Paper

Has the Internet Saved the Economy? Modeling Impact of ICT Sector and COVID-19 on GDP

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Abstract—This paper presents the influence of the COVID-19 pandemic on gross domestic product (GDP) per capita for the 27 countries of the European Union. A panel model with fixed effects was applied to a dataset from 2010 to 2020. The analysis covered 13 independent variables, including nine related to the telecommunications market, and assessed their impact on GDP per capita. A variable related to the number of COVID-19 deaths per one thousand inhabitants was then added to the model. The results showed that COVID-19 is a significant factor and is negatively correlated with GDP per capita. The analysis described in the article has also shown that the importance of the ICT sector increased during the pandemic, i.e. the household broadband Internet variable became statistically significant.

Keywords*—*COVID-19, European Union, GDP, ICT sector.

1. Introduction

The impact that technology exerts on the economy is indisputable, as evidenced by theoretical and empirical research conducted in this area. Nowadays, innovative technologies play a very significant role: they increase productivity, redefine the manufacturing paradigms, remodel supply chain relations and influence consumption [1]–[3].

In this paper, we examine how the relationship between the market of information and communication technologies (ICT) and the economy was affected by the COVID-19 pandemic. An analysis of the increasing number of publications indicates that modern technologies help mitigate the outcomes of the pandemic. In fact, studies conducted by international organizations suggest that countries with high technological potential cope with the pandemic crisis better than others [4]–[5].

Singh and Garg have also indicated that the telecommunications industry, in response to the changes in customer demand for telecommunication services resulting from COVID-19, must offer new digital products and tools and has to upgrade its network infrastructure due to increasing network traffic [6].

In contrast, Sale, Wood and Rebbeck show that revenues of telcos in developed countries declined by 3.4% in 2020 compared to 2019. This is due to reduced activity of telcos' customers – a phenomenon triggered by increased unemployment and economic slowdown [7].

Do the conclusions drawn from global studies apply to the more homogeneous structure of the 27 European Union (EU) countries? Has the pandemic in the EU affected the ICT market and economy? Is the ICT market affecting the economy with the same strength as it did before the pandemic? In this paper, authors will attempt to provide answers to those questions.

In this article, an econometric model will be constructed to verify whether there is a statistically significant relationship between the ICT market and gross domestic product per capita in the EU. The model will also examine the potential impact of COVID-19, measured as a number of deaths per 1,000 inhabitants.

So far, the impact of COVID-19 on the global economy and ICT market has not been the subject of extensive research. Only the International Telecommunication Union (ITU) has dealt with this issue extensively [4]–[5].

There have also been a few unrelated publications on the changes that the pandemic caused in the telecommunications market, but they focused on specific issues, e.g. on the increase in network traffic [8].

Several other studies devoted to regulations and the need for post-pandemic changes may also be identified. Research conducted in relation to this paper fills a certain gap in the existing work on EU countries and the impact of COVID-19 on their economies.

2. Theoretical Framework

The role of technological progress in the economy, presented from the point of view of different economic theories, serves as the point of departure for the considerations presented in this article. Solow proposed his model of economic growth by introducing a technological factor [9], [10]. The production function has the following form:

$$Y\ (t)\ =\ A(t)F[K(t),\ L(t)]\ , \tag{1}$$

where t is the year, $Y(t)$ is total production, $A(t)$ is technological progress, $K(t)$ is capital accumulation, $L(t)$ is labor force, and $F[K(t),\ L(t)]$ is the production function.
The Cobb-Douglas function is most commonly taken here as the production function, hence the production equation takes the following form:

$$Y(t) = AK(t)^{\alpha}\ L(t)^{\beta},\ \alpha,\beta > 0,\ \alpha+\beta = 1\ , \qquad (2)$$

where α is elasticity of capital and β is elasticity of production.
Variable A is sometimes introduced endogenously into the production function as technical progress embedded in labor (also the so-called labor-augmenting technical progress) or in capital (the so-called capital-augmenting technical progress). Then, the formula of such a production function is:

$$Y(t) = K(t)^{\alpha} AL(t)^{\beta}\ , \qquad (3)$$

or, respectively:

