EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Volume 8, Issue 1, 2022
ISSN 2694-7161
www.ejobsat.cz

EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Volume 8, Issue 1
2022

Mendel University in Brno
www.ejobsat.com

EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Editorial Office Address
EJOBSAT, Mendel University in Brno, Zemědělská 1, 613 00 Brno, Czech Republic
Registration number MK ČR E22009
The journal is published twice a year.
First edition
Number of printed copies: 80
ISSN 2336-6494 (Print)
ISSN 2694-7161 (Online)

Number 1, 2022 was published on July 31, 2022 by Mendel University Press

CONTENTS

MULTIVARIATE MODELLING OF MOTOR THIRD PARTY LIABILITY INSURANCE CLAIMS

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ABSTRACT

The aim of the study is to identity the main factors that affect claims amount paid by insurers in case of road accidents and to predict losses from valid third-party liability insurance (MTPLI) policies until their expiration. Such an assessment is essential to adequately cover MTPLI policies and ensure the sustainable development of insurance companies.

The geography of the study covers the MTPLI market of Europe in the main areas, but a deeper analysis of the impact of various factors, interactions, and interrelationships in MTPLI product is focused on Latvian market data due to availability of high-quality primary data.

The research is based on the analysis of primary Latvian MTPLI policies data of more than 128,000 road traffic accidents that have occurred during the time period from 2014 till 2020. Risk driver selection was performed based on the existing scientific studies and correlation analysis of the sample set. Both linear and nonlinear forms of relationships were used for modelling. A multivariate modeling was used to identify significant risk factors and to quantify their impact on loss of incidents.

Statistical stability of the models was tested using chi-squared, t-tests and p-values. Validation of models calibrated where done using prediction errors measurements: mean square error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) assessment both within sample and out of sample technics. The results indicated that the driver's behavior (penalties and Bonus-Malus) as well as vehicle parameters (weight and age), had significant impacts on crash losses.

KEY WORDS

road traffic accidents, risk drivers, non-life insurance, MTPL insurance, private insurance, passenger cars, Bonus-Malus system, MTPL insurance claims paid, multivariate modelling

JEL CODES

G22, C38

SPILBERGS, Aivars, FOMINS, Andris, and KRASTIŅŠ, Māris. 2022. Multivariate Modelling of Motor Third Party Liability Insurance Claims. *European Journal of Business Science and Technology*, 8 (1): 5–18. ISSN 2694-7161, DOI 10.11118/ejobsat.2022.002.

1 INTRODUCTION

Road safety is not only a public health concern, but a seroius socioeconomic issue as well. The World Health Organization (WHO) estimates that about 1.3 million people lose their lives annually in road traffic accidents and millions of people sustaining injuries (World Health Organization, 2021). Road traffic accidents globally are the main cause of death among young people aged up to 29 years (World Health Organization, 2021). Although the number of road traffic fatalities in EU has dropped significantly over the past 20 years, about 22,800 people died in road traffic accidents in the EU in 2019: 44.2% of those killed were car drivers or passengers; 20.2% were pedestrians (Eurostat, 2021).

Motor premiums accounted for 36% of all property and casualty (P&C) insurance in Europe in 2019 and totaled €147 billion, therefore is Europe's most widely purchased P&C insurance line (Insurance Europe, 2021). That has been demonstrated by various studies of European Motor insurance market and has high degree of actuality for insurance business, as well as for the researchers.

The European insurance market is not homogeneous. Significant differences in the development of this market segment can be observed, including opposite trends. While in the Baltic states (Latvia and Estonia) a decrease in insurance premiums is observed in 2020, Slovakia and the Czech Republic show significant increase of premiums. If we look at the stability of the trends, the Baltic region stands out too, in a relatively short period of time, completely opposite trends can be observed – both in Latvia and Estonia there are periods of the largest increase in premiums (more than 15% in 2017–2019), but in the following period the largest decrease in premiums can be observed (10% in Latvia in 2020). Similar trends could be observed during the 2008 crisis in the Baltic insurance markets – from record market growth to record decrease, especially in the Latvian market (Insurance Europe, 2021).

Portugal, Finland, Sweden, Slovakia, and the Czech Republic show a positive trend in increase of insurance premiums for motor insurance, compared to the opposite situation that can be observed in Greece, Poland, Italy, Estonia. Very strong negative trend has been observed in Latvia, 10% decrease in 2020 compared to the period of 2017–2019. As for the share of insurance claims, historical fluctuations in the opposite directions can be observed in almost all European countries. If the period 2017–2019 clearly showed an increase in insurance claims paid (growth more than +4%), then for most European countries 2020 brought an even greater reduction in claims (more than 5%; see Fig. 2), apart from Latvia and Bulgaria, where we can observe a continuing increase in claims (Insurance Europe, 2021).

Analyzing the motor claims paid (Fig. 2), we can observe a decrease in claims paid in 2020 in most EU countries, although an opposite trend can be observed in Latvia and Bulgaria, where motor claims have increased in 2020 compared to the period of 2017–2019. Thus, it is obvious that the trend observed in countries such as Bulgaria and Latvia is definitely negative for the participants of the insurance market – insurance companies. In Europe overall, most of the countries show a decline in insurance premiums (negative trend for the insurance industry). At the same time a decrease in the claims (which has a positive effect on the insurance industry as a whole) can be observed. The decrease in claims is larger than the decrease in insurancepremiums, that means increase in profitability of insurance companies. In this respect Latvia stands out as well, where both the decrease in insurance premiums and the increase in claims clearly indicates negative trend in the insurance market (FKTK, 2021).

Taking into account the specifics of the study, the MTPLI claims paid amounts per road traffic accident in Latvia during 2014–2019 was analyzed, see Fig. 3.

As shown in Fig. 3, the amount of claims paid per RTA in Latvia is increasing, and there is a steady upward trend in claims (approx. 20% increase 2019 vs. 2014). The above trend points

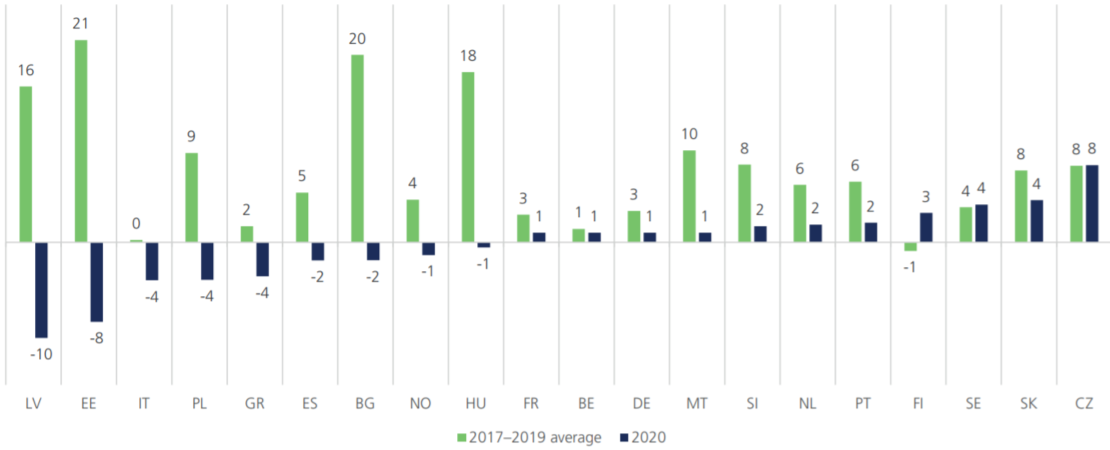

Fig. 1: Year-to-year change in motor premiums in Europe, 2020 compared to 2017–2019 average (%).
Source: Insurance Europe, 2021.

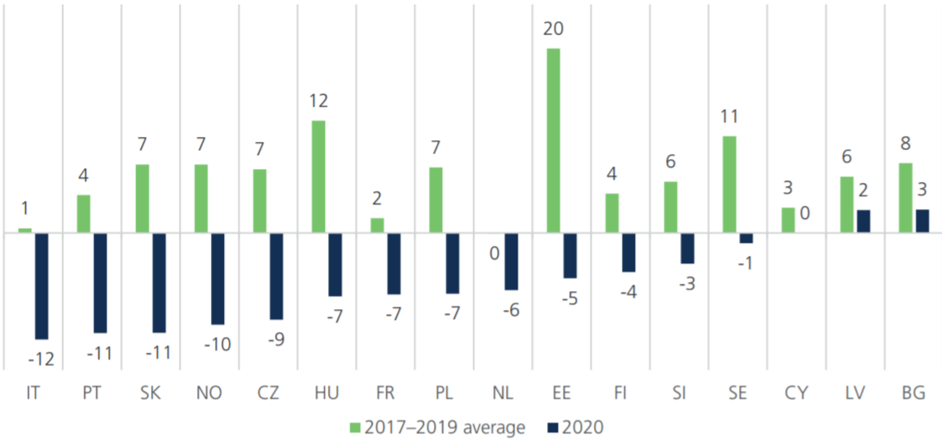

Fig. 2: Year-to-year change in motor claims in Europe, 2020 compared to 2017–2019 average (%).
Source: Insurance Europe, 2021.

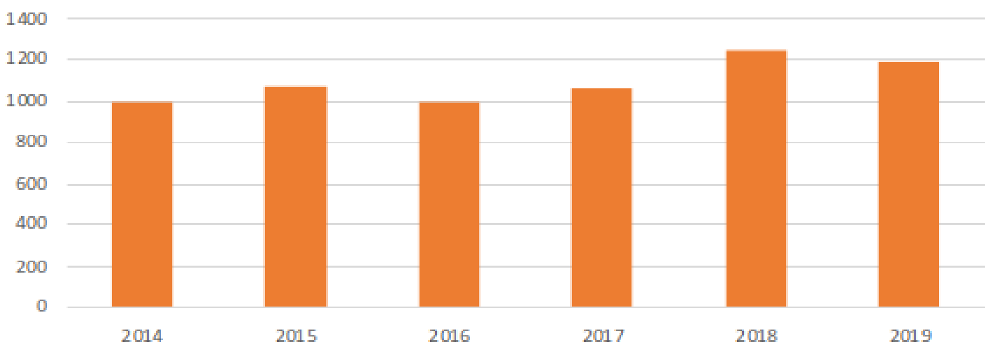

Fig. 3: MTPLI claims paid amounts in Latvia per road traffic accident, EUR.
Source: Created by authors based on MIB data.

to the need for a more accurate and detailed analysis of the causes of insurance costs.

We can conclude that the market situation is unstable, and an important task for insurers is to diversify clients even more carefully, by analyzing factors that affect the risk level of each specific group of clients, which, in turn, will increase the overall profitability of the company's insurance portfolio. In this study the authors evaluate the influence of different factors on the size of MTPLI claims, which will help to understand the main risk factors for this insurance product. The authors performed analysis of claim severity in motor third party liability insurance by using the general linear model.

Generally two approaches are being used to determine net premiums in non-life insurance. Either the target variable is equal to the net premium (euros of loss per exposure) or it is separately modelled the claims frequency (number of claims per exposure) and the claim severity (average loss per claim).

2 LITERATURE REVIEW

2.1 Risk Factors Influence on Claim Severity in Road Traffic Accidents

One of the insurers' main concerns is establishing a tariff structure that distributes these claims and losses among policy holders most equitably and reasonably. This task of determining the pure premium belongs predominantly to actuaries who evaluate the probability of the risk occurrence, determine the risk factors in order to establish commensurate tariffs for each class so that everyone and each pay premium that, in one way or the other, reflects their riskiness.

Insurance principle of sharing danger or risk among a group of individuals requires grouping individual risks into various categories or classes with a homogeneous set of characteristics. Such classification usually boils down to different classes for which members of a given class share the same set of risk characteristics; in that respect, each class will have a certain number of insurance claims and accumulated losses and pay the same premium rate. To reasonably estimate this premium and price insurance policies, insurers must predict the expected loss accurately, often referred to as the "pure premium" (El Kassimi and Zahi, 2021).

In estimating claims distributions for motor insurance, the cost of claims is often associated with two components: the probability of an accident and the amount of claim per accident, if it occurs. Claims frequency and severity components are being termed by actuaries. This is the traditional way of decomposing this so-called "two-part" data, where one can think of a zero as arising from a vehicle without a claim. This approach allows to incorporate multiple claims per vehicle (Frees and Valdez, 2008).

Denuit and Lang have observed, that technical profit margins in European motor third party liability insurance (MTPLI) markets have been very small. In this situation the actuaries have to design a tariff structure that will fairly distribute the burden of claims among policyholders (Denuit and Lang, 2004).

According to Oh et al. (2020), the insurance premium based on a Bonus-Malus system can be viewed as a discretely approximated analogy of the Bayesian premium. Traditionally, insurers have been using the frequency driven Bonus-Malus systems, which ignore the claim severity information. More sophisticated Bonus-Malus systems are based on both frequency and severity of claim and adopt the assumption of independence between frequency and severity. This is often invalid in real-life insurance practice (Oh et al., 2020).

Denuit and Lang see MTPLI rate-making as classifying policies by their risk characteristics. They imply that some risk characteristics are observable and are typically seen as non-random covariates, and some are unobservable and must be seen as unknown parameters (Denuit and Lang, 2004).

Šoltés, Zelinová and Bilíková in their research have revealed the impact of factors, that have the major impact on claim severity in road traffic accidents. According to their study engine power and engine displacement are strongly correlated factors, that have the highest impact on claim severity. Significant interaction between the age group of the driver and the place of driver's residence was confirmed. The results of their empirical study show that a substantial increase of claims paid occurs only with higher power vehicles. Drivers age is second significant factor, that leaves an impact on insurance claims paid. The highest average severity of road traffic accidents was found among the drivers in the age group over 60 whose place of residence is certain regional cities. They showed 7.8-fold higher average severity of road traffic accidents, with other variables fixed, as compared to owners under the age of 50 living in other regional towns of Czech Republic which were the least risky in terms of claim severity (Šoltés et al., 2019).

The study of Adanu, Smith, Powell and Jones indicated that drivers under 30 had a 0.46 probability of being at-fault in any crash. This group of drivers had 0.45 probability of the crash they have been involved as being serious. At-fault male drivers had probabilities of being involved in a crash or a serious injury crash of 0.54 and 0.52, respectively. The results of their study suggest that the risk of these drivers' groups being at-fault for crashes and being involved in a crash with serious injury are parallel (Adanu et al., 2017).

Employment status of the driver has a significant impact on probability of being involved in a road traffic accident and on its severity as well. According to the results of the study of Adanu et al. (2017), the unemployed drivers had a probability of 0.23 of being at-fault in a crash and the probability that they were at-fault in a serious crash was 0.57, thus probability of an unemployed driver being at-fault for a serious crash was 1.32 times higher than an employed, self-employed, or retired driver (Adanu et al., 2017).

The probability of distracted or intoxicated driver being at-fault for a serious injury crash was 1.89 and 1.14 times higher, respectively. Driver, who does not observe the speed limit, increased the risk of a crash being serious by 2.17. The probability of 0.86 that a crash involving a driver not wearing a seatbelt was serious suggests that the risk of serious injury in this type of crashes almost six times higher than average (Adanu et al., 2017).

The gender of drivers has fixed effect on the occurrence of serious injury crashes. The study of Adanu et al. (2017), shows that the impact of such factors as of age, employment status, and race of at-fault drivers show varied impact across regions. Lack of seatbelt usage, distracted driving and drugs and alcohol usage also showed varied impact across regions. Regional parameters affect the probability of serious injury crashes significantly. Credit score correlates to driving behavior significantly as well (Adanu et al., 2017).

Szymańska concluded, that the use of the age of the insured as one of the ratemaking variables can be justified. Insured persons aged from 18 to 25 cause on average more damage per year with higher average value, and therefore should pay higher premiums. The contribution range is between 140% and 150% of the basic premium. The insured under the age of 25 pay 300% of the basic premium if they buy insurance for the first time in this company, and 200% of the basic premium on the continuation of insurance. People aged from 25 to 28, cause on average more damage, slightly above the average value. Their contribution rate should be 119%. Another group that should have raised contributions are the insured at the age from 43 to 53. Insured persons in this age group should pay premiums increased by 4%. Persons aged 28–43 and over 53, on the other hand, could have a small discount (Szymańska, 2017).

Ayuso et al. (2010) concluded that the cost of accidents depends substantially on the number of bodily injuries. There are some traffic violations that are associated with a higher probability of serious or fatal accidents. For every possible combination of traffic violations, probability that the accident is slight, serious or fatal can be predicted. The costliest traffic violation is exceeding the speed limit, which increases the expected cost of an accident by two-thirds, compared to accidents that do not involve any traffic violations (Ayuso et al., 2010).

In the case of independent, net premiums are proportional to the total claim frequency and total claims severity and are inversely proportional to the age of the policy. This means that the more frequent the claim frequency and the larger the severity of the claim, the higher the net premium while the larger the policy age, the smaller the net premium. Insured persons that historically have large claim severity are charged higher net premiums than persons that have a small claim severity. This shows that net earned premiums are fairer than the net premiums on the classic Bonus-Malus System (Pratama et al., 2020).

3 METHODOLOGY AND DATA

3.1 Data

Calculations of motor insurance premiums are based on detailed statistical analyses of large data bases maintained by insurance companies, recording individual claim experience. The actuarial evaluation relies on a statistical model incorporating all the available information about the risk.

The data on MTPLI used in this research is obtained from Motor Insurers' Bureau of Latvia (MIB). Our study sample comprises of a total more than 128 thousand road traffic incidents resulted in claims to MTPLI policies issuer in Latvia during time period 2014–2020 in relation to passenger cars owned by private persons. Based on the policy parameters available in the MIB database, the following parameters were selected for further research (Fig. 4).

Policies which had missing values or values out of expected range were excluded from the analysis. No further elimination of outliers was undertaken, since we argue that their effect on the results of regression analysis is negligible due to the large sample size. A more detailed description of the parameters of MTPLI policies included in the study with descriptive statistics is provided in Tab. 1.

Due to the large data set selected (more than 128 thousand incidents) and to ensure a comprehensive validation of the calibrated models, it was divided into two parts, i.e., training sample of policies (70%) for modeling and 30% for out of sample model validation. We used stratified sampling to achieve an even distribution of accident events.

Tab. 1: Descriptive statistics of the initial MTPLI policies sample (based od MIB data)

Variable group	Variable	Observations	Min	Max	Median	Mean	1st Quantile	3rd Quantile
Car holder	Age	128,144	18	96	41	43.1	31	54
	Experience	128,144	0	73	16	19.79	8	25
	Gender	128,144	Categorical					
Driver behavior	Penalties	128,144	0	18	0	0.67	0	0
	BM class	128,144	1	17	9	8.99	7	11
Vehicle	Brand	128,144	Categorical					
	Age	128,144	0	58	13	12.96	10	17
	Engine cap.	128,144	599	7,536	1,984	2,084	1,781	2,401
	Power	128,144	51	478	96	101.8	77	120
	Weight	128,144	960	6,577	2,000	2,043.1	1,795	2,195
Policy	Maturity	128,144	Categorical					

		EUR mio.	Min	Max	Median	Mean	1st Quantile	3rd Quantile
Claims	Amount	129.80	50	864,057	516.12	1,150.76	276.35	1,079.67

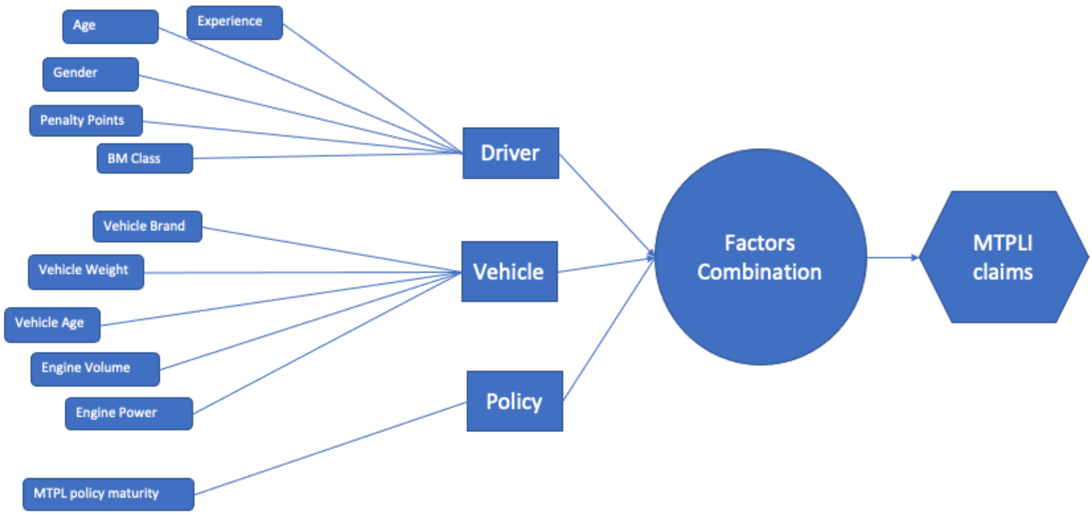

Fig. 4: Parameters selected for the research of MTPLI claims.
Source: Created by authors based on MIB data.

3.2 Methodology

Fig. 5 illustrates the process of claims paid risk assessment, regression models calibration and validation.

Based on the results of the previous studies, authors put forward the following hypotheses:

1. Multivariable regression makes it possible to significantly improve the degree of model's determination for road traffic accidents likelihood evaluation;

2. The grouping of independent variables values significantly improves the adequacy of road traffic accidents risk assessment models.

Over the last few decades, generalized linear models have been widely used in insurance claims valuation practice (Haberman and Renshaw, 1996; de Jong and Heller, 2008; Kaas et al., 2008; Frees, 2010; Agresti, 2015).

As claims paid data are positive values and skewed to the right, we applied log transformation of the losses and thus, the relationships between the MTPLI claims amounts and the selected independent variables can be expressed in the following form:

$$\begin{aligned}\log \mathrm{CP} = \beta_0 &+ \beta_1\, x_{\mathrm{POLM}} + \beta_2\, x_{\mathrm{CDG}} + \\ &+ \beta_3\, x_{\mathrm{CDA}} + \beta_4\, x_{\mathrm{CDE}} + \\ &+ \beta_5\, x_{\mathrm{BM}} + \beta_6\, x_{\mathrm{CDP}} + \\ &+ \beta_7\, x_{\mathrm{VA}} + \beta_8\, x_{\mathrm{VCA}} + \\ &+ \beta_9\, x_{\mathrm{VPO}} + \beta_{10}\, x_{\mathrm{BR}} + \\ &+ \beta_{11}\, x_{\mathrm{VWE}},\end{aligned} \tag{1}$$

where CP – claims paid amount per MTPLI policy; β_0 – intercept or constant of model; $\beta_1, \ldots, \beta_n$ – vector of regression coefficients; x_{POLM} – MTPLI policy maturity; x_{CDG} – MTPLI policy holder gender; x_{CDA} – MTPLI policy holder age; x_{CDE} – MTPLI policy holder experience; x_{BM} – bonus-malus of MTPLI policy holder; x_{CDP} – penalties of MTPLI policy holder; x_{VA} – vehicle age; x_{VCA} – vehicle engine capacity; x_{VPO} – vehicle engine power; x_{BR} – vehicle brand; x_{VWE} – vehicle weight.

3.3 Simulations and Grouping of Variable Values

Training sample and R version 4.0.5 was used for associations analysis (R Core Team, 2021). During the study, univariate linear and polynomial models were first calibrated using ungrouped factor values.

Fig. 5: Process of claims paid risk assessment, regression models calibration and validation.

Tab. 2: Statistics of initial models (based on simulation results)

Model type	AIC	BIC	Residual deviance	F-statistic	p-value
Univariate linear	118,452	118,548	18,868	145.7	<2.2E−16
Univariate polynomial	117,481	117,577	18,707	109.2	<2.2E−16
Multivariate linear	94,886	94,914	15,125	62.08	<2.2E−16
Multivariate polynomial	94,815	94,853	15,113	45.48	<2.2E−16

Calibrated model's performance was evaluated using traditional statistics such as Akaike information criterion (AIC; see Akaike, 1974), Bayesian information criterion (BIC; see Schwarz, 1978) and residual deviance was used for evaluation of selected models (Hosmer et al., 2013). These statistics are relative measures that evaluates model fit and penalizes overfit. Lower residual, AIC and BIC values indicate better model fit to the data.

From univariate models, as one can see from Tab. 2, the best fit was polynomial model with driver penalties as independent variable. Among the multivariate models, the best fit was also shown by polynomial model.

In the next step, in order to ensure a better fit of the model, the grouping of independent variables values was performed, taking into account the results of previous research, the experience of industry experts, and the correlations shown by actual claims paid amount statistics.

As can be seen from Tab. 3, the age distribution of MTPL policyholders is fairly even, while that of drivers with experience over 12 years is almost two-thirds. There is a visible tendency for the average amount of compensation paid in case of RTA to decrease as the age and experience of the driver increases.

Tab. 4 summarizes the impact of drivers' behavioral indicators on the average level of compensation paid.

Tab. 3: Descriptive statistics of independent variables – car driver age and experience (based on MIB data)

Variable	n	Average claims paid (EUR)
Age group (years)		
0–27	20,097	1,073.55
28–37	33,942	992.61
38–47	27,376	1,003.17
48–57	22,136	998.49
58+	24,593	990.61
Experience (years)		
0–2	11,205	1,050.51
3–5	10,554	1,074.08
6–8	11,135	999.73
9–11	13,168	1,016.03
12+	82,082	993.84

Tab. 4: Descriptive statistics of independent variables – car driver behaviour (based on MIB data)

Variable	n	Average claims paid (EUR)
Penalties (points)		
0	97,301	966.55
1–3	22,554	1,169.86
4–6	5,439	1,010.53
7–9	2,237	1,143.07
10+	613	1,157.44
Bonus-Malus		
1–3	1,135	1,465.05
4–6	29,018	1,115.56
7–9	45,182	987.34
10–12	35,732	949.86
13+	17,077	972.60

Tab. 5: Risk groups by vehicle brand (based on MIB data)

Risk group	Brand
1	Buick, Cadillac, Daewoo, Daihatsu, Daimler, GAZ, Lamborghini, Maserati, MG, Moskvich, Oldsmobile, Proton, Puch, Rolls-Royce, Saturn, Vauxhall, ZAZ
2	Austin, Citroen, Honda, Kia, Lancia, MCC, Mercury, Mitsubishi, Pontiac, Saab, Toyota
3	Alfa Romeo, Audi, Chevrolet, Chrysler, Dacia, Dodge, Fiat, Ford, Hyundai, Infiniti, Jeep, LADA, Land Rover, Lexus, Mazda, Mercedes Benz, Mini, Nissan, Opel, Peugeot, Porsche, Renault, Seat, Skoda, Smart, Ssang Yong, Suzuki, Tesla, Volvo, VW
4	BMW, Hummer, Isuzu, Jaguar, GMC, Plymouth, Rover
5	Acura, Bentley, Lincoln, Subaru, Range Rover

In the absolute majority (76%) of RTA cases, car holders did not have penalty points and the average amount of compensation paid was the lowest in this group. As the penalty points, which characterize the behavior of drivers, increases, there is a tendency to increase the average amount of paid compensation. Similar associations are formed between the Bonus-malus class and the MTPL claims paid – as the BM class improves, the average amount of claims paid decreases.

In order to assess the impact of the car brand on the amount of claims paid as a result of the RTA, it was divided into five groups according to the average amount of claims paid over the period from 2014–2020, see Tab. 5.

Tab. 6 summarizes the results of grouping vehicle parameters and the average amount of claims paid for each group.

As can be seen in Tab. 6, as a result of grouping all five car parameters, there is a clear trend: as the car age, brand risk group, weight, engine capacity and power increases, the average amount of claims paid increases.

The ANOVA test was used to evaluate the grouping results and it showed the difference of average claims paid in the groups as statistically significant (p-values < 0.05).

For regression analysis, the values of regressors x_{CDA}, x_{CDE}, x_{BM} x_{CDP}, x_{VA}, x_{VCA}, x_{VPO} and x_{VWE} were set equal to the means of the respective group, but x_{CDG} and x_{BR} were treated as categorical variables.

Tab. 6: Descriptive statistics of independent variables – vehicle parameters (based on MIB data)

Variable	n	Average claims paid (EUR)
Vehicle age (years)		
0–4	8,199	978.49
5–9	23,544	974.63
10–14	47,404	1,007.89
15–19	34,483	1,018.70
20+	14,514	1,055.41
Vehicle brand		
Group 1	100	728.01
Group 2	23,270	943.91
Group 3	88,381	1,003.14
Group 4	13,736	1,115.93
Group 5	2,657	1,192.75
Vehicle weight (kgs)		
<1,600	8,963	961.57
1,600–1,899	39,408	978.36
1,900–2,199	47,826	1,001.93
2,200–2,499	15,426	1,053.61
2,500+	16,521	1,080.38
Engine (cc)		
<1,400	9,494	958.97
1,400–1,799	27,762	977.18
1,800–2,199	50,396	992.19
2,200–2,599	21,823	1,022.86
2,600+	18,669	1,105.39
Power (kW)		
<60	8,769	972.54
60–94	51,948	982.66
95–129	44,521	1,006.34
130–164	14,563	1,058.80
165+	8,343	1,126.25

4 RESULTS

4.1 Statistical Test Results

A stepwise variables selection procedure was applied to find 'best fit' model using grouped values of variables. Using the function `step()` in R package (R Core Team, 2021), various combinations of variables were simulated and the three best according AIC criteria model's were evaluated in depth. Model '1' includes all 11 investigated variables, Model '2' does not include the variable 'Experience', and Model '3' does not include the variable 'Age'.

Using the gouped values of the variables, the fit of the models improved, as can be seen in Tab. 7, where chi-squared test results, AIC and BIC for comparable model's is summarized.

Tab. 7: Chi-squared test results of comparable regression models (based on simulation results)

Model	Residual df	Residual deviance	AIC	BIC
Model 1	89,659	14,996	94,200.92	94,614.70
Model 2	89,663	14,997	94,199.77	94,575.94
Model 3	89,663	15,000	94,214.29	94,590.46

Tab. 8: LRT statistics of selected models (based on simulation results)

	Model 1			Model 2			Model 3		
Factor	**df**	**Deviance**	***p*-value**	**df**	**Deviance**	***p*-value**	**df**	**Deviance**	***p*-value**
POL_M	4	20.513	***	4	20.513	***	4	20.513	***
CD_Ge	2	14.172	***	2	14.172	***	2	14.172	***
CD_Age	4	5.369	***	4	5.369	***	na		
CD_Exp	4	1.931	*	na			4	3.077	**
CD_BM	4	15.505	***	4	15.963	***	4	15.935	***
CD_Pen	4	50.712	***	4	50.917	***	4	50.974	***
VE_Age	4	8.345	***	4	8.266	***	4	8.905	***
VE_Bra	4	3.521	***	4	3.539	***	4	3.606	***
VE_We	4	24.624	***	4	24.775	***	4	24.208	***
VE_Cap	4	4.279	***	4	4.308	***	4	4.251	***
VE_Pow	4	4.337	***	4	4.364	***	4	4.116	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Tab. 9: VIF multicollinearity test results (based on simulation results)

	Model 1			Model 2			Model 3		
Factor	**GVIF**	**df**	**$\mathbf{GVIF}^{\frac{1}{2df}}$**	**GVIF**	**df**	**$\mathbf{GVIF}^{\frac{1}{2df}}$**	**GVIF**	**df**	**$\mathbf{GVIF}^{\frac{1}{2df}}$**
POL_M	1.2711	4	1.0304	1.2663	4	1.0299	1.2483	4	1.0281
CD_Ge	1.1192	2	1.0285	1.1032	2	1.0248	1.0910	2	1.0220
CD_Age	2.8268	4	1.1387	1.3294	4	1.0362	na		
CD_Exp	2.8497	4	1.1399	na			1.3402	4	1.0373
CD_BM	1.3182	4	1.0351	1.2402	4	1.0273	1.3075	4	1.0341
CD_Pen	1.0625	4	1.0076	1.0614	4	1.0075	1.0569	4	1.0069
VE_Age	1.6250	4	1.0626	1.6170	4	1.0619	1.6127	4	1.0616
VE_Bra	1.4310	4	1.0458	1.4302	4	1.0457	1.4211	4	1.0449
VE_We	4.5494	4	1.2085	4.5367	4	1.2081	4.5282	4	1.2078
VE_Cap	9.4315	4	1.3238	9.4286	4	1.3237	9.4129	4	1.3235
VE_Pow	6.6353	4	1.2669	6.6304	4	1.2668	6.6140	4	1.2664

The grouping of variables provided an opportunity to improve the degree of claims amounts paid determination compared to ungrouped variables. According to the chi-squared test results the is statistically significant difference in performance of models with grouped variables values and ungrouped. The differences between the three best fit models with grouped variable values are not statistically significant.

Three best fit models were subject to in-depth evaluation: According to the statistics summarized in Tab. 7, it can be seen that all three selected models fit relatively equal: AIC prefers the sequence of models 2, 1 and 3; BIC – sequence 2, 3 and according residual deviance 1, 2 and 3.

Likelihood ratio test (LRT) was used to estimate factor's, included in models, statistical significance. The LRT test statistics summarized in Tab. 8 show that estimates of all independent variables included in the tree best fit models are statistically significant at least at $\alpha = 0.05$ level.

Judging by the effect of each variable on the total deviation, the car driver's penalty points (33.5%), car weight (16.2%) and MTPLI policy term (13.5%) have the greatest impact.

The multicollinearity test of the variables included in the model was performed using variance inflation factor (VIF) statistics $\mathrm{GVIF}^{\frac{1}{2\mathrm{df}}}$. As can be seen from Tab. 9, the test result does not show multicollinearity at the level of independent variable groups.

4.2 Model's Validation Results

After multivariate simulation and testing, it is common to compare a number of alternative models based on the training and on the test samples. For the training sample, the within-sample comparisons are typically based on k-fold cross-validation (Refaeilzadeh et al., 2016).

Tab. 10: Five- and Ten-fold cross validation results (based on simulation results)

Model	**Five-fold cross-validation**	**Ten-fold cross-validation**
Model 1	0.1503992	0.1504042
Model 2	0.1606585	0.1606482
Model 3	0.1680324	0.1679897

According to the obtained results, the stability of all three models is high and both results indicate preferences 1, 2 & 3.

Comparison among models using test data – out-of-sample – comparisons are important in MTPLI cause many of these models are used for predictive purposes such as assessment of premiums un reserves for new MTPLI policies. Out-of-sample measures compare held-out during model calibration observations to those predicted by the model. Traditionally, mean absolute errors (MAE), mean squared error (MSE) and the root-mean-square error (RMSE) have been used to summarize differences between these two (Oh et al., 2020; Yunos et al., 2019).

Similar to cross-validation results were obtained from analysis of MSE, RSME and MAE estimation results, see Tab. 11.

Tab. 11: MSE, RMSE and MAE of bet fit models (based on simulation results)

	Within-sample			**Out-of-sample**		
Model	**MSE**	**RMSE**	**MAE**	**MSE**	**RMSE**	**MAE**
Model 1	0.1671767	0.4088725	0.3282445	0.1669904	0.4086446	0.3279425
Model 2	0.1671895	0.4088881	0.3282511	0.1670094	0.4086679	0.3279522
Model 3	0.1672165	0.4089212	0.3282862	0.1670052	0.4086627	0.3279751

5 DISCUSSION AND CONCLUSIONS

When studying the European motor insurance market, we can observe great volatility both between the reference periods and different, often opposite trends within the same period between countries. In general, there is a downward trend in the market for both insurance premiums and insurance claims, which is generally a negative trend, but MTPLI markets maintain stable. On the other hand, some trends are even dangerous for market stability: for example, in case of Latvia, where insurance premiums decrease and insurance claims increase in the same time period, which can potentially endanger market stability in the future. These signals increase the pressure on insurers to look for profit-seeking segments and to identify segments from which insurers should opt out or make tariff adjustments.

The results of the study confirmed that a multivariate regression model with grouped variable values offers the potential to improve significantly the ability to explain the effects of independent variables (car drivers behavior, age and experience, Bonus-Malus, vehicle parameters and MTPLI policy maturity) on claims paid amount in case of RTA, which is largely consistent with the studies of Klein et al. (2014), Charpentier et al. (2016), Adanu et al. (2017) and Šoltés et al. (2019).

The most important factor group that influences the amount of MTPLI claims paid was the car driver's behavior, which was assessed according to the current car driver penalty points and Bonus-Malus, total determining 43% of claims paid amount variation. Car driver penalties determine about 33% of the variation of losses. Assuming that the other variables in model '1' are constant, one additional penalty point causes an increase in MTPLI losses by about 11 EUR. This conclusion is largely consistent with the results of the study on road traffic regulations violations (Ayuso et al., 2010).

