in industries such as petroleum gasses, natural gas, and other types of gas, hard coal, coke, briquette coal, animal feed, and mineral chemical fertilizers. The author also noted that the similarity between the product groups exported by the two countries is quite low and that most of the trade between the two countries takes place between different sectors.

Reyes (2014) who analyzed the competitiveness of the 6 ASEAN countries separately, analyzed the comparative advantage using the Balassa RCA index and the Lafay index between 2007-2011. The results of the analysis show that Brunei has the largest comparative advantage in petroleum. While Indonesia and Malaysia have an advantage in animal and vegetable oils, semi-finished products, and related products. The Philippines has a significant advantage in electrical and electronic equipment and Singapore in organic chemicals. The author also notes that among the 6 ASEAN countries, only Thailand has a competitive advantage in vehicles other than railroads and streetcars.

Yılmaz and Genç (2021) who examined the level of competition in the food and beverage industry with low technology intensity within the scope of OECD Rev.3 in Turkey, calculated the Balassa RCA Index from 2010-2019. As a result of the calculation, it was found that little comparative advantage was achieved in the food and beverage industry.

The paper by Kılıçarslan and Dumrul (2022) assessed the competitiveness of each of the BRICS countries in 12 different sub-industries of the service sector with data from 2016-2020. The results of the analysis show that the BRICS countries are globally competitive in construction services, telecommunications, computer and IT services and other commercial services. China has a competitive advantage in manufacturing and construction services, while Russia has a comparative advantage in construction services. In India, Brazil, and South Africa, however; it is noted that there is no specific sub-sector of the services sector where a strong comparative advantage is achieved.

Paksadze and Çelik (2022) examined Turkey's competitiveness in the Georgian market and analyzed the period before and after the COVID-19 outbreak separately using the Balassa RCA Index from 2019-2020. As a result of the analysis, the authors found that Turkey's competitiveness against Georgia decreased in the first half of 2019, the year of the COVID-19 outbreak, while competitiveness increased again in the following months.

4. DATABASE, METHODOLOGY AND FINDINGS

4.1. Database and Methodology

This paper uses annual export data classified according to the SITC Rev.3 compiled from the UN Comtrade database and provided by UNCTADstat from 1995-2021. In order to assess Turkey's competitiveness within the BSEC market, the SITC technology classification has been employed, encompassing low technology products (LT1, LT2), medium-technology products (MT1, MT2, and MT3) and high-technology products (HT1, HT2) within the analytical framework. The analysis does not include Armenia and Serbia, as some SITC Rev.3 technology intensity export data for the period 1995-2021 are unavailable. Consequently, RCA index coefficients have been calculated for 11 BSEC countries and seven product groups, comprising Albania, Azerbaijan, Bulgaria, Georgia, Moldova, Romania, Russia, Ukraine, Greece, North Macedonia and Turkey.

4.1.1. Revealed Comparative Advantage

This study examines the level of Turkey's export competitiveness in the BSEC market as a function of technology classification. For this purpose, the RCA index, first introduced by Lisner (1958) and further developed by Balassa (1965) is calculated.

The RCA index or Balassa index which is the leading measure of specialization in international trade is the ratio of a country's share of total exports of a particular product or product group to its share of total world exports. The index is a measure that assesses whether a country has a greater export advantage in a particular industry or product compared to other countries (Balassa, 1965; Akyüz at al., 2020). The RCA index is used to identify a country's weak and strong export industries (Aiginger, 2000; Bojnec & Fertö, 2007). In the analysis, an RCA index value of more than 1 indicates that the country has competitiveness in the sense of comparative advantage in the product or product group in question, while an RCA index value of less than 1 indicates that the country has no comparative advantage in the product or product group in question (Balassa, 1965, 1989; Akyüz at al., 2020). The formula for the RCA index is given in equation (1):

$$RCA_{ij}=\frac{X_{ij}/X_j}{X_{iw}/X_w} \qquad (1)$$

RCA_{ij} is the comparative advantage of the country (j) in exports of the product (i)

X_{ij} is the export of products (i) to country (j)

X_j is the total export of all products in the country (j)

X_{iw} is the total export of products (i) to the world

X_w is the total export of all products in the World

The numerator of the RCA index shows the percentage share of a product or industry in national exports. while the denominator expresses the percentage share of the same product or industry in total world exports (Mykhnenko, 2005).

If RCA >1 this means that country j has a comparative advantage in the export of products. On the other hand, if RCA <1 this means that country j has a competitive disadvantage in product i. Hinloopen and Marrewijk (2001) have proposed four different levels to provide a more effective and detailed interpretation of Balassa’s coefficient of RCA ındex:

Category 1: ($0 < RCA \leq 1$): there is no competitive advantage

Category 2: ($1 < RCA \leq 2$): there is low competitive advantage

Category 3: ($2 < RCA \leq 4$): there is average competitive advantage

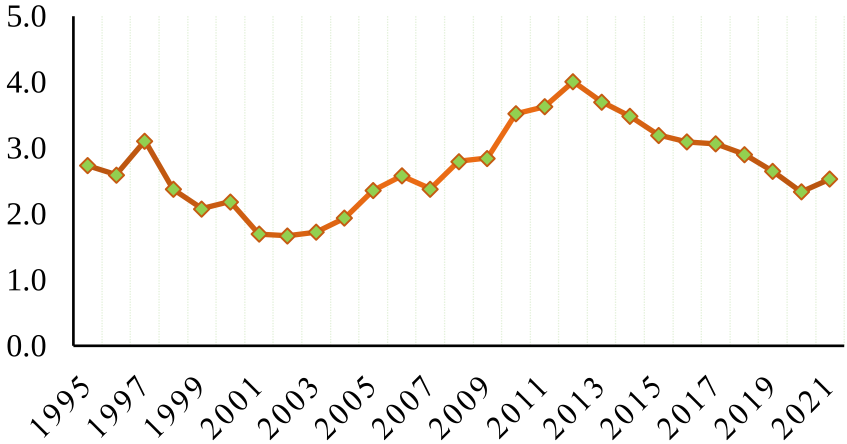
Category 4: ($RCA > 4$): there is strong competitive advantage

The higher the value of the RCA coefficient the greater the country’s comparative advantage for a specific product or product group.

4.2. Findings

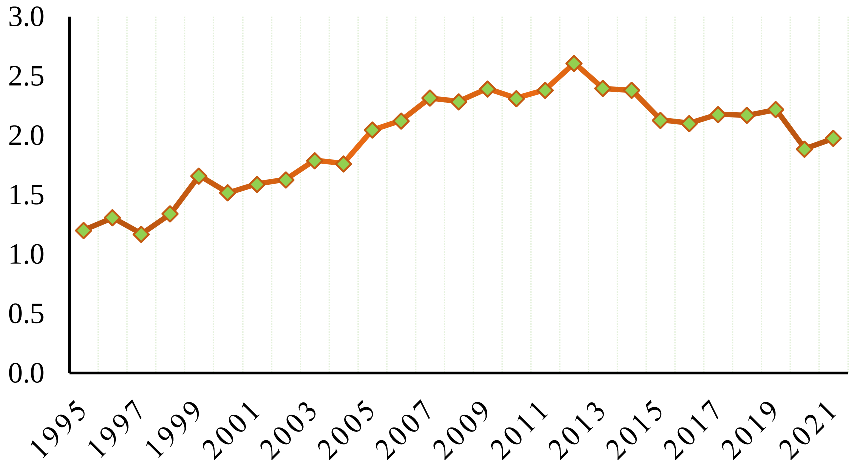
LT1, LT2, MT1, MT2, MT3, HT1 and HT2 technology-intensive products in the Turkish BSEC market, the values of the RCA index was calculated and is shown Graph 3, 4, 5, 6, 7, 8, 9 and 10. Additionally, the Appendix provides detailed coefficients for these product groups.