$$Y(t) = aK(t)^{\alpha} L(t)^{\beta}\ . \qquad (4)$$

However, due to the key importance of ICT, growth models that explicitly include variables related to this sector are becoming increasingly popular in the literature. Researchers test the importance of the ICT market for the economy by measuring its influence on GDP and productivity, but also test the impact of regulations on investment in new technologies. The following function is an example of such an approach [10]:

$$Y = AL^{\alpha}(N-ICT)^{\beta} ICT^{\gamma}\ , \qquad (5)$$

where: Y is the denotation of a country's GDP, ICT is the capital spent on ICT, N-ICT is the remaining capital (non-ICT), α – is elasticity of production, and β – is elasticity of non-ITC capital.
Modeling for Poland was carried out by Kaczmarczyk [11], who used 16 variables describing the ICT sector in detail and several control macroeconomic variables, in his study of the interaction between ICT and GDP. The model originally included, inter alia, the number of people employed in the ICT sector, the number of ICT entrepreneurs (production and services), the value of net sales (production and services), the number of employees in ICT (production and services), and the research and development (R&D) expenditure.
Unlike the majority of other approaches, the author used net sales of the ICT sector as the explanatory variable. He then attempted to explain it mainly by R&D expenditure, because this variable was the only one that was statistically significant for ICT.
Models created in DELab UW are closer to their theoretical counterparts [12]. They rely on both general macroeconomic variables and factors that are directly related to the ICT sector to estimate the relationship between output (GDP per capita) and the ICT market. In their analyses of the latter variables, the authors selected 53 indicators, some of which proved to be statistically insignificant. Starting directly from the Solow model, the authors derived the following function:

$$\ln(GDP)_{it} = \ \beta_0 + (\beta_1+1)\ \ln GDP_{i,t-1} + x'_{it}\beta + \alpha_i + \varepsilon_{it}, \qquad (6)$$

where: GDP_{it} is gross domestic product in year t for country i, $\mathrm{GDP}_{i,t-1}$ is gross domestic product in year $t-1$ for country i, x'_{it} is vector of explanatory variables, α_i is the country-specific effect, ε_{it} is the random component.
The inclusion of GDP in period $t-1$ is explained by income level convergence (i.e. countries with a higher baseline GDP per capita experiencing lower GDP growth). The individual effect for a given country results, in turn, from the high diversity of the countries analyzed (the model considers data from Europe, Asia and Africa).
Recent econometric models, including those attempting to account for effects of the pandemic, are based on a similar convention. ITU attempts to estimate the relationship between ICT and the economy by designing a structural model in which the first equation takes the form of [4]:

$$\begin{aligned} \log(GDP)_{pc_i} &= \mu_i + \theta\log(GFKF)_{it} + \sigma\log(HK)_{it} \\ &+\beta\log(BB\ PEN)_{it} + \delta COVID_{it} + \gamma(BB\ PEN\cdot COVID^2)_{it} \\ &+\rho_{i,2020} + \tau_t + \varepsilon_{it}\ , \end{aligned} \qquad (7)$$

where: $\mathrm{GD}P_{pc}$ is Gross Domestic Product per capita, GFKF stands for gross fixed capital formation, HK is human capital, BB PEN is broadband penetration, $\rho_{i,2020}$ is the individual country effect, τ_t are the control variables, COVID is the number of deaths from SARS-CoV-2 per 100 people.
In addition, ITU measures the impact of digitization on the economy based on a variable called *digitization index*, as well as other factors: labor force, capital, and previous year's GDP. The results of the study showed that in countries with a more developed ICT market, the impact of the pandemic on GDP was lower. This means that the ICT market remains an important factor in the development of the economy, even during a pandemic.

3. Data – Empirical Specification

Development of the following models was based on the Solow model, with later modifications, while the selection of variables was determined by econometric studies performed around the world and by data availability. The data used for this analysis are sourced from Eurostat, the World Bank, and ITU databases. The modeling considered annual data for the 27 EU countries, from the period between 2010 and 2020 decade. The variables that were used in the models are presented in Table 1.
The modeling started with the analysis of raw data and of the GDP per capita variable mentioned above, and relied on the histograms of its individual determinants. In the