The second single most important factor influencing the amount of MTPLI claims paid is the weight of the vehicle, determining ca. 16% of the variation of losses – when the weight increases by 100 kg, the amount of compensation increases by an average of 13.5 EUR, assuming that the other variables are constant.

The third important factor was the maturity of the MTPLI policy, determining 13.4% of the variation of losses – for policies with a maturity of less than 3 months, the losses are 53% higher than the average. There are few studies on the effect of this factor on the amount of claims paid.

Bonus-Malus is also an important loss driver – for classes below 8 on the scale, the amount of losses increases rapidly as the score decreases and this is largely in line with, for example, Frangos and Karlis (2004), Klein et al. (2014) or Charpentier et al. (2016).

Similar to, for example Frangos and Karlis (2004) or Adanu et al. (2017), the claims paid in case of RTA caused by men are 9.2% higher than by women.

Car driver age – losses caused by drivers under the age of 28 are 6.5% higher than the average, which largely coincides with studies by other authors, such as National Safety Council (2022), Adanu et al. (2017), or Szymańska (2017). On the other hand, no increase in induced losses was observed for elderly car drivers – contrary to the suggestions of other studies, such as Denuit and Lang (2004), Frangos and Karlis (2004) or Klein et al. (2014).

Vehicle age – as the car age increases by one year, the average amount of MTPL insurance indemnities increases by about 3.8 EUR. A similar conclusion follows from studies by other authors, such as Denuit and Lang (2004).

Similar to other studies such as Klein et al. (2014) or Šoltés et al. (2019), the effect of engine power is not linear – when the power increases above 100 kW, the amount of losses caused by RTA increases much faster.

As can be seen in Fig. 6, the impact of certain factors on the amount of claims paid is different from the impact on the likelihood of a RTA.

The statistical tests performed within the framework of the research allow concluding that both hypotheses are confirmed:

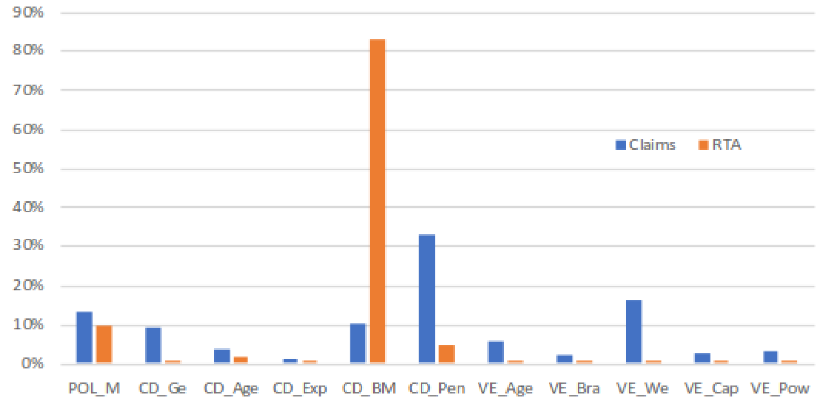

Fig. 6: Weights of factors determining the variation of claims paid and RTA likelihood

1. multivariable regression makes it possible to significantly improve the degree of model's determination for road traffic accidents likelihood evaluation;
2. the grouping of independent variables values significantly improves the adequacy of road traffic accidents risk assessment models.

The results of the research are significant for a reasonable assessment of MTPLI risk factors and pricing of policies to ensure the sustainable development of the insurance business. Product managers of three Latvia's leading transport insurance companies were involved in the approbation of the obtained results and they confirmed its practical applicability.

6 ACKNOWLEDGEMENT

This particular study has been funded by the Research Grant Fund of BA School of Business and Finance. The primary data for the study were provided by the Motor Insurers' Bureau of Latvia.

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THE COST OF RENEWABLE ELECTRICITY AND ENERGY STORAGE IN GERMANY

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EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Volume 8 Issue 1
ISSN 2694-7161
www.ejobsat.com

ABSTRACT

Renewable power generation, especially wind power and solar power, is experiencing a strong expansion worldwide and especially in Germany. With high shares of these methods of power generation, energy storage is needed to enable a demand-oriented power supply even with weather-related fluctuations in generation. Against the background of a power supply based entirely on wind and solar power, the question arises as to what total costs arise with the inclusion of storage systems, which is the subject of this article. The calculation model uses hourly resolved real data of German electricity generation from the years 2012 to 2018 to determine the required storage capacities. The electricity generation costs used range between 0.02 and 0.10 EUR/kW/h. The costs for the considered energy storages are calculated based on the Levelised Cost of Storage (LCOS) metric. It is concluded that in an electricity supply system based on wind and solar power, it is not the electricity generation that causes the greatest costs, but the storage. With electricity generation costs of 0.06 EUR/kW/h, the total system costs are in a range of 0.19 to 0.28 EUR/kW/h. This means that, in terms of costs, energy storage is more significant than electricity generation.

KEY WORDS

energy storage, renewable energy sources, Germany, levelised cost of storage

JEL CODES

C32, C53, O13, Q40

1 INTRODUCTION

A high share of weather-depended renewable energy sources requires fundamental changes in today's power supply in order to account for short-term and long-term fluctuations in creating a demand-oriented supply. To compensate for the volatile generation characteristics,

WEHRLE, Nico Peter Benjamin. 2022. The Cost of Renewable Electricity and Energy Storage in Germany. *European Journal of Business Science and Technology*, 8 (1): 19–41. ISSN 2694-7161, DOI 10.11118/ejobsat.2022.005.

energy storage systems (ESS) are seen as an essential potential for flexibility and as a contribution to security of supply. Technically suitable energy storage technologies include, for example, pumped hydro storage, various batteries technologies, and power-to-gas (PtG; see IRENA, 2019a, 2019b).

Renewable energy sources (RES), in particular wind power and solar power, will continue to gain significantly in importance and thus represent an essential part of the global energy transformation. According to the International Renewable Energy Agency (IRENA), it is expected that by the year 2050 wind power will account for more than 35% and solar power for about 25% of total electricity generation. The reasons for this trend lie in the targeted reduction of CO_2 emissions, in accordance with the Paris agreement to limit global warming below to 2 °C, compared to pre-industrial levels. Other significant causes are seen in sharply falling costs for these renewable power sources, as well as the resulting improvement in air quality (IRENA, 2019a, 2019b).

With the "Energiewende", the German Federal Government is pursuing the goal of making its energy supply sustainable. The share of renewable energies in gross electricity consumption was 42% in 2019. The target of at least 35% in 2020 was already exceeded in 2017. By the year 2030, the goal is to increase the share of RES in Germany to 65%. The final goal in 2050 is a completely renewable and climate-neutral energy supply. Electricity generation from onshore wind power grew to a total of 101.2 TWh in Germany in 2019, while offshore plants generated a total of 24.7 TWh. In the solar power sector, a total of 46.4 TWh of electricity was generated in the same year. In total, gross electricity generation from renewable energy sources amounted to 242.5 TWh out of a total electricity generation of 610.2 TWh. The growing share of wind and solar power indicates that renewable energy sources will play a central role in Germany's future power supply (BMWi, 2021).

Electricity generation from brown coal has decreased in recent years as a result of lower power plant availability. The decrease in nuclear energy since 2006 has been based on the decision to phase out nuclear energy in accordance with the Atomic Energy Act (AtG) of 2002. The share of oil in electricity generation has changed only slightly. The use of natural gas for electricity generation is almost three times as high as in 1990, with more new gas-fired power plants being connected to the grid recently. The share of renewable energies (hydropower, wind energy, biomass, photovoltaics and geothermal energy) has increased more than twelvefold since 1990. This development is particularly due to the introduction of the Renewable Energy Sources Act (EEG). The composition of production from 1990 to 2018 is shown in Fig. 1. The various renewable energy sources contribute differently to the increase in renewable energy in Germany. Hydropower recorded only small increases overall and was responsible for the largest share of renewable electricity production until the year 2000. Thereafter, it was overtaken by solar power, wind power and biomass plants. Today, hydropower generates less than 10% of renewable electricity. In recent years, the importance of wind power has increased most rapidly and today more than half of renewable electricity is generated by onshore and offshore wind turbines. The development of the renewable energy sources in Germany is shown in Fig. 2 (Umwelt Bundesamt, 2020a).

Electricity from renewable energies will be increasingly generated in a decentralised manner in the future. It will therefore be necessary to expand both the generation capacities and the associated transmission grids together and to integrate energy storage systems. In the short term, the expansion of RES will result in additional costs, as investments will have to be made in the construction of new plants. In the long term, however, significant cost advantages are seen compared to conventional electricity generation based on fossil fuels (Umwelt Bundesamt, 2020c).

This raises the question of how much storage capacity is required, which technologies can be used for storing and what costs are associated with it. Several studies have already been carried out to determine the necessary storage capacity for electricity supply with a high share of volatile RES.

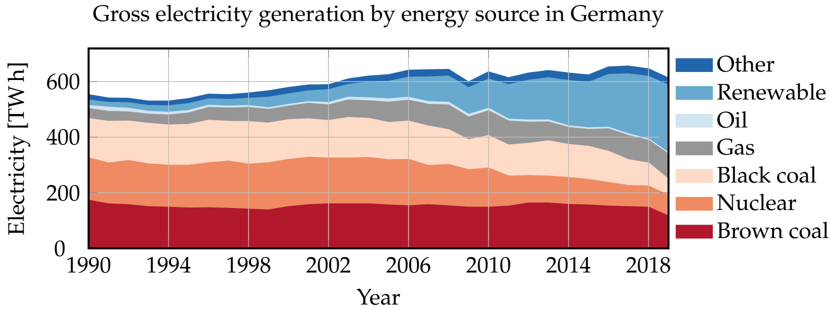

Fig. 1: A significant increase in the amount of renewable electricity generation can be observed (Umwelt Bundesamt, 2020b).

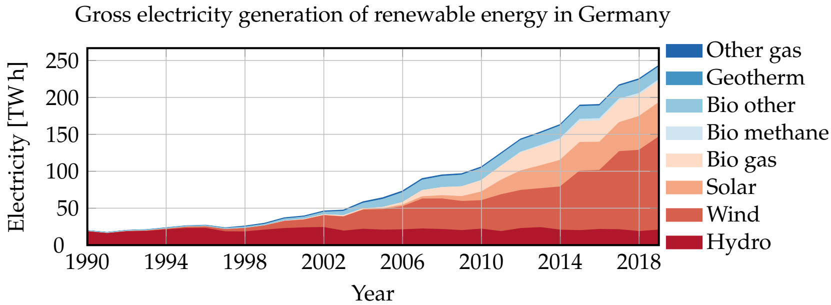

Fig. 2: The majority of RES is generated from wind power and solar power (Umwelt Bundesamt, 2020b).

Popp (2010) determines the required storage capacity for various wind power and solar power generation configurations on the basis of wind speeds and solar radiation data for Germany, resulting in daily loads. A daily load is the energy that is converted in a supply area on a long-term average per day and assumes a value of 1.64 TWh for Germany. The greatest storage demand among the scenarios shown is in the European average of about 104 daily loads (171 TWh for Germany) for supply by solar power alone, without continental interconnection. Heide et al. (2010) are calculate the necessary storage capacity for Europe on the basis of normalised generation data, from the years 2000–2008, based on a power supply from wind and solar power. A total required storage capacity of 400 to 480 TWh is calculated.

Weitemeyer et al. (2015) state that with a lossless storage system in combination with full renewable electricity generation, the required energy capacity would amount to about 80 TWh, which is many times the capacity available today. Estimates of the required storage capacity must always be made in the context of several years in order to cover long-term, seasonal influences.

Schill and Zerrahn (2018) investigate the requirements for electricity storage depending on the share of renewable electricity generation. If the share of RES increases further to 100%, electricity storage requirements almost triple compared to calculations with 80% RES. The growing importance of energy storage systems is highlighted by this.

Cebulla (2017) investigates the demand of energy storage capacity in European scenarios with high shares of volatile RES (more than 80%) and identifies main factors influencing the electricity storage demand. The results lie in a range between 30 and 55 TWh. The calculated capacities underline the need for balanced, diversified storage methods.

In the work of Hameer and van Niekerk (2015), it is concluded that various technologies are suitable for storing energy of several hundred MWh. These include thermal storage, pumped storage, flow batteries, lithium-ion batteries and sodium sulphur batteries.

1.1 Cost of Storage Technologies

Calculating the complete costs of different technologies for energy storage is a more complex issue compared to determining the costs of electricity generation. Storage systems have more technical parameters to take into account, to establish a well-founded calculation method of the costs.

An approach to deriving a calculation method for determining specific storage costs is taken from Mayr and Beushausen (2016) and presented in the following. It starts with the requirement that the sum of all costs must equal the sum of all remunerations.

Time has an impact on the value of capital. Future cash flows have a lower present value than currently generated cash flows. Therefore, a discount factor reflecting the cost of capital, typically the weighted average cost of capital (WACC), must be applied to all outgoing and incoming funds. It is important to "discount" costs as well as remunerations:

$$\sum_{t_l=1}^{\max} \frac{\text{cost}\ (t_l)}{(1+r)^{t_l}} = \sum_{t_l=1}^{\max} \frac{\text{remuneration}\ (t_l)}{(1+r)^{t_l}}. \tag{1}$$

In order to represent all cost drivers, it is useful to map a constant price per unit of energy over the applicable life of the storage facility. The resulting cost metric is called the Levelised Cost of Storage (LCOS). For this reason the remuneration can be expressed by the product of LCOS and electrical energy generated:

$$\sum_{t_l=1}^{\max} \frac{\text{cost}\ (t_l)}{(1+r)^{t_l}} = \sum_{t_l=1}^{\max} \frac{E_{\text{out}}(t_l) \cdot \text{LCOS}}{(1+r)^{t_l}}. \tag{2}$$

Rearranging the formula to LCOS finally produces the general form, in which the sum of all costs is given by the total amount of energy discharged and finally it is possible to express LCOS in accordance with Mayr and Beushausen (2016) as

$$\text{LCOS} = \frac{\displaystyle\sum_{t_l=1}^{\max} \frac{\text{cost}\ (t_l)}{(1+r)^{t_l}}}{\displaystyle\sum_{t_l=1}^{\max} \frac{E_{\text{out}}(t_l)}{(1+r)^{t_l}}}. \tag{3}$$

1.2 Cost Drivers

Considering the capacity, an energy storage system has two core components, the actual energy storage system and the converter required to transfer the energy into the storage medium. In storage systems, both components can be designed independently of each other, whereby the terms energy capacity C_E and power capacity C_P are used (Schmidt, 2018). The capital expenditure or *investment costs* (IC) required is determined from the necessary capacity. The specific costs IC_E for the energy capacity and IC_P for the power capacity are taken from various technical literature. The investment costs usually represent the largest cost driver in energy storage calculations (Schmidt, 2018).

In principle, all infrastructure facilities require regular minor and major maintenance and therefore cause *operating costs* (OC). Depending on the components that need to be replaced and how frequently this needs to be done, this can result in significant additional technology-specific costs. A distinction is made between specific costs in terms of energy OC_E and power OC_P, which ultimately allows the full operating cost OC to be determined. After a storage system has reached the end of its service life, it carries a certain *residual value* based on the achievable sales price for the individual components, including inverters, switchgear and transformers. The shorter the period a storage system has been used, the higher the residual value. To calculate the residual value (RES), the specific values for energy RES_E and RES_P are used.

The *cost of charging* or the cost for the purchase of electricity is defined as k_e. The future financial equivalent is taken into account by mapping the *interest rate* r. A fundamental distinction must be made between one-time payments and annually recurring payments. The time taken to build the plant is also taken into account, since a delay in start-up reduces the value of future revenues (Mayr and Beushausen, 2016). Not all technologies can completely discharge their energy and a certain amount of energy remains in the storage. This specific property is defined as a percentage value, *depth-of-discharge* and represented by the parameter DOD (Schmidt, 2018). Every technology for storing energy has an *efficiency* η. There are different ways to consider whether efficiency is calculated in terms of charging, discharging, or both. Storages with low efficiencies have higher charging costs and require a higher selling price for the discharged energy to be economically viable (Mayr and Beushausen, 2016).

The *lifetime* t_l stands for the expected service life of a storage facility. The number of complete *storage cycles* (SC) indicates the number of equivalent full storage cycles per year. This information relates to the complete energy throughput and thus provides a statement about the degree of utilisation of the system. It is the sum of all cycles that are even partially completed. The degeneration or *degradation* (DEG) refers to the progressive reduction of the nominal storage capacity. In particular, storage systems based on an electro-chemical principle are subject to this effect, while technologies that only require a large volume for storage are not affected (Schmidt, 2018).

With the parameter n the year used for the consideration is defined, or the sequence variable for the sum formulas. By introducing the described variables into equation (3), a formula is created by Mayr and Beushausen (2016) which directly allows the calculation of the levelised costs of storage

$$\mathrm{LCOS} = \frac{\mathrm{IC} + \sum_{n=1}^{t_l} \frac{\mathrm{OC}}{(1+r)^n} - \frac{\mathrm{RES}}{(1+r)^{t_l+1}}}{\mathrm{SC} \cdot \mathrm{DOD} \cdot C_n \cdot \sum_{n=1}^{t_l} \frac{(1-\mathrm{DEG}\cdot n)}{(1+r)^n}} + \frac{k_e}{\eta(\mathrm{DOD})}. \tag{4}$$

Storage costs, based on the LCOS metric for general applications for several storage technologies, can be found in Lazard (2020a, 2020b).

Schmidt (2018) calculates LCOS for the storage technologies of lithium ion batteries, pumped storage plants, Compressed Air Energy Storage systems (CAES), sodium batteries and Gravity Storage Systems. It is assumed that the energy storage units need 8 h to be completely discharged and run through a total of 330 complete storage cycles per year. The interest rate is 8%, the electricity price is 20 USD/MW/h and the ratio between storage capacity and converter power is always 0.125. The costs of the considered storage systems lie in a range between 0.094 and 0.310 EUR/kW/h of discharged electricity.

Jülch (2016) contains a detailed analysis of LCOS for different energy storage technologies. In this, LCOS is calculated for long-term, seasonal storage systems with an energy capacity of 70 GWh and a power capacity of 100 MW with one storage cycle per year. For short-term storage, systems with 400 MWh energy capacity and 100 MW of power capacity and 365 cycles per year are assumed. A distinction is also made between current costs and annual costs in 2030. For short-term storages the costs lie in a range between 0.05 and 0.36 EUR/kW/h. For long-term storages costs between 0.09 and 4 EUR/kW/h are calculated.

Giovinetto and Eller (2019) compare the construction and operating costs of 5 different long-term energy storage technologies using LCOS. In this context, the levelised average costs of molten salt batteries, lithium ion batteries, pumped storage plants, flow batteries, and CAES systems are calculated. The calculation first provides current values using parameters from the year 2019 and projects forecast values into the year 2028. For the year 2028 the calculated storage costs lie in a range between 0.15 and 0.485 EUR/kW/h.

Lai and McCulloch (2017) investigate the costs of stand-alone energy storages and system solutions based on lithium-ion batteries and redox flow batteries. As data input, a 4-year period of the Johannesburg area is investigated in order to consider the utilisation rates. The results show a total system cost of about 0.6 USD/kW/h at an interest rate of 8%.

Lai and Locatelli (2021) investigate the costs of a new type of storage, Generation Integrated Energy Storage system, and compare the main cost drivers with stand-alone storage systems such as lithium-ion storage. One of the conclusions is that stand-alone storage systems are major cost drivers for the overall system. From the author's point of view, this additionally shows the need for system-wide cost considerations.

Rahman et al. (2020) examine the current technological and cost related status of the application of energy storage systems on the basis of a total of 91 publications. Within this work, investment criteria such as the electricity production costs, as well as the required capital costs of storage systems are considered. The conclusion describes the necessity of investigations to determine the electricity supply costs of complete supply systems consisting of electricity generation and storage.

From the investigations of Mostafa et al. (2020), various storage technologies are examined with regard to their costs with given utilisation cycles. This shows that each storage technology has its own techno-economic advantages and disadvantages and that combinations of several technologies are necessary within the framework of system considerations.

1.3 Objective

The works cited above show that there are already studies that either determine the ESS capacity requirements for power supply systems, or calculate the costs of individual, stand-alone systems. Furthermore, there are studies that focus on storage capacities and the associated costs on the basis of synthetic input data sets. Many works conclude that there is a need for further detailed system-wide cost considerations. A calculation approach that maps real fluctuations in the generation of volatile electricity sources and determines the influence on the total costs of the electricity supply system is not covered. This is a key point, because the weather does not follow predetermined and regular cycles, which means that the consideration of real generation and consumption data must be taken into account for a realistic storage and cost calculation. Due to the current transformation process toward renewable electricity in Germany, the main objective of this article is to determine the required total system storage capacities and costs based on real data sets, against the background of a complete electricity supply based on wind power and solar power. Generation and consumption data of the German electricity supply system from the period 2012–2018 serve as data input. Technical and financial data for selected storage technologies are included as further input parameters. The aim is to create a cost range for the resulting total system costs against the background of a renewable electricity supply in combination with energy storage systems.

2 INPUT DATA AND METHODOLOGY

The basis of the model development are data points, resolved on an hourly basis for an arbitrarily spatially delimited area. Basically, it is sufficient to take into account the provided power, the generation capacity and the demand for electrical energy. Within the scope of the study, only the generation methods of wind power and solar power are considered. Therefore the calculation model requires the time series of the following parameter sets:

- wind power (provided energy and installed power capacity);
- solar power (provided energy and installed power capacity);
- demand for electrical energy.

For the development of the model, the German electricity grid is chosen. This area is particularly suitable for consideration of high shares of wind power and solar power due to the ongoing transformation towards renewable energy sources. The input data is taken from BNetzA and the German TSOs, which in turn were provided by the database from Neon (OPSD, 2019).

2.1 Input Data

The modeling is based on data from the period 2012 to 2018, during which large amounts of wind and solar power plants were already in

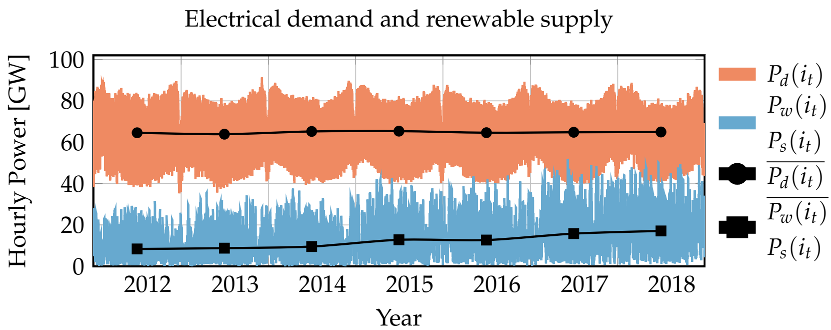

Fig. 3: The chart shows the rise of the sum of wind power and solar power $P_w(i_t) + P_s(i_t)$ (blue) and the approach to the demand $P_d(i_t)$ (orange). In addition the figure shows the annual mean values of supply and demand (black lines).

operation. The input data is available in the form of 61368 hourly resolved data sets and thus allows a representative estimate of the energy storage requirements. An essential aspect is the consideration of the wind-weak years 2013 and 2014, which cause a supply bottleneck within the framework of the data used. The input data consists of the values of the generated wind power $P_w(i_t)$, the solar power $P_s(i_t)$ and the corresponding installed generation capacities for wind power $P_{wc}(i_t)$ and solar power $P_{sc}(i_t)$.

The total electricity production excludes the power plants' own consumption during operation and takes the influences of electricity imports and exports into account. The energy balance from production and consumption is described as total load:

$$
\begin{aligned}
P_d(i_t) &= \text{total generation} \\
&- \text{power plant auxilary} \\
&- \text{power plants' own consumption} \\
&+ \text{imports} \\
&- \text{exports} \\
&- \text{consumption by storages,}
\end{aligned}
$$

whereby the data series of the total demand $P_d(i_t)$ is used further (ENTSOE, 2016b). To calculate the total demand on a realistic basis, an additional correction is required. The reason for this is that the recorded consumption values do not completely reflect the actual demand but are slightly below it. For this reason the data for the electrical demand for the years 2012 and 2013 are divided by the representativeness factor 0.91 and the values for the period 2014 to 2018 are divided by 0.98, considering the coverage ratios (ENTSOE, 2016a). From the beginning of 2012 until the end of 2018, the annual hour-average from wind power $\bar{P}_w$ increases from 5221 MW to 12393 MW. In addition, the solar average $\bar{P}_s$, increases from 3175 MW to 4707 MW. The annual hour-average of the total demand $\bar{P}_d$ remains almost the same, rising slightly from 64555 MW to 64929 MW. The chart of the generation $P_w(i_t)$ + $P_s(i_t)$ and the demand $P_d(i_t)$ are shown in Fig. 3.

Calculating the annual sum values results in produced electrical wind energy of 46 TWh for the year 2012, which increases to 109 TWh over the considered period until the end of 2018. The produced energy from solar power increases in the same period from 28 TWh to 41 TWh. The electrical demand remains relatively stable and has a 7-year average of 568 TWh. The years in the given observation period have different suitable weather conditions influencing the output of wind and solar power, expressed in the utilisation of the power plants. The increase in the output of wind power and solar power within the time period in Fig. 3 is due to the expansion of the production capacities. Comparing the data series of the produced electrical powers $P_w(i_t)$ and $P_s(i_t)$ with the generation capacities $P_{wc}(i_t)$ and $P_{sc}(i_t)$, the effects of weather-related influences on electricity generation become visible. Wind energy always experiences a higher utilisation than solar power. Wind power is more volatile and its utilisation fluctuates between 17% and 22.5%. Solar power is operated relatively evenly

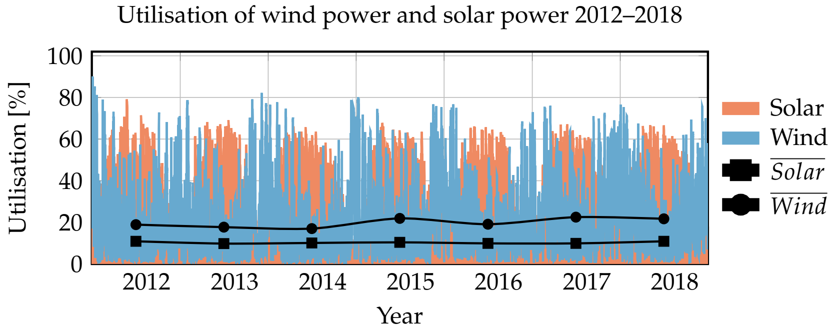

Fig. 4: Wind power shows a higher degree of utilisation especially in the winter months, while solar power is well utilised in the summer time.

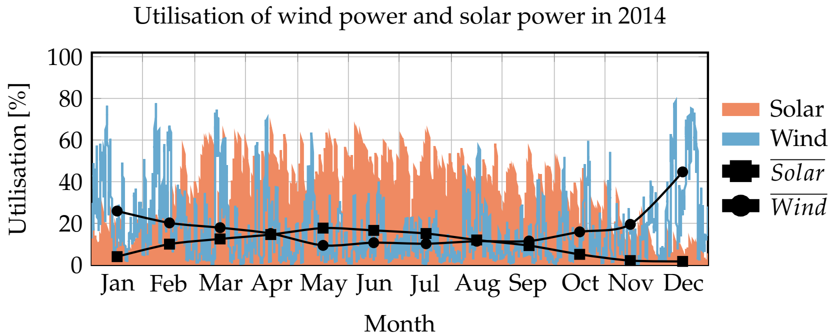

Fig. 5: The charts of the utilisation rates show a comparatively lower utilisation of 17% for wind energy. Solar energy has a utilisation rate of 10.1%.

with a utilisation of between 9.9% and 10.9%. Fig. 4 shows the utilisation of wind power and solar from 2012 to 2018.

Fig. 5 and 6 present a closer look at the utilisation rates of the years 2014 and 2017 and show a low-yielding and a high-yielding period. In 2014, the average utilisation rate in the wind energy sector was about 17% and in 2017 about 22.5%. Considering the same years the utilisation for solar power is nearly constant with 10.1% for 2014 and 9.9% for 2017. The shown weather-dependent differences of the degrees of utilisation in the considered years show that for the simulations of storage systems with a high share of renewable energy sources, always several years have to be considered. This is of crucial importance especially for long-time storage systems.

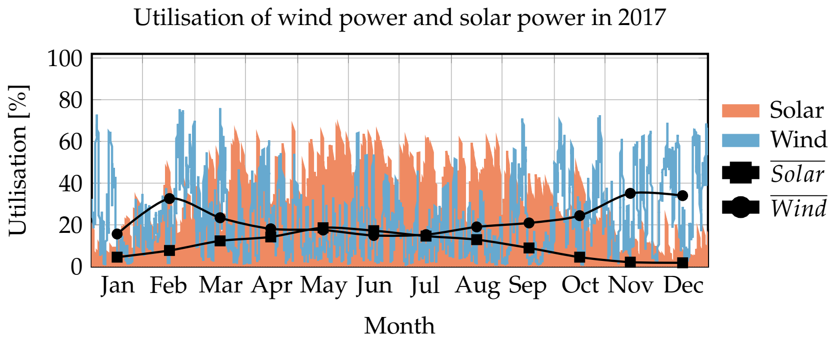

Fig. 6: The charts of the utilisation rates show a comparatively higher utilisation of 22.5% for wind energy. Solar energy has a utilisation rate of 9.9%.

Tab. 1: Annual hour-average values for generation and demand in Germany. In the year 2012 the combination of wind and solar power had a share of 13% of the demand and grew until the end of 2018 to roughly 26%.

Year	Power capacity from wind power $\bar{P}_{wc}$ [MW]	Output from wind power $\bar{P}_w$ [MW]	Power capacity from solar power $\bar{P}_{sc}$ [MW]	Output from solar power $\bar{P}_s$ [MW]	Power demand $\bar{P}_d$ [MW]
2012	27737	5221	29324	3175	64555
2013	30352	5388	34480	3388	63872
2014	34333	5839	36961	3728	65201
2015	40353	8843	38411	3985	65343
2016	45928	8767	39649	3935	64585
2017	52010	11720	41366	4096	64798
2018	57205	12393	43481	4707	64929

Tab. 1 shows the annual hour-average power outputs $\bar{P}_w$ and $\bar{P}_s$, the power capacities $\bar{P}_{wc}$ and $\bar{P}_{sc}$, the power demand $\bar{P}_d$ and the calculated utilisation factors of wind and solar for the years 2012 until 2018. Tab. 2 also shows the annual totals for production and consumption for these categories.

Tab. 2: Annual sum values for generation and demand in Germany.

Year	$\bar{E}_w$ [TWh]	$\bar{E}_w/\bar{E}_{wc}$ [%]	$\bar{E}_s$ [TWh]	$\bar{E}_s/\bar{E}_{sc}$ [%]	$\bar{E}_d$ [TWh]
2012	46	18.9	28	10.9	567
2013	47	17.7	30	9.8	560
2014	51	17.0	33	10.1	571
2015	77	21.9	35	10.4	572
2016	77	19.1	35	9.9	567
2017	103	22.5	36	9.9	568
2018	109	21.7	41	10.8	569

With the data values given, renewable energies are not sufficient to fully guarantee the supply of electricity. Accordingly, a multiplication of the generation capacities has to take place for covering the total demand, initially assuming an unlimited storage capacity. In order to simulate a complete energy supply from renewable sources, the factor m is introduced by which the scaled produced electrical power, given from the data source, is multiplied. The multiplier m is determined with an interactive calculation procedure, with the request that at the beginning and at the end of the time period the energy storage has the same charge level. The charging process of the storage compilation is thus directly scalable via m and also serves to compensate for the existing losses of the respective storage classes. Thus m represents the multiple of the actual generation capacity to completely cover the electricity demand by wind and solar power.

2.2 Storage Classes

From a technical point of view, it makes little sense to use a single technology for storing energy, as available technologies have their individual advantages and disadvantages. A stable electricity grid requires a storage method with fast reaction time and good cycle stability, while long-time storage systems in particular require a very large storage capacity. For this reason, five storage classes are introduced, differing in their technical properties and suitable for the respective application. The storage classes are arranged in descending order of efficiency and in ascending order of capacity. It should be noted that a single storage class is not to be understood as a standalone system, but as the sum of the capacities required in the area under consideration.

The entire composition of the different storage classes establishes therefore a modeling as close to reality as possible within this work. For this reason, it makes little sense, for example, to cover a large capacity requirement with pumped hydro storage plants. The technology itself may appear to be quite suitable for this purpose, but either special geographical conditions are required for the construction, or the construction is only associated with a considerable effort, the implementation of which is unlikely. To cover a wide area of applicability the selected storage technologies should therefore meet the following requirements:

1. A storage system should be independent of geographical conditions and be able to be constructed at almost any location with sufficient subsoil strength.
2. For a storage system the resources necessary for construction and operation should be available in sufficient quantity.
3. Storage systems with a high potential for causing damage to society and environment should not be considered.

Any storage technology can be used, as far as the necessary input parameters are available for the calculation. Due to the above mentioned conditions, the following technologies are chosen within the scope of this study.

For *class 1* a lithium-ion battery (Li-bat) system is selected. Due to its fast response time, this system is able to generate or consume power almost immediately when needed. Furthermore, lithium units have a high stability with regard to the possible number of cycles. Due to the worldwide increase in production capacities in recent years, this technology is available at an acceptable price.

For *class 2* a zinc-air battery system (ZnA-bat) is selected. Since this class already has to cover a multiple of the previous class in storage capacity, a storage where the converter is scalable independently from the storage is suitable. Thus, in this second class, higher amounts of energy can be stored with the same power performance, which has a positive effect on costs. In addition, this type requires high efficiency and high cycle stability as well.

For *class 3* a pumped heat energy storage (PHES) is selected. With this type of storage, the required reaction speed is less important than in the previous classes in favour of a higher storage capacity. The storage volume for thermally charged air can be mapped across different size classes at low cost and the converter can be built completely separate from the storage tank.

For *class 4* a power-to-hydrogen (P-to-H_2) system is selected. For larger energy surpluses hydrogen is directly produced by an electrolysis system. The low efficiency is compensated for at this point by the very high possible storage capacity. Combined cycle gas turbine (CCGT) power plants are used for the discharging process.

For *class 5* a power-to-methane (P-to-CH_4) system is selected. With this method it is possible to map very long, seasonal storage intervals. After the hydrogen electrolysis, a further processing to methane takes place in a separate reactor, which reduces the efficiency even further compared to class 4. If the carbon dioxide required for methanation is extracted from the atmosphere, this is a completely climate-neutral storage system. The greatest advantage and the main reason for methanation is the possibility of storing this gas in the already existing natural gas network. In analogy to class 4, the energy is fed back into the grid by dedicated CCGT power plants.

2.3 Technical Storage Description

With an increase in the generation power by the factor m the necessary performance for the energy converters of the energy storage system would increase as well. Furthermore, the multiplication leads to a higher load on the power grid. In order to exclude unrealistically high charging powers, the parameter P_{lm} is used to limit the charging amount. The energy that exceeds this value during a charging process is evaluated as loss.

The *storage capacities* $C_{E,1}, \dots, C_{E,5}$ and their sum C_{sum} define the maximum amount of energy a storage device can contain. The capacities of the storage classes $C_{E,1}, \dots, C_{E,4}$ are determined by means of a geometrical division using a quotient of the consecutive elements of q. Storage capacity $C_{E,5}$ is determined in such a way that the sum of all classes C_{sum} is sufficiently large to exclude a supply bottleneck for the complete simulation. Therefore the total amount of storage capacity C_{sum} can be expressed as

$$\begin{aligned} C_{\text{sum}} &= C_{E,1} + C_{E,1} \cdot q + C_{E,1} \cdot q^2 \\ &\quad + C_{E,1} \cdot q^3 + C_{E,5} \\ &= \sum_{i=1}^{4} C_{E,1} \cdot q^{i-1} + C_{E,5}. \end{aligned} \tag{5}$$

The following explanations refer to a majority of storage classes. For this purpose, the integer index j is introduced for selected parameters, which defines the association with the storage class.

The parameters η_j stand for the *efficiencies* as a ratio of charged to discharged energies and always refer to the electrical quantity. Since an energy storage system is represented as a self-contained subsystem, the efficiencies always represent the losses from the converter and the storage unit. They are always taken into account during the discharging process. The parameter DOD_j describes the maximum *depth-of-discharge* of an energy storage device. In the context of modeling, these parameters are entered as percentage values and thus define the effectively usable capacity. The *self-discharge* of a storage device is given by the parameter SED_j, usually in percent per day. The self-discharge represents a continuously progressing loss, which also falls below the depth-of-discharge but not below zero. The *degradation* DEG_j represents a loss of capacity which progresses over time and gradually limits the maximum load volume. This influence is indicated in an annual value. If this influence were to be included in the calculation unchanged over the entire time considered, the available storage capacity would be considerably reduced, depending on the degree of degradation. In order to represent a behaviour of degradation as close to reality as possible, the parameter *degradation reset* DER_j with the unit 1/year is additionally introduced. This is the number of complete recoveries of the nominal storage capacity per year and thus stands for a consideration of maintenance and revision work in which, for example, defective battery cells are replaced. In power plant technology, major renewal work is often carried out as part of an annual maintenance. In analogy to this, the restoration of the nominal storage capacity also follows with a value of $\mathrm{DER}_j = 1/\mathrm{year}$.