Graph 3. Turkey's Export Competitiveness in the BSEC Market by SITC Technology Classification: Balassa Index Results



Graph 3 shows the results of the RCA index, which was calculated for the low-technology-intensive product group LT1 in the textile, clothing garment and footwear industry in Turkey on the BSEC market. Accordingly, the index value generally fell in the period from 1997 to 2001. Turkey's competitive advantage in this sector weakened during this period. Between 2001 and 2004, Turkey had a weak comparative competitive advantage. In the period from 2001 to 2012 however, the index value rose in a fluctuating manner. During this period, Turkey achieved a moderate competitive advantage in the LT1 product group. In 2012, a strong comparative advantage was achieved. Although the index value decreased after 2012, a moderate comparative advantage was maintained. The results from Graph 3 show that Turkey has mostly achieved a moderate competitive advantage in the LT1 product group in the BSEC market during this period.

Graph 4. Turkey's Export Competitiveness in the BSEC Market by SITC Technology Classification: Balassa Index Results

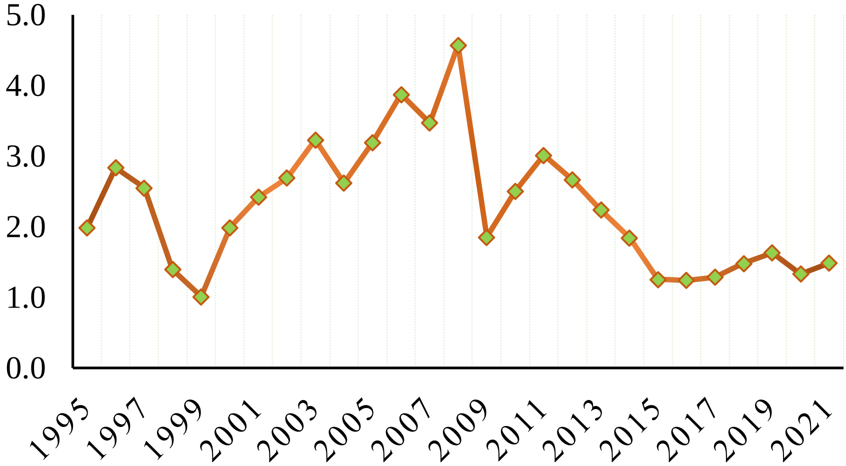


The results of the RCA index, which was calculated for the low-technology-intensive product group LT2 excluding textiles, clothing and footwear on Turkey's BSEC market are shown in Graph 4. Accordingly, it can be observed that the index value generally shows a fluctuating trend over the period. In other words, Turkey's competitive advantage in the LT2 product group changes over time.

Furthermore, the highest index value was calculated at 2.6 in 2012. This indicates that Turkey has a moderate competitive advantage in the LT2 product group.

Despite the fluctuations in the index value, it can be concluded that Turkey maintains its competitive strength and achieves a comparative advantage in this product group.

Graph 5. Turkey's Export Competitiveness in the BSEC Market by SITC Technology Classification: Balassa Index Results

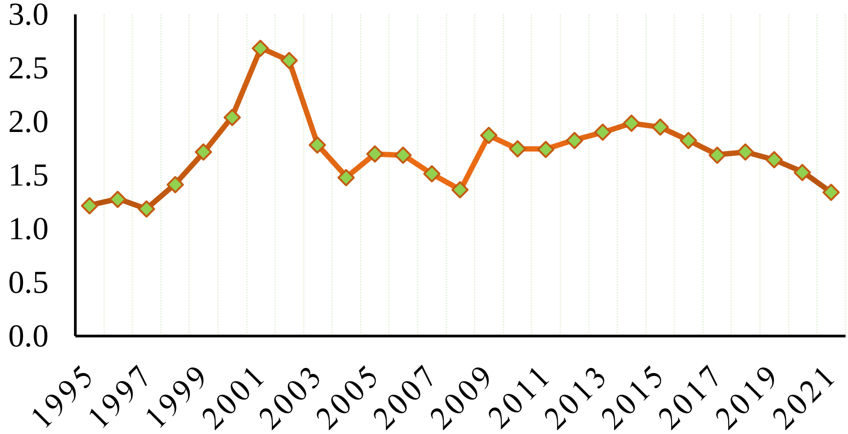


Graph 5 shows the results of the RCA index calculated for the technology-intensive product group MT1 in the Turkish automotive industry of on the BSEC market. In this graph, the highest index value is 4.6 which was reached in 2008.

In this year, the index value was calculated as MT1>4 and a strong comparative advantage was achieved. In 2009, the index value fell to 1.9 and a competitive disadvantage and a weak comparative advantage were achieved.

In 2011, the index value was calculated at 3.0 and a moderate comparative advantage was achieved. However a return to weak competitiveness was observed after 2013.

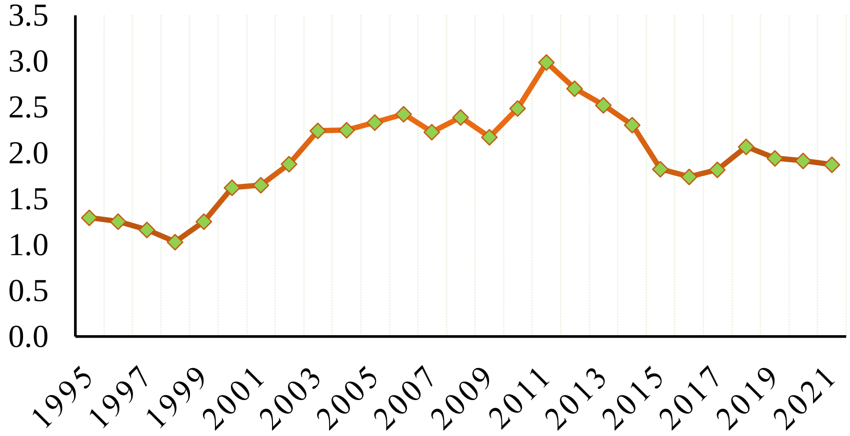
Graph 6. Turkey’s Export Competitiveness in the BSEC Market by SITC Technology Classification: Balassa Index Results



Graph 6 shows the results of the RCA index for the medium-technology-intensive product group MT2 for Turkey’s processed products on the BSEC market.