Table 1
Variables used for modeling; source: authors' analysis

Symbol	Variable	Source
gdp	GDP per capita in current prices	Eurostat
dgdp	Lagged GDP per capita in current prices	Eurostat
employment	Total employment from 20 to 64 years [in thousands]	Eurostat
employment_ICT	Total employment in ICT sector [in thousand]	Eurostat
r_d	Total government budget allocations for R&D [in millions of euros]	Eurostat
dgov_expenditure	Total general government expenditure [in millions of euros]	Eurostat
dimport_ICT	ICT goods imports as percentage of total goods imports	World Bank
dexport_ICT	ICT goods exports as percentage of total goods exports	World Bank
household_broadband	Household broadband Internet connection [percentage]	Eurostat
household_access	Households – level of Internet access [percentage]	Eurostat
household_fixed	Fixed broadband subscriptions per 100 inhabitants	ITU
household_mobile	Active mobile-broadband subscriptions per 100 inhabitants	ITU
price_fixed	Fixed broadband basket	ITU
price_mobile	Mobile broadband basket	ITU
covid	COVID death per 1000 inhabitants	John Hopkins University

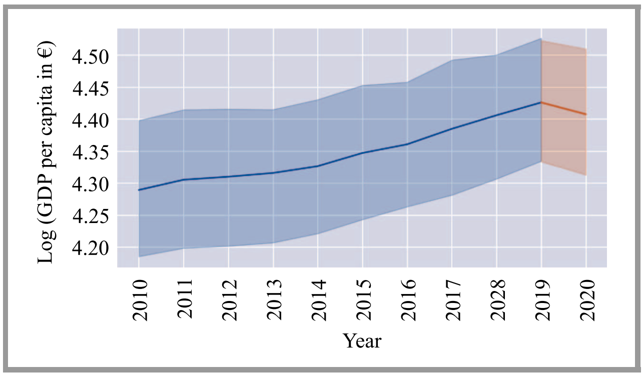

Fig. 1. GDP per capita in EU countries in 2010–2020. Source: authors' analysis.

case of GDP per capita, even a simple comparison with individual countries, through the years, shows that a clear decrease was observed in 2020 (Fig. 1).

Apart from the pandemic, no other exogenous factors affecting GDP were observed at that time. This suggests that it was COVID-19 that has led to the decrease in GDP per capita [13]. Lockdowns, health care problems, production shutdowns, electronic chip shortages or restrictions affecting the transportation of goods and services are just some of the factors that directly affect the economy.

The Hadri test for unit roots in panel data returned a p-value of 0.000. This means that we can reject the null hypothesis that no series has a unit root. By further testing each country separately, using the augmented Dickey-Fuller test (p-value threshold of 0.05), we conclude that all series are non-stationary, with the exception of Greece, Luxembourg, Slovenia, Finland, and Sweden.

To account for the 2020 pandemic, we included a control variable for the number of COVID-19 deaths per 1,000 people. The hypothesis is that with a greater number of infected people, the isolation measures enacted would be broader and harsher. This, in turn, could harm the economy. The number of deaths was chosen because the number of infections does not account for different testing strategies employed by various countries in response to the pandemic. The distributions of the individual variables were close to normal distribution, with some of them seeming to be left skewed. On the other hand, correlations between variables turned out to be strong for ICT imports and exports, as well as for GDP per capita and lagged GDP per capita. Detailed results of the correlation analysis performed are presented in Fig. 2.

4. Econometric Model Results

The models that were tested for the purpose of this analysis were based on PooledOLS, random effects models, and fixed effects models [14], [15]. The F-tests for poolability had a p-value of 0.000 for the pre-Covid era and of 0.000 with the year 2020 included. This means that we can reject the null hypothesis that the countries are homogeneous. Hence, the PooledOLS model is not a good fit for this analysis, as it does not account for the individual effects [16]–[19].

Residuals of the PooledOLS model were also tested using the Ljung-Box and Box-Pierce tests for autocorrelation of the residuals. The resulting p-values were 0.000 and 0.000, respectively. Therefore, we can reject the null hypothesis that the results are not autocorrelated. This indicates that