Another required parameter for the modeling is the *initial charging level* of the storage E_{start}. It is assumed that at the beginning of the calculation all storage devices are charged to 100%. If there is an energy surplus above this maximum charging level, it is not transferred to the storage system and can therefore be considered a loss.

2.4 Storage Class Interconnection

The simplest case is the mapping of a serial interconnection, in which the classes are triggered in a strict order depending on their current state of charge. The modeling is structured in such a way that at the beginning of a charge or discharge process always the lowest available storage class with free capacity is driven. If the capacity limits are reached, the system switches to the next higher class during the charging and discharging process. Class 1 performs the most frequent charging and discharging operations, the highest class 5 the least. The class interconnection of a fully serialised storage assembly is shown schematically in Fig. 7.

The technologies of power-to-hydrogen and power-to-methane have very high investment costs in terms of their converter power. From a technical point of view, it is suitable for the hydrogen electrolysis and the methanation processes to be as continuous as possible, which is not the case with a serial interconnection.

For this reason the semi-parallel calculation model applies a parallel charging process for classes 4 and 5, while classes 1–3 remain in serial operation. This leads to the introduction of the parameter *continuous charging* (COC_j), describing a continuous charging power over the simulation time. COC_j thus defines the required converter power for the charging process, which is lower compared to the serial classes and thus also leads to lower investment costs of the plants. Another advantage is that COC_j is taken into account before the limitation of the input power P_{lm} becomes effective. The class interconnection of the semi-parallel storage assembly is shown schematically in Fig. 8.

In the case of discharging, the parallel connected storage classes should be able to continue charging as well. Accordingly the parallel connected storage classes draw on the storage reserves in addition to the electrical demand, which leads to faster discharging. In the case of a near-empty overall system, when discharging

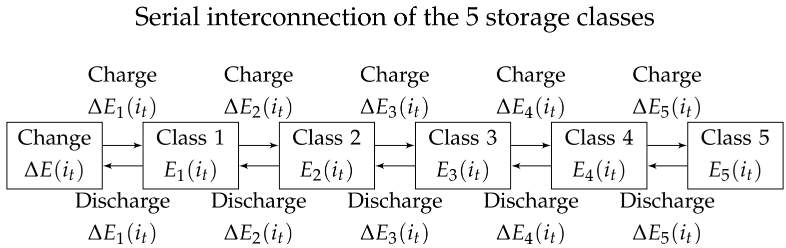

Fig. 7: The change in charge at the input side of one storage class is equal to the change in charge at the output side of the previous storage class.

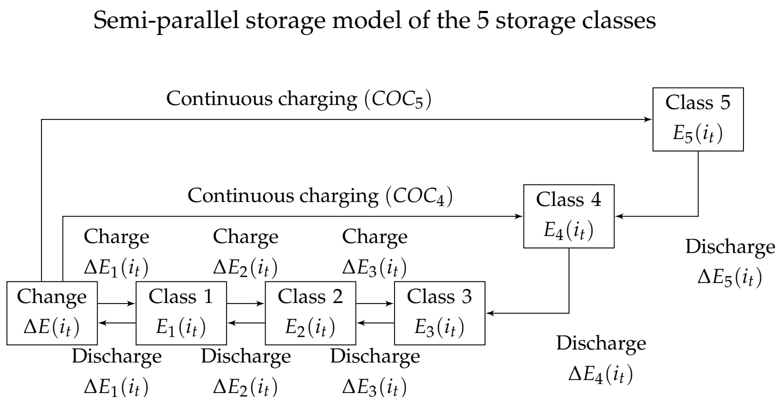

Fig. 8: Up to and including class 3, the entire system operates in serial mode. Class 4 and class 5 experience a continuous energy supply through COC_4 and COC_5.

from hydrogen and methane becomes necessary, a compensation between COC_j and the electrical demand $\Delta E(i_t)$ is thus achieved. In practice, this would be equivalent to simulated charging by electrolysis or methanation and reverse power generation by CCGT plants at the same time.

2.5 Technical Parameter Selection

The total power drawn by all electricity consumers in an electricity grid is subject to fluctuations over time. It is usually higher during the day than at night and higher in winter than in summer. The maximum power that occurs is called the annual peak load. It usually occurs in winter and is also called the winter peak load. Its level is relatively predictable, but also depends on weather conditions. The annual peak load is far smaller than the total output of all installed consumers, since all consumers are never active at the same time (Paschotta, 2012). In the power balance report of the German transmission system operators, a peak load in the range of 78 to 81.6 GW is mentioned (50Hertz et al., 2019). For this reason, the power limitation P_{lm} is set at 80 GW for all of the calculations. The lowest class 1 is dimensioned to cover the largest hourly demand value in the data set, which is 91321 MW and therefore the storage capacity is set at 92000 MWh. The following storage classes are defined with the factor $q = 5$ in ascending order according to equation (5). The last class 5 is always calculated from the remaining necessary storage demand C_{sum}.

Each class requires a set of technical parameters to simulate the respective technology as realistically as possible. The storage technologies used and their associated technical literature parameters are listed in Tab. 3. Assumptions are made for chosen parameters, since either no literature values are available or a deviation is reasonable within the calculations. This applies to the value of the depth-of-discharge for classes 3 to 5, whereby a complete possible discharge is assumed. Class 3, which is represented by a pumped thermal energy storage, has no temperature differences to the environment in the completely discharged state and is therefore considered to be completely discharged. Considering power-to-gas technologies, a similar assumption is made since, e.g. compressors can be used to adjust the pressure when the storage tank is almost empty. In the case of methane storage, there is also the possibility of feeding natural gas into the system for stabilising the working pressure. As the storage capacity of classes 3 to 5 depends on the physical volume, which does not change, a degradation of 0% is applied.

Tab. 3: Technical working parameters for the storage compilation.

Class	Techno-logy	C_E [GWh]	η [%]	DOD [%]	DEG [%/year]	SED [%/day]
1	Li-bat	92	95[a]	90[b]	3[c]	0.01[a]
2	ZnA-bat	460	80[a]	100[d]	1.5[e]	0.01[i]
3	PHES	2300	67[f]	100[i]	0[i]	1[f]
4	P-to-H_2	11500	41[g]	100[i]	0[i]	0.01[h]
5	P-to-CH_4	[j]	32[g]	100[i]	0[i]	0.05[h]

Notes: [a] η: 90–97%, SED: 0.008–0.041% (Sterner and Stadler, 2019); [b] 80–100% (Akhil et al., 2015); [c] PacifiCorp (2016) and Schmidt (2018); [d] η: 80%, DOD: 100% (Akhil et al., 2015); [e] Mongird et al. (2019); [f] η: 52–72%, DEG: 1% (Smallbone et al., 2017); [g] Jülch (2016); [h] 0.03–0.003% (Fuchs et al., 2012); [i] own assumption; [j] depending on calculation result, the parameter for degradation reset der_j is set at 1 year^{-1}.

2.6 Financial Parameter Selection

To calculate the total system costs on the basis of the Levelised Cost of Storage metric, further finance-specific parameters are required. The storage-specific cost parameters are summarised in Tab. 4 and 5.

Some storage technologies provide widely varying values in the literature, which is especially the case for battery systems, which are in the process of becoming progressively cheaper. The time parameters, the cost of electricity for storage and the interest rate used are shown in Tab. 6.

It should be noted that the literature sources provide the financial parameters in different metrics, which leads to the situation that some cost items are considered in different parameters. The power generation costs LCOS for wind power and solar power in Germany are in a range between 0.04 and 0.14 EUR/kW/h (Kost et al., 2018). According to IRENA (2019a), the costs for electricity generation are expected to fall in the future. For this reason a cost range for electricity procurement of $k_e = 0.02$ to 0.10 EUR/kW/h is used for the calculations.

Tab. 4: Parameters relating to IC (CapEx) and ICR (CapExR).

Class	Techno-logy	IC_E [EUR/kW/h]	IC_P [EUR/kW]	ICR_E [EUR/kW/h]	ICR_P [EUR/kW]
1	Li-bat	180[a]	200[a]	180[a]	200[a]
2	ZnA-bat	139.4[b]	377[b]	139.4[b]	377[b]
3	PHES	17[c]	573.5[c]	17[c]	573.5[c]
4	P-to-H_2	0.3[d]	880[d]	0[f]	0[f]
4	CCGT	0	727[d]	0	0[f]
5	P-to-CH_4	0[e]	1369[e]	0[f]	0[f]
5	CCGT	0	727[e]	0	0[f]

Notes: [a] IC_E: 140–180 EUR/kW/h, IC_P: 100–200 EUR/kW (Sterner and Stadler, 2019); [b] IC_E: 164 USD/kW/h, IC_P: 443 USD/kW/h (Akhil et al., 2015); [c] scenario 2 target system (Smallbone et al., 2017); [d] IC_E: assumption of an above-ground storage cavern: 0.3–0.6 EUR/kW/h, IC_P: charging with alkaline electrolysis: 410–880 EUR/kW, discharging with CCGT turbine: 727 EUR/kW (Jülch, 2016); [e] IC_E: feeding into the existing natural gas grid: 0 EUR/kW/h, IC_P: charging with alkaline electrolysis and methanation: 790–1360 EUR/kW, one-time investment for H_2 storage and injector system every 100 MW: 2.64 EUR/kW, discharging with CCGT turbine: 727 EUR/kW (Jülch, 2016); [f] covered by IC_E and IC_P; exchange rate: 0.85 EUR/USD.

Tab. 5: Parameters relating to OC (OpEx) and RES (residual).

Class	Techno-logy	OC_E [EUR/kW/h]	OC_P [EUR/kW]	RES_E [EUR/kW/h]	RES_P [EUR/kW]
1	Li-bat	0.5[a]	0	0[f]	0[f]
2	ZnA-bat	0.00043[b]	3.83[b]	0[f]	0[f]
3	PHES	0.0026[c]	11[c]	0[f]	0[f]
4	P-to-H_2	0.003[d]	14.1[d]	0[f]	0[f]
4	CCGT	0	0.44[d]	0	0[f]
5	P-to-CH_4	0.003[e]	30.2[d]	0[f]	0[f]
5	CCGT	0	0.44[d]	0	0[f]

Notes: [a] OC_E: 0.16–0.76 EUR/kW/h, OC_P: covered by OC_E (Sterner and Stadler, 2019); [b] OC_E: 0.0005 USD/kW/h, OC_P: 4.5 USD/kW/h (Akhil et al., 2016); [c] scenario 2 target system (Smallbone et al., 2017); [d] OC_P: charging unit: 1.6% $\cdot$ IC_P, discharging unit: 0.06% $\cdot$ IC_P (Jülch, 2016); [e] OC_P: charging unit: 1.5–2% $\cdot$ IC_P, discharging unit: 0.06% $\cdot$ IC_P, fee for natural gas grid (charging and discharging): $2 \cdot 3.2$ EUR/kW (Jülch, 2016); [f] assumed residual value after lifetime, exchange rate: 0.85 EUR/USD.

Tab. 6: Parameters relating to time values and interest rate.

Class	Techno-logy	t_l [year]	t_r [year]	t_c [year]	k_e [EUR/kW/h]	r [%]
1	Li-bat	15[a]	15[a]	1[g]	0.06[g]	8[f]
2	ZnA-bat	15[b]	15[b]	1[g]	0.06[g]	8[f]
3	PHES	20[c]	20[c]	1[g]	0.06[g]	8[f]
4	P-to-H_2	30[d]	25[e]	1[g]	0.06[g]	8[f]
5	P-to-CH_4	30[d]	20[e]	1[g]	0.06[g]	8[f]

Notes: [a] Sterner and Stadler (2019); [b] Akhil et al. (2016); [c] Smallbone et al. (2017).; [d] Sterner and Stadler (2019); [e] 20–30 years for alkaline electrolysis, 20 years for methanation isothermal reactor (de Bucy, 2016); [f] Lazard (2020a, 2020b); [g] own assumption.

3 RESULTS

3.1 Technical Results

In order to fulfil the requirement that the entire storage system is completely filled at the end of period under consideration, a multiplier of at least 6.8 is required calculating the serial model. Compared to the installed wind power at the end of 2018, this corresponds to a multiple of 4.75 and an installed power capacity of 280 GW. Solar power corresponds to a multiple of 5.7 and a total installed power capacity of 256 GW. The point in time when the entire storage system is completely discharged occurs at 2015-02-18 21:00 UTC. This system state thus defines the necessary storage capacity of 268 TWh. In particular, the comparatively low-wind years 2013 and 2014 and the increase in electricity demand in 2014 lead to a depletion of the overall system in these years. This shows that the required storage capacity is strongly dependent on the volatile power supply and the electrical demand profile. For this reason, it is imperative to always map several years with the most diverse weather conditions possible within the scope of storage simulations. Fig. 9 shows the charts of the energy charging levels of the system E_{sum} with an increase in the multiplier of $m = 1$ to $m = 6.8$. Only with $m = 6.8$ the level at the end of 2018 reaches almost the same level as at the beginning.

The class-specific results are evaluated with regard to the charging and discharging processes can be seen in Fig. 10. Graph (a) shows how often a storage class is activated. Class 1 is accessed comparatively often for discharging while the remaining classes are always dominated by the charging process. Graph (b) shows the annual volume changes where Class 5 absorbs the most energy. The differences between charging and discharging arise from the internal losses incurred and are therefore dependent on the efficiency η. Graph (c) shows the operating hours, whereby it can be seen that the utilisation times are of a similar order of magnitude for all classes. Graph (d) shows the maximum converter power. Due to the power limitation P_{lm} of 80 GW, there is a maximum during charging. The power during discharging depends on the time-dependent difference between the electricity supply and the electricity demand, with a maximum of approx. 85 GW.

Considering the semi-parallel interconnection for charging, classes 1 to 3 are arranged in a serial sequence, while classes 4 and 5 are arranged in parallel with a constant power COC of 6 GW. The charging of classes 4 and 5 also takes place when an energy bottleneck occurs and, if necessary, energy from the remaining storage classes must be used for this purpose. The reason for this structure in Power-to-Gas technologies is that different technologies are used for charging and discharging. It is suitable to operate the expensive plants for generating H_2 and CH_4 with smaller power capacities. However, in order to store sufficient energy, the plants must always be able to operate

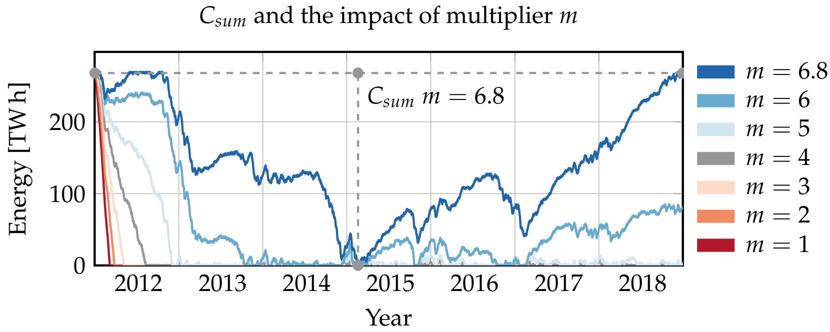

Fig. 9: Serial calculation model. In the case of $m = 1$, it can be seen how quickly the system would empty itself with the historically existing generation capacities. With at least $m = 6.8$ the system is able to reach a fully charged storage interconnection in the end of 2018.

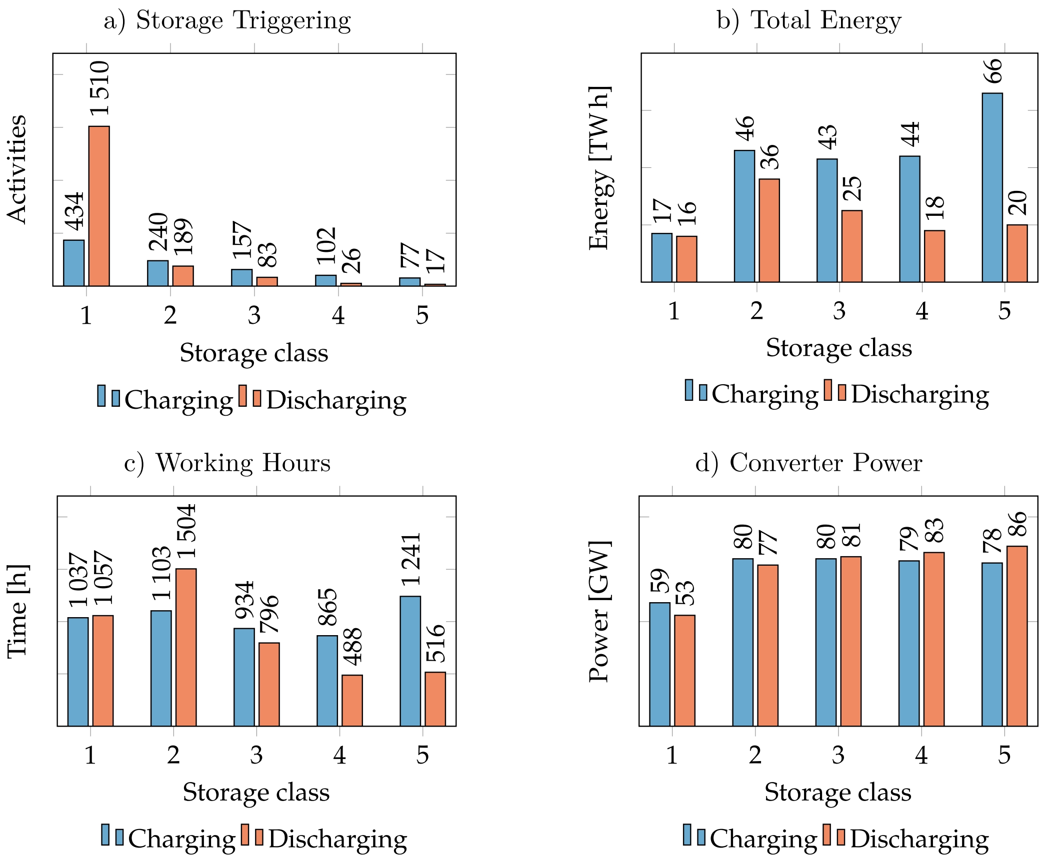

Fig. 10: Compilation of selected result variables for charging and discharging as average annual values.

when the storage capacity is not exhausted. Discharging is done completely in analogy to the serial calculation model in ascending order. The semi-parallel interconnection yields a larger multiplier of $m = 9.12$ compared to the serial consideration. This corresponds in relation to the end of the year 2018 with 375 GW to 6.37 times the installed wind power and with 344 GW to 7.64 times the installed solar power. The lowest value occurs on 2015-02-18 09:00 UTC and is thus almost congruent with the serial calculation. This

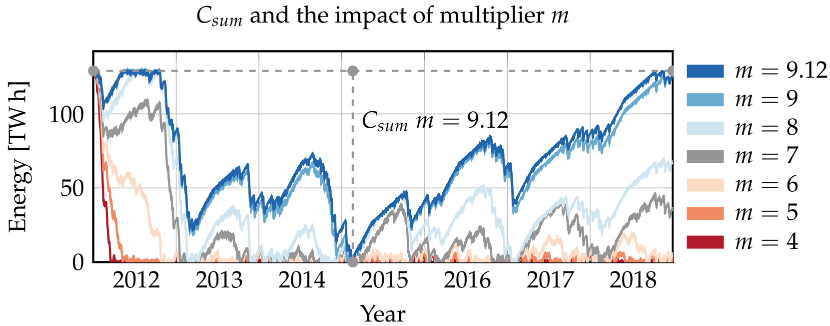

Fig. 11: Semi-parallel calculation model. With at least $m = 9.12$ the system is able to reach a fully charged storage interconnection in the end of 2018.

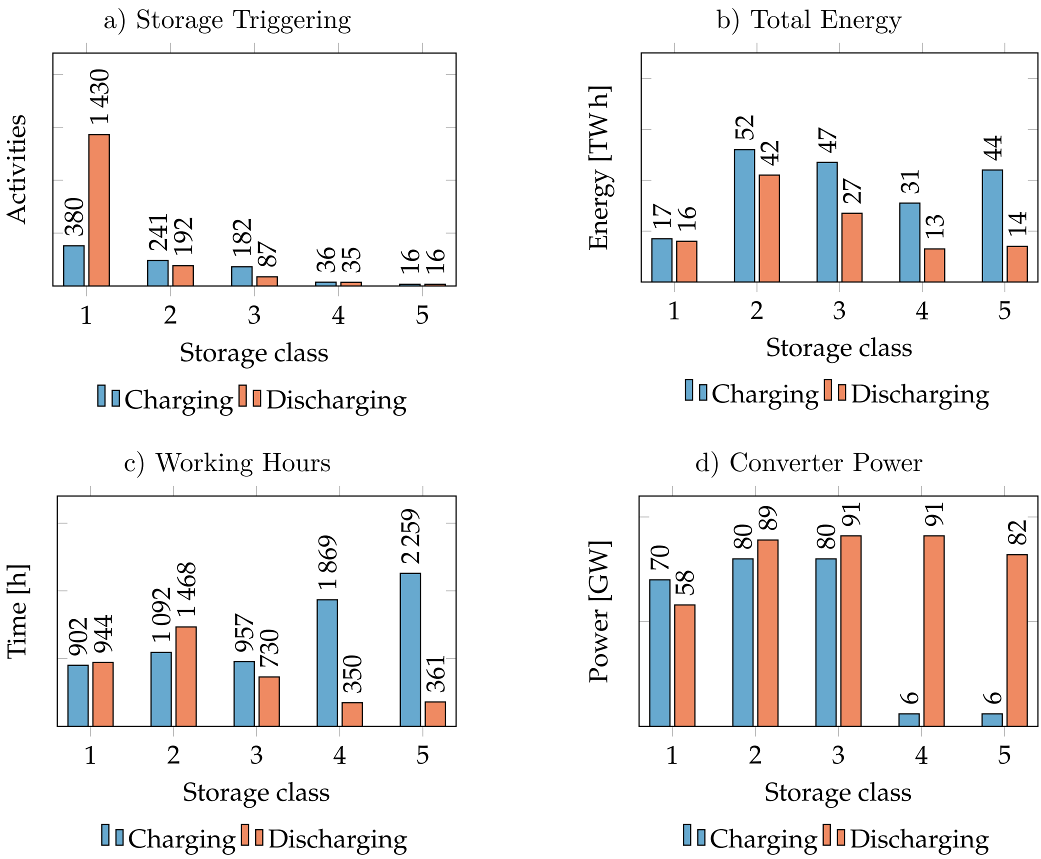

Fig. 12: Compilation of selected result variables for charging and discharging as average annual values.

results in the required total storage capacity of 129 TWh, which is less than half the value from the serial calculation. Therefore, it can be stated that the storage capacity and the generation capacity can compensate for each other. Fig. 11 shows the charts of E_{sum} with an increase in the multiplier of $m = 4$ to $m = 9.12$.

The class-specific results are evaluated with regard to the charging and discharging processes and can be seen in Fig. 12. Graph (a) shows the number of activations, with class 1 showing the most frequent operations in the semi-parallel model, especially when discharging. Graph (b) shows the total charged and

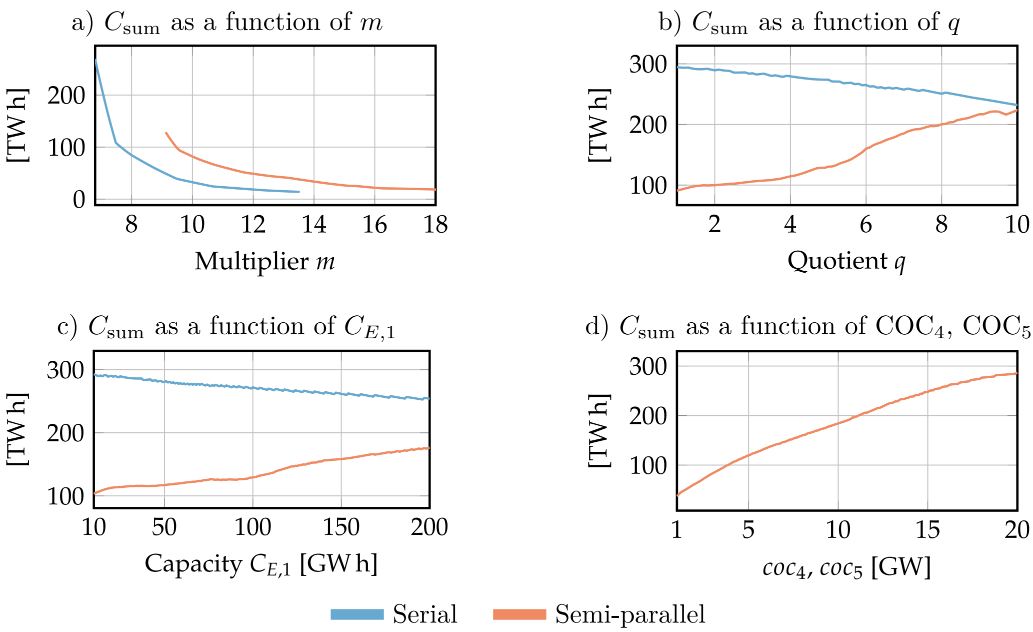

Fig. 13: The graphs show the characteristics of the total storage capacities as a function of the factor-based power production capacity m and the energy capacity ratios of the storage classes to each other, q. Furthermore, as a function of the capacity of class 1 $C_{E,1}$ and of the continuous charging power COC_4 and COC_5. Small discontinuities result from computational uncertainties or changed storage switching processes and can be neglected.

discharged energy, which reveals the influence of the internal losses. Compared to the serial calculation, less energy is stored in class 5 because the class is smaller overall. The working hours are displayed in graph (c). During charging, classes 4 and 5 experience the longest operating times, as they are obviously operated continuously for most of the time. A pause only occurs when the system has no more free capacity. In graph (d), which displays the determined converter power, the influence of the continuous charging of the Power-to-Gas technologies with a value of 6 GW is recognisable. For classes 1 to 3, the charging power is limited by P_{lm} to 80 GW. The converter powers required for charging and discharging for classes 1 to 3 are of a similar order of magnitude in contrast to classes 4 and 5.

Based on the calculated results, parameter studies are carried out to show the influence of the change in several input parameters. Within these studies the following parameters are varied: multiplier m, the quotient for the growth of storage classes q, and the capacity of the first class $C_{E,1}$. The continuous charging powers COC_4 and COC_5 only relate to the semi-parallel calculation model. The development of C_{sum} as a function of m is shown in Fig. 13, graph (a), for the serial and the semi-parallel model. It is shown that in the serial model with $m = 6.80$ and $C_{\text{sum}} = 268$ TWh a sufficient power supply is achieved. With a relatively small overproduction, C_{sum} can be greatly reduced. At $m = 8.09$, the storage capacity is $C_{\text{sum}} = 81$ TWh, which further decays as m increases. The model with semi-parallel interconnection requires smaller storage capacities, but larger power generation. Thus, the power supply is only meeting the demand from $m = 9.12$. An energy storage capacity of $C_{\text{sum}} = 129$ TWh is sufficient. This shows that the serial interconnection requires higher storage capacities, while the semi-parallel interconnection has higher power production requirements.

The variation of the parameters q and $C_{E,1}$ and their influence on the storage capacity is shown in Fig. 13, graphs (b) and (c). An opposite behaviour of the calculation interconnection can be seen, whereby in the serial case, decreasing progressions of C_{sum} and in the semi-parallel case, increasing progressions can be recognised. From this it can be stated that the required storage capacity strongly depends on the interconnection of the individual storage units and their size ratios to each other. Different configurations can cause large variations in C_{sum} of more than 100 TWh. Therefore, the dimensioning of large energy storage systems cannot only be reduced to electricity production and storage capacity, but also requires a detailed consideration of the interconnection dimensioning of storage classes.

The variation of the parameters COC_4 and COC_5 is shown in Fig. 13, graph (d). Here it can be seen that an increase in the continuous charging power is associated with an increase in the storage capacity. The multiplier m is reduced from 14.34 to 8.08 in the range shown. The continuous charging power can be seen as an additional element to control the relationship between storage capacity and generation power. By using parallel storage elements, the required converter power of selected elements can be greatly reduced.

3.2 Cost-Related Results

Based on the results of the technical calculation, detailed statements can be made about the cost aspects of the overall system. The financial calculation results of the serial interconnection show that the levelised cost of storage LCOS increases together with the connection order of the storage classes. This is mainly due to the increasing interest-bearing investment costs and the decreasing number of full storage cycles derived from the working hours. The high costs for the power converters in classes 4 and 5 are particularly striking. In addition, due to the comparatively low number of cycles, they are hardly utilised and are correspondingly expensive. The sum of the costs from the storage system, the external losses and the direct consumption thus gives the total system costs. If these costs are allocated to the total electricity demand, a statement is made about the resulting electricity cost k_{res}, which represents the costs for the complete provision of electricity. The calculation of the resulting electricity cost with the most important intermediate results is shown in Tab. 7.

The total costs of the storage classes are lower in the semi-parallel calculation compared to the serial design. In particular, class 4 and class 5 have significantly lower levelised storage costs, especially due to the lower storage capacity and the investment costs for the energy converters. The total amount of energy delivered by storage and the amount of electricity directly consumed is comparable to the serial interconnection. The costs of external losses, on the other hand, are enormous and a significant cost driver of the total costs, only insignificantly lower than in the serial interconnection. The allocation to the total electrical demand thus produces a similar result for the two calculation cases. On this basis, it can therefore be stated that the savings in the area of the storage capacities are roughly cancelled out by the higher electrical production and the increasing losses. The calculation of the resulting electricity cost for the semi-parallel calculation with the most important intermediate results is shown in Tab. 8.

The parameter studies for the cost-related calculations are carried out to show the influence of the variation of the input parameters m, q, $C_{E,1}$, COC_4 and COC_5 in analogy to the technical consideration. The resulting electricity costs k_{res} depend primarily on the technical dimensioning, on the storage class costs and on the electricity procurement costs k_e. Based on the price ranges for electricity generation in Kost (2018), the parameter studies provide insights into the changes of the resulting electricity costs depending on the input parameters in a range of electricity purchasing costs between 0.02 EUR/kW/h and 0.10 EUR/kW/h.

The parameter studies calculating the energy storage capacity C_{sum} show that an increase in electrical production through the multiplier m leads to a decrease in capacity. What is surprising here is that, with regard to the system costs, there is no reduction in the total costs; in fact, the opposite is the case. Higher production capacity increases the costs for electrical losses that cannot be consumed.

Tab. 7: Annual cost calculation for the total system (serial).

Parameter	**Energy**	**Financial amount**
Class 1 LCOS (92 GWh)		0.30 EUR/kW/h
Class 2 LCOS (460 GWh)		0.44 EUR/kW/h
Class 3 LCOS (2300 GWh)		0.55 EUR/kW/h
Class 4 LCOS (11500 GWh)		0.99 EUR/kW/h
Class 5 LCOS (254960 GWh)		1.22 EUR/kW/h
Class 1 electricity discharged	16364 GWh	4.94 EUR bn
Class 2 electricity discharged	36470 GWh	15.88 EUR bn
Class 3 electricity discharged	25001 GWh	13.63 EUR bn
Class 4 electricity discharged	17931 GWh	17.67 EUR bn
Class 5 electricity discharged	20291 GWh	24.81 EUR bn
Subtotal (k_{sto})	116057 GWh	76.94 EUR bn
Power limitation losses	43415 GWh	2.60 EUR bn
Charge surplus losses	5990 GWh	0.36 EUR bn
Subtotal (k_{los})	49405 GWh	2.96 EUR bn
Direct consumption (k_{dir})	451636 GWh	27.10 EUR bn
System costs (k_{res})	617099 GWh	107.00 EUR bn
Resulting electricity cost (k_{res})	567693 GWh	0.188 EUR/kW/h

Tab. 8: Annual cost calculation for the total system (semi-parallel).

Parameter	**Energy**	**Financial amount**
Class 1 LCOS (92 GWh)		0.32 EUR/kW/h
Class 2 LCOS (460 GWh)		0.40 EUR/kW/h
Class 3 LCOS (2300 GWh)		0.54 EUR/kW/h
Class 4 LCOS (11500 GWh)		0.76 EUR/kW/h
Class 5 LCOS (114221 GWh)		0.75 EUR/kW/h
Class 1 electricity discharged	16352 GWh	5.23 EUR bn
Class 2 electricity discharged	41911 GWh	16.79 EUR bn
Class 3 electricity discharged	27319 GWh	14.67 EUR bn
Class 4 electricity discharged	12906 GWh	9.82 EUR bn
Class 5 electricity discharged	13760 GWh	10.26 EUR bn
Subtotal (k_{sto})	112248 GWh	56.76 EUR bn
Power limitation losses	124155 GWh	7.45 EUR bn
Charge surplus losses	189428 GWh	11.37 EUR bn
Subtotal (k_{los})	313584 GWh	18.82 EUR bn
Direct consumption (k_{dir})	455446 GWh	27.33 EUR bn
System costs (k_{res})	881277 GWh	102.90 EUR bn
Resulting electricity cost (k_{res})	567693 GWh	0.181 EUR/kW/h

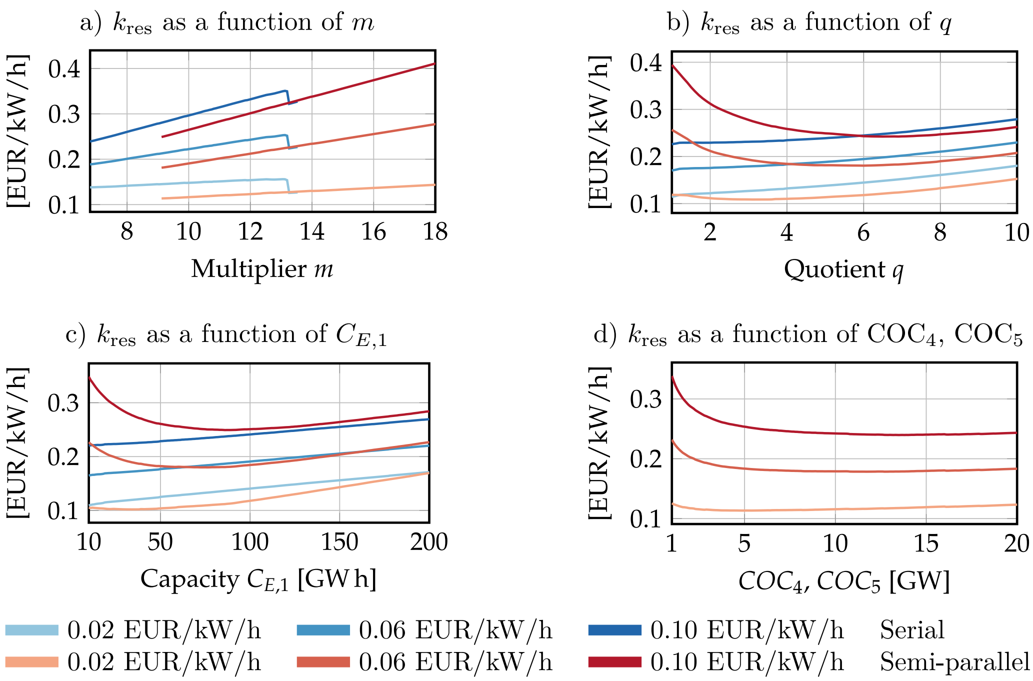

Fig. 14: The figures show the characteristics of the resulting total electricity system costs k_e as a function of the factor-based production capacity m and the capacity ratios of the storage classes to each other q. The curve of k_{res} as a function of m shows a small negative jump at $m = 13.5$. From such a large generation capacity onwards, storage class 5 is not needed, which abruptly eliminates its converter costs. Furthermore k_{res} is presented as a function of the capacity of class 1 and the continuous charging power COC_4 and COC_5.

The costs of losses have a greater impact than the savings in storage capacity. This behaviour is shown in Fig. 14, graph (a), and is similar for the serial and the semi-parallel calculation model.