The highest index value was 2.7 in 2001 and 2.6 in 2002. The lowest index values were 1.2 in 1995 and 1997, 1.3 in 1996 and 1.4 in 1998 and 2008. It can be seen that Turkey generally has a low competitive advantage in MT2 exports in the BSEC market during this period. The fluctuations in the index values show that the competitive advantage in this product group is unstable over time.

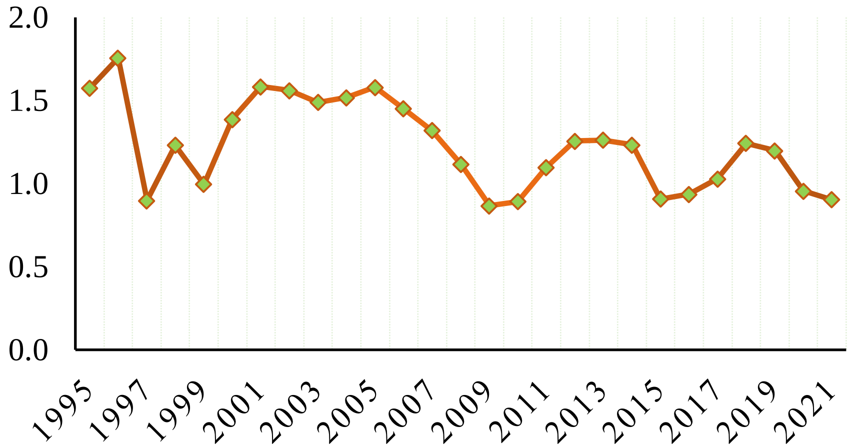
Graph 7. Turkey's export competitiveness in the BSEC market by SITC technology classification: Balassa Index Results



The RCA index values calculated for the technology-intensive product group MT3 in Turkey's mechanical engineering products on the BSEC market are shown in Graph 7. The index value followed a fluctuating trend throughout the period.

In 2011, the index value increased to 3.0 and showed a peak, but then the index value decreased. In the period 2003-2014. Turkey's exports to the BSEC had a moderate competitive advantage. After this period, however, competitiveness declined and a weak comparative advantage was achieved. To summarise, Turkey's competitiveness in engineering products fluctuated over time and generally has had a weak position during this period.

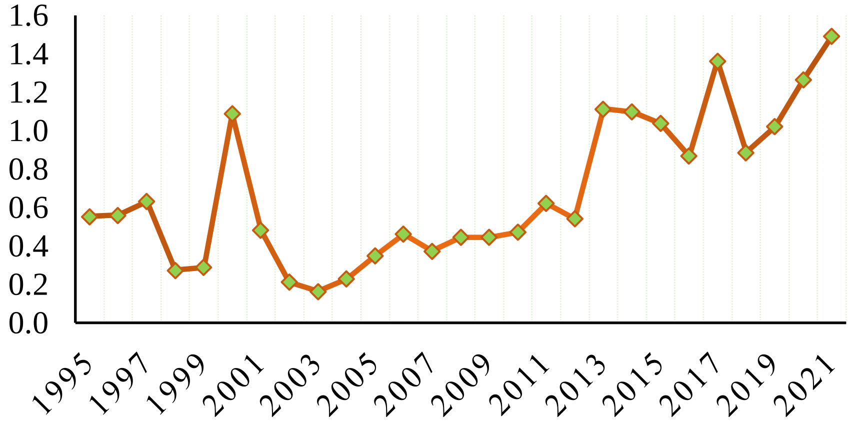
Graph 8. Turkey’s export competitiveness in the BSEC market by SITC technology classification: Balassa Index Results



Graph 8 shows the results of the RCA index, which was calculated for the highly technology-intensive HT1 product group in the electrical and electronics industry in Turkey on the BSEC market. According to this, the index values generally followed a fluctuating course over the period.

The highest index values were recorded in 1996, 2001, 2002 and 2005. The findings from Graph 8 indicate that Turkey has a weak competitive advantage in the high-tech HT1 product group in the BSEC market.

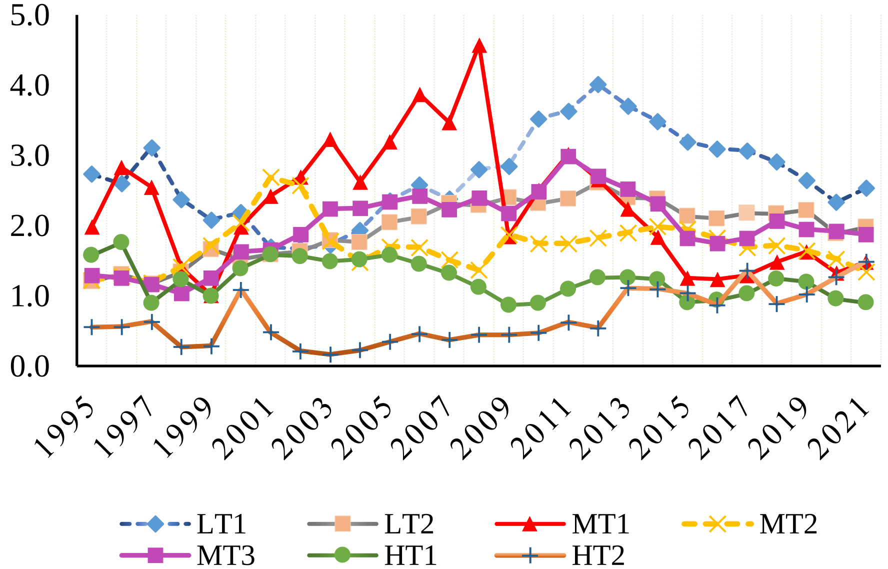
Graph 9. Turkey's Export Competitiveness in the BSEC Market by SITC Technology Classification: Balassa Index Results



The results of the RCA index calculated for the HT2 product group with high technology intensity in products other than electrical and electronic products in the Turkish BSEC market are shown in Graph 9. In general, the index values were calculated at a low level during this period.

Therefore, it can be said that Turkey has a competitive disadvantage in the high-technology product group HT2. However, it can be observed that the index values have shown an upward trend in recent years. This upward trend indicates that Turkey is in the process of reducing its competitive disadvantage in the HT2 product group in the BSEC market.

Graph 10. Demonstration of Turkey's Collective Competitiveness in the BSEC Market by SITC Technology Classification



Graph 10 shows an aggregated comparison of the competitiveness of the Turkish export industry in the BSEC market by technology intensity during regarding period. The graph shows the RCA index values, which were calculated separately for each product group. Accordingly, Turkey has a comparative advantage in the BSEC market in the period 1995-2001 for low-technology-intensive textiles, clothing and footwear (LT1) in the period 2001-2008. Turkey achieved a comparative advantage in exports of medium and technology-intensive automotive products (MT1). After 2008, competitiveness decreased and a transition from a moderate comparative advantage to a weak comparative advantage was observed. Between 2008 and 2021, Turkey gained a comparative advantage in exports of low technology-intensive LT1 products in the BSEC market. In the last period, i.e. in

2019, 2020, and 2021 the highest comparative advantage was generally achieved in low-technology product groups. These product groups are LT1 – textile, clothing and footwear industry and LT2 - other goods. Similarly in recent years technology-intensive engineering products (MT3), the automotive industry (MT1) and processed products (MT2) are the product groups where a moderate competitive advantage has been achieved in each case.