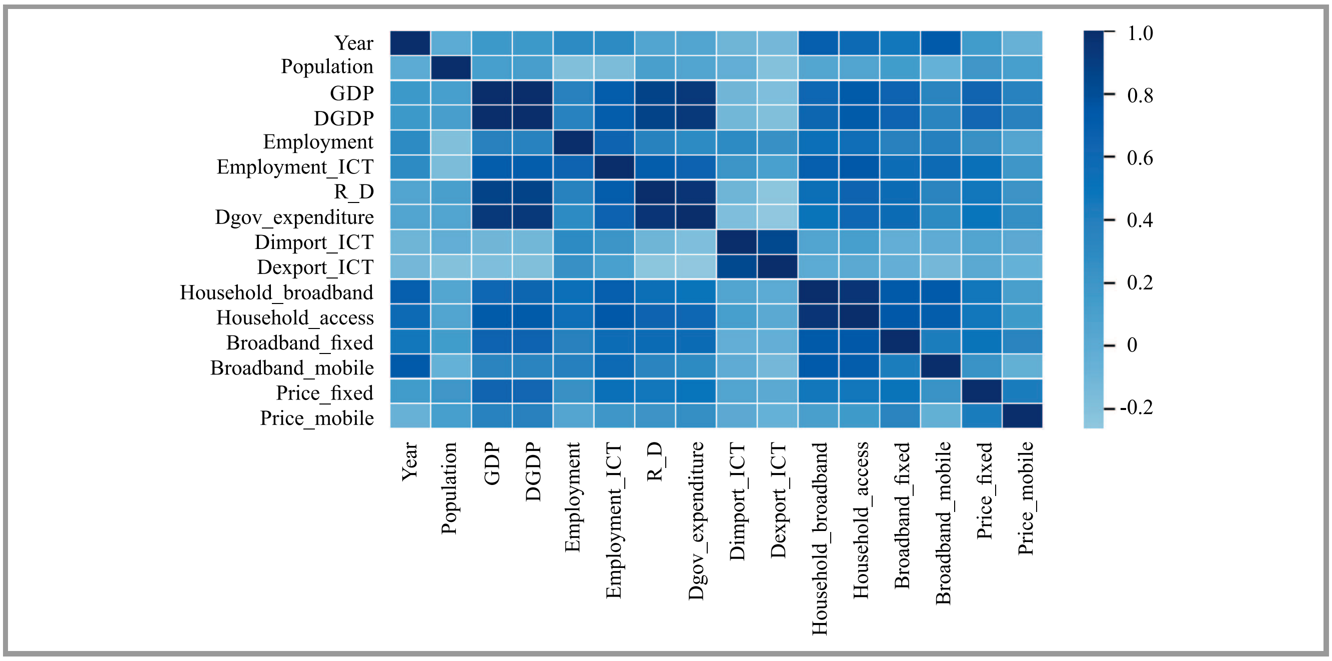

Fig. 2. Correlation between independent variables. Source: authors' analysis.

the residuals are autocorrelated, which is a second reason that the PooledOLS model is not suitable for this analysis.

The decision was made to use the Durbin-Wu-Hausman tests. The p-values were: 0.000 for the pre-Covid era and 0.000 with 2020 included. This means that we reject the null hypothesis that the random effects model is consistent, and thus the fixed effects model is preferred, because it is still consistent under the alternative hypothesis.

Estimation of the fixed effects model for 2010-2019 indicated 5 statistically significant variables, of which only the amount of government expenditure negatively affected the dependent variable. The others, i.e. previous year's GDP, total and ICT employment, and households' access to the Internet affected the GDP positively (Table 2, FE pre-Covid column).

Including year 2020 in the analysis and adding the Covid variable reduced the fit of the model but made the variable representing the price of landline calls statistically significant (Table 2, FE Covid model column).

After estimating the preliminary results, only those variables that were found to be statistically significant were left for the final analysis, with p-values equal to or less than 0.05 (Table 2, FE Covid optimized model column).

The residuals of the *FE Covid optimized* model were tested using the Breusch Pagan test for heteroscedasticity. The p-value was 0.2398, therefore there is no need to reject the null hypothesis that the residuals of the model are homoscedastic [20], [21].

Since the Durbin Watson test for autocorrelation cannot be used, as the lagged dependent variable is used as an independent one, autocorrelation was tested using the Ljung-Box test. The resulting p-value for lag = 1 is 0.2081. Therefore, there is no point to reject the null hypothesis that the residuals are not autocorrelated. The similar Box-Pierce test resulted in the p-value of 0.2104, with the same outcome.

The residuals follow a normal distribution, with 2 exceptions (Fig. 3). The residual on the right is Ireland in 2015, where the GDP rose by 26%. The residuals on the extreme left are a few countries in 2020. Each country handled the COVID-19 outbreak differently, and this variance was not fully explained by the number of deaths per capita.