Considering the serial calculation model, the growth of the parameters q and $C_{E,1}$ defining the energy storage capacity of the storage classes shows a similar behaviour. An increase in q and $C_{E,1}$ leads to rising costs, as more expensive storage classes come into operation with an increase in the parameters. The advantage of having better efficiencies within the total storage capacity is comparatively small in relation the total cost increase. Within the semi-parallel calculation model there is a flat minimum in each case, which represents an optimum from a cost perspective. The position of the optimum depends on the purchase costs for the electrical energy k_e. Basically, it can be concluded that a relatively small dimensioning of the lower storage classes leads to a significant cost increase. The curves for q and $C_{E,1}$ are shown in Fig. 14, graphs (b) and (c). A flat minimum is also seen with the variation of COC_4 and COC_5. This shows that the continuous charging power for the parallel-connected storage classes has a non-negligible influence, depending on the purchase costs for the electricity. From this it follows that the converter power for permanent parallel-connected charging processes should have at least the size of a few GW. This can be seen in Fig. 14, graph (d). Even though using relatively favourable cost data of storage technologies, the results show the significant impact of storage system costs. It should be noted that the calculated costs strongly depend on specific storage costs. Zakeri and Syri (2015) investigate the life cycle costs of several storage technologies by extensive literature research. A literature-related average of 795 EUR/kWh is given, for example, fo the investment costs of lithium battery systems.

4 CONCLUSIONS

Globally, renewable power generation is being expanded, especially wind and solar power. Against the background of the "Energiewende", Germany is striving to promote the expansion of these power generation methods. Due to their dependence on the weather, energy storage facilities are needed to compensate for weather-based shortages when there is a high proportion of volatile generation capacity.

With a complete power supply from wind and solar power, large storage capacities are needed to guarantee the power supply over short and long periods. The two calculated storage combinations lead to a storage demand of 268 TWh (serial) and 129 TWh (semi-parallel) for Germany. Compared to the average annual electricity demand of 567 TWh over the same period, these are shares of 47% and 23% respectively. The required storage capacities can be significantly reduced by changing selected technical parameters, especially by overproducing the electricity. However, this does not lead to reductions in total system costs, as the electricity that cannot be used due to overproduction must be counted as a loss.

The most important conclusion lies in the realisation that in a power supply based on wind power and solar power, it is not the generation of electricity that causes the greatest costs, but the storage. Taking into account the costs of the storage systems and the costs for the losses incurred, the resulting total costs are several times higher than the electricity generation itself, depending on the system configuration. With electricity generation costs of 0.06 EUR/kW/h, the total system costs lie in a range of 0.19 EUR/kW/h to 0.28 EUR/kW/h. This key finding shows that the inclusion of energy storage and the losses incurred from overproduction and inefficiencies must inevitably be seen as key cost drivers in renewable electricity supply systems. An exclusive focus on generation capacity leads to an incomplete and inadequate cost calculation.

Comparison of the storage costs from the work of Schmidt (2018), Jülch (2016) and Giovinetto and Eller (2019) with the total system costs from this work shows a comparable order of magnitude. However it should be noted that the costs of individual storage systems cannot in principle be compared to the costs of the entire system. Depending on which storage technologies are chosen for an overall system and which overcapacities are used, the total system costs change significantly.

Political and economic decision-makers should take these findings into account when planning future power supply systems in order to ensure a sustainable and hopefully cost-effective power supply.

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AQUACULTURE FARMERS' ECONOMIC RISKS DUE TO CLIMATE CHANGE: EVIDENCE FROM VIETNAM

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EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Volume 8 Issue 1
ISSN 2694-7161
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ABSTRACT

Climate change poses a serious threat for aquacultural productivity. Employing the Autoregressive Distributed Lag (ARDL) model, this research aims to evaluate the economic impact of climate change on aquaculture in Vietnam, drawing on time series data from 1981 to 2013 and including aquaculture yield, acreage, investment, labor, temperature, rainfall, and damage costs to aquaculture caused by natural disasters. The results show that aquaculture yield depends not only on the current value of inputs, but also on their lag values and the yield itself. The results also show that rainfall, storm surges and tropical cyclones negatively affect aquaculture production. After any natural disaster, it takes at least two years to recover from the repercussions for productivity and return to the previous norm. To reduce the vulnerability of aquacultural communities, this study suggests that the state could establish a climate resilience fund specifically for small and medium-scale aquaculture farmers, providing special financial support for those affected by natural disasters.

KEY WORDS

climate change, ARDL model, aquaculture, vulnerability, Vietnam

JEL CODES

C22, D24, F63, O47, O53, Q22, Q54

1 INTRODUCTION

Likely to be seriously affected by climate change, Vietnam is one of the most vulnerable countries in the world (Yusuf and Francisco 2009; Minderhoud et al., 2019). Vietnam's coastal region spans about 3,000 km populated by more than 20 million people, most of whom are low-income and dependent mainly on aquaculture or agriculture. The multidimensional impact of climate change can be observed in coastal areas, and damage due to extreme

NGUYEN, Thanh Viet, TRAN, Tuyen Quang, and AHSAN, Dewan. 2022. Aquaculture Farmers' Economic Risks Due to Climate Change: Evidence from Vietnam. *European Journal of Business Science and Technology,* 8 (1): 42–53. ISSN 2694-7161, DOI 10.11118/ejobsat.2022.006.

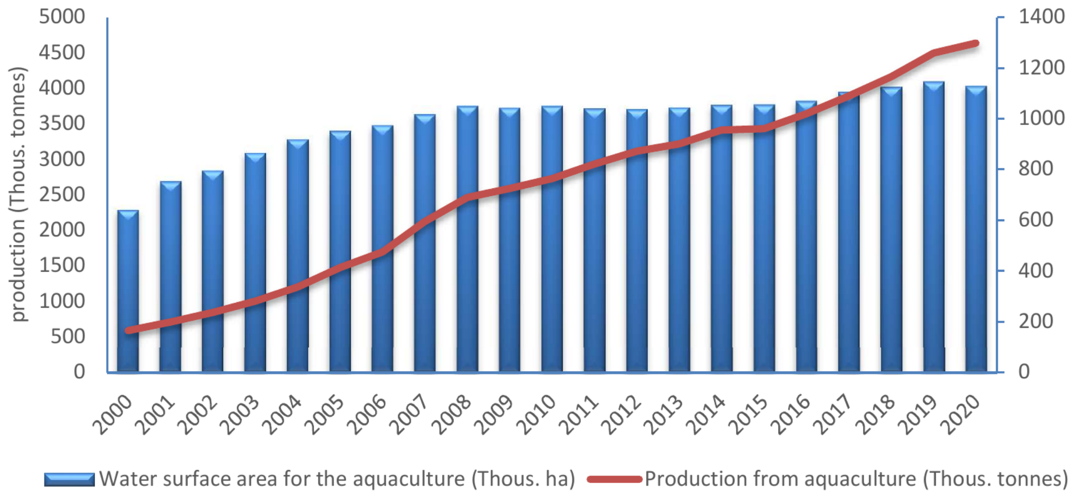

Fig. 1: Production of aquaculture in 2000–2016 (GSO, 2020)

weather events, such as hurricanes, floods, and tidal surges, are becoming increasingly frequent (McElwee et al., 2017; Bangalore et al., 2016). Arndt et al. (2015) estimate that in Vietnam overall, climate change is likely to reduce national income by between one and two percent by 2050. Rising sea levels and increasingly violent cyclones will be the main causes for these economic losses.

A long coastline and tropical weather provide Vietnam with ideal conditions for aquaculture which, in fact, is one of the country's major foreign exchange earners. Its most important seafood products are shrimp and pangasius fish which Vietnam exports to many countries, including Europe, Japan, and the USA. Over the last 20 years, seafood production from aquaculture in Vietnam has increased even though the total water surface area for aquaculture has remained stable (Fig. 1). In 2020, Vietnam earned 3.2 billion USD from the export of seafood products (VASEP, 2021).

However, fish production from aquaculture is frequently affected by climate change and climate-related natural disasters. Not only has climate change significantly altered the intensity and frequency of rainfall, temperature and cyclones, but it has also contributed to rising sea-levels in Vietnam (IPCC, 2014).

The Vietnamese aquaculture and fisheries sector also faces business risks from climate change. According to the latest report (2012) made by DARA (an independent NGO) and the Climate Vulnerable Forum (CVF), Vietnam ranked highest among countries where fisheries losses due to climate change are at a threatening (red warning) level, totaling approximately USD 1.5 billion in 2010, a figure that will increase to USD 25 billion by 2030 (DARA and CVF, 2012). The annual average temperature in Vietnam rose by 0.5 to 0.7 °C, and precipitation also evidenced change by periods and regions, though not by significant amounts (MONRE, 2008).

Furthermore, in a disaster-prone country the Vietnamese aquaculture sector has experienced product loss and property damage almost every year due to coastal storm surges (CCFSC, 2017), see Fig. 2. The highest number of storms over the past 20 years occurred in 2017, resulting in damage to 60,400 ha of aquaculture area and the loss of 76,500 aquaculture cages. Total economic losses due to storms in 2017 totaled approximately USD 2.63 billion (CCFSC, 2017).

A World Bank study (2010) reported that if no strategy was worked out to mitigate risk from climate change in the Mekong Delta region, by 2020 the income of pangasius farmers (Vietnam is one of the foremost countries in pangasius production in the world) might decline by USD 120,000 per hectare and that

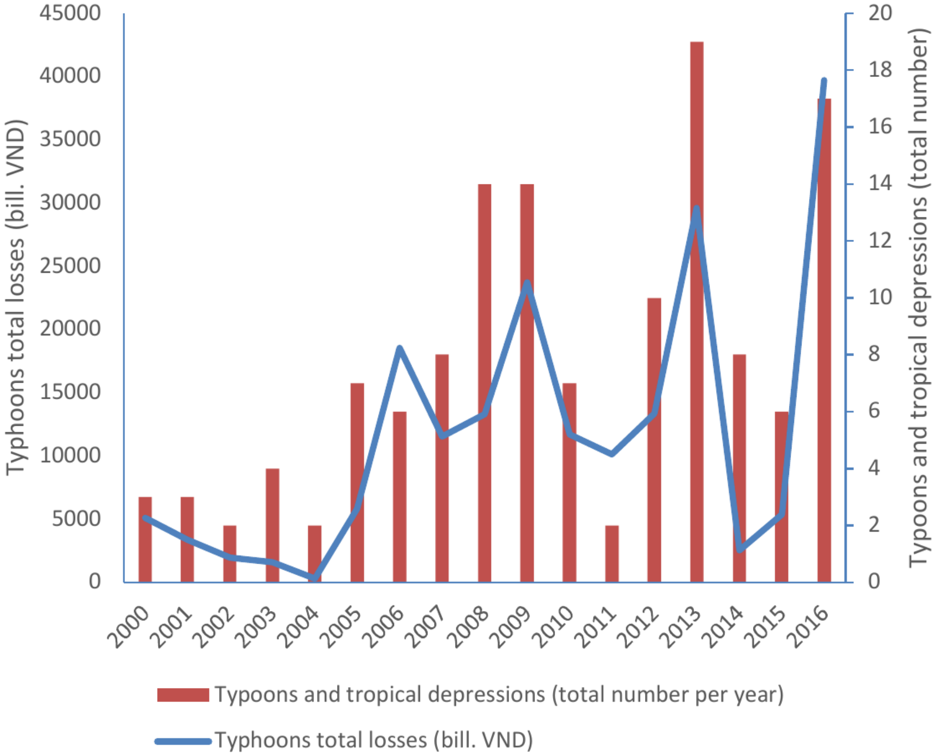

Fig. 2: Tropical typhoons and their consequences on Vietnamese aquaculture sector

of shrimp farmers by about USD 5,000 per hectare, eventually resulting in income losses of up to USD 38,000 per hectare by 2050. Furthermore, costs for climate change mitigation in shrimp culture may increase due to the rising cost of pumping water, raising the height of dikes and constructing new drainage systems. These extra costs for shrimp farms could account for about 2.4% of total annual costs (covering the period 2010–2050; see World Bank, 2010).

However, the above-mentioned studies offer only a limited qualitative assessment, for example identifying vulnerabilities, or they provide a quantitative small-scale evaluation at the household or communal levels, but they do not quantify the economic impact of climate change on aquaculture at the national level.

The key objective of this study is to evaluate the economic risks of climate change for aquaculture in Vietnam by using the ARDL model. The basic assumption is that farmers maximize their aquaculture production by using a combination of different inputs. To achieve this objective, our research raises the following two questions:

1. What are climate change risk factors that affect aquaculture production in Vietnam?
2. How can we quantify the economic risks of climate change for the aquaculture sector in Vietnam?

This paper is structured as follows: Section 2 presents a literature review, the following section describes the methodology used, the results are presented in Section 4 and Section 5 discusses the implications of the results and potential policy measures.

2 LITERATURE REVIEW

Climate change appears to be one of the most influential risk factors for human society. Several studies have shown that climate change and its effects influence environmental and economic factors, and directly and indirectly affect people's lives (Stern, 2007; Heal and Millner, 2014; Kahn, 2016). Vulnerability to climate change has three key elements: the probability of adverse events, their severity, and the capacity to respond to vulnerability (adaptation capacity). Stern (2007) estimates that if countries take no action to mitigate natural disasters or adapt to them, the overall costs of climate change will be the equivalent of losing 5–20% of global GDP each year.

Meanwhile, the cost of acting to reduce greenhouse gas emissions and avoid the worst effects of climate change can be limited to around 1% of global GDP each year. Therefore, an assessment of the effects of climate change is not a country-specific issue but rather demands global action. Sustainable development may be the best way to combat the effects of climate change on human society. The term "sustainable development" includes poverty reduction, human development, including health and job-oriented education, and sustainable environmental management. The United Nations puts heavy emphasis on the implementation of UN SDGs (sustainable development goals) but achieving these goals is always challenging for developing nations. Not only are their resources and capabilities limited but also many of them are highly vulnerable to climate change.

The literature survey shows that several past studies have focused on the risks of climate change for aquaculture productivity, farm income and farmers' livelihoods (World Bank, 2010; Chen, 2011; Ha, 2011; Narita et al., 2012). In their study, for instance, Narita et al. (2012) performed a partial-equilibrium analysis to estimate the global and regional economic costs resulting from the loss of production of mollusks due to ocean acidification. The study revealed that economic losses could total more than 100 billion USD by 2100. Climate change has a tremendous impact on the physicochemical parameters of water (e.g., temperature, salinity, rainfall, dissolved oxygen, sedimentation, and pH) which largely determine the productivity of an aquacultural pond. Evidence shows, for example, that increased water temperature and CO_2 emissions have enormous negative impact on the reduction of dissolved oxygen concentration, increases in ocean acidification, and the reduction of plankton production, which in turn affect the growth rate of fishes and production (Hargreaves and Tucker, 2003; Edwards and Richardson, 2004; Morrill et al., 2005; Allison et al., 2009).

Some studies make use of modeling to quantify the impact of climate change on the world's fisheries. In 2011, research carried out by the Economic Commission for Latin America and the Caribbean – ECLAC (2011) employed econometric models to assess the relationship between fisheries' production (including aquaculture and capture) and factors such as seafood export prices, sea surface temperature and mean annual precipitation. Their results indicated that sea surface temperature and average rainfall were inversely proportional to aquaculture production in Guyana. Losses to the fisheries sector by 2050 according to an A2 scenario would be $15 million (at a discounted rate of 4% per year) to $34 million (with a discount rate of 1%). According to a B2 scenario, estimated losses by 2050 would be $12 million (discount, 4%) to $20 million (discount, 1%). As aquaculture is heavily exposed to environmental conditions and production largely depends on various climatic factors, climate change has a severe impact on aquaculture. Accordingly, aquaculture is a riskier business in comparison with other agro-businesses (Ahsan and Roth, 2010; Ahsan, 2011).

3 METHODOLOGY AND DATA

This research utilizes the Autoregressive Distributed Lag (ARDL) model to build a model for evaluating the risks of climate change on aquaculture in Vietnam. The ARDL model aims to describe the relationship between the inputs and outputs of the production process. It presents the maximum number of outputs from the use of any combination of certain inputs. To quantify the effects of climate change on aquaculture, the ARDL model used in this

Tab. 1: Data description (1981–2013)

Variable	Observations (years)	Maximum value	Minimum value	Mean value	Standard deviation
P = Ln(Produce)	33	15.021	12.101	13.375	0.965
A = Ln(Acreage)	33	13.908	12.346	13.336	0.465
K = Ln(Capital)	33	14.609	10.807	12.935	1.313
L = Ln(Labor)	33	14.503	12.179	13.312	0.869
Dam = Ln(Damage)	33	11.837	6.172	9.274	1.199
Temp	33	26.67	22.96	25.572	0.696
Rainfall	33	2288.6	1311.33	1790.072	249.573
Typhoon	33	5	0	1.485	1.302
Depression	33	5	0	1.364	1.365

Tab. 2: Database description

Variable	Description	Source
Produce_t	Aquaculture yield in year t (tonnes)	"Vietnam fisheries sector in 50 years", Vietnam Institute of Fisheries, Economics and Planning; Provincial agricultural and rural development database, Planning Department of the Ministry of Agriculture and Rural Development
Acreage_t	Aquaculture acreage in year t (hectares)	"Vietnam fisheries sector in 50 years", Vietnam Institute of Fisheries, Economics and Planning; Provincial agricultural and rural development database, Planning Department of the Ministry of Agriculture and Rural Development
Capital_t	Total capital investment in the aquacultural sector in year t (million Vietnamese Dong)	"Vietnam fisheries sector in 50 years", Vietnam Institute of Fisheries, Economics and Planning
Labor_t	Total number of laborers in the aquacultural sector in year t (persons)	"Vietnam fisheries sector in 50 years", Vietnam Institute of Fisheries, Economics and Planning
Damage_t	Acreage of ponds damaged due to natural disasters in year t (hectares). Missing data is estimated by the GROWTH function in MS Excel, expressing the exponential relation between the total number of typhoons and damaged acreage.	Data from the Standing Office of the Central Committee for Flood and Storm Control (1989–2009)
Tempt_t	Average air temperature in year t (°C)	Database of the Ministry of Agriculture and Rural Development
Rainfall_t	Average precipitation in year t (mm)	Database of the Ministry of Agriculture and Rural Development
Typhoon_t	Number of typhoons (wind speed > 100 km/h) in year t	Database of the Ministry of Agriculture and Rural Development
Depression_t	Number of tropical depressions in year t	Data from the Ministry of Natural Resources and Environment
D_1	Governmental fisheries export policy in 1990; D_1 has the value of 1 for 1990–2013 and 0 for earlier periods	The authors have defined this variable
D_2	Renovation period; D_2 has the value of 1 for 1986–2013 and 0 for earlier periods	The authors have defined this variable

study describes the relationship between outputs and inputs, including traditional factors such as yield, capital, and acreage, and some additional climate change factors. The ARDL model has the following form:

$$\begin{aligned}\ln(\text{Produce}_t) = \beta_0 + \beta_1\, T + \\ + \beta_2 \ln(\text{Acreage}_t) + \\ + \beta_3 \ln(\text{Capital}_t) + \\ + \beta_4 \ln(\text{Labour}_t) + \\ + \beta_5 \ln(\text{Damage}_t) + \\ + \beta_6\, \text{Temp}_t + \beta_7\, \text{Rainfall}_t + \\ + \beta_8\, \text{Typhoon}_t + \\ + \beta_9\, \text{Depression}_t + \\ + \beta_{10}\, D_1 + \beta_{11}\, D_2 + \epsilon_t, \qquad (1)\end{aligned}$$

where Produce_t – aquaculture yield in year t (tonnes); T – time trend; Acreage_t – acreage of aquaculture in year t (hectares); Capital_t – total capital investment in the sector in year t (million Vietnamese dong); Labor_t – total number of employees in the sector in year t (persons); Damage_t – acreage of damaged ponds due to natural disasters in year t (hectares); Temp_t – average temperature in year t (°C); Rainfall_t – average precipitation in year t (mm); Typhoon_t – number of typhoons with a wind speed of more than 100 km/h in year t; Depression_t – number of tropical depressions in year t. Dummy is a proxy for policy, including D_1 – governmental fisheries export policy in 1990; D_1 has a value of 1 for 1990–2013 and a value of 0 for earlier periods; D_2 – renovation period; D_2 has a value of 1 for 1986–2013 and a value of 0 for earlier periods; β_i – empirical coefficients ($i = 0, 1, 2, \ldots, 11$).

Time series data for 1981–2013 were collected from various sources, presented in Tab. 1 and 2.

In a time-series model, the value of the dependent variable (aquacultural yield) in a given year may depend on those of the previous years, and the values of the independent variables in previous years may also affect the aquacultural yield in the current year. Consequently, the ARDL (autoregressive distributed lag) model is applied to express these dependences. The model has the following form:

$$\begin{aligned}Y_t = v + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \\ + \beta_0 X_t + \beta_1 X_{t-1} + \ldots + \beta_q X_{t-q} + \\ + u_t, \qquad (2)\end{aligned}$$

in which Y_{t-p} and X_{t-q} are the lags p and q years of Y_t and X_t respectively, and u_t is white noise.

Tab. 3: Tests of lag length for variables (p-values in paretheses)

	Lag 1	**Lag 2**
P	27.925 (0.0009)	3.112 (0.959)
A	27.709 (0.001)	10.718 (0.296)
K	10.097 (0.343)	7.57 (0.578)
L	43.654 (0.0000)	28.39 (0.0008)
Dam	3.682 (0.931)	4.602 (0.868)
Temp	3.894 (0.918)	5.852 (0.755)
Rainfall	1.278 (0.998)	4.798 (0.852)
Typhoon	3.494 (0.941)	3.632 (0.934)
Depression	4.956 (0.838)	7.841 (0.550)
Joint	400.972 (0.000)	382.235 (0.000)

In many years, aquacultural yield is not affected by all possible factors. We choose the variables for the model depending on the lags of such variables as aquaculture acreage, capital investment, labor, damaged pond acreage, the number of typhoons and tropical depressions. Since there is only a small number of observations, the maximum number of lags should be 2. To identify the lag length of the model, we employ lag (−2) with independent endogenous variables. The results show that lag (−2) is appropriate (Tab. 3). We continue by choosing he optimal lag length for the model based on AIC with 2 lags.

4 RESULTS

Stationarity is an important assumption in time series analysis techniques. The stationarity test aims to determine whether a time series is independent of time. A series is stationary if its statistical properties remain unchanged over time. The ADF test (Augmented Dickey-Fuller) can be used to identify the stationarity of a time series. Based on SIC for lag 8, the ADF tests give the results for the stationarity of the yield series. These results show that the ADF statistic is 1.388, which is larger than the 5% critical value (−2.957). Therefore, we cannot reject the null hypothesis of a unit root, and the yield series may be integrated of order one $I(1)$.

Using a similar ADF test based on SIC for lag 8, we have the stationarity results for the depression series. These show that the ADF value is −3.198, which is smaller than the 5% critical value of 5% (−2.957). Therefore, we may conclude that the series is integrated of order zero $I(0)$. Similar tests reveal that the time series on the number of typhoons, damaged pond acreage and rainfall are also integrated of order zero. We choose the optimal lag length for the model based on AIC. The results indicate that lag 2 is optimal in the AIC test, therefore, we run the model regression for lag 2. To obtain the final, more statistically significant model, we drop some variables that have low absolute t values ($t < 1$). The Breusch-Godfrey test (Breusch, 1978) for autocorrelation gives the Chi-square p-value of 0.2275, which is larger than $\alpha = 0.05$, i.e., the model has no autocorrelation problem. We run the model regression for the final selection yielding the estimates shown in Tab. 4.

Tab. 4: Estimates for the optimal lag length

Variable	**Estimate (standard deviation)**
Constant	12.297** (2.966)
T	0.073** (0.017)
A	−0.225 (0.180)
A(−2)	−0.397** (0.137)
K(−2)	0.043 (0.041)
L	0.262 (0.273)
L(−2)	0.384** (0.134)
Temp	−0.047* (0.025)
Rainfall	−0.00014* (0.00006)
Dam	0.039* (0.015)
Dam(−1)	−0.020* (0.011)
Dam(−2)	0.027* (0.014)
Typhoon	0.032* (0.011)
Typhoon(−1)	0.019 (0.011)
Typhoon(−2)	0.044** (0.011)
Depression	−0.012 (0.013)
Depression(−1)	0.042** (0.013)
Depression(−2)	0.039** (0.011)
D_1	−0.360*** (0.061)
D_2	0.088 (0.119)
R^2	0.9991
F statistic	648.4
DW statistic	2.24

Note: The dependent variable is Ln(Produce), $n = 31$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

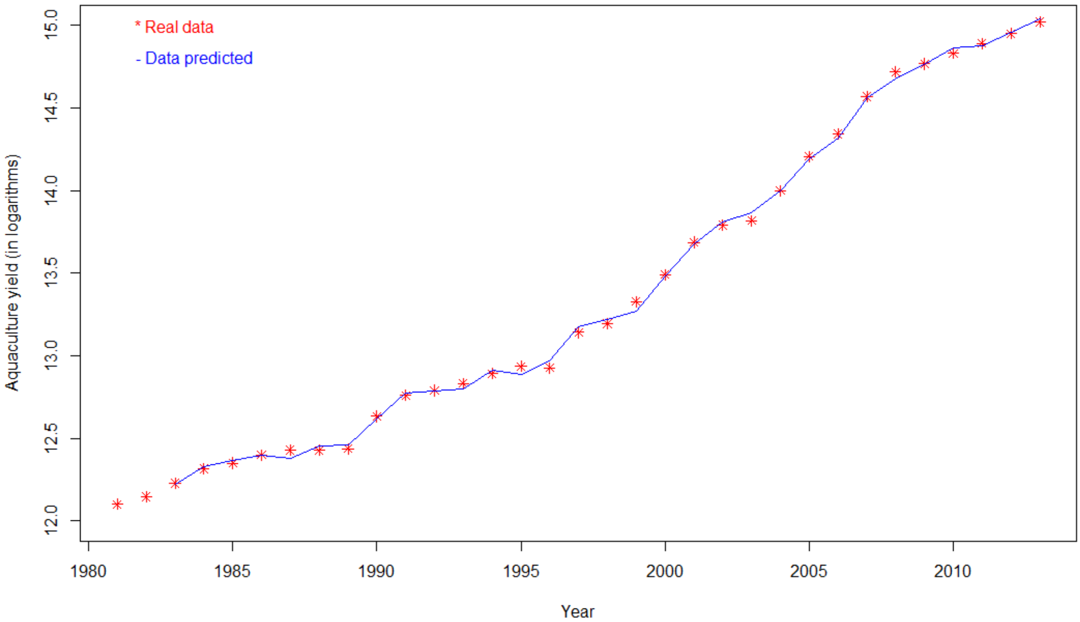

Fig. 3: Original and estimated aquaculture production

The final model for evaluating the impact of climate change on the aquacultural sector in Vietnam is as follows:

$$
\begin{aligned}
\ln(\mathrm{Produce}_t) = 12.297 + 0.073\,T\, - &\\
- 0.225 \ln(\mathrm{Acreage}_t) - &\\
- 0.397 \ln(\mathrm{Acreage}_{t-2}) + &\\
+ 0.043 \ln(\mathrm{Capital}_{t-2}) + &\\
+ 0.262 \ln(\mathrm{Labor}_t) + &\\
+ 0.384 \ln(\mathrm{Labor}_{t-2}) - &\\
- 0.047\, \mathrm{Temp}_t - &\\
- 0.00014\, \mathrm{Rainfall}_t + &\\
+ 0.039 \ln(\mathrm{Damage}_t) - &\\
- 0.02 \ln(\mathrm{Damage}_{t-1}) + &\\
+ 0.027 \ln(\mathrm{Damage}_{t-2}) + &\\
+ 0.032\, \mathrm{Typhoon}_t + &\\
+ 0.019\, \mathrm{Typhoon}_{t-1} + &\\
+ 0.044\, \mathrm{Typhoon}_{t-2} - &\\
- 0.012\, \mathrm{Depression}_t + &\\
+ 0.042\, \mathrm{Depression}_{t-1} + &\\
+ 0.039\, \mathrm{Depression}_{t-2} - &\\
- 0.360\, D_1 + 0.088\, D_2 &
\end{aligned}
\tag{3}
$$

To assess the quality of the estimated model, we have drawn the graph with original and estimated production in Fig. 3. The predicted production fits well with the real data.

Results from the estimated model indicate that besides the contribution of production inputs, including aquaculture area, investment capital, and labor, factors reflecting climate change (including damage caused by natural disasters, storms, and tropical depressions) also have an impact on aquacultural production. These factors have either positive or negative effects and can last for 1 to 2 years. The model shows that a 1% increase in acreage will reduce the yield two years later by 0.397%. Growth of 1% in the number of employees raises aquaculture yield by 0.262% in the same year and by 0.384% in the following two years. If the average temperature rises by 1 °C, aquaculture yield declines by 4.7%.

Rainfall also adversely affects aquaculture. If average rainfall goes up by 100mm, yield decreases by 1.4% accordingly. The model also indicates that if damage to acreage increases by 1%, fish production will rise 0.039% in the current year, then decline 0.02% the following year. If the number of tropical depressions increases by 1 in a given year, output will fall 1.2% in that year, then go up 4.2% and 3.9% in the next two years, respectively. A rise in the number of typhoons (> 100 km/h) by 1 will raise aquacultural yield by 1.9% and 4.4% respectively in the following year and the year after that.

5 DISCUSSION AND CONCLUSIONS

Aquacultural yield is influenced by many factors, including environmental factors induced by climate change and their lags. This study reveals that the aquacultural acreage is one of the important factors. Extending water surface acreage increases yield. However, as per the model used in this research, a 1% increase in acreage will result in a decrease of 0.397%. in yield two years later. The reason may be shortcomings in planning and management, inadequate technical and technological conditions for farming a large acreage, and output scale. Investment capital and labor have a positive impact on aquaculture production. If the number of employees grows by 1%, aquacultural yield will rise 0.262% in the same year and 0.384% in the following two years. Growth in labor increases aquacultural yield, raising people's incomes and attracting more workers to engage in this sector.

Environmental factors generally have a negative impact on aquaculture production. Temperature is a very important factor affecting the growth of aquatic species. If the average temperature rises by 1 °C, aquacultural yield declines by 4.7%. Rainfall also may adversely affect aquaculture. If average rainfall goes up by 100 mm, yield will decrease accordingly by 1.4%. Heavy unseasonal rainfall causes inundation, changing the salinity of aquaculture ponds and lakes. Frequently occurring natural disasters result in a decline in aquacultural production, represented by the acreage of damaged ponds. However, the model indicates that if there is a 1% increase in damaged acreage, fish production will rise 0.039% in the current year, but then decline by 0.02% the following year. The reason may be the additional investment of capital and technology to compensate for the damage and to expand production. But if the damage continues, recovery work becomes difficult, and the investment will be inefficient. There is also an indirect effect from cyclones and storm-surges on the productivity of aquaculture ponds because a cyclonic event changes the quality of aquatic habitat and ecosystem productivity (Edwards and Richardson, 2004; Hall-Spencer et al., 2008).

Due to climate change, there will be an increasing number of severe storms and tropical depressions. If the number of tropical depressions increases by 1 in a given year, output will fall 1.2% in that year, then rise by 4.2% and 3.9%, respectively, in the following two years. A rise in the number of typhoons (> 100 km/h) by 1 raises aquacultural yield by 1.9% and 4.4%, respectively, in the following year and the year after, as noted in this study.

Aquaculture farmers' incomes are often higher than those of others in the rural population, but earnings from aquaculture are highly uncertain and not evenly distributed within the sector. Climate change results in more uncertainty in farm production and in the physical structure of aquacultural ponds, and so in overall farm income. There is no doubt that natural disasters, like tropical storm surges and cyclones, cause direct damage to aquaculture production not only in the year in which a disaster takes place but also results in continuing losses during the next 2–3 years and even longer. These are the key reasons behind the rural population's higher vulnerability and lower adaptive capacity to recover from disaster.

After any natural disaster, the recovery phase is crucial, and action is needed to return to a state of normality. If someone asks the question, how can an aquaculture farmer recover the economic losses incurred as the result of a natural calamity, the answer is not simple because the capacity to recover depends on many factors, especially on the individual farmer's financial situation and proper mitigation strategies. It is obvious that additional capital is essential to recover production losses and restart an aquaculture business in the aftermath of any climatic disaster. To recover from sudden economic shock by securing additional capital is always a major challenge for small-scale farmers. Ahsan's study (2011) noted that in Bangladesh, it is very difficult for small-scale aquaculture farmers to recover their economic losses consequent on extreme weather conditions and disasters because with their lack of proper collateral, these farmers have very limited capital and greatly restricted access to formal credit systems. The lack of financial and political support after weather shocks is also considered to be a major hindrance in the socio-economic situation of small and medium-scale aquaculture farmers in developing countries.

In Vietnam, small-scale farmers face similar challenges. Additional capital, improved technology, and strengthening the environmental monitoring and warning system can contribute significantly to enhancing the adaptive capacity of aquacultural farmers to mitigate their production and income losses. An individual farmer (especially the small-scale farmer) in a developing country like Vietnam does not have these resources. Consequently, a supportive public policy is essential so that small-scale farmers can adapt to extreme weather conditions.

This research argues that since climate change is a global phenomenon, a determined initiative on the part of the Vietnamese government will not suffice to reduce the negative impact of climate change on aquaculture business. An effective climate-risk mitigation policy always requires a global response through multinational collaboration, negotiation and joint effort since the contribution of an individual country is not enough to fight climate change (Ahsan and Brandt, 2014).

This study uses short time series data from 1981–2013, which may be a limitation for analysis. As in other developing countries, however, the database for Vietnam is not very rich since the country only started to collect data in 1981. To improve the results from the model, future studies could aim to collect additional information to make up for the missing data and increase the number of observations for analysis and testing.

The ARDL model is used in the study to measure the impact of climate change on the aquacultural sector in Vietnam. The results show that rainfall, storm surges and tropical cyclones negatively affect aquaculture production. After any natural calamities, it takes at least two years to recover from the shock to productivity and return to the previous normal situation. However, farmers' capacity to recover largely depends on the availability of additional capital to reinvest in the farm, a steady supply of inputs at regular market prices, and labor. Therefore, additional institutional support, such as easy access to credit at low interest rates and consultancy services from government field officials, is necessary for at least 2–3 years to strengthen aquacultural farmers' ability to deal with risk and economic loss due to cyclones and storm surges. To reduce the vulnerability of aquacultural communities, this study suggests that the state could establish a climate resilience fund especially for small and medium-scale aquaculture farmers, to provide those affected by natural disasters with special financial support.

6 ACKNOWLEDGEMENT

We would like to thank anonymous reviewers for helpful comments. This research is funded by Vietnam National University, Hanoi (VNU) under project number QG.17.35.

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ON THE INVESTMENT ATTRACTIVENESS OF UKRAINIAN COMPANIES

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EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Volume 8 Issue 1
ISSN 2694-7161
www.ejobsat.com

ABSTRACT

The geographical location of Ukraine provides a multitude of possibilities for successful investment activity. There are rich natural resources, a fertile soil and a qualified low-cost labour force. On the other hand, investors have to deal with historical ties to the Soviet Union, corruption, and political instability exacerbated by occupation of part of the territory by Russia. This paper deals with the possibility of identifying the investment attractiveness of the particular sectors in Ukraine by the level of concentration measured by the Herfindahl-Hirschman index. Accounting data of companies taken from the Orbis database are evaluated by ABC analysis and the general linear model. The results point to significant dependency of variables representing investment attractiveness on the Herfindahl-Hirschman index, where deviations are explained by sectoral specifics.

KEY WORDS

ABC analysis, Herfindahl-Hirschman index, investment attractiveness, Ukrainian companies and sectors

JEL CODES

C21, F21

1 INTRODUCTION

A deep understanding of a nation's investment attractiveness and the accompanying inherent risks possessed by companies is very important in improving the success rate of investment processes and the resulting effects on the investment market. The right indicators or metrics are needed for analysis and decision-making by potential investors, who must be convinced of the feasibility of their investment in order to be successful. At present, there is no unified view of the methodological approaches to this type of analysis and evaluation of investment attrac-

VESELÁ, Natálie, RODCHENKO, Volodymyr, and HAMPEL, David. 2022. On the Investment Attractiveness of Ukrainian Companies. *European Journal of Business Science and Technology*, 8 (1): 54–71. ISSN 2694-7161, DOI 10.11118/ejobsat.2022.001.

tiveness. Searching for appropriate approach is motivated by business needs and provides another basis for further research in this direction. Such a single view can be developed, in detail, for each market segment, while factoring in the relative effects on other segments.

According to Pylypenko (2009), approaches to assessing the investment attractiveness of companies can be divided into three groups with respect to the relationship to the source of information. First, there are methods based on expert evaluations; then further methods based on statistical information and calculations; and thirdly, combined methods. Blank (2001) looks at investment attractiveness in terms of the company's financial position. He considers suitable characteristics for evaluating the investment attractiveness of companies to be those derived from indicators such as sales volumes, use of assets and their efficiency, financial stability, liquidity, and solvency.