5. CONCLUSION AND ASSESSMENT

In this study, the competitiveness of the Turkish export industry in the BSEC market for the period 1995-2021 is analyzed using Balassa's (1965) RCA index. The SITC Rev.3 technology classification developed by Lall (2000) was used for the analysis. According to this classification, the product groups with low technology intensity LT1 (textile, garment and footwear industry) and LT2 (other products), the product groups with medium technology intensity MT1 (automotive industry), MT2 (processed products) and MT3 (technical products) and the product groups with high technology intensity HT1 (electrical and electronic products) and HT2 (other products) were analyzed. The level of competitiveness in each product category was calculated separately and the results were compared.

The results of the study show that Turkey's export competitiveness in the BSEC market has varied over the period. In the period 1995-2001. Turkey gained a competitive advantage in the low technology intensity product group. In other words, it can be said that Turkey is competitive in traditional industries such as textiles, apparel and footwear. In the period 2001-2008, Turkey was found to have gained a competitive advantage in the technology-intensive automotive sector industry. This shows that Turkey has increased its capacity to produce more complex products in more technology-intensive industries. In the period 2008-2021, Turkey has again gained a competitive advantage in the low technology-intensive product group. As of this period, Turkey is expected to be competitive in the BSEC market, generally in traditional labor-intensive products.

Considering the fact that processed products with medium technology intensity have gained a competitive advantage over the years. It is clear that Turkey should make more efforts to produce more complex products by processing raw materials. On the other hand, in recent years, the competitive disadvantage of medium-technology products in the engineering industry has decreased. So it can be said that new policies should be adopted to encourage the design and development of original products in this industry.

When the RCA ındex values for electrical and electronic products and other product groups in the high technology sector are analyzed. It can be seen that Turkey is far from being competitive in these products in the BSEC market. Turkey needs to make more efforts for these products and develop strategies that will give it a competitive advantage.

APPENDIX

Turkey's Export Competitiveness in the BSEC Market by SITC Technology Intensities: Balassa Index Results

Year	LT1	LT2	MT1	MT2	MT3	HT1	HT2
1995	2.7	1.2	2.0	1.2	1.3	1.6	0.6
1996	2.6	1.3	2.8	1.3	1.3	1.8	0.6
1997	3.1	1.2	2.6	1.2	1.2	0.9	0.6
1998	2.4	1.3	1.4	1.4	1.0	1.2	0.3
1999	2.1	1.7	1.0	1.7	1.3	1.0	0.3
2000	2.2	1.5	2.0	2.0	1.6	1.4	1.1
2001	1.7	1.6	2.4	2.7	1.7	1.6	0.5
2002	1.7	1.6	2.7	2.6	1.9	1.6	0.2
2003	1.7	1.8	3.2	1.8	2.2	1.5	0.2
2004	1.9	1.8	2.6	1.5	2.3	1.5	0.2
2005	2.4	2.0	3.2	1.7	2.3	1.6	0.3
2006	2.6	2.1	3.9	1.7	2.4	1.5	0.5
2007	2.4	2.3	3.5	1.5	2.2	1.3	0.4
2008	2.8	2.3	4.6	1.4	2.4	1.1	0.4
2009	2.8	2.4	1.9	1.9	2.2	0.9	0.4
2010	3.5	2.3	2.5	1.7	2.5	0.9	0.5
2011	3.6	2.4	3.0	1.7	3.0	1.1	0.6
2012	4.0	2.6	2.7	1.8	2.7	1.3	0.5
2013	3.7	2.4	2.2	1.9	2.5	1.3	1.1
2014	3.5	2.4	1.8	2.0	2.3	1.2	1.1
2015	3.2	2.1	1.3	2.0	1.8	0.9	1.0
2016	3.1	2.1	1.2	1.8	1.7	0.9	0.9
2017	3.1	2.2	1.3	1.7	1.8	1.0	1.4
2018	2.9	2.2	1.5	1.7	2.1	1.2	0.9
2019	2.6	2.2	1.6	1.6	1.9	1.2	1.0
2020	2.3	1.9	1.3	1.5	1.9	1.0	1.3
2021	2.5	2.0	1.5	1.3	1.9	0.9	1.5

Source: UN Comtrade; UNCTADstat (2024).

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BÖLÜM 3

MOBILE PHONE OWNERSHIP AND ITS IMPACT ON KAZAKHSTAN'S DIGITAL ECONOMY

Prof. Dr. Rajkhan Osama
Ayaulym Baitekova
Artur Kan

Introduction and Historical Background

Urbanization, characterized by the growth of cities and the migration of people from rural areas, is a crucial driver of economic and social transformation. As urban populations expand, cities become centers of commerce, innovation, and digital transformation. This study examines the relationship between mobile phone ownership and various aspects of the digital economy in Kazakhstan, including e-commerce, digital literacy, and internet usage by organizations. The findings are essential for understanding how urbanization and increased access to mobile technology contribute to digital development, especially in rapidly urbanizing nations like Kazakhstan [1-5].

Urbanization amplifies the demand for digital infrastructure and services as more individuals and organizations in cities adopt digital tools for daily activities. This shift necessitates improved digital literacy and widespread mobile phone ownership, which together enable access to e-commerce platforms, digital services, and online education. As urban centers grow, understanding the relationship between mobile phone penetration and the digital economy becomes even more critical for policymakers and businesses looking to capitalize on the opportunities presented by urbanization.

Kazakhstan provides a compelling case study due to its rapidly urbanizing population and growing digital economy. Between 2018 and 2022, the country saw a significant increase in mobile phone ownership and e-commerce activity. However, despite high mobile penetration, challenges remain in fully integrating e-commerce into retail and promoting digital literacy across all regions. Infrastructure limitations, consumer trust, and organizational adoption of internet technologies are key factors influencing the digital landscape [6-9].

Historically, the expansion of mobile phone usage has been a major catalyst for economic development, particularly in emerging economies. As mobile phones become more ubiquitous, they serve as the primary gateway to the internet, especially for those in urban areas with limited access to other forms of digital technology. Studies in other countries have shown that mobile phones contribute to the growth of digital literacy, facilitating participation in e-commerce and improving organizational efficiency through internet adoption. However, the extent to which mobile phone ownership alone can drive these changes remains debated, particularly in contexts where digital infrastructure and literacy programs are unevenly distributed.

In Kazakhstan, urbanization and technological adoption have gone hand in hand. The government's efforts to promote digital literacy and expand e-commerce platforms have been instrumental in shaping the digital economy. However, the urban-rural divide remains a challenge, with rural areas often lagging in terms of internet access and mobile phone penetration. As cities grow and become more interconnected, addressing these disparities will be critical to ensuring that the benefits of digital transformation are evenly distributed across the population.

By analyzing the impact of mobile phone ownership on Kazakhstan's digital economy, this study sheds light on the broader implications of urbanization for digital development. The findings highlight the need for a comprehensive approach to digital transformation that goes beyond simply increasing mobile phone ownership. Investments in infrastructure, digital education, and e-commerce ecosystems are essential to fully harness the potential of urbanization in driving digital and economic growth [10-15].