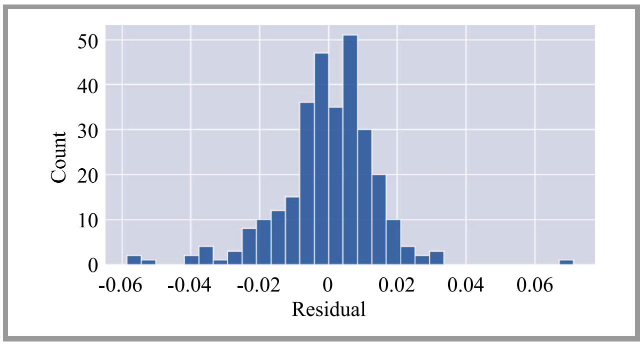

Fig. 3. Distributions of residuals in the FE Covid optimized model.

The assumptions of the fixed effects model residuals are as follows: they have a mean of 0, they are normally distributed and their variance is constant. They are also not autocorrelated. The residuals of the *FE Covid optimized* model meet these assumptions.

Finally, it was decided to use the model in its general form:

$$y_{it} = \beta_0 + \ \beta X_{it} + \alpha_i + u_{it} \tag{8}$$

for $t = 1, \ldots, T$ and $i = 1, \ldots, N$, where: β_0 is the constant, β is the matrix of estimated parameters, X_{it} is the

Table 2
Estimation results

Symbol	FE pre-Covid	FE Covid	FE Covid optimized
const	0.7634 (0.0000)[1)]	0.7496 (0.0000)[1)]	0.6769 (0.0000)[1)]
dgdp	0.7870 (0.0000)[1)]	0.7981 (0.0000)[1)]	0.8182 (0.0000)[1)]
employment	0.3341 (0.0001)[2)]	0.2886 (0.0006)[2)]	0.2896 (0.0001)
employment_ICT	1.3542 (0.0131)	1.1061 (0.0460)	
r_d	-0.0000 (0.7802)	-0.0000 (0.3429)	
dgov_expenditure	-0.0000 (0.0000)[1)]	-0.0000 (0.0001)[1)]	-0.0000 (0.0000)[1)]
dimport_ICT	0.0010 (0.3836)	0.0008 (0.4808)	
dexport_ICT	-0.0005 (0.4215)	-0.0002 (0.7656)	
household_broadband	0.0003 (0.2461)	0.0006 (0.0298)[2)]	0.0023 (0.0023)[1)]
household_access	0.0004 (0.2504)	-0.0000 (0.8122)	
household_fixed	-0.0000 (0.8828)	-0.0001 (0.8332)	
household_mobile	0.0001 (0.0480)[2)]	0.0001 (0.0392)[2)]	0.0002 (0.0025)[1)]
price_fixed	0.0002 (0.1739)	0.0003 (0.0242)[2)]	0.0003 (0.0088)[1)]
price_mobile	-0.0000 (0.9062)	0.0000 (0.9156)	
covid		-0.0330 (0.0000)[1)]	-0.0325 (0.0000)[1)]
observations	270	297	297
number of countries	27	27	27
R-squared	0.9576	0.9515	0.9276

[1)], [2)], [3)] significant at 1 per cent, 5 per cent and 10 per cent critical value, respectively. Note: dgdp is expressed as a decimal logarithm.

time-variant vector containing independent variables, α_i is the time-invariant, unobserved effect of each individual entity, and u_{it} is the error term.

After filling it in with data, Eq. (8) took the form:

$$\begin{aligned}\log(gdp)_{it} &= 0.6769 + 0.8182\log(gdp)_{i,t-1} \\ +0.2896\ employment_{it} &- 0.000004303\ gov.expenditure_{it} \\ &+0.0005\ household.broadband_{it} \\ +0.0002\ broadband.mobile_{it} &+ 0.0003\ price.fixed_{it} \\ &-0.0325 covid_{it} + \alpha_i + u_{it}\end{aligned} \tag{9}$$

for $t = 1, \ldots, 11$ and $i = 1, \ldots, 27$.

4.1. Interpretation of Model Results

We find R-squared value of 0.9276 to be a good result indicating the models may be used to examine the relationship between the economy, the ICT market and COVID-19. All variables in the final *FE Covid optimized* model are significant with p-values of less than 0.01.