Gaidutskiy (2004) requires that the comparative method cover the following elements of the investment process: comparison of investment objects, comparison of investors and comparison of factors of investment attractiveness. According to Chernysh (2013), a high-quality system of indicators for assessing investment attractiveness must consider the following circumstances: a limited number of indices directly influencing investment decisions; the calculation of indicators from public accounting and statistical data, the minimum use of internal information; the possibility of carrying out a rating assessment of the company's activities over time (as well as in relation to other economic entities).

Ukraine has the investment potential to realize good gains in growing sectors. Being a large, fertile and resource-rich country with a relatively low-cost labour force. The factor of low-cost labour is however considered overrated and mitigated by poor management of low productivity, see Kharlamova (2014). Ukraine is a very specific country with limited availability of information, and this fact represents the risk portion of investors' facts to consider before taking investment action. A comprehensive survey of positive and negative aspects affecting DFI investment in Ukraine in 2010–2017 is given by Furdychko and Pikhotska (2018). This survey maps the development of FDI over time in detail and gives a good overview of the major social economic and political factors.

The negative phenomena affecting DFI in Ukraine include massive oligarchism (Pleines, 2016), unfair competition, clientelism and the vulnerability of businesses through raider attacks just to name a few. Foreigners do not want to invest money in Ukraine, because they have no confidence in a stable and predictable law enforcement environment. Due to the difficult conditions for investment and business development, investors tend not to pay any attention to Ukraine when it comes to thinking about where to invest their money and choose less regulated and more predictable environments.

In Serhieieva (2015) the dynamics of investment attractiveness and DFI investment in Ukraine in 2008–2015 are investigated and internal DFI structure is analysed. The most important factor affecting the business climate is considered to be the "Ukrainian mental mind set" and measures to act on this are suggested. Apart from these socio-psychological reasons, geopolitical instability, poor legislation and economic uncertainty also negatively impact the investment climate in Ukraine.

In order to assist potential investors with the investment decision-making process, an assessment of regional investment attractivity was developed by Kharlamova (2014). This mathematically grounded methodology tries to capture the effect of regional factors on inward FDI. The method is based on the long-term detailed investment monitoring of 26 Ukrainian regions and their subsequent multi-stage rating assessment. Integral outputs yield rating indicators for investment potential (IP), investment risks (IR) and investment activity (IA) for each of these 26 Ukrainian regions. For marketing purposes IP-IR, IP-IA matrixes are assembled. enabling an analysis of the distribution of the regions by investment attractiveness. Lastly, the regions are graphically plotted on a 2D graph of investment activity versus investment attractiveness. This arrangement allows us to classify the regions according to investment efficiency and construct analogue variants to BSG (IA versus IP) and DPB (investment attractiveness versus IP) matrixes. The major novelty of this approach is the ability to encompass territorial investment marketing.

Comprehensive analysis of the investment climate in Ukraine is engaged in by Krupka and Bachinskiy (2014). In his work, the author examines possible directions for improving methods for evaluating companies, in order to attract new investments through greater transparency. It recommends estimating the investment attractiveness of companies using a thorough analysis of the economic activity of the company: property relations, capital turnover, profitability and financial stability, liquidity, and market activity. Krupka and Bachinskiy (2014) also propose an index of investment attractiveness. In Malko (2015) the essence of categories such as "investment climate" and "investment attractiveness" is examined. The factors which influence the formation of a state's investment climate are identified. The investment attractiveness of Ukraine at its present stage of development is evaluated.

The aim of this paper is to assess the effect of business concentration on the investment attractiveness of selected sectors of the Ukraine economy. For detailed insight, the ABC method will be employed and a comparison with corresponding sectors of the Romanian economy will be made.

2 THEORETICAL BACKGROUND

The relationship between concentration within a sector and investment attractiveness and hence the volume of investment in the sector is not straightforward. In this section, we will lay out the theoretical links between the economic phenomena linking concentration and investment attractiveness and further illustrate them using results from other papers relevant to the Ukrainian economy.

We first focus on the effects of sector concentration on the efficiency of companies and the form of competition in the market, and hence on the competitiveness of companies. Higher concentration in a sector results in potentially higher production efficiency of certain companies, which implies a competitive advantage and will ultimately shape the type of competition in the market. An increase in concentration in a sector can affect different economic levels: production within an enterprise, the enterprise itself, the industrial sector. It will have an impact on regions across the country, but the most important impact will be on the competitiveness of the enterprise itself as a major component of the whole economy.

In the current difficult economic conditions, enterprises may lack a clear strategy regarding financial and economic targets and criteria, but the key will still be to keep up with the times, to update technology, innovate and set investment strategies correctly and in a timely manner. As Ratnayake (1999) writes, many enterprises in Ukraine have found themselves struggling to survive in market conditions. The only way to survive was to integrate with other businesses and corporations. Under the conditions of Ukraine's unstable and developing economy, holdings began to form that allowed the original smaller enterprises to exist at all due to the greater efficiency given by higher concentration. According to Rastvortseva et al. (2012), the increasing concentration of business activities in a region creates the conditions for the emergence of the agglomeration effect: the economic benefits of enterprises arising due to the positive effect from the higher scale of production.

Rodchenko (2013) examines asymmetries between regions, including differential industrial concentration, and their impact on the development of cities and urban complexes. The author concludes that regional asymmetries cause mainly negative consequences and require state regulation of asymmetries in the socio-economic development of regions. As part of the study, a model for managing the socio-economic development of cities was developed.

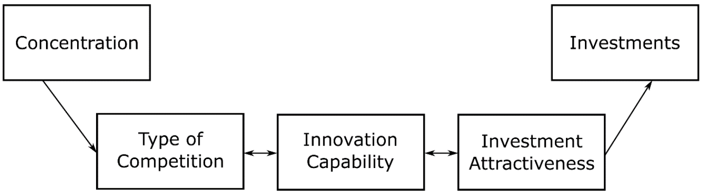

Fig. 1: Scheme of link between concentration of the sector and investment attractiveness of the sector resulting in investments to the sector

The productivity of firms increases with increasing levels of concentration, see Cieślik et al. (2018). According to Aritenang (2021), it can be observed that a higher level of concentration of companies in the market increases the competitiveness of larger companies, and this is especially true for foreign-invested companies.

Efficiency and profitability of production, as well as increasing its volume, effective management with elements of innovation, and (foreign) investment under conditions of market competition are the basis for increasing the profitability of the enterprise, which will lead to its further growth and may overall lead to a change in the market structure. Aleskerova and Fedoryshyna (2018) point out that enterprises operating at full capacity and increasing the production of high-quality products are competitive mainly due to the financing of innovation. Aritenang (2021) argues that, in addition to the size of a firm, investment and innovation also lead to an increase in its competitiveness. Ilyash et al. (2018) demonstrate the dependence of the efficiency or competitiveness of enterprises on the development of the innovative potential of Ukrainian industry and concludes at the industry level that the level of efficiency in an industry depends on its level of innovation. According to Cordano and Zevallos (2021) investment depends on competitiveness and vice versa. The investment climate is a source of competitiveness.

A paper by Malyutin and Sokolov (2012) addresses competitiveness at the national level. The authors conclude that Ukraine has low investment attractiveness, resulting in low competitiveness. For stable healthy economic growth it is very important to solve the problem of increasing investment by introducing effective incentives through the tax system (tax rate reduction, tax exemptions). Ilyash et al. (2018) deal with the relationship between the index of competitiveness and the index of innovation at a national level and empirically prove direct dependency.

On the basis of the above, we can conclude that concentration, innovation and investment are essential factors in ensuring the competitiveness of firms and the efficiency of entire industries. Concentration and increasing competitiveness also create a positive investment climate that stimulates investment attraction. It follows that industry concentration and the investment it generates are interlinked. The cited articles confirm that also in Ukraine, increasing sector concentration increases the efficiency of the market as a whole and the competitiveness of the individual business entity. In addition to concentration, investment (especially foreign investment) and innovation are competitiveness factors.

The relationship between the categories discussed can be expressed through the scheme in Fig. 1. The degree of concentration of an industry will be reflected in the differences in competitiveness between companies and consequently in the type of competition in a given market. Among other things, the size and profitability of firms is influenced by the innovation potential of firms. Taken together, this shapes the investment attractiveness of individual companies and thus of the sector as a whole, which determines the volume of investment. Our subject of interest is the causal link between sector concentration and investment attractiveness, hence the use of unidirectional arrows in Fig. 1; however, it would also be possible to explain the reverse causality from investment volume to sector concentration.

3 METHODOLOGY AND DATA

The required accounting data for companies are obtained from the Orbis database of Bureau van Dijk. Specifically, we use total assets, profitability, solvency ratio, liquidity ratio, value added and ROA. We deal with companies with prevailing activities in sectors NACE 1 Crop and animal production, hunting and related service activities; 10 Manufacture of food products; 21 Manufacture of basic pharmaceutical products and pharmaceutical preparations; 28 Manufacture of machinery and equipment; 35 Electricity, gas, steam and air conditioning supply. The sectors analysed were selected regarding information on the sectors of the Ukrainian economy according to the governmental UkraineInvest organization, which presents Energy, Manufacturing, Agritech and Innovations as the dominant sectors of the Ukrainian economy, see UkraineInvest (2020). A further important fact is that for the remaining sectors, the Orbis database contains relatively many more empty items than for the sectors analysed. This will lead to a distortion of results in the case of the joint analysis of all Ukrainian sectors. The analysis is carried out for the years 2009–2016, and except for Ukraine we will also deal with Romania as an EU member with roughly similar characteristics to Ukraine. Concentration of the sector is measured by the Herfindahl-Hirschman index (HHI), which is calculated as the sum of squared shares of the companies. Total assets are used for this purpose.

In addition to analysis based on the total dataset, we provide an ABC analysis based on total assets which divide companies of particular explored sectors into categories A, B and C, which account for 80, 15 and 5% of cumulative total assets. ABC analysis is traditionally used for different purposes (typically for inventory management), but in our case it can help to distinguish among variously "important" companies and their properties. A general discussion is given for example in Ultsch and Lötsch (2015). We follow the approach of Lapshyn and Kuznichenko (2017), who estimated the socio-economic state of regions of Ukraine using the Gini coefficient and ABC-XYZ analysis; also Pawełek et al. (2017) may be mentioned, where ABC analysis is used in corporate bankruptcy prediction.

The general linear model is employed to assess dependencies between characteristics which can serve as investment attractiveness and HHI accompanied by factors (country, sector, year, ABC group). A total of 240 observations (a combination of two countries, seven years, five sectors and three ABC groups) were used to estimate the individual regression models; in the case of the regression for group A only, 80 observations were used. Based on these regressions, predictions for combinations of countries and sectors are formed to show the results graphically. All calculations were performed in the MATLAB R2019b computational system and Genstat 19 software, the significance level was set at 0.05.

4 RESULTS

General linear models were estimated for particular investment attractiveness measures. Complete estimates are placed in Appendix. An analysis of variance for the entire dataset is presented in Tab. 1. Note that for gross profit many values for Romania are missing, which distorts results. For this reason, gross profit was assessed using Ukraine data only. HHI is assessed by F-test as a significant variable in all cases (line HHI F). The statistical significance of accompanying factors is also evaluated. The sector denoted as NACE is always significant. The country × sector interaction is significant except Value added, which means that this variable is determined by sector, not by country. HHI is also assessed by t-test, where the result

Tab. 1: Analysis of variance and HHI parameter assessment for particular models of investment attractiveness characteristics based on total dataset. Except sign of HHI parameter estimate, p-values are tabulated. Gross profit is available for Ukraine only, so factor country and interaction Country × NACE are not used here.

Factor	**Liquidity**	**Profit**	**ROA**	**Solvency**	**Value added**
HHI par. sign	−	+	+	+	−
HHI t	0.227	0.373	0.047	0.006	0.059
HHI F	<0.001	<0.001	<0.001	<0.001	<0.001
Country	0.028	×	0.198	<0.001	0.719
Year	0.044	0.811	<0.001	0.998	0.520
NACE	<0.001	<0.001	<0.001	<0.001	<0.001
ABC group	<0.001	<0.001	0.010	0.930	<0.001
Country × NACE	<0.001	×	<0.001	<0.001	0.417

Tab. 2: Analysis of variance and HHI parameter assessment for particular models of investment attractiveness characteristics based only on ABC group A. Except sign of HHI parameter estimate, p-values are tabulated. Gross profit is available for Ukraine only, so factor country and interaction Country × NACE are not used here.

Factor	**Liquidity**	**Profit**	**ROA**	**Solvency**	**Value added**
HHI par. sign	−	+	−	−	−
HHI t	0.010	0.001	0.022	0.821	0.527
HHI F	<0.001	<0.001	<0.001	0.012	<0.001
Country	0.625	×	0.438	0.171	1.000
Year	0.128	0.123	0.179	0.914	0.029
NACE	<0.001	<0.001	<0.001	<0.001	<0.001
Country × NACE	<0.001	×	<0.001	<0.001	0.341

can be interpreted as significance of HHI after elimination of other factors. This is true for ROA and Solvency ratio, where HHI has a positive effect.

An analogical analysis was provided for ABC group A only, which should cover the key companies in the given sectors, see Tab. 2. Results are similar to those for the entire dataset, the main result – significance of HHI – remains. There is a change in HHI significance after elimination of the other variables, where Liquidity ratio and ROA are affected negatively and Gross profit positively.

Predictions of country × sector interaction, which can serve as adjusted effects combinations, were calculated. This can be depicted based on HHI to illustrate the dependency. The case of liquidity and solvency ratios is presented in Fig. 1. Direct dependency on HHI is visible for both the entire dataset and for group A only.

The reason for a visible deviation in the level of liquidity of Ukrainian companies in the sector NACE 1 Crop and animal production may be the absence of a land market in Ukraine and insufficient regulation of the system of relations concerning land use. The result is a relatively low share of fixed assets, and thus high values of coefficients, taking into account elements of short-term assets. This is reflected in companies' balance sheets through a higher share of assets involved in one turnover cycle and a relatively smaller share of fixed assets, the creation of which is associated with longer-term investments, which become riskier due to the unsatisfied land market.

In the case of important companies from group A, there is also visible a lag between Romanian companies from the pharmaceutical industry and the remaining companies. Large companies in the pharmaceutical industry are the companies that usually secure the production of the most mass-produced drugs. Marginality is significantly increased with these drugs. The reasoning is as follows: drug development costs are generally of a conditionally constant nature, and as sales increase (which

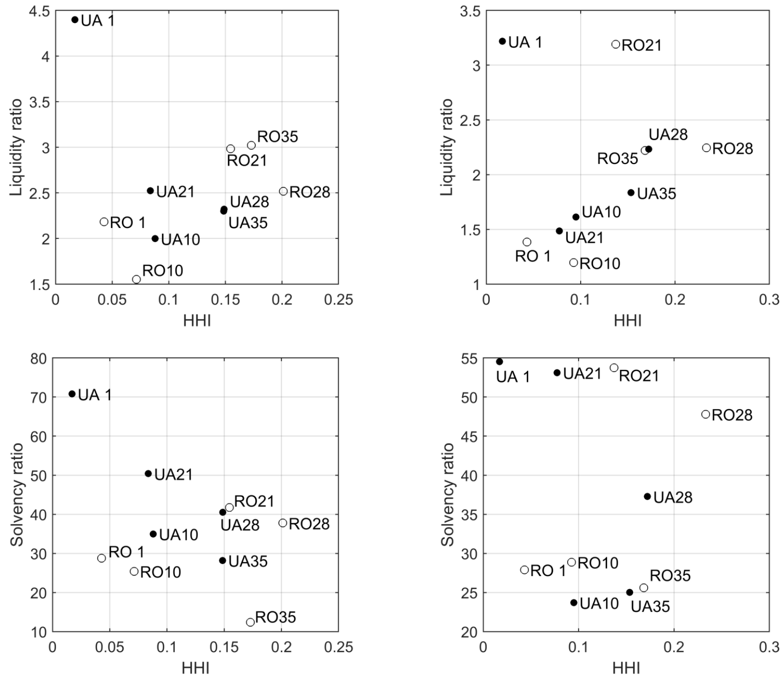

Fig. 2: Scatter plots of predicted Liquidity and Solvency ratios with relation to HHI prediction based on total dataset (left-hand graphs) and based only on ABC group A (right-hand graphs). RO means Romania, UA Ukraine and the number denotes the sector.

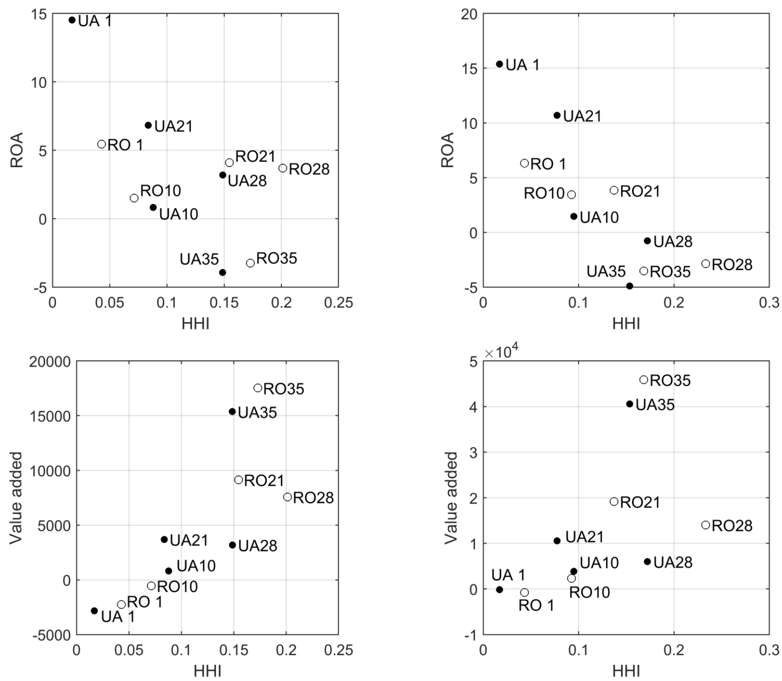

Fig. 3: Scatter plots of predicted ROA and Value added with relation to HHI prediction based on total dataset (left graphs) and based only on ABC group A (right graphs). RO means Romania, UA Ukraine and the number denotes sector.

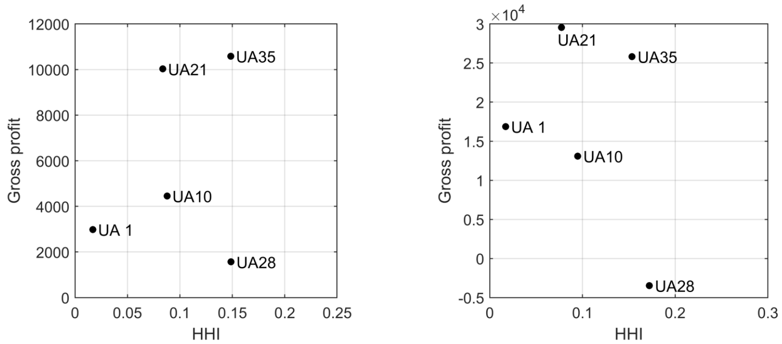

Fig. 4: Scatter plots of predicted Gross profit with relation to HHI prediction based on total dataset (left graph) and based only on ABC group A (right graph). UA means Ukraine and the number denotes the sector.

is typical of bulk drugs), their margins increase significantly.

In the case of the solvency ratio (see Fig. 2), for all companies the situation is unclear. When we focus on group A only, we can see a similar picture as for the liquidity ratio. The differences in the values of liquidity and solvency ratios for Ukraine and Romania lie in the peculiarities of the distribution of the company's owners and the aggressiveness of the asset financing policy (at the expense of equity or borrowed capital). In Romania, the main revenues come from well-known large companies, which do not require large investments in development and production. Increased solvency in Ukraine suggests that the pharmaceutical sector is owned by the state or foreign residents.

In Fig. 3 there are illustrated relations of HHI and ROA or value-added characteristics. Visible indirect dependency in the case of ROA can be explained in the case of NACE 28 Manufacture of machinery and equipment sector. As far as engineering companies are concerned, it can be stated that Ukrainian industry was generally focused on the markets of the CIS countries. Changes in relations with Russia and redirection to other markets, including the European market, have led to some companies entering a state of crisis. This was especially acute in large companies. Small- and medium-sized enterprises were able to redirect quickly. Large companies could not survive the break-up of historical links quickly and painlessly. They suffer losses due to differences in technological standards and other difficulties in integrating into European chains. In addition, the negative situation in the main sales markets of the engineering industry significantly worsened the performance of large companies in Romania and Ukraine.

The extreme case, negative ROA, is visible for NACE 35 Electricity, gas, and steam sector. The negative values of relative profit indicators, and thus the return on assets, are explained by the peculiarities of state regulation and subsidies of companies providing these services, namely state regulation of tariffs. On the other hand, the high level of wear and tear on the networks available to these companies causes them to increase their operating costs, which also affects the creation of a negative ROA.

Value added seems to be directly dependent on HHI, see Fig. 3, bottom graphs. There is a visible lag between NACE 35 Electricity, gas, and steam sector and the remaining companies. The value added of this sector is higher due to the relatively higher level of capital consumption (utilities, production facilities, etc.) and as a result of the relatively large volumes of depreciation. It can also be noted that the level of wages in this sector is usually slightly higher, which also contributes to a higher level of value added.

Unfortunately, the Orbis database includes Gross profit values for Ukraine companies, but not for Romania ones. In Fig. 4 we show the relationship between gross profit and HHI, which seems not to be systematic. Similarly to the ROA case, large companies from the NACE 28 Manufacture of machinery and equipment

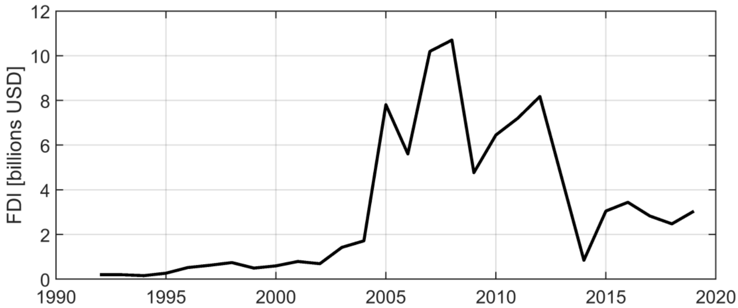

Fig. 5: Development of foreign direct investment in Ukraine (excluding occupied territories). Source: State Statistics Service of Ukraine

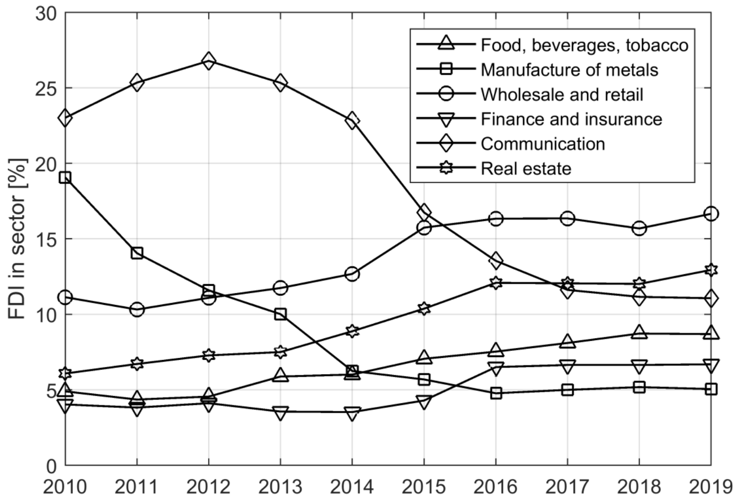

Fig. 6: Development of foreign direct investment in Ukraine (excluding occupied territories) sectors (the six sectors with the largest share were selected). Source: State Statistics Service of Ukraine

sector show worse average results than when all companies are involved. The reason is the change in the structure of the engineering market in Ukraine, the division of the USSR market from perestroika, the negative impact on eastern Ukraine due to the military conflict. Large enterprises which were part of the engineering complex in the USSR, which was the only economic complex, suffered in this.

An extremely serious problem, which without doubt affects foreign investment in Ukraine, is the territories currently occupied by Russia or by forces allied with Russia: the Autonomous Republic of Crimea, the city of Sevastopol, the regions of Donetsk and Luhansk. The occupation of these territories in 2014 led to a sharp decline in foreign investment, see Fig. 5, which has not been fully offset yet. Also, the distribution of FDI seems to be affected by this situation, see Fig. 6. Apart from long-term trends, changes are visible after 2014. The proportion of FDI distribution in particular sectors can be affected not only by attractiveness of the sector, but also by newly increasing risks, which can result for example in higher investment in the Wholesale and retail sector. It can be said that since 2016, the distribution of investment between sectors has been more or less stable. Unfortunately, this period is already outside the scope of the data analysed by us.

5 CONCLUSIONS

Based on the analysis performed, we can conclude that the level of concentration of the sector measured by HHI is a significant factor for determining key characteristics of investment attractiveness. Of course, sectoral specifics in the country should be taken into account, because deviations from visible dependencies exist. Moreover, application of ABC analysis enables assessment of the main companies' specifics, as discussed for the NACE 28 Manufacture of machinery and equipment sector.

For stronger results, it will be necessary to analyse more sectors in more countries, the limiting factor here will be the availability of data. For further analysis of the Ukrainian economy, it will also be important to separate the occupied areas from the areas fully controlled by the Ukrainian government. These topics will be the subject of our further research.

6 ACKNOWLEDGEMENT

Supported by the grant No. PEF_DP_2019039 of the Internal Grant Agency PEF MENDELU.

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8 DETAILED RESULTS OF REGRESSION MODELS

In the case of including complete data, models are of the form

$$\begin{aligned} Y = \;& \text{Constant} + \text{HHI} + \text{Country} + \\ & + \text{Year} + \text{NACE} + \text{ABC} + \\ & + \text{Country.NACE}, \end{aligned}$$

where for Y we gradually set Liquidity, Profit, ROA, Solvency and Value added (for Profit, the model is estimated for Ukraine only). Parameters for factors are differences compared with the reference level Country Romania, Year 2009, NACE 1 and ABC group A.

8.1 Liquidity

Tab. 3: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	1.552	0.215	7.23	<0.001
HHI	−2.1	1.74	−1.21	0.227
Country Ukraine	2.217	0.2	11.06	<0.001
Year 2010	0.409	0.175	2.34	0.020
Year 2011	0.449	0.175	2.57	0.011
Year 2012	0.247	0.175	1.41	0.159
Year 2013	0.321	0.178	1.81	0.072
Year 2014	0.349	0.176	1.99	0.048
Year 2015	0.62	0.177	3.5	<0.001
Year 2016	0.508	0.177	2.86	0.005
NACE 10	−0.631	0.202	−3.13	0.002
NACE 21	0.802	0.275	2.91	0.004
NACE 28	0.336	0.337	1	0.321
NACE 35	0.838	0.299	2.81	0.005
ABC B	0.535	0.109	4.93	<0.001
ABC C	0.979	0.108	9.09	<0.001
Country Ukraine NACE 10	−1.771	0.286	−6.2	<0.001
Country Ukraine NACE 21	−2.678	0.287	−9.33	<0.001
Country Ukraine NACE 28	−2.415	0.28	−8.63	<0.001
Country Ukraine NACE 35	−2.938	0.276	−10.64	<0.001

Tab. 4: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	18.0513	18.0513	39.45	<0.001
Country	1	2.2251	2.2251	4.86	0.028
Year	7	6.737	0.9624	2.1	0.044
NACE	4	56.3583	14.0896	30.79	<0.001
ABC	2	39.8516	19.9258	43.55	<0.001
Country NACE	4	64.8383	16.2096	35.42	<0.001
Residual	220	100.6699	0.4576		
Total	239	288.7315	1.2081		

8.2 Profit

Tab. 5: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	9527	2451	3.89	<0.001
HHI	23451	26235	0.89	0.373
Year 2010	979	2556	0.38	0.702
Year 2011	2999	2561	1.17	0.244
Year 2012	2005	2622	0.76	0.446
Year 2013	3760	2564	1.47	0.145
Year 2014	1084	2555	0.42	0.672
Year 2015	426	2556	0.17	0.868
Year 2016	661	2558	0.26	0.797
NACE 10	1474	2745	0.54	0.592
NACE 21	7048	2672	2.64	0.010
NACE 28	−1417	4005	−0.35	0.724
NACE 35	7604	3998	1.9	0.060
ABC B	−14721	1605	−9.17	<0.001
ABC C	−16221	1567	−10.35	<0.001

Tab. 6: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	7.91E+08	7.91E+08	16.15	<0.001
Year	7	1.81E+08	2.59E+07	0.53	0.811
NACE	4	1.60E+09	3.99E+08	8.16	<0.001
ABC	2	6.28E+09	3.14E+09	64.18	<0.001
Residual	105	5.14E+09	4.90E+07		
Total	119	1.40E+10	1.18E+08		

8.3 ROA

Tab. 7: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	1.71	1.02	1.67	0.096
HHI	16.55	8.28	2	0.047
Country Ukraine	9.071	0.955	9.49	<0.001
Year 2010	−0.183	0.833	−0.22	0.826
Year 2011	1.046	0.833	1.26	0.211
Year 2012	0.857	0.833	1.03	0.305
Year 2013	0.487	0.848	0.57	0.566
Year 2014	1.136	0.84	1.35	0.177
Year 2015	3.749	0.844	4.44	<0.001
Year 2016	4.02	0.846	4.75	<0.001
NACE 10	−3.956	0.961	−4.12	<0.001
NACE 21	−1.36	1.31	−1.04	0.301
NACE 28	−1.76	1.61	−1.1	0.274
NACE 35	−8.71	1.42	−6.12	<0.001
ABC B	1.421	0.518	2.74	0.007
ABC C	0.038	0.514	0.07	0.941
Country Ukraine NACE 10	−9.74	1.36	−7.15	<0.001
Country Ukraine NACE 21	−6.34	1.37	−4.63	<0.001
Country Ukraine NACE 28	−9.58	1.34	−7.17	<0.001
Country Ukraine NACE 35	−9.75	1.32	−7.4	<0.001

Tab. 8: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	883.66	883.66	84.9	<0.001
Country	1	17.33	17.33	1.67	0.198
Year	7	410.47	58.64	5.63	<0.001
NACE	4	3125.83	781.46	75.08	<0.001
ABC	2	98.2	49.1	4.72	0.010
Country NACE	4	848.77	212.19	20.39	<0.001
Residual	220	2289.86	10.41		
Total	239	7674.12	32.11		

8.4 Solvency

Tab. 9: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	21.91	2.71	8.08	<0.001
HHI	61	21.9	2.78	0.006
Country Ukraine	42.02	2.53	16.6	<0.001
Year 2010	0.29	2.21	0.13	0.894
Year 2011	−0.19	2.21	−0.09	0.932
Year 2012	−0.78	2.21	−0.35	0.725
Year 2013	0.78	2.25	0.35	0.728
Year 2014	−0.36	2.22	−0.16	0.871
Year 2015	0.96	2.24	0.43	0.667
Year 2016	1.38	2.24	0.61	0.539
NACE 10	−3.35	2.55	−1.32	0.189
NACE 21	12.96	3.48	3.73	<0.001
NACE 28	9.01	4.26	2.11	0.036
NACE 35	−16.38	3.77	−4.34	<0.001
ABC B	−0.71	1.37	−0.52	0.606
ABC C	−0.17	1.36	−0.13	0.898
Country Ukraine NACE 10	−32.47	3.61	−8.99	<0.001
Country Ukraine NACE 21	−33.33	3.63	−9.19	<0.001
Country Ukraine NACE 28	−39.28	3.54	−11.1	<0.001
Country Ukraine NACE 35	−26.23	3.49	−7.51	<0.001

Tab. 10: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	1338.11	1338.11	18.31	<0.001
Country	1	10272.27	10272.27	140.58	<0.001
Year	7	50.65	7.24	0.1	0.998
NACE	4	23145.02	5786.26	79.19	<0.001
ABC	2	10.64	5.32	0.07	0.930
Country NACE	4	11256.55	2814.14	38.51	<0.001
Residual	220	16075.1	73.07		
Total	239	62148.35	260.03		

8.5 Value Added

Tab. 11: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	11667	2673	4.36	<0.001
HHI	−41004	21635	−1.9	0.059
Country Ukraine	−576	2496	−0.23	0.818
Year 2010	198	2176	0.09	0.928
Year 2011	1451	2176	0.67	0.506
Year 2012	−1282	2176	−0.59	0.556
Year 2013	2039	2214	0.92	0.358
Year 2014	−953	2193	−0.43	0.664
Year 2015	−1322	2205	−0.6	0.549
Year 2016	−678	2209	−0.31	0.759
NACE 10	1715	2511	0.68	0.495
NACE 21	11404	3429	3.33	0.001
NACE 28	9835	4203	2.34	0.020
NACE 35	19793	3720	5.32	<0.001
ABC B	−13437	1353	−9.93	<0.001
ABC C	−14256	1342	−10.63	<0.001
Country Ukraine NACE 10	1928	3559	0.54	0.589
Country Ukraine NACE 21	−4878	3576	−1.36	0.174
Country Ukraine NACE 28	−3818	3488	−1.09	0.275
Country Ukraine NACE 35	−1587	3440	−0.46	0.645

Tab. 12: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	1.76E+09	1.76E+09	24.81	<0.001
Country	1	9.21E+06	9.21E+06	0.13	0.719
Year	7	4.39E+08	6.27E+07	0.88	0.520
NACE	4	4.25E+09	1.06E+09	14.95	<0.001
ABC	2	9.78E+09	4.89E+09	68.84	<0.001
Country NACE	4	2.80E+08	6.99E+07	0.98	0.417
Residual	220	1.56E+10	7.10E+07		
Total	239	3.21E+10	1.35E+08		

In the case of including ABC group A only, models are of the form

$$\begin{aligned} Y = {} & \text{Constant} + \text{HHI} + \text{Country} + \\ & + \text{Year} + \text{NACE} + \text{Country.NACE}, \end{aligned}$$

where for Y we gradually set Liquidity, Profit, ROA, Solvency and Value added (for Profit, the model is estimated for Ukraine only). Parameters for factors are differences compared with the reference level Country Romania, Year 2009 and NACE 1.