Methodology

This study employs regression modeling and trend forecasting to explore the relationships between mobile phone ownership and key digital economy indicators in Kazakhstan. The primary goal is to understand how mobile phone ownership influences digital literacy, e-commerce volume, the share of e-commerce in retail, and internet usage by organizations. Data was collected for a five-year period (2018-2022), focusing on mobile phone ownership (% of population aged 6 and older), e-commerce volume (mln Tenge), the share of e-commerce in retail (%), digital literacy (% of population aged 6-74), and the number of organizations using the internet.

Multiple linear regression models were used to assess the relationships between mobile phone ownership and each dependent variable, testing the following hypotheses: mobile phone ownership significantly influences digital literacy, e-commerce volume, the share of e-commerce in retail, and internet usage by organizations. The models were evaluated using R-value, R^2, and p-values. Standardized regression coefficients, standard errors, t-values, and p-values were computed, and the Shapiro-Wilk test was applied to check residual normality.

Based on the regression results, future trends were forecasted for 2023 to 2026 using projected mobile phone ownership. Simple linear regression models were constructed for each dependent variable. Projections were made for e-commerce volume, the share of e-commerce in retail, digital literacy, and internet usage by organizations.

Suggested methodology allows analyzing the role of mobile phone ownership in promoting digital literacy, while noting that factors beyond mobile phone ownership affect e-commerce growth and internet adoption by organizations [9-15].

Results and discussion

The e-commerce sector in Kazakhstan has seen remarkable growth between 2018 and 2022, driven by technological advancements, increased internet penetration, and shifts in consumer behavior, especially in the context of significant global events such as the COVID-19 pandemic (Table 1).

TABLE 1. Dynamics of E-commerce, Digital Literacy, and Internet Usage in Kazakhstan (2018-2022)

Year	Volume of E-commerce (mln. Tenge)	Share of E-commerce in Retail Trade (%)	Volume of E-commerce (services, mln. Tenge)	Share of People Owning Mobile Phones (%, 6+ years)	Digital Literacy of Population (%, aged 6-74)	Number of Organizations Using Internet
2018	144,606	1.4	136,123	88.15	79.6	100,720
2019	206,253.9	1.8	121,115.3	90.5	82.1	105,531
2020	476,651.5	4.1	209,164.7	92.6	84.1	110,246
2021	419,187.6	3.6	349,993.7	92.8	87.3	107,121
2022	1,963,493.2	12.5	1,186,536.7	92.8	88.3	124,603

The total volume of e-commerce surged from 144,606 million tenge in 2018 to an impressive 1,963,493.2 million tenge in 2022. This nearly fourteen-fold increase reflects a major transformation in consumer purchasing habits, as more people shifted from traditional retail to online platforms, particularly during the pandemic when movement restrictions and health concerns limited physical shopping. The surge in e-commerce can be tied to increased digital engagement and the growing trust in online transactions, with the pandemic acting as a catalyst for accelerated adoption.

Share of E-commerce in Retail: The share of e-commerce in total retail sales also experienced exponential growth, increasing from 1.4% in 2018 to 12.5% in 2022. This significant rise demonstrates the growing importance of online shopping in Kazakhstan's retail sector.

The pandemic amplified this trend as consumers, confined to their homes, turned to online platforms to meet their needs. The expansion of e-commerce platforms and the improvement in logistics and delivery services further supported this shift.

The volume of e-commerce services followed a similar upward trajectory, rising from 136,123 million tenge in 2018 to 1,186,536.7 million tenge in 2022. A notable spike occurred in 2020, with the volume increasing to 209,164.7 million tenge. The rise in e-commerce services during this period can be attributed to increased demand for digital services, particularly in areas such as online education, telemedicine, and remote working solutions, all of which were bolstered by the necessity to adapt during the pandemic.

Mobile phone ownership: Mobile phone ownership among individuals aged six and above increased from 88.15% in 2018 to 92.8% in 2022. The widespread availability of mobile phones, combined with the increased functionality of smartphones, has made online shopping more accessible, allowing consumers to easily browse, compare, and purchase goods and services from their devices.

The increase in mobile ownership played a significant role in facilitating the expansion of e-commerce by providing consumers with on-the-go access to digital platforms.

Digital literacy: Digital literacy among individuals aged 6 to 74 grew from 79.6% in 2018 to 88.3% in 2022.

This improvement in digital skills among the population was crucial for the growth of e-commerce, as it enabled more people to confidently navigate online platforms, manage digital payments, and participate in the digital economy.

The government's initiatives to improve digital literacy, coupled with the increasing integration of digital tools in everyday life, contributed to this trend.

Internet Usage by Organizations. The number of organizations, including government agencies, using the internet rose from 100,702 in 2018 to 124,603 in 2022. This increase reflects the growing recognition of the importance of digital services for organizational efficiency and competitiveness.

The adoption of internet-based solutions by businesses and government agencies, particularly during the pandemic, when remote work and online service delivery became necessary, further facilitated the expansion of the digital economy.

Overall, the data underscores the dynamic shift in Kazakhstan's digital market, driven by a combination of technological advancements, government initiatives, and the COVID-19 pandemic, which accelerated digital transformation.

E-commerce has not only become a key player in the retail sector but has also integrated itself into the broader economy, shaping the way businesses operate and consumers engage with the market.

The increase in mobile phone ownership, digital literacy, and internet usage by organizations, along with the growth of e-commerce services, reflects a broader digital evolution in Kazakhstan's economy.