From the resulting model it was obtained that, ceteris paribus, if the previous year's GDP increased by 1%, then the current year's GDP would increase by 0.7981%. Ceteris paribus, an increase in employment in the economy by 1% would result in an increase in GDP by 0.336%. Smaller differences can be observed for other variables related to the ICT market, the change of which would result in an increase in GDP ranging from 0.02% to 0.23% (ceteris paribus). On the other hand, an increase in COVID-related deaths by 1 per 1000 inhabitants would decrease GDP by 0.032% (ceteris paribus).

The *FE Covid optimized* model seems to confirm the hypothesis that there could be a causal link between the number of deaths due to COVID-19 and GDP dynamics. The correlation is significant, the time sequence is correct, i.e. the causes precede the consequences, and there exists a plausible explanation of the relationship between the variables.

However, the model exhibits some outliers in 2020. This means that the COVID-19 death variable alone is not enough to account for the unobserved, time-variant variable that represents the isolation measures introduced.

5. Further Research Areas

Despite the good fit of the model, it is not free of flaws and limitations. First, the studied group of countries is not homogeneous – both geopolitically and in terms of economic development. The formal regulations existing in the ICT sector and the level of awareness of modern technologies differ as well. These factors were not considered directly in this analysis, but a model was used that takes such diversity into account using the time-invariant unobserved effects of the individual entities. An additional rule used to offset this heterogeneity is the introduction, to the model of the lagged GDP per capita variable. Admittedly, it explains a large portion of the explanatory variable variance, but this makes the impact of other variables more comparable and closer to reality.

Some unusual observations were made concerning the raw data, showing that four countries deviate significantly from the remaining group. The degree of these deviations is large enough to consider removing them from further analysis, which could further improve the model's fit. The observed anomalies are:

- Ireland, which experienced record high GDP growth of over 26% in 2015 (explained in the literature as an accounting effect),
- Cyprus and Malta – which are small island countries, hardly comparable in terms of ICT develop-

ment, clearly different from the other countries under analysis,

- Sweden – where the residuals of the model strongly deviate from the residuals of the model for other countries.

A certain weakness of the model and the analysis performed may also be that a small number of independent variables was examined. However, this is a limitation that is difficult to overcome, because it is external and results from the changing data collection methodology and the lack of available comparable statistics for different countries. Due to the panel nature of the data, any single deficiency in the statistics methodology results in the exclusion of individual variables from the model.

Another limitation of the model is the relatively small number of observations that include the COVID-19 pandemic. This variable (although statistically significant) appears only in 2020. Inclusion of the pandemic in the following year may affect the results of the model. It is expected to strengthen the effect of the pandemic and the ICT market itself. The estimation is undoubtedly worth repeating, but also (with enough data) one might be tempted to create a separate model exclusively for data from the pandemic period, and to compare its results with the model from the period before the pandemic (up to 2019).

It is worth paying attention to the COVID-19 variable itself and introducing it into the model in a modified form, not only as the number of deaths per 1,000 inhabitants. It turns out that in this form it does not explain all the variability. Other variables representing the economic impact (number and severity of lockdowns, travel bans, etc.), would certainly help explain more of the variances.

It is expected that the results of further, in-depth research will not substantially change the basic conclusions of the presented analysis. However, few details of the model may be modified, and some variables that were initially insignificant may finally become statistically significant.

6. Conclusions

Based on the study which covered 27 EU countries, the statistical impact of COVID-19 on the economy may be confirmed. Firstly, it was shown that the COVID-19 variable is statistically significant. Secondly, and more importantly, the results obtained show that with the outbreak of the pandemic, the ICT market has gained in importance. The previously statistically insignificant variable of household broadband Internet penetration has become statistically significant.

Real world observations lead us to conclusions that are similar to the model results - the introduction of lockdowns forced households to work and study remotely. Network traffic was not the only metric that increased. So did the quality of service requirements. The need to handle larger data volumes with minimal latency has emerged, and broadband connectivity is the answer here.

This study has shown that differences between EU countries do matter and cannot be ignored in the modeling. A comparison of the model that treats the EU countries as a relatively homogeneous structure with models that take into account variations existing between countries (by introducing additional variables for each country) clearly favors the latter. This observation is consistent with the results of previous market research [12].

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