8.6 Liquidity

Tab. 13: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	2.077	0.305	6.81	<0.001
HHI	−8.91	3.33	−2.68	0.010
Country Ukraine	1.834	0.292	6.28	<0.001
Year 2010	0.458	0.249	1.84	0.071
Year 2011	0.641	0.249	2.57	0.013
Year 2012	0.275	0.25	1.1	0.275
Year 2013	0.364	0.255	1.43	0.159
Year 2014	0.334	0.252	1.33	0.189
Year 2015	0.685	0.254	2.7	0.009
Year 2016	0.176	0.255	0.69	0.492
NACE 10	−0.187	0.324	−0.58	0.565
NACE 21	1.806	0.419	4.31	<0.001
NACE 28	0.862	0.692	1.25	0.217
NACE 35	0.838	0.501	1.67	0.100
Country Ukraine NACE 10	−1.419	0.405	−3.5	<0.001
Country Ukraine NACE 21	−3.538	0.41	−8.63	<0.001
Country Ukraine NACE 28	−1.846	0.411	−4.49	<0.001
Country Ukraine NACE 35	−2.22	0.396	−5.61	<0.001

Tab. 14: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	21.9253	21.9253	70.55	<0.001
Country	1	0.0751	0.0751	0.24	0.625
Year	7	3.6799	0.5257	1.69	0.128
NACE	4	10.92	2.73	8.78	<0.001
Country NACE	4	24.5969	6.1492	19.79	<0.001
Residual	62	19.2681	0.3108		
Total	79	80.4653	1.0185		

8.7 Profit

Tab. 15: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	−3605	3401	−1.06	0.299
HHI	161392	44774	3.6	0.001
Year 2010	2794	3861	0.72	0.476
Year 2011	8082	3871	2.09	0.046
Year 2012	2745	4051	0.68	0.504
Year 2013	10996	3870	2.84	0.008
Year 2014	2796	3860	0.72	0.475
Year 2015	1500	3864	0.39	0.701
Year 2016	1907	3861	0.49	0.625
NACE 10	−3776	4630	−0.82	0.422
NACE 21	12691	4073	3.12	0.004
NACE 28	−20339	7580	−2.68	0.012
NACE 35	8956	6821	1.31	0.200

Tab. 16: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	1.22E+09	1.22E+09	32.84	<0.001
Year	7	4.76E+08	6.80E+07	1.83	0.123
NACE	4	4.64E+09	1.16E+09	31.15	<0.001
Residual	27	1.01E+09	3.72E+07		
Total	39	7.35E+09	1.88E+08		

8.8 ROA

Tab. 17: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	0.26	1.53	0.17	0.865
HHI	39.5	16.8	2.35	0.022
Country Ukraine	9.06	1.47	6.17	<0.001
Year 2010	0.05	1.25	0.04	0.968
Year 2011	1	1.26	0.79	0.430
Year 2012	1.39	1.26	1.1	0.274
Year 2013	1.7	1.28	1.32	0.191
Year 2014	0.19	1.27	0.15	0.882
Year 2015	3.18	1.28	2.49	0.016
Year 2016	3.42	1.28	2.67	0.01
NACE 10	−2.88	1.63	−1.77	0.081
NACE 21	−2.49	2.11	−1.18	0.243
NACE 28	−9.19	3.48	−2.64	0.010
NACE 35	−9.85	2.52	−3.9	<0.001
Country Ukraine NACE 10	−11.04	2.04	−5.41	<0.001
Country Ukraine NACE 21	−2.2	2.06	−1.07	0.290
Country Ukraine NACE 28	−6.96	2.07	−3.36	0.001
Country Ukraine NACE 35	−10.44	1.99	−5.24	<0.001

Tab. 18: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	483.991	483.991	61.5	<0.001
Country	1	4.805	4.805	0.61	0.438
Year	7	83.384	11.912	1.51	0.179
NACE	4	688.062	172.015	21.86	<0.001
Country NACE	4	352.27	88.067	11.19	<0.001
Residual	62	487.951	7.87		
Total	79	2100.463	26.588		

8.9 Solvency

Tab. 19: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	28.9	2.68	10.8	<0.001
HHI	−6.6	29.2	−0.23	0.821
Country Ukraine	26.64	2.56	10.39	<0.001
Year 2010	−0.08	2.19	−0.04	0.970
Year 2011	0.49	2.19	0.23	0.823
Year 2012	−0.25	2.2	−0.12	0.908
Year 2013	0.54	2.24	0.24	0.811
Year 2014	−2.26	2.21	−1.02	0.311
Year 2015	−0.68	2.23	−0.31	0.760
Year 2016	0.51	2.24	0.23	0.819
NACE 10	0.98	2.84	0.35	0.731
NACE 21	25.84	3.68	7.02	<0.001
NACE 28	19.9	6.07	3.28	0.002
NACE 35	−2.31	4.4	−0.53	0.601
Country Ukraine NACE 10	−31.8	3.56	−8.94	<0.001
Country Ukraine NACE 21	−27.27	3.6	−7.58	<0.001
Country Ukraine NACE 28	−37.16	3.61	−10.3	<0.001
Country Ukraine NACE 35	−27.22	3.48	−7.83	<0.001

Tab. 20: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	160.95	160.95	6.72	0.012
Country	1	45.88	45.88	1.92	0.171
Year	7	62.58	8.94	0.37	0.914
NACE	4	9054.39	2263.6	94.52	<0.001
Country NACE	4	3280.55	820.14	34.25	<0.001
Residual	62	1484.83	23.95		
Total	79	14089.18	178.34		

8.10 Value Added

Tab. 21: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	2027	4321	0.47	0.641
HHI	−29993	47196	−0.64	0.527
Country Ukraine	606	4136	0.15	0.884
Year 2010	1031	3533	0.29	0.771
Year 2011	4123	3534	1.17	0.248
Year 2012	−3043	3544	−0.86	0.394
Year 2013	7495	3614	2.07	0.042
Year 2014	−1365	3565	−0.38	0.703
Year 2015	−1940	3594	−0.54	0.591
Year 2016	−179	3609	−0.05	0.961
NACE 10	3094	4586	0.67	0.502
NACE 21	19949	5941	3.36	0.001
NACE 28	14809	9800	1.51	0.136
NACE 35	46656	7103	6.57	<0.001
Country Ukraine NACE 10	925	5743	0.16	0.873
Country Ukraine NACE 21	−9217	5808	−1.59	0.118
Country Ukraine NACE 28	−8623	5825	−1.48	0.144
Country Ukraine NACE 35	−5911	5610	−1.05	0.296

Tab. 22: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
HHI	1	3.06E+09	3.06E+09	49.04	<0.001
Country	1	2.41E+01	2.41E+01	0	1.000
Year	7	1.06E+09	1.52E+08	2.43	0.029
NACE	4	1.40E+10	3.51E+09	56.28	<0.001
Country NACE	4	2.87E+08	7.18E+07	1.15	0.341
Residual	62	3.87E+09	6.24E+07		
Total	79	2.23E+10	2.83E+08		

To forming predictions of HHI, we employ model for full data

$$\begin{aligned}\text{HHI} = \; & \text{Constant} + \text{Country} + \text{Year} + \\ & + \text{NACE} + \text{ABC} + \text{Country.NACE}\end{aligned}$$

and for ABC group A only model

$$\begin{aligned}\text{HHI} = \; & \text{Constant} + \text{Country} + \text{Year} + \\ & + \text{NACE} + \text{Country.NACE}.\end{aligned}$$

Parameters for factors are differences compared with the reference level Country Romania, Year 2009, NACE 1 and – when included – ABC group A.

8.11 HHI Full Data

Tab. 23: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	0.05707	0.00737	7.74	<0.001
Country Ukraine	−0.02576	0.00756	−3.41	<0.001
Year 2010	−0.00203	0.00676	−0.3	0.764
Year 2011	0.001	0.00676	0.15	0.883
Year 2012	0.00071	0.00676	0.1	0.917
Year 2013	−0.01893	0.00676	−2.8	0.006
Year 2014	−0.01259	0.00676	−1.86	0.064
Year 2015	−0.01644	0.00676	−2.43	0.016
Year 2016	−0.01761	0.00676	−2.6	0.010
NACE 10	0.02869	0.00756	3.79	<0.001
NACE 21	0.11171	0.00756	14.77	<0.001
NACE 28	0.15843	0.00756	20.95	<0.001
NACE 35	0.13008	0.00756	17.2	<0.001
ABC B	−0.01094	0.00414	−2.64	0.009
ABC C	−0.00728	0.00414	−1.76	0.08
Country Ukraine NACE 10	0.0422	0.0107	3.94	<0.001
Country Ukraine NACE 21	−0.045	0.0107	−4.21	<0.001
Country Ukraine NACE 28	−0.0266	0.0107	−2.49	0.014
Country Ukraine NACE 35	0.0014	0.0107	0.13	0.894

Tab. 24: Accumulated analysis of variance

Factor	d.f.	s.s.	m.s.	F	p-value
Country	1	0.059052	0.059052	86.02	<0.001
Year	7	0.016801	0.0024	3.5	0.001
NACE	4	0.680401	0.1701	247.8	<0.001
ABC	2	0.004961	0.00248	3.61	0.029
Country NACE	4	0.052321	0.01308	19.05	<0.001
Residual	221	0.151706	0.000687		
Total	239	0.965242	0.004039		

8.12 HHI ABC Group A Only

Tab. 25: Estimates of parameters

Parameter	Estimate	s.e.	T	p-value
Constant	0.04928	0.00972	5.07	<0.001
Country Ukraine	−0.026	0.0105	−2.47	0.016
Year 2010	−0.00127	0.00943	−0.13	0.894
Year 2011	0.00221	0.00943	0.23	0.816
Year 2012	0.00617	0.00943	0.65	0.515
Year 2013	−0.01618	0.00943	−1.72	0.091
Year 2014	−0.01024	0.00943	−1.09	0.281
Year 2015	−0.014	0.00943	−1.48	0.143
Year 2016	−0.01566	0.00943	−1.66	0.102
NACE 10	0.0494	0.0105	4.69	<0.001
NACE 21	0.094	0.0105	8.92	<0.001
NACE 28	0.19	0.0105	18.03	<0.001
NACE 35	0.1251	0.0105	11.87	<0.001
Country Ukraine NACE 10	0.0284	0.0149	1.9	0.062
Country Ukraine NACE 21	−0.0338	0.0149	−2.27	0.027
Country Ukraine NACE 28	−0.0351	0.0149	−2.35	0.022
Country Ukraine NACE 35	0.0111	0.0149	0.75	0.458

Tab. 26: Accumulated analysis of variance

Factor	**d.f.**	**s.s.**	**m.s.**	F	p**-value**
Country	1	0.020348	0.020348	45.77	<0.001
Year	7	0.00553	0.00079	1.78	0.108
NACE	4	0.278657	0.069664	156.69	<0.001
Country NACE	4	0.012512	0.003128	7.04	<0.001
Residual	63	0.028009	0.000445		
Total	79	0.345055	0.004368		

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THE POSITION OF NETFLIX IN THE CZECH REPUBLIC BEFORE AND DURING THE COVID-19 PANDEMIC

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EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Volume 8 Issue 1
ISSN 2694-7161
www.ejobsat.com

ABSTRACT

This article is focused on the differences in the brand equity of the streaming service Netflix before and during the COVID-19 pandemic in the Czech Republic. Brand equity is measured by a specially modified conceptual model. Based on a two-wave questionnaire survey, the possible impact of the pandemic on the dimension of the conceptual model was examined. The results showed that there was no statistically significant change in the level of brand equity but there was a change in its structure. It was also found that although the number of people who tried Netflix's services increased during the COVID-19 pandemic, they did not become long-term users.

KEY WORDS

COVID-19, Netflix, brand equity, perceived marketing mix

JEL CODES

M310, L820

1 INTRODUCTION

Streaming services are fast becoming an essential part of everyday life. Streaming services are mainly used for the storage of audiovisual content, which can be watched by a customer in real time with no need to download it beforehand. This makes streaming services a really comfortable solution, because the only requirement is a connection to the Internet. Streaming services may be considered as a modern alternative to cable or satellite TV. Also, unlike the cable or satellite TV, streaming services are very simple to start with. There is no need for professional installation. The customer just signs up to the desired streaming service via their website and is immediately able to stream their content. These streaming services include Netflix, HBO MAX, YouTube, Disney+ and many more.

This article is focused on Netflix, more specifically on its brand equity and the impact of the

KREJČÍ, Michal, and STAŇKOVÁ, Michaela. 2022. The Position of Netflix in the Czech Republic Before and During the COVID-19 Pandemic. *European Journal of Business Science and Technology*, 8 (1): 72–83. ISSN 2694-7161, DOI 10.11118/ejobsat.2021.010.

COVID-19 pandemic. During the COVID-19 pandemic it is well known that people were significantly more active on streaming services like Netflix (Netflix, 2020), which is also supported by the fact that Netflix and other streaming services had to cut down on video quality due to overloading (Cuthbertson, 2020; Alashhab et al., 2020). Dunton et al. (2020) and Robinson et al. (2021) proved that people during lockdown are less physically active and more engaged in sedentary behavior. Furthermore, according to Pandita et al. (2021) or Porubčinová et al. (2020) it has been found that many students turned towards digital recreational activities like watching Netflix, YouTube, and TikTok. In the case of Netflix, this also led to an increase in share price (Levitsky, 2020). Generally, streaming services developed a lot during this time because of lockdown and other contact restrictions. Sheth (2020) says that people started replacing their normal activities (like going to theatres for example) with those that could be done at home (streaming services included). During the pandemic, people were forced to use alternative ways to communicate instead of personal contact. Streaming (in this case live-streaming) was used for example for school lectures, work meetings, and also for interest group courses. These days, people are more and more used to streaming and during COVID-19, streaming proved itself to be a very comfortable solution for times when many contact restrictions are needed. Unlike other companies, it is safe to say that streaming services may have benefited from the pandemic. The question remains whether this growth was also in terms of brand equity.

1.1 Brand Equity and Its Dimensions

Aaker (2016) points out that brand equity is often misinterpreted as brand value. There is a difference between these two terms. While brand value means the financial value of the company, brand equity is a more complex term. Brand equity is the answer to questions about a customer's preference. The stronger and better the brand equity is, the more a customer is likely to prefer that company compared to others.

Brand equity is a dimension that is furthermore determined by partial dimensions. These partial dimensions are brand loyalty, perceived quality, and brand awareness with associations. Therefore, there are four dimensions in total – brand equity as the main dimension and three partial dimensions.

The first partial dimension is brand loyalty. Brand loyalty simply means customer's trust in products or services. It is proved that once the customer gains enough confidence in a specific brand then he or she is more likely to buy its products or use its services more often. Kotler and Armstrong (2017) say that in the case of insurance companies, this may be up to 50% more often than before.

Probably the most important partial dimension is that of perceived quality. According to Kotler and Armstrong (2017) perceived quality significantly stimulates a customer's satisfaction, which leads to a higher profit. Aaker (2009) says that it is crucial to be aware of the fact that a high-quality product does not mean high perceived quality. Most people are not able to objectively assess quality because of a lack of knowledge. Aaker (2009) points out that people are able to perceive high quality, which means that it is firstly important to convince them about high quality. That is what perceived quality does.

The last partial dimension is brand awareness with associations, which means general knowledge of a specific brand. According to Aaker (2009), strong brand awareness with associations does not necessarily mean a positive influence on brand equity. It depends on whether that awareness is connected to a positive or negative experience. Measuring this dimension is further divided into recall and recognition. Recall is active knowledge, which may be for example the first brand that comes into a customer's mind when thinking of a specific class of products. On the other hand, recognition is passive knowledge. Recognition was largely used in the case of Intel microprocessors when its logo was placed in advertisements for personal computers. During

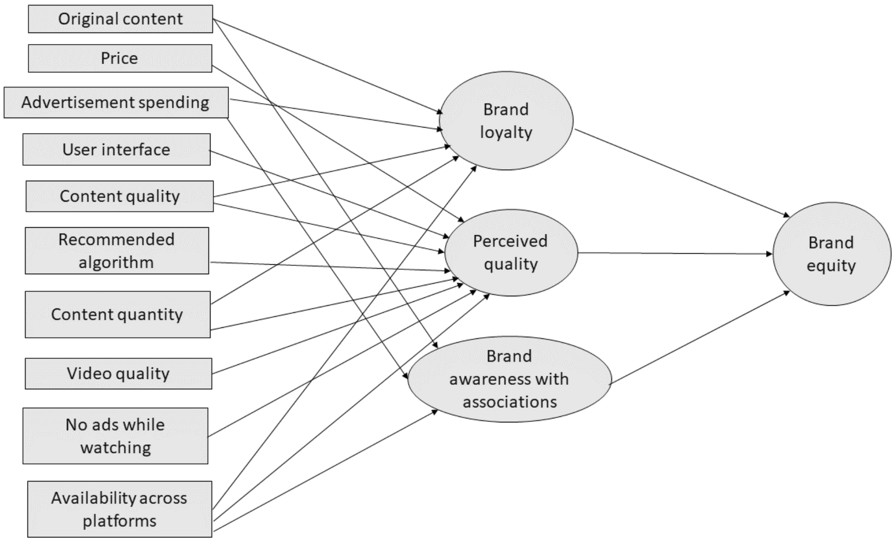

Fig. 1: Conceptual model originally developed to measure Netflix's brand equity

that time, worldwide sales of Intel products increased by up to 63%.

1.2 Proposed Conceptual Model

Brand equity is measured by means of a conceptual model. The conceptual or derived types of models are widely used in management, see, for example, Porubčinová and Fidlerová (2020). The conceptual model used in this article was developed based on the model by Yoo et al. (2000) and customized to better fit its application on Netflix. Yoo et al. (2000) designed their model mainly for application on products. Since Netflix does not provide a product but a service, it was necessary to replace certain elements of the marketing mix with those that relate to Netflix.

Each partial dimension is thought to be stimulated by specific elements of the marketing mix. The first dimension, brand loyalty, is considered to be stimulated by original content, advertisement spending, content quality, content quantity, and service availability across platforms. The second dimension, perceived quality, is stimulated by price, user interface, content quality, recommended algorithm, content quantity, video quality, no ads while watching, and service availability across platforms. The last dimension, brand awareness with associations, is stimulated by original content, advertisement spending, and service availability across platforms. A scheme of our proposed conceptual model is given in Fig. 1.

1.3 Netflix and Its Current Situation

Netflix was established in 1997 as an online DVD rental store. Ten years later, Netflix started its own streaming service. Before the COVID-19 pandemic, Netflix was dealing with serious deceleration in gain of subscribers. According to Netflix (2020), in Q2 2019 they predicted a gain of about 300 thousand new subscribers in America and about 5 million new subscribers worldwide. The reality was notably below both predictions – the actual worldwide gain was only about 2.7 million and in America there was no gain at all but a loss of about 130 thousand subscribers compared to Q1 2019. Despite the decline in the first half of 2019, for the rest of the year the predictions matched reality.

The prediction for Q1 2020 was a gain of about 7 million worldwide subscribers. The reality was 15.7 million new worldwide subscribers, which is more than twice the predicted gain (Netflix, 2020). For the rest of 2020, the actual gains were above the predictions (except for Q3 2020, which was very slightly below the prediction). Based on this, it is possible to assume that the pandemic supported a worldwide membership growth. However, membership growth does not necessary mean growth in terms of brand equity and also there is no straightforward proof of whether the Czech Republic corresponds with the worldwide tendency.

The main aim of this article is to evaluate Netflix's brand equity in the period before and during the COVID-19 pandemic in the Czech Republic. This is an attempt to find out whether, after a year of living in a pandemic, there has been a significant change not only in the popularity of Netflix, but also whether the pandemic has affected the perception of the brand itself.

2 METHODOLOGY AND DATA

The required data were determined by means of a questionnaire survey, where a random sample of respondents was chosen. The questionnaire survey was conducted in two waves, which were exactly one year apart. More precisely, the collection of answers took place in January 2020 (i.e., the period when there was no problem regarding COVID-19 in the Czech Republic, hereinafter referred to as the first period) and January 2021 (i.e., the period when the inhabitants of the Czech Republic had been living for several months with strict measures due to the pandemic, hereinafter referred to as the second period).

The questionnaire was distributed to Czech respondents online via social networks (such as Facebook), as it is possible to assume that most Netflix customers are on these networks. The questionnaire contained filter questions to ensure the suitability of the respondent, see Tab. 1. However, the main part of the questionnaire consisted of scaling questions (range 1 to 5). The questionnaire also contained several identification questions that made it possible to derive basic information about the respondents.

During the first period, 209 responses were received and during the second period 250 responses. The most common reasons for people deciding to cancel their Netflix subscription were the price, lack of free time, and unwillingness to pay for streaming services in general.

Most of the respondents in both periods were people from 17 to 30 years old, which corresponds to the target group of Netflix. The overriding majority of the respondents were students working part-time, followed by students but unemployed. In terms of income, the most common answer was from 5001 to 10,000 CZK (more than 35% of all answers).

Tab. 1: Results of the filter questions

Filter question	**1st period (% of positive answers)**	**2nd period (% of positive answers)**
Do you use streaming services in general?	94.8	92.8
Are you aware of the streaming service Netflix?	93.5	96.1
Have you ever used Netflix?	81.8	92.8
Are you currently an active user of Netflix?	88.9	91.3

The questionnaire was compiled so that it was possible to identify any statistically significant links between the various components of brand equity. To determine the possible dependence, we used a chi-square test based on contingency tables and the strength of the relationship between the observed quantities was expressed using the Cramer coefficient (Cramer's V). This coefficient takes values between 0 and 1. The closer it is to 1, the closer the relationship between the variables. This approach is widely used questionnaire surveys; see Stojanová et al. (2018), Skýpalová et al. (2016), Stojanová et al. (2015), Stojanová and Tomšík (2014) and Zámková and Blašková (2012).

During the testing, it was checked whether the assumptions of the use of the test regarding the theoretical frequency were violated. The null hypothesis of chi-square test assumes that there is no dependence between the two quantities. When rejecting this null hypothesis, it is possible to argue that there is a statistically significant dependence between the observed quantities. The hypotheses were divided into four blocks, see Tab. 2. The first block examined the relationship between brand loyalty and five other variables – for example, the first block of hypotheses verified the relationship between brand loyalty and original content and was assigned the code H1a. The second block of hypotheses verified the relationship between perceived quality and eight other variables (hypotheses H2a to H2h). The third block and the fourth block (i.e., brand awareness with associations and brand equity) each contained three hypotheses. All of these sets of hypotheses followed the conceptual model (Fig. 1), which points to four sets of hypotheses, with each set representing one dimension of brand equity. The number of hypotheses in each set was given by the number of elements of the perceived marketing mix that are considered to have an impact on the dimension of brand equality in question.

Similarly to Zámková and Blašková (2013) and Qiu et al. (2021), a two-sample test of relative frequencies was used to determine whether there was a statistically significant difference in the use of Netflix before and during the pandemic. Part of the use of this test was to check that the variance of the alternative distribution is greater than the generally required value of nine.

Like Swain et al. (2019), a non-parametric Mann-Whitney test was used to determine the possible change in the level of the brand value before and during the pandemic, as the monitored values cannot be expected to meet the assumption regarding the normal distribution.

Tab. 2: Hypotheses codes for the relation between the perceived marketing mix and dimension of brand equity

Brand loyalty	
H1a:	Original content
H1b:	Advertisement spending
H1c:	Content quality
H1d:	Content quantity
H1e:	Availability across platforms
Perceived quality	
H2a:	Price
H2b:	User interface
H2c:	Content quality
H2d:	Recommended algorithm
H2e:	Content quantity
H2f:	Video quality
H2g:	No ads while watching
H2h:	Availability across platforms
Brand awareness with associations	
H3a:	Original content
H3b:	Advertisement spending
H3c:	Availability across platforms
Brand equity	
H4a:	Brand awareness with associations
H4b:	Brand loyalty
H4c:	Perceived quality

Last but not least, it was necessary to verify the reliability of the data. Cronbach's alpha was used for this purpose as in Warrens (2015). Cronbach's alpha ranges from zero to one, and its values should not fall below 0.5 to maintain consistency and reliability.

3 RESULTS

The reliability of the data used for both of the periods under review was verified based on Cronbach's alpha, see Tab. 3. The results of Tab. 3 show that the reliability of the data differs from concept to concept. Typically, the Cronbach's alpha is higher than 0.5 (in some cases higher than 0.8, which points to good or even excellent data). The only exception is in the case of perceived price in the second period, which had a Cronbach's alpha of 0.46. As this is the only exception that is not significantly far from the recommended value of 0.5 (which is the limit for general acceptability of data), the data for this research may still be considered suitable for further analysis.

Tab. 3: Results of the reliability analysis

Concept/Period	Cronbach's alpha 1st	2nd	Number of items 1st	2nd
Brand loyalty	0.54	0.53	3	3
Brand awareness with associations	0.67	0.62	3	3
Perceived product	0.74	0.76	7	7
Perceived price	0.58	0.46	2	2
Perceived advertisement spending	0.67	0.78	3	3
Perceived intensity of distribution	0.82	0.91	2	2
Perceived quality	0.83	0.92	2	2
Brand equity	0.84	0.82	3	3

3.1 Netflix's Brand Equity

The significance of each element of the marketing mix was analyzed with contingency tables. The results of analysis of brand loyalty are shown in Tab. 4, where the resulting values of the Cramer coefficient and the p-value determining the statistical significance of the relationship are included. In the first period, only two elements were statistically significant – original content and content quality. In the second period, the situation is different, as four out of five elements are now statistically significant. The only insignificant element in both periods was content quantity (a p-value higher than the significance level of 0.05, which points to insignificant Cramer's V).

This leads to the conclusion that before the pandemic the only elements related to brand loyalty were original content and content quality. Today, there are four relating elements, which means that brand loyalty has the potential of becoming stronger. This also means that there was a change in the structure of brand loyalty. Before the pandemic, people were not noticing Netflix's advertisement enough. But one year after, this marketing element became statistically significant, which is relevant considering the fact that people were forced to stay inside and find different types of activities than they usually did. This also corresponds to the significance of the element "availability across platforms". This may be explained by the presumption that people were probably looking for alternative ways of using Netflix since not every household has a TV, so they noticed that Netflix may be used on different platforms, which made them more loyal to Netflix, because it is easily accessible. A summary of the chi-square test analysis is included in Tab. 5.

Tab. 6 and 7 show the results of the analysis of the perceived quality dimension. This dimension analysis also proved that more elements became significant since the beginning of pandemic. Before the pandemic, two of the elements were insignificant (price and recommended algorithm). Now, based on the p-values for the Cramer coefficient, all of the considered elements are significant, which means that people perceive the quality of Netflix and that their perception is based on more elements than it used to be. In the case of price, the significance means that people now consider the price of subscription as a reasonable cost for the streaming service. Price is an element that many people consider as a quality measurement and since they perceive Netflix as a high-quality service, they are willing to pay a higher amount of money for this service. The significance of recommended algorithm may be simply explained by the fact that people had more time to spend with the service, which gives enough space for these algorithms to learn more about viewer preferences and give better and more accurate recommendations. Subscribers probably subconsciously noticed that the recommendations are now very close to their preferences and consider this element as high quality, which as a result now stimulates this dimension of the perceived quality of Netflix.

The results for the dimension of brand awareness with associations are included in Tab. 8 and 9. Before the pandemic, the only significant element for the dimension of brand awareness with associations was original content. During the pandemic, availability across platforms also had a significant relationship with awareness with associations. This change may be con-

Tab. 4: Results of the dependence analysis of the brand loyalty dimension

Period	Original content		Advertising spending		Content quality		Content quantity		Availability across platforms	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
Cramer's V	0.282	0.238	0.091	0.237	0.231	0.247	0.197	0.155	0.198	0.207
P-value	0.001	0.002	0.897	0.006	0.025	0.001	0.104	0.139	0.255	0.044

Tab. 5: Summary of rejection/non-rejection of the null hypotheses for the brand loyalty block of hypothesis

Hypothesis	Item of marketing mix	Result (1st period)	Result (2nd period)
H1a	Original content	H_0 rejected	H_0 rejected
H1b	Advertisement spending	H_0 not rejected	H_0 rejected
H1c	Content quality	H_0 rejected	H_0 rejected
H1d	Content quantity	H_0 not rejected	H_0 not rejected
H1e	Availability across platforms	H_0 not rejected	H_0 rejected

nected to the changes in brand loyalty. People now associate Netflix with smartphones, notebooks etc. The element advertisement spending remained insignificant for both periods, which points to the conclusion that Netflix's advertising still does not draw enough attention.

In the case of the separate dimension of brand equity, the results did not change over time, see Tab. 10 and 11. Before the pandemic, every partial dimension was significant, which remained during the pandemic. Simply said, in the main dimension there was neither an improvement nor change in structure.

3.2 Impact of the COVID-19 Crisis on Brand Equity

Fig. 2 shows the box plots for each dimension in both periods. There was almost no change between the plotted descriptive characteristics of the dimensions for both the time periods.

Based on the median values, it is possible to state that regardless of the time, half of the respondents assigned a value greater than or equal to 4, which means that Netflix's brand equity and its dimensions may be considered as strong variables. In other words, subscribers are loyal to Netflix, perceive Netflix as a high-quality service and are strongly aware of this brand, which leads to its strong brand equity.

Brand awareness with associations now has a higher interquartile range, which means that during the second period, the responses in this case were more variable. On the other hand, the interquartile range decreased in the case of the individual dimensions of brand equity.

The data from both periods were compared to each other based on the Mann-Whitney test and the results are listed in Tab. 12. Generally, it is possible to say that there was no significant difference between these two periods. This result corresponds with the results of the descriptive characteristics mentioned above.

Last but not least, changes in the answers to the filter questions (presented in Tab. 1) were examined. The final test to be performed was the two-sample test of relative frequencies to investigate whether a relevant difference in use of Netflix and in use of streaming services in general occurred between periods, see Tab. 13. There was a statistically significant difference in the case of the third question (*Have you ever used Netflix?*) but no difference in the other questions between the monitored periods. It may be assumed that during the pandemic more people in the Czech Republic signed up to Netflix but did not continue using this service regarding the result of the fourth question (*Are you currently an active user of Netflix?*). The difference in the first question remained insignificant, which suggests that there was no change in the use of streaming services in general.

Tab. 6: Results of the dependence analysis of the perceived quality dimension

	Price		User interface		Content quality		Recommended algorithm	
Period	**1st**	**2nd**	**1st**	**2nd**	**1st**	**2nd**	**1st**	**2nd**
Cramer's V	0.161	0.215	0.237	0.439	0.456	0.311	0.191	0.249
P-value	0.171	0.013	0.004	<0.001	<0.001	<0.001	0.292	0.001
	Content quantity		**Video quality**		**No ads while watching**		**Availability across platforms**	
Period	**1st**	**2nd**	**1st**	**2nd**	**1st**	**2nd**	**1st**	**2nd**
Cramer's V	0.339	0.233	0.286	0.335	0.359	0.301	0.365	0.303
P-value	0.001	<0.001	0.004	<0.001	<0.001	<0.001	<0.001	<0.001

Tab. 7: Summary of rejection/non-rejection of the null hypotheses for the perceived quality block of hypotheses

Hypothesis	Item of marketing mix	Result (1st period)	Result (2nd period)
H2a	Price	H_0 not rejected	H_0 rejected
H2b	User interface	H_0 rejected	H_0 rejected
H2c	Content quality	H_0 rejected	H_0 rejected
H2d	Recommended algorithm	H_0 not rejected	H_0 rejected
H2e	Content quantity	H_0 rejected	H_0 rejected
H2f	Video quality	H_0 rejected	H_0 rejected
H2g	No ads while watching	H_0 rejected	H_0 rejected
H2h	Availability across platforms	H_0 rejected	H_0 rejected

Tab. 8: Results of the dependence analysis of the brand awareness with associations dimension

	Original content		Advertisement spending		Availability across platforms	
Period	**1st**	**2nd**	**1st**	**2nd**	**1st**	**2nd**
Cramer's V	0.419	0.297	0.163	0.158	0.253	0.271
P-value	<0.001	<0.001	0.123	0.150	0.130	0.003

Tab. 9: Summary of rejection/non-rejection of the null hypotheses for the brand awareness with associations block of hypotheses

Hypothesis	Item of marketing mix	Result (1st period)	Result (2nd period)
H3a	Original content	H_0 rejected	H_0 rejected
H3b	Advertisement spending	H_0 not rejected	H_0 not rejected
H3c	Availability across platforms	H_0 not rejected	H_0 rejected

Tab. 10: Results of the dependence analysis of the brand equity dimension

	Brand awareness with associations		Brand loyalty		Perceived quality	
Period	**1st**	**2nd**	**1st**	**2nd**	**1st**	**2nd**
Cramer's V	0.253	0.219	0.352	0.268	0.526	0.312
P-value	0.002	0.001	<0.001	<0.001	<0.001	<0.001

Tab. 11: Summary of rejection/non-rejection of the null hypotheses for the brand equity block of hypotheses

Hypothesis	Item of marketing mix	Result (1st period)	Result (2nd period)
H4a	Brand awareness with associations	H_0 rejected	H_0 rejected
H4b	Brand loyalty	H_0 rejected	H_0 rejected
H4c	Perceived quality	H_0 rejected	H_0 rejected

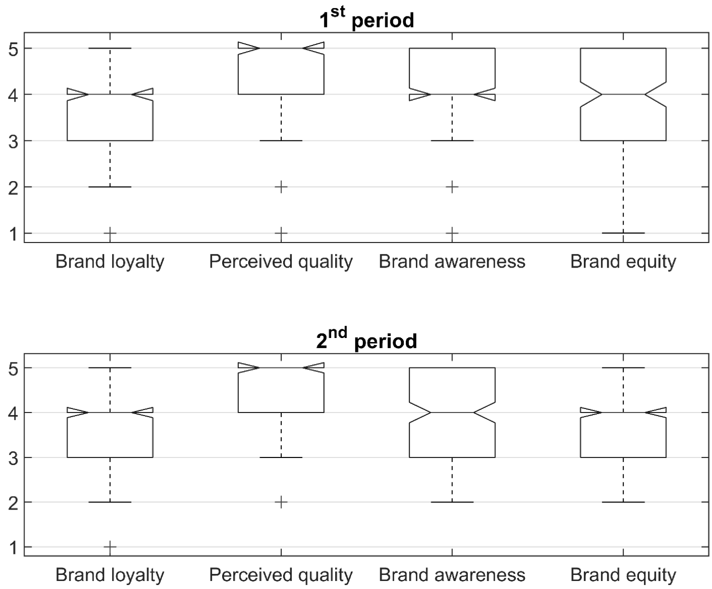

Fig. 2: Box plots for the individual dimensions of brand equity in both periods

Tab. 12: Results of the Mann-Whitney test

Dimension	***P*-value**	**Dimension**	***P*-value**
Brand loyalty	0.266	Content quantity	0.749
Perceived quality	0.585	Availability across platforms	0.312
Brand awareness with associations	0.247	Price	0.424
Brand equity	0.519	User interface	0.277
Original content	0.786	Recommended algorithm	0.491
Advertisement spending	0.128	Video quality	0.204
Content quality	0.192	No ads while watching	0.132

Tab. 13: Results of the two-sample test of relative frequencies

Question	**1** **Do you use streaming services in general?**	**2** **Are you aware of the streaming service Netflix?**	**3** **Have you ever used Netflix?**	**4** **Are you currently an active user of Netflix?**
P-value	0.396	0.208	<0.001	0.420

4 DISCUSSION

Based on the results of this research it is possible to state that the COVID-19 pandemic positively affected the position of Netflix in the Czech Republic in terms of usage, as the share of respondents who tried Netflix during the pandemic increased. This difference was identified as statistically significant. Therefore, it may be stated that in this respect the Czech Republic corresponds to the worldwide tendency. The result in terms of usage also goes hand-in-hand with other research, that proved that people during the pandemic were physically less active (Robinson et al., 2021) and started replacing physical activities with sedentary behavior (Dunton et al. 2020) and in-home activities (Sheth, 2020), and furthermore turned toward digital recreational activities like watching Netflix, YouTube, and TikTok (Pandita et al., 2021).

However, the change in terms of usage was probably only short-term since the only statistically significant difference was in the case of the question *"Have you ever used Netflix?"* but not in the question *"Are you currently an active user of Netflix?"*. This result may be interpreted as in the short run the pandemic definitely supported and improved the situation of Netflix but not in the long run. People probably only using Netflix during restrictions like quarantine but once those restrictions were lifted (during the summer in the Czech Republic), they cancelled their subscriptions, which meant that Netflix was not able to retain these new viewers. This also corresponds with no change in the level of brand equity, because if there actually was a change, there would probably also be an improvement in the long run.

As mentioned earlier, no change in the level of brand equity does not mean no change at all, the results proved a statistically significant change in its structure. Subscribers of Netflix now perceive more elements of the marketing mix, which now has the potential to stimulate brand equity. Netflix should now focus on these new significant elements and use them to its advantage to improve its brand equity, which may also help retain new subscribers.

It would not be appropriate to generalize the results of this article for the whole population, because the study focused primarily on Netflix's target customers, which are generations Y and Z, and the research methodology was adapted accordingly. Unfortunately, there are currently no similar studies in the Czech Republic or other countries, so it is not possible to compare the results.

The pandemic undoubtedly had an impact on the behavior of individuals and on the functioning of all market players. Only future research will reveal how the situation regarding Netflix and its brand equity will develop. It may be possible to conduct a questionnaire survey in the next wave (i.e., in January 2022) and find out whether the results remain unchanged. It would certainly be very beneficial to extend the analysis to other countries.

5 CONCLUSIONS

The results of this study show that the COVID-19 pandemic in the Czech Republic did not affect brand equity in terms of its level but affected its structure. Before the COVID-19 pandemic many elements of the perceived marketing mix were statistically insignificant but during lockdown and other contact restrictions these elements became statistically significant. The newly significant elements were for example advertisement spending and availability across platforms in the case of brand loyalty, and price and recommended algorithm in the case of the dimension of perceived quality. Every dimension of brand equity was significant before the pandemic and remained significant during the pandemic. These conclusions mean to Netflix that the brand itself has now more space and a greater potential to improve its brand equity.

It was also found that although the number of people who tried Netflix increased during the pandemic, they did not become long-term users. This may point to the conclusion that brand equity in general is strong, but it is not strong enough to retain those new subscribers that joined Netflix during the pandemic.

6 ACKNOWLEDGEMENT

This article was supported by the grant IGA-PEF-TP-22-003 of the Grant Agency MENDELU.

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PREFERRED FORMS OF ONLINE SHOPPING BY THE YOUTH GENERATION

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EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Volume 8 Issue 1
ISSN 2694-7161
www.ejobsat.com

ABSTRACT

The aim of the paper is to determine the preferred forms of online shopping and preferred device for online shopping for different product categories by the youth consumers. The research showed that the smartphone plays not only an important role in the consumer behaviour of youth consumers, but they also frequently shop using this device. The paper also identifies the situational and demographic factors affecting online shopping based on which consumer segments were created. Cluster analysis using the K-means algorithm formed consumer segments in the online market in the Czech Republic. Four segments were defined – economically decisive from a city, emotively decisive, rationally thinking from a town, economically active. The results can be purposefully used in creating recommendations for e-shops and for their marketing management.