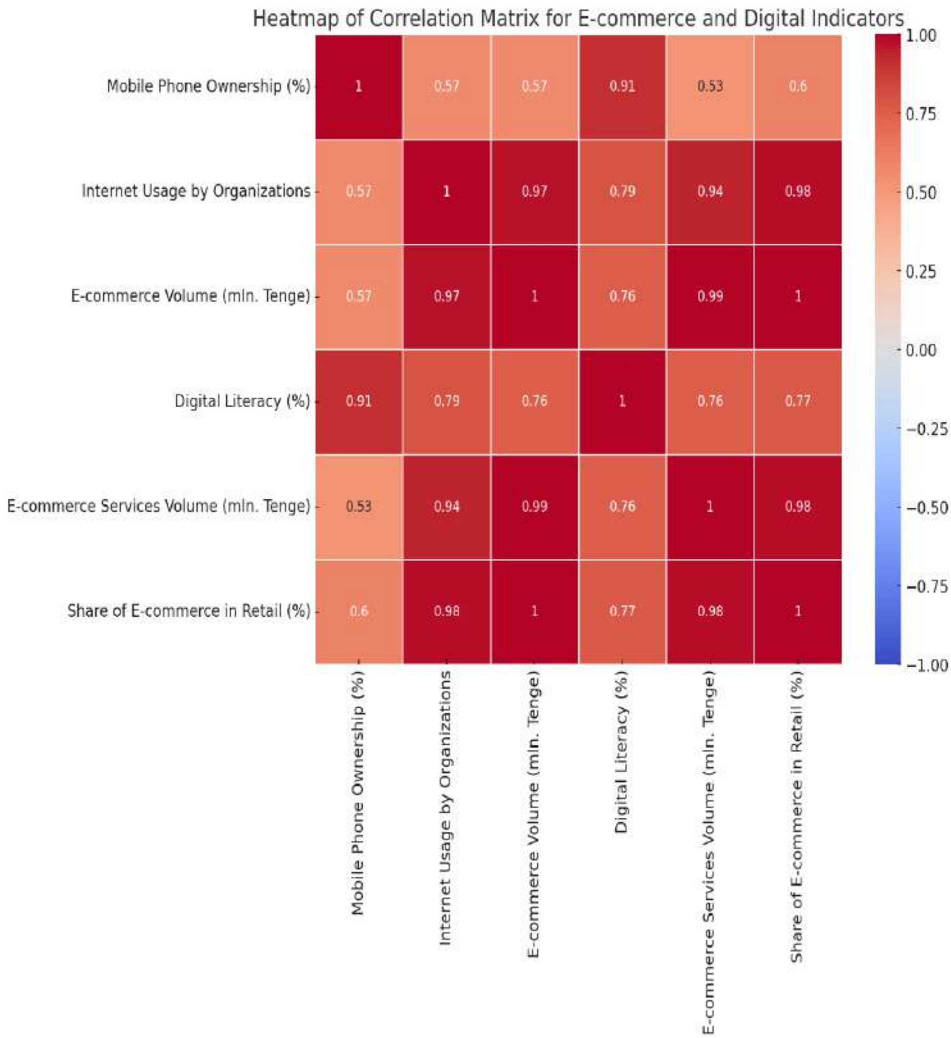

Figure 1. Correlation Matrix
Note: complied based on calculations

The proportion of people with mobile phones and the number of organizations using the Internet shows a moderate positive correlation (r = 0.697), suggesting that as mobile phone ownership increases, more organizations tend to use the Internet. However, with a p-value of 0.191

($p > 0.05$), this relationship is not statistically significant, indicating that the observed correlation could be due to chance.

Similarly, the proportion of people with mobile phones and the volume of e-commerce has a moderate positive correlation ($r = 0.570$), indicating a tendency for higher e-commerce volumes with increased mobile phone ownership. However, the p-value of 0.316 implies that this relationship is not statistically significant, meaning that the association between mobile phone ownership and e-commerce volume is not strong enough to be considered significant in this dataset.

In contrast, the proportion of people with mobile phones and the level of digital literacy shows a strong positive correlation ($r = 0.907$), which is statistically significant ($p = 0.034$, $p < 0.05$). This suggests that mobile phone ownership plays a crucial role in increasing digital literacy. In other words, as more people own mobile phones, the population's ability to navigate and utilize digital tools improves significantly.

The relationship between the number of organizations using the Internet and the volume of e-commerce is extremely strong, with a very high positive correlation ($r = 0.973$) and a statistically significant p-value ($p = 0.005$). This indicates that the expansion of Internet use among organizations directly boosts e-commerce activity. More organizations being connected to the Internet leads to substantial growth in e-commerce, highlighting the importance of digital infrastructure in driving the e-commerce economy.

There is also a very high positive correlation between the number of organizations using the Internet and the volume of e-commerce services (r = 0.942), which is statistically significant (p = 0.017). This demonstrates that Internet connectivity plays a critical role in fostering the growth of e-commerce services, suggesting that improvements in Internet access for businesses are directly linked to the expansion of the digital services sector.

The relationship between e-commerce volume and the share of e-commerce in retail shows an almost perfect positive correlation (r = 0.998), with a p-value less than 0.001. This near-perfect correlation strongly indicates that the growth in total e-commerce volume is directly mirrored by an increase in its share of retail, confirming that e-commerce is becoming a dominant force in the retail sector in Kazakhstan.

Finally, the correlation between the level of digital literacy and the volume of e-commerce services is moderately high (r = 0.766), indicating that higher digital literacy tends to support the growth of e-commerce services. However, with a p-value of 0.139, this correlation is not statistically significant, suggesting that while there is a noticeable relationship, it is not strong enough to be conclusively established in this analysis.

In summary, the results highlight the significant role of mobile phone ownership and organizational Internet usage in driving both digital literacy and e-commerce growth in Kazakhstan. The findings also underline the importance of enhancing digital infrastructure to support the continued expansion of the e-commerce sector. However, some of the relationships, while moderately strong, were not statistically significant, indicating that other factors may also influence these dynamics.

In Table 2, there is provided summary of models.

Table 2. Models' summary

Model	**R**	**R^2**
1 Volume of e-commerce, million tenge	0.570	0.325
2 The share of e-commerce in total retail trade, %	0.603	0.363
3 The level of digital literacy of the population aged 6-74 years, %	0.907	0.822
4 The level of digital literacy of the population aged 6-74 years, %	0.697	0.486
Note: Models estimated using sample size of N=5; Independent Var: Percentage of people with a mobile phone (mobile phone owners) aged 6 years and older (%)		

Note: complied by authors based on calculations

Model 1: E-commerce Volume (mln Tenge)

The first model evaluates the relationship between mobile phone ownership and the total volume of e-commerce. The correlation coefficient (R = 0.570) indicates a moderate positive correlation between these two variables. In other words, an increase in mobile phone ownership is moderately associated with an increase in e-commerce volume. However, the R^2 value of 0.325 suggests that only 32.5% of the variance in e-commerce volume can be explained by mobile phone ownership. This relatively low R^2 value indicates that while mobile phone ownership does play a role in driving e-commerce, other factors (e.g., internet infrastructure, income levels, or logistics) may also be contributing significantly to the growth of e-commerce in Kazakhstan.

Model 2: Share of E-commerce in Retail (%)

In this model, the relationship between mobile phone ownership and the share of e-commerce in total retail sales is evaluated. The correlation coefficient (R = 0.603) points to a moderate positive correlation, suggesting that regions or periods with higher mobile phone penetration are likely to see a higher share of e-commerce in retail trade. The R^2 value of 0.363 indicates that 36.3% of the variation in the share of e-commerce can be attributed to mobile phone ownership. This highlights that mobile phone ownership is a relevant factor in the expansion of e-commerce's share in retail, though other factors, such as consumer trust, payment systems, and internet availability, may also be playing important roles.

Model 3: Digital Literacy (Aged 6-74)

This model shows a strong positive correlation (R = 0.907) between mobile phone ownership and digital literacy. The high R-value indicates that there is a significant relationship, where regions with higher mobile phone ownership tend to have a population with higher digital literacy levels. The R^2 value of 0.822 suggests that 82.2% of the variance in digital literacy can be explained by mobile phone ownership, making it a dominant factor in shaping digital literacy. This result is logical, as mobile phones often serve as the first digital tool for accessing the internet and digital platforms, allowing individuals to acquire and improve digital skills. The high explanatory power of this model underlines the critical role of mobile phones in fostering digital competence across populations.

Model 4: Digital Literacy (Aged 6-74)

In the final model, the relationship between mobile phone ownership and digital literacy is again explored, but with a lower correlation coefficient ($R = 0.697$).

While this indicates a moderate to strong positive relationship, it is not as robust as in the previous model. The R^2 value of 0.486 suggests that mobile phone ownership explains 48.6% of the variance in digital literacy. While still significant, this model suggests that other factors (e.g., educational programs, government initiatives, or access to digital infrastructure) may play a larger role in promoting digital literacy in addition to mobile phone ownership.

Across all four models, mobile phone ownership is positively correlated with key economic and digital indicators, such as e-commerce volume, the share of e-commerce in retail, and digital literacy.

However, the explanatory power of mobile phone ownership varies. It plays a significant role in digital literacy (R^2 values of 0.822 and 0.486), but its influence on e-commerce outcomes (R^2 values of 0.325 and 0.363) is more limited, suggesting that other factors are also driving e-commerce growth in Kazakhstan.

In Table 3, there are results for regression analysis.

Table 3. Regression analysis results for all models

Model	Predictor	Bec	SE	t	p
Model 1	The volume of e-commerce, million tenge	-1.85e−7	1.60e+7	-1.16	0.330
		210061	174917	1.20	0.316
Model 2	The share of e-commerce in total retail trade, %	-118.05	93.80	-1.26	0.297
		1.34	1.03	1.31	0.282
Model 3	The level of digital literacy of the population aged 6-74 years, %	-62.94	39.548	-1.59	0.210
		1.61	0.433	3.72	0.034
Model 4	The number of organizations using the Internet (including public administration organizations)	-174391	168752	-1.03	0.377
		3109	1847	1.68	0.191

Note: complied by authors based on calculations

Model 1: E-commerce Volume (mln Tenge)

Predictor 1: The coefficient for the volume of e-commerce is -1.85e-7 with a standard error (SE) of 1.60e+7, t-value of -1.16, and p-value of 0.330. This negative coefficient indicates that an increase in mobile phone ownership is associated with a very slight decrease in e-commerce volume, but the result is statistically insignificant ($p > 0.05$), suggesting that the effect of mobile phone ownership on e-commerce volume is not substantial or definitive in this model.

Predictor 2: The second predictor has a positive coefficient of 210,061 with SE of 174,917, t-value of 1.20, and p-value of 0.316. Although the coefficient is positive, the p-value is above 0.05, indicating that the relationship is not statistically significant, and thus mobile phone ownership does not have a significant impact on e-commerce volume in this model.

Model 2: Share of E-commerce in Retail (%)

Predictor 1: The coefficient for the share of e-commerce in retail is -118.05 with SE of 93.80, t-value of -1.26, and p-value of 0.297. The negative coefficient suggests that increased mobile phone ownership may be associated with a slight reduction in the share of e-commerce in retail, but this relationship is not statistically significant ($p > 0.05$).

Predictor 2: The second predictor has a coefficient of 1.34 with SE of 1.03, t-value of 1.31, and p-value of 0.282. This result is also statistically insignificant, indicating that there is no meaningful relationship between mobile phone ownership and the share of e-commerce in retail based on this model.

Model 3: Digital Literacy (Aged 6-74)

Predictor 1: The coefficient for digital literacy is -62.94 with SE of 39.548, t-value of -1.59, and p-value of 0.210. Although the coefficient is negative, the p-value suggests that the effect of mobile phone ownership on digital literacy is not statistically significant.

Predictor 2: The second predictor shows a strong positive coefficient of 1.61 with SE of 0.433, t-value of 3.72, and p-value of 0.034. This indicates a statistically significant relationship ($p < 0.05$), where increased mobile phone ownership is associated with higher digital literacy. This result confirms that mobile phone ownership plays an important role in increasing digital literacy in Kazakhstan.

Model 4: Number of Organizations Using the Internet

Predictor 1: The coefficient for the number of organizations using the Internet is -174,391 with SE of 168,752, t-value of -1.03, and p-value of 0.377. This negative coefficient suggests that an increase in mobile phone ownership might be associated with fewer organizations using the Internet, but the result is not statistically significant.

Predictor 2: The second predictor has a coefficient of 3,109 with SE of 1,847, t-value of 1.68, and p-value of 0.191. Although this shows a positive relationship between mobile phone ownership and the number of organizations using the Internet, the p-value indicates that this relationship is not statistically significant.

Across all models, the most significant result is found in Model 3, where the positive relationship between mobile phone ownership and digital literacy is statistically significant. For the other models (e-commerce volume, share of e-commerce in retail, and the number of organizations using the Internet), the predictors indicate some level of association, but the relationships are not statistically significant. This suggests that while mobile phone ownership plays a critical role in digital literacy, its influence on other digital and e-commerce indicators may be more complex or driven by additional factors beyond mobile access (Table 4).

Table 4. The Normality Test (Shapiro-Wilk)

Model	**Statistics**	**p**
1	0.825	0.128
2	0.842	0.170
3	0.958	0.796
4	0.921	0.533

Note: complied by authors based on calculations

The Shapiro-Wilk test is used to assess whether the residuals of a model follow a normal distribution, which is an important assumption in regression analysis. A p-value greater than 0.05 suggests that the residuals are normally distributed, while a p-value less than 0.05 indicates a deviation from normality.

Model 1. For Model 1, the Shapiro-Wilk statistic is 0.825, and the p-value is 0.128. Since the p-value is greater than 0.05, we do not reject the null hypothesis of normality. This indicates that the residuals of Model 1 are approximately normally distributed, and the normality assumption holds.

Model 2. Model 2 has a Shapiro-Wilk statistic of 0.842 and a p-value of 0.170. Similar to Model 1, the p-value is greater than 0.05, meaning that the residuals are normally distributed. Thus, the normality assumption is met for Model 2.

Model 3. For Model 3, the Shapiro-Wilk statistic is 0.958, and the p-value is 0.796, which is well above 0.05. This indicates that the residuals are normally distributed, and the normality assumption is strongly satisfied for this model.

Model 4. In Model 4, the Shapiro-Wilk statistic is 0.921, with a p-value of 0.533. Again, since the p-value exceeds 0.05, the residuals are normally distributed, and the assumption of normality holds.

All models in the analysis have p-values greater than 0.05, meaning that none of them violate the normality assumption. The residuals in each model are approximately normally distributed, allowing the regression results to be interpreted without concerns about the validity of the normality assumption.

The results highlight the varying impact of mobile phone ownership on different aspects of the digital economy:

-The regression models for e-commerce volume and e-commerce's share in retail showed moderate positive correlations ($R = 0.570$ and $R = 0.603$, respectively), but these relationships were not statistically significant ($p > 0.05$). This suggests that while mobile phone ownership is associated with the growth of e-commerce, other factors, such as logistics infrastructure, consumer trust, and payment systems, likely play a significant role in driving e-commerce growth.

-The model for digital literacy showed a strong and statistically significant positive correlation ($R = 0.907$, $p = 0.034$). This indicates that mobile phone ownership has a substantial impact on improving digital literacy in Kazakhstan. As more people own mobile phones, their ability to navigate and engage with digital tools improves, which in turn supports broader digital and economic development in the country.