KEY WORDS

forms of shopping, online shopping, shopping frequency, young consumers, online consumer segmentation

JEL CODES

D12, M31, O35

1 INTRODUCTION

Shopping and its form is the fourth part of the shopping behaviour process (after the identification of the problem, searching for information, assessing alternatives), which leads to satisfying human needs. It is, therefore, an essential part of consumer behaviour as a whole and this is the way it needs to be approached. The importance of the Internet in the purchasing process is constantly growing. More and more consumers are shopping on the Internet. This trend has been accelerated by the Covid-19 pandemic when consumers were forced to stay at home, shops were closed and consumers had to look for new ways of buying.

PŠURNÝ, Michal, ANTOŠOVÁ, Irena, and STÁVKOVÁ, Jana. 2022. Preferred Forms of Online Shopping by the Youth Generation. *European Journal of Business Science and Technology,* 8 (1): 84–95. ISSN 2694-7161, DOI 10.11118/ejobsat.2022.003.

As a society, it is material and technical resources, and climatic conditions develop lifestyle, the hierarchy of moral and ethical values changes so that new factors influence consumers in the process of satisfying needs. Young people grew up with new technologies and the internet has been, is, and will be a part of their daily lives. Their needs and shopping behaviour are different from older people who did not grow up with the Internet. Young people also represent great purchasing power in the future. Therefore, it is necessary to understand their shopping behaviour so that online stores can adapt their marketing strategies.

New e-shops are also emerging and existing businesses are moving to the Internet. It is important not only for new businesses but also for existing entrepreneurs operating on the Internet to adapt their marketing strategies to these people – their behaviour, needs and responses to marketing communications.

The aim of the submitted paper is to determine the preferred forms of online shopping and the use of devices for online shopping for different product categories. The paper also identifies the situational and demographic factors affecting online shopping based on which consumer segments are created in the online market in the Czech Republic. The results obtained using appropriate methods of data processing from questionnaire construction of the created online shopper segments can be purposefully used to create recommendations for e-shops and for their marketing management.

2 LITERATURE REVIEW

Consumer behaviour relates to the consumption of material and immaterial goods. The economic concept of consumer behaviour is based on the premise that it is the outcome of the consumer's rational thinking, with the knowledge that most decisions are made during uncertainty (Varian, 2010). Post-Keynesians claim that the consumer does not have perfect and adequate information, and moreover, limited abilities to use this information, whereas neoclassical economists are of the opinion that the consumer is well-informed and works with uncertainty as with a risk. The marketing concept of consumer behaviour respects both attitudes that intertwine and complement each other and the outcome is its complex concept. A series of factors enter decision-making from cultural to economic, demographic, psychological and others that are well elaborated theoretically (Kotler, 2001). The significance of these factors over the course of time gains in differing intensity. What is relatively significant is the influence of income which is considered one of the decisive factors for satisfying needs according to Gour (2018).

New factors enter the decision-making of the consumer. For example, a series of investigations was engaged in the influence of the method of payment on the volume of consumer expenses, i.e. on the satisfaction of their needs. The conclusion of this research focused on the fact that a card payment leads to more frequent decisions to buy and to greater expenses. On the other hand, consumers have a strong aversion to debts, above all to credit card ones. Thus, if credit cards can encourage spending, their excessive use is something that consumers try to avoid (Wilcox et al., 2011).

In his study, Ouanphilalay (2017) investigated the impact of loans on total household consumption. The results point to the fact that the total consumption of households that borrow money tends to be higher than the consumption of households without credit or loans. However, it was shown that looking at consumption by items (food items and "non-food" items) only formally provided credit has a positive effect on food consumption. As Carlson et al. (2015) explain, this is credit provided by a bank. Apart from the credit, there are also informal loans (friends, family, etc.) and semi-formal (above all institutions specialising in micro-financing) and it is interest-free informal loans and semi-formal loans that have a negative impact on food consumption. In the case of non-food item consumption, the effect of all stated types of loans was rated as positive and statistically significant.

Online shopping is increasingly popular and this method is used by a growing number of consumers (Sabou et al., 2017; Karthikeyan, 2016). At the European level, differences exist in individual countries in online shopping which came about particularly as a consequence of the differently attained level of economic growth. So that the consumer can shop online, he needs access to a device to allow him to do this (computer, tablet, mobile phone etc.) and certain knowledge of how to use this device (Sabou et al., 2017). Kráľ and Fedorko's study (2021) shows that from 2011–2019 there was a significant increase in the share of online shopping for goods and services among internet users in the V4 countries.

The Covid-19 pandemic contributed to a large extent to a change in the approach to interest in online shopping (Pollák et al., 2022; Eger et al., 2021; Gu et al., 2021; Di Crosta et al., 2021; Pantano et al., 2020; Donthu and Gustafsson, 2020). As a consequence of the pandemic, the number of consumers shopping online increased. The restriction to the movement of people in public and limited access to brick and mortar stores, limited range or lack of goods to brick and mortar stores or also health reasons contributed to this (Kráľ and Fedorko, 2021).

The Eger et al. study (2021) conducted in September 2020 in the Czech Republic showed that health concerns during the Covid-19 pandemic or economic worries are leading to changes not just in the amount, content, but also in the forms of consumer behaviour. The study even showed that the greater the fear the greater the change in shopping behaviour. The study of Eger et al. (2021) and the study of Gu et al. (2021) show that the percentage of impulsive shopping decreased whereas the percentage of planned shopping increased.

The Kopřivová and Bauerová study (2021), engaged in the consumer behaviour of Millennials in the Czech market, identified the characteristics that determine the Millennials segment – four psychographic (ecology, lifestyle, traditionality and sociability) and four behavioural characteristics (using a mobile phone, method of shopping, attitudes to marketing communication tools and use of marketing communication tools). Online shopping is more popular among younger people (Karthikeyan, 2016), therefore online shopping websites should develop a strategy that addresses the problems of younger generation online consumers.

People that avoid online shopping do so, among other things, because of worry about online theft and think that online shopping websites are unreliable (Karthikeyan, 2016).

The study by Pollák et al. (2022) has found that during the first wave of the pandemic, the number of interactions on Facebook of the biggest Czech e-shops increased. The dominant part of the interactions moved to the working week. This indicates that people are being more active online during the period of the pandemic in a standard working week than in the period before the pandemic. These interactions have moved from brick and mortar stores to the virtual environment of the internet. As a consequence of pandemic lockdowns, consumer behaviour has to a certain extent maintained the characteristics of the pre-pandemic period, only it has moved to the internet.

So far, there are not many studies that have examined reviews and registrations in e-shops. According to research Pollák and Dorčák (2015) conducted in Slovakia (634 respondents) showed, "good reviews" are important for more than 70% of online shoppers. Providing a sufficient amount of "relevant product information" is a decisive factor in choosing an e-shop for more than 60% of respondents. In both categories, we can also see an increase compared to the reference survey of 2009 by more than 15%. From this study is also obvious that the price is important for 80% of respondents.

The Huang et al. study (2021) dealt with the registration with the website at the beginning of their shopping journey (ex-ante) and after the shopping journey (ex-post). The results showed that customers who had the opportunity to ex-ante register, on average, they 58.08% relatively more likely to register and they are 10.89% relatively more likely to make a purchase, place a 16.76% relatively greater number of orders.

Cluster analysis has been used in various studies of online shoppers (Jayawardhena et al., 2007; Aljukhadar and Senecal, 2011; Ladhari et al., 2019; Akar, 2021; Kondo and Okubo, 2022). Jayawardhena et al. (2007) identified segments based on distinct purchase orientations. Aljukhadar and Senecal (2011) segmented online consumers more generally through the internet use patterns – internet use, internet experience, psychological characteristics, and user experience. Ladhari et al. (2019) segmented women from Generation Y who made purchases on the fashion retailer's website. Research of Kondo and Okubo (2022) segmented consumers of multi-channel purchases by product category and overall products. Study of Akar (2021) analyzed pandemic-related concerns on customers' purchase intentions their role in customer segmentation.

3 METHODOLOGY AND DATA

Secondary data on the share of individuals that shopped online in the last year were used (source Eurostat) for the characteristics of the online shopping market, above its size.

The data of the price comparison websites Czech e-commerce (2021) and Heureka Group (2021) were used for the characteristics of using the price comparison of goods sold online. Information was also used from these sources about the categories of products most sold online. These data were taken into account in the choice of categories of products used in questionnaire construction.

For the primary data collection, structured questionnaire was constructed and was distributed in two-time stages (May 2021, December 2021). In total 351 respondents representing the young generation, most often aged 19 to 26 (mean = 20.5; SD = 6.27) completed the questionnaire. More detailed characteristics of the research sample can be found in Tab. 1.

Questions were related to their online shopping behaviour. For example, How often do you shop online using which devices? What method of shopping do you prefer for a given product category? State the extent of agreement with the following statements about online shopping. This was mostly about matrix questions based on the Likert agreement scale. These matrix questions had more choices of answers, so the sums of the answers given in the contingency tables in the results do not correspond to the number of respondents. The questionnaire also contained selected demographic data of respondents – apart from age, gender, economic activity, and size of the municipality in which they live. The questionnaire was constructed and extended using the Umbrela app (see `https://umbrela.mendelu.cz/`).

Tab. 1: Characteristics of the research sample (n = 351)

Specification	Absolute Number	Percentage
Gender		
Men	182	51.85
Women	169	48.15
Education		
Primary	4	1.14
Lower secondary	23	6.55
Secondary	281	80.06
Post-secondary non tertiary	7	1.99
University degree	36	10.26
Economic activity		
Employed (<40 h/week)	33	9.40
Employed (>40 h/week)	62	17.66
Unemployed	3	0.85
Student	232	66.10
Business	20	5.70
Handicap	1	0.28
Size of municipality		
Less than 2000	95	27.07
2000–19999	101	28.77
20000–99999	66	18.80
More than 99999	89	25.36

Frequency tables were constructed between Shopping Frequency and Preferred Devices used for shopping and between the Product Type and Preferred Form of Shopping.

In order to determine possible dependence between Shopping Frequency using smartphones and Shopping Frequency using laptops, the χ^2 test of independence was applied where the null hypothesis assumes the independence of analysed variables. These two devices are the two most often used devices for online shopping. The significance level is $\alpha = 0.05$ (Balakrishnan, 2010).

Due to the ordinal nature of the data Spearman and Gamma correlation coefficients were calculated to determine the strength of the dependence. Responses from respondents who answered in the case of a smartphone or laptop – I have none (laptop: $n = 16$; smartphone: $n = 1$), I have not shopped as yet (laptop: $n = 13$; smartphone: $n = 25$) were deleted. Therefore, a total of 296 responses remained for this analysis.

The application of the cluster analysis determines the segments of consumers who shop online. The selected variables used as the cluster criteria are: Registration in the e-shop so they do not have to fill in their personal data again; Registration in the e-shop for an expected benefit (discount); Access to the e-shop using the app; Preferred access to the e-shop from the web browser; Reading reviews before making a purchase; Discount as motivation to shop; Effect of advertising on the opinion of a product; Effect of emotions on the purchase; Search for the given product with the lowest price on the internet; Active use of goods price comparison websites. Also demographic variables: Gender; Economic activity; Size of residence. Out of a total of 351 respondents, only 328 finally entered the cluster analysis. Responses from respondents who did not answer key questions to creating the segments were deleted.

The purpose of the cluster analysis is to sort the data objects (in this case the consumer) into several clusters (in this case segments), when the rule is that the objects inside the cluster are as similar as possible and with the objects from the other clusters that are as different as possible. The individual objects are gradually connected to the smaller clusters that are connected to the bigger clusters of objects with common attributes (Greene, 2018).

The applied cluster algorithm is the K-means algorithm suitable for data files containing hundreds of objects and bigger. The cluster procedure then follows. Initial clusters are created and a centroid, i.e. vector of mean values of individual variables, is created for each cluster. The objects are then classified in the cluster whose centroid comes closest to their values (Greene, 2018).

The K-means algorithm minimises the following functions (Greene, 2018):

$$f_{\mathrm{KP}} = \sum_{h=1}^{k} \sum_{i=1}^{n} u_{ih} \left\| x_i - \bar{x}_h \right\|^2 , \tag{1}$$

where the elements $u_{ih} \in \{0, 1\}$ identify if the i object is (value 1) or is not (value 0) classified in the h cluster, and $\bar{x}_h$ is the vector of the mean values of the h cluster. At the same time, the following must be met:

$$\begin{gathered} \sum_{h=1}^{k} u_{ih} = 1 \quad \text{for } i = 1, 2, \ldots, n, \quad \text{and} \\ \sum_{i=1}^{n} u_{ih} > 0 \quad \text{for } h = 1, 2, \ldots, k. \end{gathered} \tag{2}$$

The statistical analyses are carried out in IBM SPSS Statistics software.

4 RESULTS

As the results of the research of many authors show and the situation observed on the market in the last 10 years, there has been a high increase in internet sales (Fig. 1). When analysing the intensity of the use of the internet for the purchase of goods and services, the data of Czech e-commerce (2021) must be considered which informs that in the Czech Republic the share of internet users over the age of 16 is 78.5% (55% have access to the internet from a mobile device). 49% of purchases in 2019 were made on desktops (desk computers, laptops), 47% from mobile devices, and 4% from tablets.

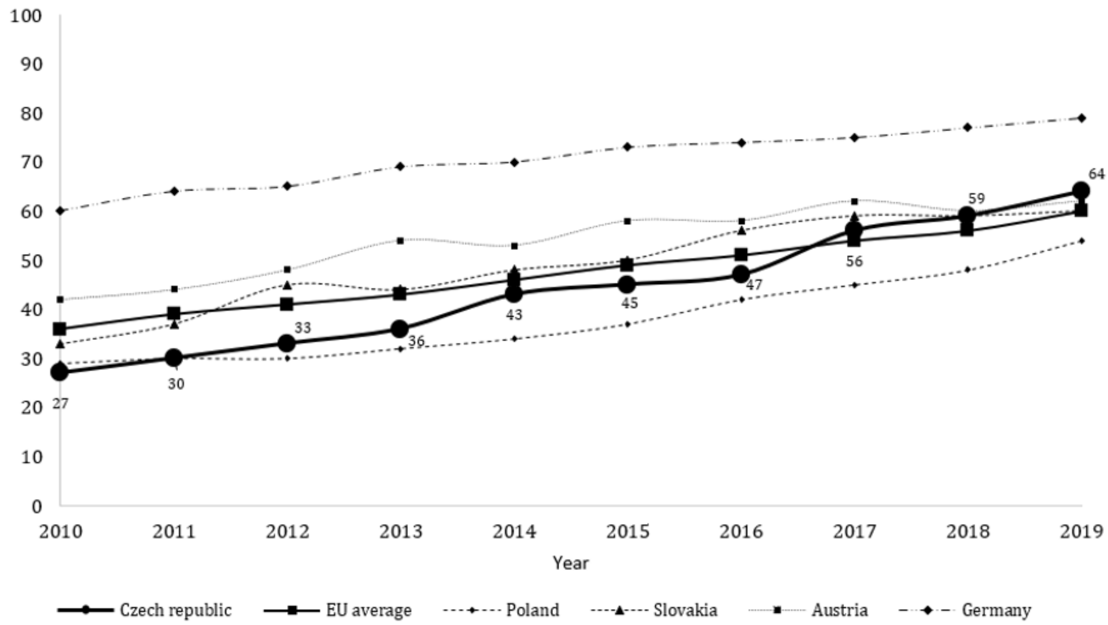

Fig. 1: Percentage of individuals that purchased goods or services online in the given year in the selected countries. Source: Eurostat, 2021.

As shown in Fig. 1, the percentage of individuals in the population of countries that purchased goods or services online is growing. In 2010, this percentage of individuals that purchased goods or services online was lower than in all countries bordering the Czech Republic except Germany (where this high percentage is well above the EU average constantly). However, the Czech Republic is struggling with the phenomenon that the number of e-shops per capita is very high (this ratio is the highest in the EU countries; see Czech e-commerce, 2021). At the same time, the percentage of individuals that purchased goods or services online is growing more than in bordering Countries and, as you can see in Fig. 1, this percentage in 2017 also exceed the EU average. This share had already reached 64% in 2019 in the Czech Republic; the EU average was 60%.

The results of the research conducted among 351 respondents in the Czech Republic show how young people (mean = 20.5) use the internet to shop for goods and services to satisfy their needs, what devices they use for shopping online – whether they use a smartphone, desk computer, laptop, tablet, virtual reality or television and what factors influence them the most. Tab. 2 shows how often young people shop online and what devices they use.

As Tab. 2 shows, a smartphone and laptop are the most common devices used for shopping, followed by a desk computer. The use of a tablet, television, and virtual reality for shopping is almost negligible. For example, television had never been used by more than 90% of respondents. Information about ownership of the given devices is used as information for marketers. Almost all own a smartphone and laptop. About 70% of respondents own a television but do not use it for shopping. Over 40% own a desk computer, just as a tablet. Almost 90% do not own, have no access, and also do not consider using virtual reality for shopping.

The χ^2 test with the subsequent p-value of 0.00000 confirmed the dependence between Shopping Frequencies of smartphone and laptop devices. This is a medium dependence because the Gamma correlation coefficient has a value of $\gamma = 0.547$ and Spearman's $r_{\mathrm{Sp}} = 0.451$. The test, therefore, confirmed that those who shop frequently on the smartphone buy less frequently shop on the laptop and vice versa.

Tab. 2: Shopping frequency and preferred online shopping devices

	Smartphone	Desktop computer	Laptop	Tablet	Virtual reality	Television
Weekly	64	8	30	7	1	9
Monthly	129	38	149	16	2	4
Quarterly	63	36	86	16	0	2
Less than quarterly	45	19	58	5	1	2
I have not shopped as yet	25	23	13	70	43	244
I have none	1	197	16	217	295	76

Tab. 3: Preferred method of shopping in the given product categories

	Brick & mortar stores	Online shopping	Online selection: shopping in brick and mortar store	Selection in store: online shopping	I do not shop for this category
Food	324	13	7	0	6
Clothes	161	118	54	17	0
Cosmetics	170	63	35	21	60
Fashion accessories	121	114	23	14	75
Consumer electronics	67	201	50	28	3
Ready meals	197	113	25	9	0
Furniture	162	48	60	22	58
Kitchen accessories	168	66	30	8	77
Toys	95	67	12	5	169
Gift items	113	168	33	9	0
Sex toys	22	114	10	6	197

The results show that purchases made by phone are more common on a monthly basis. In contrast, a desk computer is more commonly used for shopping with a yearly frequency. It is evident from the relationship between the weekly and monthly use of a device that the choice prevails of the same devices and the monthly purchases are more frequent (in all device categories except television). Those devices used most frequently in a month (smartphone, laptop) are used less often for shopping on a quarterly or annual basis. In contrast, devices such as desk computers are used less often in a week and more frequently on a quarterly and annual basis. The conclusive dependence with almost 100% likelihood between shopping frequency and preferred device used for shopping can be affected not only by the acquisition price of the device but also by the financial volume of the given product or service.

Tab. 3 shows what method of shopping respondents prefer in a given category of products, whether online or in brick and mortar stores, and what preferences in the (choice × purchase) link respondents choose.

It is evident from Tab. 3 that for most observed categories of products, i.e. brick and mortar stores prevail in the purchase of food, ready meals, cosmetics, fashion accessories, clothes, furniture, kitchen accessories, and toys. Only online purchases prevail of consumer electronics, gift items, and sex toys.

Information can be interesting to brick and mortar store retailers that for all products the order prevails of firstly making a selection online and then making the purchase in a brick and mortar store. This approach appears to be logical since the selection made online means a lot of the time obtaining initial information and considering making a purchase. The procedure of viewing in store and purchasing online was not used for any product. The research did not confirm the common worry of brick and mortar store retailers that a customer would try the

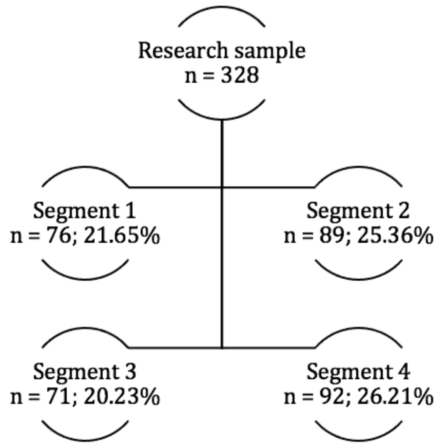

Fig. 2: Size of the arisen segments, calculation in IBM SPSS Statistics

product in store and then purchase it for less money online.

The cluster analysis was applied to customer segmentation which allows the better targeting of an offer for a group of customers with similar product and service requirements and similar shopping behaviour. The application of the cluster analysis method using the K-means algorithm resulted in the creation of four segments of similar online shopping behaviour. We can see the size of the segments in Fig. 2.

Segment 1 (economically decisive from a city) includes 76 cases (21.65%). These are men and women – students living in cities with a population of 100,000 and more. If an e-shop offers registration, they prefer not to register and instead fill in data again when making the next purchase. But if an e-shop offers some benefit during the first purchase, such as a discount arising from registration then they prefer to register. If an e-shop has its own app from which access is possible, they prefer not to download it and instead prefer to use a web browser. They also think that advertising cannot affect their opinion of a product and allow their emotions to influence their purchase. They do not actively use goods price comparison websites but search for the lowest price of a given product online themselves.

Segment 2 (emotively decisive) includes 89 respondents (25.36%). These are mostly women students living in smaller municipalities (population of 10,000–19,000). If the e-shop offers registration, they prefer to register so they do not have to fill in data again when making the next purchase. Equally, they like to register if the first purchase offers some benefit. These women like to enter an e-shop from a web browser and from an app. Before purchasing a product from an e-shop they read the reviews about the given product. For them a discount is more a guide for the purchase. They also believe that advertising may influence their opinion of a product and when making the purchase they prefer to be influenced by their emotions. They prefer searching the internet for the product with the lowest price and do not use price comparison websites.

Segment 3 (rationally thinking from a town) includes 71 respondents (20.23%). These are men and women, students who live in towns (population of 10,000–19,000). If the e-shop offers registration, these consumers prefer to register so they do not have to fill in data again when making the next purchase. If the e-shop has its own app they prefer not to use it and enter the e-shop from a web browser. Before purchasing a product they will certainly read the reviews. For them a discount is a guide for the purchase. Advertising may influence their opinion of a product, but they do not let emotions influence them. On the internet, they will certainly be searching for the product with the lowest price and will also use price comparison websites.

Segment 4 (economically active) includes 92 cases (26.21%). These are mostly men who work for 40 hours a week and more. These men usually do not register with an e-shop. But if the registration offers some benefit, such as a discount, they will prefer to register. If the e-shop has its own app, they will prefer not to use it and will enter the e-shop from a web browser. Before purchasing a product they prefer to read the reviews and a discount can be a guide to the purchase. Advertising may influence their opinion of a product. But they prefer not to be influenced by emotions. They search the internet for the product with the lowest price and use goods price comparison websites.

5 DISCUSSION

Sabou et al. (2017) state that if the consumer wants to shop online, he needs a device allowing him to shop. The conducted research shows that young people do not use a desk computer to a great extent and instead shop using a smartphone or a laptop. They also do not own relatively technologically new devices such as a tablet or virtual reality.

The study of Kopřivová and Bauerová (2021) identified using a mobile phone by Millennials as one of four behavioural characteristics of consumer behaviour in the Czech market. Even though the respondents of our research were not strictly the generation of Millennials (part of the respondents can be considered Millennials) this study confirms the results of Kopřivová and Bauerová (2021). The smartphone plays an important role in the shopping behaviour of younger people and this must be considered when marketing strategies are created. This study confirmed that frequently the actual purchase is made using smartphones.

The conducted research shows that the most commonly sold categories of products are consumer electronics, gift items, clothes, and fashion accessories. If in the questionnaire construction the clothes and fashion accessories categories were to be combined, then they would be the most common. In such a case, we would reach the same conclusions as stated by Czech e-commerce (2021). According to Czech e-commerce, the food category is in third place in terms of the most frequently purchased products online. Our research shows that the respondents purchase food as the least of all the product categories. This may be influenced by the fact that the respondents are usually young people aged 19–26, who typically make smaller purchases according to their current needs. The most frequently purchased category according to the questionnaire construction is consumer electronics which does not correspond to the data from Czech e-commerce, which states that consumer electronics accounts for only 5% of online purchases. The described situation may be caused by the Covid-19 pandemic and its developmental stages. The second factor may again be the age of the respondents who purchase consumer electronics on a greater scale than the older generation.

Cluster analysis is a commonly used method for consumer segmentation, although there are not many of them. The cluster analysis has made it possible to divide the consumers into segments according to the selected factors of the online shopping behaviour of young people, similar to research (Ladhari et al., 2019), where segments were formed within the young generation Y in Canada and the United States: (1) price shoppers; (2) discovery shoppers; (3) emotional shoppers; (4) strategic shoppers; (5) fashionistas; (6) shopping fans.

It is clear from this analysis that in all segments the consumers search for the product with the lowest price however the segments can be differentiated by the different reactions to shopping stimuli or the influence of the situation factors. Two segments of consumers do not like to register with e-shops, but if there is some benefit offered by registration, such as a discount, usually they all register, and this leads to the recommendation for e-shops – to offer a reward for registration such as in the form of further purchase. According to cluster analysis, a study by Daryanti and Simanjuntak (2016) of 232 respondents in Indonesia divided internet users into four groups: (1) savvy users; (2) loyal users; (3) value users, and (4) traditional users.

In one segment where there are more women, it turned out that emotions play a role during a purchase. This segment partially corresponds to the segment defined by Ladhari et al. (2019) – emotional shoppers. In this segment, unlike all the others, it also turned out that if the e-shop has an app, they download it. So if the e-shop selects a target group of young emotively decisive women – there is the potential here of investing in the development of an e-shop app. Consumers from all segments prefer to enter from a web browser – so it is important to be particular during the operation of e-shops about the technical solution, user-friendliness (UX) – so that making a purchase from the web browser is as convenient as possible. The differences in the technical solution of different browsers should be taken into account.

In all the segments it turned out that the younger consumers read reviews before making a purchase. So it is important for the e-shop to monitor what reviews appear about their e-shops on the internet and address this if some negative ones appear. It is also good to have reviews posted directly on the given e-shop.

Goods price comparison websites are actively used by only one segment – rationally thinking. The segment of price sensitives consumers was created also in the study of Jayawardhena et al. (2007). This study conducted in the United Kingdom on 151 respondents identified five distinct purchase orientations: (1) active shoppers; (2) price sensitives; (3) discerning shoppers; (4) brand loyals; and (5) convenience-oriented. This information is important for creating online marketing communication. This is despite the fact that the data published by the Heureka Group (2021) shows that Heureka.cz, i.e. the biggest Czech price comparison website, has 4.6 million users a month and the average age of shoppers via this price comparison website is 25–34 years.

6 CONCLUSIONS

It is clear from the secondary data obtained that the Czech e-commerce market is growing and is bigger than is the European Union average. Czech consumers shop online more often when compared to the EU average. Eurostat data are only available until 2019, before the first wave of the Covid-19 pandemic. It can therefore be expected that after the first wave and others there was a rapid increase percentage of individuals that shopped online.

The primary research showed that the most commonly used device for online shopping among the younger generation is the mobile phone. In addition, the frequency of mobile phone use for online purchases has been shown to be dependent on the frequency of laptop use for online purchases. The p-value obtained by the χ^2 test confirms this relationship. Correlation coefficients (Spearman, Gamma) indicate a moderate dependence. It is clear from the data that laptops and phones are very often used by young people for shopping. Surprisingly, young people usually don't even own a desktop computer anymore.

Using cluster analysis, four segments of young consumers were created based on the factors that define their consumer behaviour on the Internet. These segments were named according to their typical consumer characteristics: economically decisive from a city, emotively decisive, rationally thinking from a town and economically active.

In all segments, consumers access the Internet from a web browser on computers (laptops and desktops) and from the phone. E-shops have to watch what their store looks like on different devices that have different screen sizes. Young emotionally decisive women access online stores not only from web browsers but also from applications, which is why there is room for e-shops to invest in development. Reviews are very important because young people read them and they can have a final impact on the decision on which e-shop to buy from.

7 ACKNOWLEDGEMENT

This paper is the result of a research project supported by the grant of the Grant Agency IGA Faculty of Business and Economics, MENDELU No. PEF_DP_2021017.

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MACROECONOMIC DETERMINANTS OF INFLATION IN ETHIOPIA: ARDL APPROACH TO COINTEGRATION

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EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Volume 8 Issue 1
ISSN 2694-7161
www.ejobsat.com

ABSTRACT

Maintaining inflation rate at optimal level is among important mechanism of balancing macroeconomic volatility to ensure steady economic growth. This study aims to examine macroeconomic determinants of inflation in Ethiopia. The study employed ARDL model using annual data for period 1981–2020. The ARDL bound test was applied to examine the presence of con-integration between inflation and independent variables. The study also uses augmented Dickey-Fuller and Phillips-Perron unit root tests to check stationarity of the variables. The test result reveals that almost all variables become stationary after the first difference. Accordingly, the result from bound test indicated existence of long run relationship between the dependent variable and explanatory variables entered into the model. The estimated error correction model (ECM) with -0.53 coefficient also confirms the existence of co-integration with high speed of adjustment towards the long run equilibrium. In the long run: real GDP, real effective exchange rate, lending interest rate are positive and significant determinants of inflation whereas broad money supply, real GDP, population growth, gross national saving and previous year imports are found to be the short run drivers of inflation. The finding recommends, among others, measures on reducing real effective exchange rate and utilizing broad money supply in productive economic activities along with supply side should be designed to contain inflation in Ethiopia.

KEY WORDS

ARDL model, bound test, co-integration, ECM, Ethiopia, inflation, macroeconomic determinants

JEL CODES

C01, C19, E31, E00

TOLASA, Samuel, TOLLA WHAKESHUM, Sisay, and TAMIRAT MULATU, Negese. 2022. Macroeconomic Determinants of Inflation in Ethiopia: ARDL Approach to Cointegration. *European Journal of Business Science and Technology,* 8 (1): 96–120. ISSN 2694-7161, DOI 10.11118/ejobsat.2022.004.

1 INTRODUCTION

Achieving macroeconomic stability is among essential mechanisms that help to ensure healthy functioning of an economy. Like other countries do, an important objective of economic policies in Ethiopia is making macroeconomic variables balanced with steady economic growth and maintaining lower inflation. Stability in level of prices is among factors that highly contribute to and determine growth rate of an economy. In their paper, Yesigat Taye and Nandeeswara Rao (2015) state if inflation is not kept at reasonable level, it adversely affects a social welfare and makes domestic economy not to perform efficiently. They further argue that in investment environment of both foreign and domestic investors, it creates uncertainty and destroys the terms of trade in the country by raising the price of domestic goods and services beyond regional and world market price level. Consequently, the domestic trade become uncompetitive in international market. For this reason, reducing inflationary rate is a main concern in any economic policy agenda.

Over the last two decades, Ethiopia's economy has gone through various phases of inflation and economic progress. Since 1981 to 2000 considerable fluctuation in output growth was seen with minimum growth rate −7.2% in 1991, which could be associated with civil war and agricultural supply shock occurred in the year. However, it has been observed that since 2003/04 the country has continuously performed accelerated real GDP growth than the average growth rate achieved by the continent. The maximum economic growth was documented during 2004 and 2011, which are on average 13.6%, 13.2% per annual respectively. Such consistent performance in real GDP growth made the country among economically better performed countries in sub-Saharan Africa. Again in 2008/09, 11.2% annual growth rate was attained though inflation shock was historically highest during the year. According to the study of EEA (Ethiopian Economic Association, 2018), after two years challenges of macroeconomic imbalance which was caused largely by agricultural supply shock, macroeconomic stability was successfully maintained in 2012/13 as observed by declined inflation from double to single digit. Since then the trend indicates persistency of the output growth although the progress was not as fast as the previous path. However, the country is facing several challenges including the soaring price level, which could potentially hinder national reform agendas like the goal of attaining middle-income earner country by 2025 (UNDP, 2014; Bekele, 2017).

The recent high inflationary situation even relative to lower income earner African countries is among macroeconomic instability challenging the Ethiopian economy. The problem could be partly explained by expansionary monetary and fiscal policies and devaluation that followed by unnecessary accrual of foreign exchange reserves. In its country report, IMF (2018) pointed out that since 2015 inflation has moved up above the NBE single-digit objective (8%) even though growths of monetary aggregates were slow. The report also points that upward trending since 2015 could be, to some extent, due to an accommodative monetary stance which was worsened as a result of devaluation, especially in October 2017. The devaluation action was progressively continued until 2019.

The authority, National Bank of Ethiopia (NBE), only began narrowing the monetary stance in 2018 while broader monetary aggregate credit continued to durably increase due to transmission lags until late 2018. In the next year, inflation surged up with annual average rate 20.8%, mainly driven by food price inflation, which in part has been affected by interruptions of logistics networks, decline in average rainfall in selected areas, delays in delivering inputs such as fertilizer to some areas, and higher transportation costs. Nonfood inflation also surpassed 10 percent between 2017 and 2019 (IMF, 2020). Knowing the underlying source of inflation at macro level is therefore very crucial in an attempt to take stability measures.

In other developing countries, several empirical researches were conducted on macroeconomic determinants of inflation in different years. For example, Enu and Havi (2014), Ruzima and Veerachamy (2015), and Lim and Sek (2015) have attempted to discourse the fundamental causes of the price rise at global and national level. In various specific countries, these causes range from long-term economic and demographic trends to short-term problems, like export bans, bad weather, high oil prices and speculation. At global level, economic variables like GDP growth, money supply, oil price, national expenditure and imports of goods and services are among variables most frequently highlighted as influential sources of CPI growth rate.

When we come back to the case of Ethiopia, recently double-digit inflation has become worrisome for policy makers as well as the society as it reflected by it outstrip beyond the threshold identified by some researchers (Bezabeh and Desta, 2014; Mera, 2018; Gashe, 2017 among others). For example, the first researcher studied the optimal level of inflation in Ethiopia around which inflation optimally affects economic growth by applying threshold approach. Analyzing data from 1971–2010, the study then concluded that conducive inflation level for Ethiopia is about 8–10%. The second researcher also explained in his analysis of inflation and economic growth for the period 1991 to 2013, the estimated price level growth rate that supposed to be attractive to the economy is 10%. Hence, any inflation level exceeding the estimated threshold level or the target, may not allow long-term and sustainable economic growth.

Furthermore, number of recent studies such as Jalil and Feridun (2011) or Kahssay (2017), among others, has devoted in identifying the possible macroeconomic sources of inflationary experience in Ethiopia. The main causes of inflation considered in the literature are: growth in money supply, unjustified level of GDP growth, national saving, the spreading overall budget deficit and ways of financing this deficit, and import of goods and services. However, we know less about the effect of population size, measured as population growth rate, on CPI growth in Ethiopia and to the best knowledge of the researchers the influence of this variable has not been empirically considered while the country is among the most populous countries in the continent. Additionally, empirical researches tried to consider real effective exchange rate as one of the important factors influencing growth rate of inflation in Ethiopia, but there is inconsistency in the effects of this variable. Some researchers (Ruzima and Veerachamy, 2015; Kahssay, 2017) claim that exchange rate depreciation negatively affects consumer price index while others (Getachew, 2018; Gashe, 2017) argue in support of positive association between exchange rate and the variable of interest.

In addition, there is a debate among scholars about impacts of real GDP on inflation growth rate. Respecting theoretical correlation of price and output, some researchers such as Bezabeh and Desta (2014) and Denbel et al. (2016) argue for existence of negative causality between real GDP and price level in Ethiopia. Contrarily, other researchers such as Enu and Havi (2014) and Gashe (2017), among others, have found that economic growth stimulates inflation by serving producers as an incentive to produce more outputs. In the recent growth and inflation literatures, the former argument has got strong theoretical influence, advocating price rise can adversely affect growth of the economy through its channel with wage and profit redistribution. Therefore, this inconclusive argument among scholars whether real GDP is positively or negatively linked to inflation is another literature inconsistency that motivated the researchers to conduct the study. Moreover, lack of consensus on factors influencing inflation, which characterized by unpredictability even when considered at quarterly bases of a year, leads to conflicting policy prescription. It is therefore a sound argument that re-identifying those elements behind a rise in price level in the country is paramount important.

This study is significant in the aspect that it tries to carefully identify, after extensive literature reviews, and hypothesizes macroeconomic variables including population size which could play indispensible role in explaining the inflationary situation, but ignored by previous studies. It also applies most reliable and recent approach to estimate the specified model. Thus, it can have significant importance to government policy makers and other stakeholders in pursuit of providing consistent scientific information on the subject in addition to its contribution in adding more knowledge and insights to the subject's literature. The purpose of this study is therefore to examine the macroeconomic determinants of inflation in Ethiopia using updated time series data spanning over 1981 to 2020.

The next sections of the paper are structured as follow: in section two, the most related theoretical and empirical literature reviews are discussed. The next section presents materials and econometric methods used to organize and process the data. The findings from econometric data analysis are presented and discussed in section four and five respectively. Finally, concluding remarks and policy implications are forwarded in the last section.