-The relationship between mobile phone ownership and the number of organizations using the Internet was moderately strong ($R = 0.697$), but not statistically significant ($p > 0.05$). This suggests that while mobile phone penetration may support organizational adoption of the internet, other factors such as government policies, business incentives, and internet infrastructure might be more decisive in fostering digital transformation among organizations.

Given the statistically significant impact of mobile phone ownership on digital literacy, we can use this relationship to forecast future trends in digital literacy in Kazakhstan. Assuming mobile phone ownership continues to rise and the correlation remains strong, we can project the increase in digital literacy over time.

Figure 2. Forecasts on Mobile Phone Ownership in Kazakhstan

Extended Discussion of Forecast Trends for Kazakhstan

The forecast trends for digital literacy, e-commerce volume, share of e-commerce in retail, and internet usage by organizations reveal important insights into the potential impact of mobile phone ownership on Kazakhstan's digital economy. These projections help to understand which areas of the digital landscape are most responsive to the increase in mobile phone penetration and highlight areas where other factors may have a more substantial influence.

1. Digital Literacy (Aged 6-74)

The forecast for digital literacy based on mobile phone ownership shows a clear upward trend, with digital literacy levels expected to exceed 80% by 2026. The strong positive relationship observed in the regression model ($R^2 = 0.822$) indicates that mobile phone ownership is a significant driver of digital skill acquisition in Kazakhstan. As mobile phones are often the primary tool for accessing the internet, they serve as a key enabler for learning how to navigate digital platforms and services.

This growth in digital literacy is particularly important for Kazakhstan's ongoing digital transformation efforts, as a more digitally literate population is better equipped to engage in the digital economy, access online education, utilize e-government services, and participate in remote work. This trend suggests that continued efforts to increase mobile phone access, especially in rural or underserved regions, could have substantial socio-economic benefits by improving digital inclusion across the country.

2. E-commerce Volume (mln Tenge)

The forecast for e-commerce volume shows only a slight increase over time, despite growing mobile phone ownership. This result aligns with the moderate positive correlation observed in the regression analysis (R^2 = 0.325), which indicates that while mobile phone ownership does play a role in the rise of e-commerce, it is not the dominant factor.

The relatively flat trend in the forecast suggests that other structural factors, such as logistics infrastructure, payment system integration, and consumer trust in online transactions, are likely more significant contributors to the growth of e-commerce in Kazakhstan. The country's ability to improve these areas will be crucial for realizing the full potential of e-commerce. Initiatives to enhance delivery networks, promote secure digital payment systems, and build consumer confidence in online shopping could drive more substantial increases in e-commerce activity, even as mobile phone ownership continues to rise.

3. Share of E-commerce in Retail (%)

The forecast for the share of e-commerce in retail indicates a slight downward trend. This may seem counterintuitive given the expected rise in mobile phone ownership, but it reflects the weak relationship observed in the regression analysis (R^2 = 0.363). While mobile phones facilitate online shopping, the share of e-commerce in total retail is influenced by broader economic factors, such as the overall retail landscape, consumer preferences, and the availability of physical stores.

The modest decline in this forecast suggests that e-commerce may continue to grow in absolute terms but may struggle to capture a larger share of retail unless specific efforts are made to strengthen the ecosystem. Investments in digital platforms, partnerships with retailers, and consumer awareness campaigns could help boost e-commerce's share in retail. Additionally, policy measures that promote competition among e-commerce platforms and improve last-mile delivery services could make online shopping a more attractive alternative to traditional retail.

4. Internet Usage by Organizations

The forecast for the number of organizations using the Internet shows a moderate increase, indicating a positive but not overwhelming impact of mobile phone ownership on organizational internet adoption ($R^2 = 0.486$). While mobile phone penetration may contribute to greater connectivity within organizations, the relationship is more complex, with factors such as business needs, government regulations, and technological infrastructure playing key roles.

This trend suggests that Kazakhstan is likely to see gradual increases in internet adoption among businesses and government agencies, but further efforts are required to accelerate the process. Programs aimed at encouraging digital transformation within businesses, providing technical support for small and medium enterprises (SMEs), and promoting e-government services could help drive more widespread internet use in organizations. Additionally, the development of high-speed internet infrastructure, particularly in rural areas, will be critical to ensuring that all organizations have equal access to the digital tools necessary for growth and efficiency.

The forecast trends based on mobile phone ownership highlight important dynamics in Kazakhstan's digital economy. Digital literacy is projected to rise sharply as mobile phones become more ubiquitous, which will empower a larger segment of the population to engage with digital services. However, the relatively flat trends in e-commerce volume and the share of e-commerce in retail suggest that while mobile phone ownership is necessary for digital growth, it is not sufficient on its own to drive substantial increases in e-commerce activity. To fully realize the potential of e-commerce, Kazakhstan needs to focus on improving the broader ecosystem, including logistics, payment systems, and consumer trust.

Similarly, the forecast for internet usage by organizations shows a moderate increase, reflecting the need for additional efforts to support businesses in adopting digital technologies. This could involve policy interventions, such as offering incentives for digital transformation, expanding access to high-speed internet, and providing technical support to businesses, particularly SMEs.

In summary, while mobile phone ownership is an important enabler of Kazakhstan's digital transformation, other factors will need to be addressed to accelerate growth in areas like e-commerce and organizational internet use. A multi-faceted approach that combines infrastructure development, digital literacy promotion, and targeted business support will be key to unlocking the full potential of Kazakhstan's digital economy [1-15].

CONCLUSION

The analysis confirmed that mobile phone ownership significantly increases digital literacy, showing that mobile phones play a crucial role in improving digital skills in Kazakhstan (H1). However, the hypotheses suggesting that mobile phone ownership strongly influences e-commerce volume (H2), increases the share of e-commerce in retail (H3), and affects the number of organizations using the internet (H4) were not confirmed. While there were positive correlations, these relationships were not statistically significant, indicating that other factors, such as infrastructure and organizational readiness, have a greater impact on these areas.

The results indicate that mobile phone ownership has a strong and statistically significant impact on digital literacy. The analysis showed that as mobile phone ownership increases, so does digital literacy among the population aged 6 to 74. Forecasts suggest a continued rise in digital literacy, underscoring the role of mobile phones as an essential tool for enhancing digital skills in Kazakhstan.

In contrast, the influence of mobile phone ownership on e-commerce volume, the share of e-commerce in retail, and internet usage by organizations was found to be positive but statistically insignificant. This suggests that mobile phones contribute to growth in these areas, but other factors—such as infrastructure, consumer trust, online payment systems, and organizational readiness—play a more substantial role.

The forecasts for these indicators suggest slow or limited growth driven by mobile phone ownership alone. Improvements in logistics, consumer education, and policy initiatives are necessary to foster the further development of e-commerce and internet usage by organizations.

In conclusion, while mobile phone ownership is a critical driver of digital literacy in Kazakhstan, its impact on other areas of the digital economy is less pronounced. A comprehensive approach, including infrastructure improvements and supportive government policies, will be required to strengthen Kazakhstan’s digital transformation [1-15].

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