2 LITERATURE REVIEW

2.1 Theoretical Literature Review on Inflation

This section briefly discusses an overview of some theoretical backgrounds about inflation. As there are many theories formulated on the macroeconomic problem in different year by different schools of thought, we focus on the most relevant and widely tested theories. Some of them are extension of its preceding school of thoughts' central ideas on causes of inflation while other theories attempt to hypothesis the issue differently. These theories include: Quantity Theory of Money (QTM), the reformulated theory of money (Keynes's version), monetarism theory and structuralism theory. Embedding on their respective proposition on determinant(s) of price growth, the paper also attempts to identify factors contributing to inflation and test the hypothesis in subsequent sections, but in this part we present brief focus points of each theory with their respective hypothesis.

2.1.1 Quantity Theory of Money

The theory essentially gives credit to central bank as key regulator of price level because the huge proportional change in price resulted from monetary expansion. According to the QTM (Quantity Theory of Money), inflation is occurred because of the central bankers' repudiation to control money supply. Hetzel (2007) explains that the theory was later supported, but modified by Friedman (1976), who asserted that a discrepancy in price mostly driven by monetary phenomenon. The quantity equation ($MV = PY$) of Fisher (1911) was the classical theorists' (QTM) fundamental investigation. In this case, P is general price level, Y is real output, V is velocity of money i.e., the average number of times a unit of currency is circulated in a year, and M denotes volume of money supply. The proposition is founded on the assumption of fixed velocity and real output. Under the assumption of flexible wage and price, the theory argues that a change in money supply causes price level to be changed with the same proportion.

2.1.2 Reformulated Quantity Theory of Money

The QTM was later reformed by Keynes which commonly known as reformulated QTM (Keynes's version). The theory states as far as material and human resources' unemployment exist, an increase in level of price resulted from the rise in money supply induces growth of output, income and employment. But, when supply of production inputs are turn into inelastic and full employment is achieved, real inflation will be occurred. Hence, the Keynes's version recommends an intervention when money rises beyond full employment. Nevertheless, effective demand does not respond in the same proportion with quantity of money. Prices also do not change in equal variation in response to changes in effective demand in case the effective demand partially determined by employment and partially by price changes (Klein et al., 2004; Nelson et al., 2007).

Both versions of QTM are however similar after the economy attains its full employment level, recognizing the full impact of money growth on the general price level. The Keynes's version reveals the elasticity of price with respect to any monetary shock be equal to zero in an economy with idle resources. In such economy, according to him, monetary injections would enable to utilize idle resources and rises employment which in turn increase output in a proportion to changing aggregate demand; hence there would be no impact on prices in the short run (Dutt and Skott, 2005). If the elasticity becomes one given the level of output and employment fixed at full capacity, then 'true inflation' occurs as to the Keynes's version. Thus, any monetary growth while the economy is operating at full capacity induces price to be increased in same proportion.

2.1.3 Monetarism Theory

Monetarists are economists who advocate for monetary policy as a powerful tool to stabilize the economy than fiscal policy, especially price. According them, expansion of money supply beyond the growth of real output causes inflation. For this reason, they state "inflation is always and everywhere a monetary phenomenon that arises from a more rapid expansion in the quantity of money than in total output." (Jalil and Feridun, 2011). As to the explanation of Friedman and Schwartz (1963), price is dominantly (not exclusively) determined by money supply both in short run and long run, but money supply only affects output in short run. Hence, central bank should pursue growth rate of money to optimize economic growth which also maintain price growth fairly at safe level for both consumers and producers.

2.1.4 Structuralism Theory

According to the structuralism economists, inflation is attributed to structure of the developing countries' economy. For them, the industrial sector is more responsive to economic policies than agricultural sector. For example, Baumol (1967) used the coexistence of segmented sectors: a progressive (industrial) sector and a traditional (agricultural) sector to show the link between inflation and income distribution. He argues that growth in aggregate demand results from rising output and employment of the industrial sector in the short run. This increases wages in the industrial sector and consequently the wage increment induces demand for goods, including price of agricultural products (food). The rise in agricultural prices will increase wages of the sector to be raised too. It in turn increases demand for industrial products. This cycle of income distributional conflict pushes prices continuously.

Kalecki (1963) also suggests a related but provides slightly a different explanation based on an economy producing two types of goods (necessities and non-essentials) to explain the inherent distributional conflict that derives inflation. He argues that if national income grows at a rate faster than warranted by supply of necessities, price of necessities will rise. He also states equilibrium condition will be restored if real income of the vast proportion of the population is fallen. Further, structuralists argue the level of competition and section of society who owned large share of national income is another hidden source of inflation especially for countries with high investment (Jalil and Feridun, 2011). Therefore, structuralists hypothesize real income and the way national income shared among the society determines inflationary condition.

2.2 Empirical Literature Review

This section discusses the empirical evidences from Ethiopia and rest of the World. It includes selected most relevant and recently done empirical papers from all over the globe. Even if some of them were done using cross country data, most of these studies employ time series data. Variables incorporated in to their respective model were based on the context of that particular country's source of inflation.

Iya and Aminu (2014) studied "An Empirical Analysis of the Determinants of Inflation in the case of Nigeria" on the data spanning over 1980 to 2012 using OLS estimation method. This study also uses the Granger causality test in order to examine causation between inflation and its hypothesized determinants: money supply, exchange rate, government expenditure, and interest rate. Furthermore, co-integration and vector error correction techniques were applied to examine the long run and short run association between price level and the independent variables. The outcomes from Johansen co-integration test reveals existence of long run relationship between inflation and the variables under consideration. As pointed by the authors, there is positive and significant relationship between money supply and interest rate, and inflation but, exchange rate and government expenditure have negative influence on it. In line with their finding, the forwarded policy implication by the researchers is in fact appropriate that the economy's good performance in terms of price stability can be attained by bringing money supply down and interest rate, and also improving exchange rate and government expenditure in context of the country is vital to ensure macroeconomic stabilization.

An empirical study was undertaken by Lim and Sek (2015) on high and low inflation countries with their paper entitled "An Examination on the Determinants of Inflation studied factors causing inflation in high inflation and low inflation countries" using annual panel data from 1970 to 2011. To test the short run and long run influence of the explanatory variables on inflation, an Error Correction Model (ECM) was employed based on the Autoregressive Distributed Lag (ARDL) modelling. Accordingly, GDP growth and imports of goods and services have been found to have significant long run effect on inflation in low inflation countries. Further, results from ECM show that money supply, GDP growth, and national expenditure have been determining trends of price level in high inflation countries in long run. This study also indicates that money supply has positive influence on price growth while GDP growth and imports of goods and services have negative and significant impact on price level of low inflation countries.

Using time series data for the period from 1970 to 2013, Ruzima and Veerachamy (2015) have examined determinants of inflation in Rwanda by employing ordinary least square regression estimation method. This paper aimed at investigating the influence of import of goods and services, government spending, population growth, agricultural output and foreign direct investment on inflation. According to their finding, the major determinants of inflation in Rwanda are agriculture output and import of goods and services.

Uncommon to recent studies except a study conducted by Enu and Havi (2014), this paper examines the impact of population growth impact on inflation, and their investigation reveals statistically significant and negative link of this variable with inflation. However, the influence of government spending and foreign direct investment on inflation is observed to have insignificant negative and positive effect on the variable of interest, respectively.

By their investigation on macroeconomic factors that have been deriving inflation in Ghana during the period 1990 to 2009, Gyebi and Boafo (2013) found that real output, real exchange rate and money supply were the strongest factors behind the rising price level in the country. According to this study, the depreciation of exchange rate and ERP (Economic Recovery Program) implementation played an important role in dropping the raising price level in Ghana, witnessing that the program achieved its aim of bringing down inflationary trend in the country. Unfortunately, we criticize this paper on two grounds. The included variables were very limited in number. It simply tested structural and monetarist theory in the context of Ghana neglecting other supply side important variables like agricultural output, foreign direct investment and export of goods and services. The econometric model used, on the other hand, is not rigorous and extensive enough to predict the short run and long run determinants of inflation in Ghana. Whether these variables were co-integrated or not is not checked using appropriate analysis.

Applying co-integration approach, Enu and Havi (2014) investigated on macroeconomic factors affecting inflation in Ghana which aimed at examining whether foreign direct investment, population growth, foreign aid, agricultural and service's output have significantly impacted the inflationary experience in the country over 1964 to 2008 years. According to them, all included variables were found to be have stationary property and integrated of first order one, i.e.

$I(1)$. The result from Johansen co-integration test and VEC (Vector of Error Correction) estimation reveals the existence of both long run and short run relationship among the variables. The main identified long run determinants of inflation in Ghana are: foreign direct investment, population growth, service's output and foreign aid. Unlike those previously conducted investigations on the subject matter, the study's inclusion of macroeconomic variables like population growth and service's output makes it peculiar.

Using co-integration analyses, Loua et al. (2018) scrutinized the factors that have contributed to growth of price level in Republic of Guinea, for the time series data spanning from 1990 to 2015. The study aimed to investigate whether gross domestic per capita, money supply, and exchange rate have significantly influenced the inflationary experience for the duration of the mentioned period. Accordingly, money supply and exchange rate positively and significantly affected inflation. The effect of GDP per capita, on the other hand, is found to be negative and significant on price level. Johansson's co-integration test result also shows the existence a long-run and short-run link between inflation, gross domestic product per capita money supply, and exchange rate in Guinea.

Furrukh et al. (2016) analysed demand and supply side factors causing inflation in Pakistan using time series data spanning over 1972 to 2014. This study uses autoregressive and distributed lag (ARDL) model to examine long run and short run impact of variables. The identified demand side causes of inflation are: roads, population, and government expenditure whereas supply side inflation factors are: government revenue, imports, external debt and electricity generation. According to the finding, demand side variables: population, government expenditure, roads have significantly affected inflation. On the other hand, imports, electricity generation, government revenue, and external debt are the supply side factors which have found to have significant influence on inflation in Pakistan. In this rigorous analysis of price dynamism, variables like government expenditure, roads, imports, government revenue and external debt are the long run causes of inflation. In addition, in the long run, a negative association between price level and foreign direct investment, electricity generation and population is witnessed by result of the investigation.

Gofere (2013) studied source of price dynamics in Ethiopia by combining equation of weighted price with expected price level equation using OLS model and annual data spanning over 1971–2014. Real GDP, nominal average deposit interest rate, average exchange rate, fiscal deficit, international petroleum price index and Bain's monopoly mark-up index were employed. The outcome of his study showed that monetary and fiscal fundamentals are important determinants of price dynamics in the short run. But in the long run, real GDP is the most essential variable though weak relationship between inflation and foreign prices is detected by the investigation. In fact, some studies confirm both conclusions.

Bedada et al. (2020) investigated determinants of inflationary experience in Ethiopia using time series data from the period 1974/75 to 2014/15. This study used Johansen Cointegration methodology and Vector Error Correction approach with two lag length, in order to examine long run and short run macroeconomic variables. They used macroeconomic variable such as broad money supply, real effective exchange rate, overall budget balance and real gross domestic product as explanatory variables and consumer price index as dependent variable. Accordingly, the study's finding revealed, in long run, money supply, real gross domestic product and overall budget deficit have positive and statistically significant impact on Consumer's Price Index (CPI). In short run, budget deficit in the preceding year is the only variable dedicated in explaining current year consumer price index. This study also recommended suitable policy implication, emphasizing on the long run influence of money supply growth and budget deficit in pacing up inflationary situation in Ethiopia. Nevertheless, we criticize the study for it incorporated only limited number of variables in to the specified model. It would have been more sensible if important variables in affecting inflation like national saving and agricultural output were included.

Kahssay (2017) also examined determinants of Inflation in Ethiopia using the ordinary least square method. And the data obtained span from 1975 to 2014. In the study, consumer price index treated as dependent variable, while: broad money supply, gross domestic product, credit facility, exports of goods and services, imports of goods and services and gross national saving included as explanatory variables. To check the existence of a short-run and long-run association between inflation and its determinants, the author employed co-integration test.

The empirical analysis resulted from error correction and co-integration reveals that GDP is the only variable that positively and significantly affects inflation both in the short and long-run. According to him, 98 percent of variation of inflation during the study period was explained by GDP. In addition, broad money supply, and gross national saving and import of goods and services have been found to have significant positive and negative impact on consumer price index respectively. Here is a suggested recommendation by the study; "... broad money supply is to be controlled and gross national saving is to be encouraged to reduce inflation in the country". Although the suggested implication is appropriate according to the investigation outcome, it gives more credit to GDP as principal explaining variable which contradicts with other papers done on the same area.

Finally, we conclude by summarizing the most recent paper result undertaken by Abate (2020). The study aimed mainly at identifying and examining macroeconomic determinants of inflation in Ethiopia using annual data spanning over 1985 to 2018. The author identified economic variables influencing inflationary situation during the study period by specifying both long run and short run version of the OLS econometric model. The researcher found that, both in long run and short run, real interest rate and real effective exchange rate are significant determinants of inflation during the study time. On the other hand, broad money supply affects inflation only in the long run while gross domestic saving found to have insignificant impact on price growth both in the short run and long run. The study, however, excludes important variables which considered by other researchers such as real GDP. Thus, the conclusion and recommendation forwarded by the researcher may not be reliable in case key variables are not considered.

To sum up, the number of papers done on the macroeconomic determinants in Ethiopia is limited and those existing researches mostly devoted to examine the influence of GPD growth, money supply, import and export of goods and services and budget deficit on CPI though they come up with different conclusion. The difference in their finding is attributed to dissimilarity of number of hypothesized determinants and combination of the explanatory variables included in their respective model specification. This lack of consensus on factors that cause inflation, which characterized by unpredictability even when considered at quarterly bases of a year, leads to conflicting policy prescription. Therefore, it is sound argument that re-identifying those elements behind a rise in price level in the country is paramount important.

3 MATERIALS AND METHODS

3.1 Source and Method of Data Collection

The research entirely applies secondary data. The data were extracted from published and unpublished materials, and databases of concerned institutions and organizations. The data for both dependent variable (CPI) and independent variables: real GDP, broad money supply, lending interest rate, gross national saving, population size, real effective exchange rate and import of goods and services were collected from domestic institution namely National Bank of Ethiopia (NBE), and internationally, World Bank and IMF's database websites were accessed. Specifically, data on variables like real GDP, broad money supply, gross national saving and import of goods and services were taken from world development indicator database website of World Bank whereas data on consumer price index (CPI), real effective exchange rate and lending interest rate were received from National Bank of Ethiopia (NBE) in document. Population size data were obtained from online database of World Economic Outlook (WEO) of the IMF.

3.2 Method of Data Analysis

For the purpose of data analysis, the study employed inferential method of data analysis. The bound test of ARDL model of time series econometric method of data analysis was employed to examine the long run and short run relationship between macroeconomic variables and inflation.

In econometric procedures, first unit root test was conducted to check for the stationarity of the time series model using Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test. The co-integration test was applied using ARDL bound co-integration approach to examine whether the variables have long run relationship. Co-integration test serves as a bridge whether to specify both long run and short run model or the latter alone. If bound test of co-integration leads to conclude the presence of long run relationship between the variables, both models should be estimated. The coefficients of long run model are estimated from level form of the variables without differencing, but short run model (ECM) is derived from the ARDL model by transforming the equation in to the re-parameterized form. The long run information will not be lost in case coefficient of error correction term captures evidence of the relationship through its speed of adjustment interpretation. However, short run version of the ARDL model is specified if the bound test does not indicate the existence of long run relationship (Nkoro and Uko, 2016).

3.3 Model Specification

3.3.1 ARDL Model

The study employed autoregressive distributive lag (ARDL) model of 'Bounds Testing Approach' to co-integration which was developed by Pesaran et al. (2001). The model is selected based on the theoretically defined relationship between dependent and independent variables and finite nature of the selected sample size. Given the endogenous variable, the ARDL approach of co-integration testing procedure specifically helps us to know whether the underlying variables in the model are co-integrated or not. Besides, the model is relatively efficient when the sample size is small or finite which is suitable to the chosen sample size.

In addition, the researchers selected ARDL procedure of co-integration method because of its several advantages. Firstly, the procedure can be applied whether the regressors are $I(1)$ or $I(0)$ or combination of both. Secondly, the ARDL model is statistically a stronger approach in determining the co-integration relationship between variables when sample size is small, but other techniques like VAR models require large data samples for validity. Thirdly, the ARDL procedure does not restrict variables to have the same optimal lags as other models do. Moreover, endogeneity is less of a problem in this approach since each of the underlying variable stands as a single equation. Fourth, the ARDL procedure can distinguish dependent and explanatory variables when there is a single long run relationship that only a single reduced form of equation is assumed in the model (Pesaran et al., 2001). The final and an important advantage of ARDL model is that the Error Correction Model (ECM) can be derived from ARDL model through a simple linear transformation, which integrates short run adjustments with long run equilibrium without losing long run information. To capture the data generating process from general to specific modelling frameworks, the related ECM model takes an adequate number of lags (Nkoro and Aham, 2016).

The general form of ARDL model is specified as follow:

$$y_t = \alpha_{0i} + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{j=0}^{q} \beta_j X_{t-j} + \epsilon_{it}, \quad (1)$$

where y_t is rate of inflation (INF); α_{0i} is the constant, $i = 1, 2, \ldots, k$; X_t is a vector of explanatory variables; γ_i are coefficients of dependent variable lags; β_j are coefficients of independent variables and their corresponding lags; p and q are number of lags of the dependent variable and vector of explanatory variables respectively, and ϵ_t is uncorrelated error term with zero mean. All variables are expressed in logarithm excluding lending interest rate and dummy variable and data on each variable shall be annual. The fact that interest rate by itself has percentage interpretation; it does not require expressing it logarithmically. By extending the above general equation, the long run ARDL model can be specified to examine the relationship between various explanatory variables and inflation growth rate. Specifically, we run the following long run regression equation.

$$\begin{aligned} \mathrm{LCPI}_t = \alpha_0 &+ \sum_{i=1}^{p} \gamma_{1i} \, \mathrm{LCPI}_{t-i} + \quad (2) \\ &+ \sum_{j=0}^{q_1} \beta_{1j} \, \mathrm{LBMS}_{t-j} + \\ &+ \sum_{j=0}^{q_2} \beta_{2j} \, \mathrm{LRGDP}_{t-j} + \\ &+ \sum_{j=0}^{q_3} \beta_{3j} \, \mathrm{LREER}_{t-j} + \\ &+ \sum_{j=0}^{q_4} \beta_{4j} \, \mathrm{LPOP}_{t-j} + \\ &+ \sum_{j=0}^{q_5} \beta_{5j} \, \mathrm{IR}_{t-j} + \\ &+ \sum_{j=0}^{q_6} \beta_{6j} \, \mathrm{IM}_{t-j} + \\ &+ \sum_{j=0}^{q_7} \beta_{7j} \, \mathrm{LGNS}_{t-j} + \\ &+ \beta_8 \, \mathrm{DUM} + \beta_9 \, T + \epsilon_{it} \end{aligned}$$

By denoting p and q_i, we are allowing explanatory variables to have different lag orders, where $i = 1, 2, \ldots, k$, and T denotes trend. For the purpose of lag choice (p, q_1, q_2, q_3, q_4, q_5, q_6, q_7), the Akaike Information Criterion (AIC) was used given its well-known property of consistent model selection in finite-dimensional models (Shao, 1997).

3.3.2 Description of the Variables

Consumer Price Index (CPI): it measures changes in the prices of basket of goods and services that households consume. Such changes have an effect on the real purchasing power of consumers' income and thereby affect the society's welfare. When prices of different goods and services vary by different rate, a price index can only reflect their average movement. A price index is usually given a value of unity, or 100, in some reference period and the values of the index for other periods of time are intended to show the average proportionate or percentage change in prices from price reference period (Fitsum et al., 2016). In the study, the annual average of CPI for each year was used.

CPI in logarithm form is used as a proxy to inflation growth rate in the study because it has advantages over GDP deflator by measuring the price level of all goods and services that domestic consumers buy. Unlike the GDP deflator which does not include changes in the price of imported goods, CPI incorporates all imported goods and also represents a proportion of all domestically produced goods and services because it exclusively focuses on consumer goods. Since Ethiopia imports considerable amount products from abroad, using GDP deflator to measure percentage changes in price level can underestimate the cost of living. Therefore, CPI is more suitable when consumers' cost of living is desired to be measured (Zeder, 2018).

Money supply (BMS): Broad money (M_2) is a measure of the domestic money supply which includes M_1 plus Quasi-money (savings and time deposits), overnight repurchase agreements, and personal balances in money market accounts. Mostly, M_2 includes money that can be quickly converted to M_1 (Mishkin, 2009). Money supply is linked with inflation through financial resources and instruments used by monetary policy. Inflation is occurred if central banks cease regulating financial intermediaries to maintain legislative liquidity requirement of time and deposits. Inflation also gets accelerated when central bank decreases interest rate or purchases the prevailing government bonds (Sbhatu, 2010). Thus, positive relationship between the BMS and CPI growth is expected. The NBE takes the broader definition of money or M_2 as money supply and also in the study this definition was used in United States' Dollar (USD) unit.

Real Gross Domestic Product (RGDP): it is an aggregate measure of the size of an economy adjusted for price changes. Real GDP inflation mainly related to inflation through capital accumulation and progress in the efficiency of factor of production. Feldstein (1996) argues that return on capital could be reduced under complete expectation of rise in inflation, provided that the taxation system of many industrialized countries remains neutral. Moreover, uncertainty in inflation dampens foreign investor's attraction and also reduces confidence on the future monetary policy. Real GDP can also be associated with inflation through its factors such as investment on research and development (R&D) and hence human capital (Jones et al., 1993). Therefore, negative relationship between real output and inflation is expected even though there is controversy among the scholars on link between the two variables.

Population size (POP): Lebreton et al. (1992) defines population size as "range of the number of individuals present in a subjectively designated geographic". In case of this study, however, logarithmic form of population size expresses it as population growth rate. Both supply and demand side cause of inflation could be driven by population growth. Accelerated population growth can cause inflation by enhancing aggregate demand and housing market instrumental variable; this explains why inflation is persistently insubstantial in some places where population size is low (Ozimek and Förster, 2017).

Real Effective Exchange Rate (REER): is the weighted average of a country's currency in relation to an index or basket of other major currencies. The weights are determined by comparing relative trade balance of a country's currency against other countries' currency within the index. The variable is expressed in terms of ratio of national currency (ETB) to United States' dollar. Under flexible exchange rate regime of open economy, it is most likely that depreciation in exchange rates influence the price of imported goods, aggravating consumer and producer price indexes to be driven up (Şen et al., 2019). Thus, positive relationship between real effective exchange rate and growth CPI is expected.

Lending interest rate (IR): Interest rate is a worth gained from an asset or wealth either invested or saved. Semuel and Nurina (2015) suggest that both demand and supply side of an economy can be affected by interest rate. Moreover, they argue that returns on wealth, financial assets as well as money can affect the overall price level as it acts as an incentive to save or lend. Based on the Fisher's hypothesis, Ayub et al. (2014) argue that interest rate is negatively correlated with inflation. Therefore, this study hypothesises that there is negative relationship between lending interest rate and inflation.

Imports (IM): is the monetary value of foreign goods and/or services that are produced abroad, but bought by firms, households, organizations and government agencies of a country in a certain period of time. They include payments for visible and invisible imports. Visible imports comprise final products, oil products, finished and semi-finished components, whereas invisible imports include payments for financial services, tourist expenditure from abroad and organizational services.

Theoretically, imports of goods and services exert pressure on inflation through exchange rate and purchasing power parity channels. According to Houck (1979) explanation, inflation can be reduced by maintaining yearly exchange rate at lower level which overvalues currency of the country. Overvaluation in turn raises imports and discourages exports. On the other hand, domestic price can be influenced by altering purchasing power parity of the country's currency. Policy makers can either overvalue currency of their own country by spending foreign exchange assets to purchase the domestic currency or devalue it by purchas-

Tab. 1: Summary of variables' description

Variable	Description	Unit of measurement	Expected relationship
CPI	Consumers Price Index	Price index	Dependent variable
BMS	Broad Money Supply	Millions of USD	+
RGDP	Real Gross Domestic Product	Millions of USD	–
REER	Real Effective Exchange Rate	ETB per USD	+
IM	Import of Goods and Services	Millions of USD	+
POP	Population Size	Millions	+
IR	Lending Interest Rate	In percent	–
GNS	Gross National Saving	Millions of USD	–

ing foreign exchange and thereby lower price of their own currency. Therefore, relationship between import and CPI as a proxy to inflation is usually positive in theory (Islam, 2013).

Gross national saving (GNS): Domestic national saving measures the amount of income saved by: households, businesses and government of a country during a given quarter, semi annual or a year. Fundamentally, it is calculated as the difference between national income and consumption. It also measures status of a nation's financial health because it is saving that generates investment (Mesfin, 2016). According to the hypothesis of standard life-cycle model, the single way through which inflation is affected by domestic saving is real interest rate. Higher level of interest rate encourages the people to save more and vice versa. However, based on Keynes's "Theory of liquidity preference" and Friedman's "Modern quantity theory of money", Abou El-Seoud (2014) argues that there are more two ways in which inflation and saving are related to each other. As to the first theory, inflation can create doubt about the future earning streams and hence consumers may save more for cautionary purpose. But for Friedman, inflation could be correlated with saving through its effect on real wealth. Saving can reinforce inflation if consumers seek to hold certain level of liquid assets or wealth relative to their income. Hence, we can reasonably consider the variable as additional explanatory variable. Nonetheless, negative correlation between gross national saving and inflation is expected in either of the two hypotheses.

Dummy variable: It is a formed variable which serves as a proxy for the effect of changed policy from socialism to market-based economy that happened in 1991. Since policy change has an impact on overall performance of an economy in general and price level in particular, it would be vital to capture if there were shocks in inflation rate resulted from such government action. In Ethiopia, policy shift from command economy to market-oriented economy was undertaken immediately after the Ethiopian People Democratic Republic Front (EPDRF) came to power during the aforementioned year. As price and wage flexibility is inevitable in market-based economy, we expect the general price level to be raised as a result of the policy change. From the sample period 1981–2020, the years between 1991 and 2020 take artificial number one (1), and zero (0) otherwise in order to take the phenomenon in to account.

4 RESULTS

4.1 Lag Length Selection

Prior to undertaking unit root tests and estimating the underlying model, maximum lags length must be determined at early stage. Because the estimation results are highly sensitive to lag length of variables, the optimum number of lags needs to be selected before conducting other tests or estimations. These lag numbers are selected by information criterions:

Tab. 2: Lag order selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	184.2475	NA	1.28E−15	−8.749869	−7.97417	−8.47388
1	402.6830	310.409	1.08E−18	−15.98331	−11.7169*	−14.4654
2	516.3241	107.66*	4.78E−19*	−17.70127*	−9.94428	−14.9414*

Note: * indicates lag order selected by the criterion

Likelihood Ration (LR), Akaike Information Criterion (AIC), Schwartz-Bayesian Information Criterion (SC), Final prediction error (FPE), and Hannan-Quinn information criterion (HQIC). These criterions automatically select the maximum lag length of variables to be incorporated in to the specified model, but they may not necessarily give the same result due to their applicability in different sample sizes. For example, AIC and FPE are appropriate for small sample sizes (60 or less) while SC and HQIC better perform for large (greater than 60) sample sizes (Liew, 2004). This study therefore uses AIC due to its better performance comparing to other information criterions when relatively small sample size is applied, i.e., $n < 60$ observations. The Tab. 2 shows the computed result using EViews 10.

From the Tab. 2, the asterisks (*) mark the maximum lag length automatically selected by the criterions. Accordingly, all criterions except SC indicated that the optimum lag length that minimizes their corresponding values is two. However, we should note that it does not necessarily mean each variable has two lag lengths. It rather shows the maximum lengths above which lag(s) should not be included. Thus, it is possible for some variables to be lagged lower than the automatically determined. For example, when each of them tested individually, dummy variable and logarithmic form of other variables – CPI, RGDP, POP and REER – have one maximum lag length while the rest explanatory variables have two.

4.2 Unit Root Test

Lag length determination is followed by conducting stationarity test. It is a pre-requisite for co-integration test of the time series data because estimation without undertaking unit root test may lead to spurious result. This test is also essential to make sure that all variables are integrated of order zero or one so that the method ARDL bound test will not be hindered. The Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit root testing methods were employed for this purpose. In ADF test, the Akaike information criterion (AIC) was selected because the lag length of the time series was determined based on this criterion due to its good performance in small finite sample size. Besides, Newey-West bandwidth automatically selects lag for Phillips-Perron (PP) unit root test. The Tab. 3 summarizes the stationary test results from both methods.

The ADF and Phillips-Perron (PP) unit root tests results reveal that all variables interred into the model are non-stationary at level except logarithm of population size (LPOP), which is stationary under PP unit root test with intercept at 5 percent level of significance. From ADF test, we can observe that at least at 5 percent level of significance all variables, except logarithm of import of goods and services (LIM), become stationary after first difference in both intercept and intercept & trend cases. However, we find the differenced LIM is stationary with intercept & trend only. Similar outcome is found from Philips-Perron (PP), but logarithm of broad money supply (LBMS) is the exceptional in this case. First differenced LBMS is stationary at 5 percent without trend while first differenced version of all other variables is stationary at 1 percent level of significance in both intercept and intercept & trend cases. In general, the results of ADF and PP stationarity test provide similar outcome that almost all included variables are $I(1)$, i.e., integrated order one. Having this guarantee from unit root test, we can reasonably estimate the underlying model.

Tab. 3: Augmented Dickey-Fuller and Phillips-Perron Unit Root Tests

Series	At level Intercept	At level Intercept & trend	At first difference Intercept	At first difference Intercept & trend
ADF test				
LCPI	1.591	−0.882	−5.342***	−5.775***
LBMS	−0.317	−3.161	−3.956***	−3.883**
LGNS	1.027	−1.028	−6.393***	−6.685***
LIM	0.265	−1.512	−2.195**	−8.914***
LIR	−2.58*	−2.926	−4.333***	−4.258***
LPOP	−1.673	−0.989	−6.265***	−6.768***
LREER	−1.746	−1.685	−6.351***	−6.335***
LRGDP	2.384	−1.412	−4.945***	−5.212***
DUM	−0.978	−3.000	−8.599***	−8.638***
Philips-Perron test				
LCPI	1.661	−0.884	−5.352***	−5.775***
LBMS	−0.574	−2.01	−2.906**	−2.820**
LGNS	0.615	−1.833	−8.204***	−9.120***
LIM	−0.011	−1.811	−8.398***	−8.409***
LIR	−1.478	−2.183	−4.374***	−4.302***
LPOP	−3.027**	−0.608	−6.273***	−8.775***
LREER	−1.746	−1.685	−6.452***	−6.620***
LRGDP	2.437	−1.397	−5.034***	−5.855***
DUM	−1.716	−2.975	−9.197***	−12.880***

Source: compiled by the authors based on the result of EViews 10 computation, 2021.
Note: The values represent t-statistics of the ADF (upper panel) and PP (lower panel) unit root tests. The asterisks ***, ** and * denote statistical significance of the test at 1, 5 and 10 percent level of significance respectively.

4.3 ARDL Model Estimation Results

The study employs autoregressive distributive lag (ARDL) model. The model applies 'Bounds Testing Approach' to co-integration which was developed by Pesaran et al. (2001). Prior to estimation the optimum lag length was chosen using Akaike information criterion (AIC). Accordingly, dependent and independent variables take one and two lag orders respectively. Then, the ARDL parameters' estimates are estimated. Tab. 4 reports the parameters' estimates of the regression with CPI (a proxy variable to inflation) as the dependent variable and BMS, RGDP, POP, REER, IM, GNS, IR and dummy variable (DUM) as independent variables. All variables were expressed in logarithm except IR and DUM. The chosen lag structures by the AIC for the above variables are $[p, q_1, q_2, \ldots, q_8]$ $= [1, 2, 1, 1, 0, 2, 2, 0, 1]$ respectively. All coefficients have the expected sign except LRGDP, LIM and IR. Even though the sign of LIM coefficient contradicts the theory, the ARDL regression result sows that the variable is statistically insignificant.

Coming up with such outcome may not be associated to the technique or model employed. Neither had it occurred due to endogeneity effect because such challenge is less problematic in ARDL approach since each of the underlying variable stands as a single equation. Even when the same data are regressed using VAR and Granger causality techniques, no change in sign of these variables is observed. Hence, endogeneity problem is less suspected to affect direction of these variables' impact on dependent variable. Rather we believe that contradiction of the sign to the prior hypothesis has empirical implication about the economy.

Tab. 4: ARDL model estimation result

Variable	**Coefficient**	**Std. error**	***t*-statistic**	**Prob.***
LCPI (−1)	0.465652***	0.162450	2.866431	0.0103
LBMS	0.576537**	0.249709	2.308830	0.0330
LBMS (−1)	−0.522915**	0.236330	−2.212649	0.0401
LBMS (−2)	0.326507**	0.158004	2.066451	0.0535
LRGDP	0.379384	0.289846	1.308917	0.2070
LRGDP (−1)	1.176211***	0.290012	4.055728	0.0007
LPOP	0.91631***	1.966616	4.659326	0.0002
LPOP (−1)	−4.247535*	2.207937	−1.923757	0.0703
LREER	0.369465***	0.131393	2.811915	0.0115
LIM	0.021306	0.075753	0.281255	0.7817
LIM (−1)	0.069397	0.085437	0.812262	0.4273
LIM (−2)	−0.324808***	0.093507	−3.473619	0.0027
LGNS	−0.091353	0.055260	−1.653159	0.1156
LGNS (−1)	−0.116179**	0.053728	−2.162344	0.0443
LGNS (−2)	−0.126656**	0.055563	−2.279512	0.0350
IR	0.035321***	0.012575	2.808793	0.0116
DUM	−0.050070	0.050676	−0.988054	0.3362
DUM (−1)	−0.087986**	0.040938	−2.149265	0.0455
C	−33.91097***	9.045080	−3.749106	0.0015
@TREND	−0.160352**	0.069876	−2.294798	0.0340

Source: own computation using EViews 10, 2021.
Notes: Sample period used for estimation is 1981–2020. The asterisks ***, ** and * mark statistical significance of coefficients at, 1, 5 and 10 percent level of significance respectively.

The economic intuition why coefficients of these variables come out in opposite of the prior expectation was reflected in discussion part.

From Tab. 4 we can infer that the first lag of CPI is significant at 1 percent, implying considerable effect of previous year price aggregates on the current year general price level. All coefficients of LBMS (current level, first and second lags) are also significant at five percent significance level. Both current and lagged coefficients of RGDP are positive, but coefficient of the first lag is statistically significant only. In addition, variables selected without lags such as LPOP, REER and IR are highly significant too and they all positively associated to consumer price index. Nevertheless, the result displays insignificance of current year coefficients of LIM and LGNS, but both first and second lag of LGNS are statistically significant at 5 percent while import of goods and services is significant only at second lag. Finally, we can note that the model has constant and trend as reflected by their statistical significance at 1 and 5 percent level of significance respectively. The next subsection presents statistical reliability checks of the model.

4.4 Post Estimation Diagnostics and Stability Tests

The post estimation tests are required to check reliability of the estimated result. The most commonly used tests in dynamic models are: normality, autocorrelation, heteroscedasticity, and model specification and stability tests. Such tests are undertaken to guarantee regression of the model that the obtained results are free from spurious regression. Moreover, they warrant robustness of the model.

As we can see from Tab. 5, the model passes all post estimation diagnostic tests. The Breusch-Godfrey Lagrange Multiplier autocor-

Tab. 5: Summary of diagnostics tests

Types of tests	F-statistics	DF	Prob.	Prob. Chi-Square
Breusch-Godfrey test	1.32	$F(2,16)$	0.29	0.068
Heteroscedasticity (BPG)	0.88	$F(19,18)$	0.60	0.5021
Heteroscedasticity (ARCH)	0.65	$F(2,33)$	0.52	0.50
Normality test (JB-statistics)	0.26		0.87	
Ramsey RESET Test	1.002	$F(1,17)$	0.33	
Durbin-Watson test	2.24 (d-stat)			

Source: Compiled from diagnostics tests after ARDL model estimation using EViews 10, 2021

relation test fails to reject null hypothesis of no residual autocorrelation at 5% level of significance. In addition, Durbin-Watson d-statistics lies between 1.7 and 2.3, which supports the evidence from Breusch-Godfrey LM test. The d-statistics also confirms non-spuriousness of the regression since its value exceeds the adjusted R-squared. To check heteroscedasticity problem the conducted Breusch-Pagan-Godfrey test conveys that both standard (0.60) and Chi-squared probability (0.50) values are greater than 5% level of significance. This result leads to accept null hypothesis stating homoscedastic nature of the error variance. At $F(2,33)$ degrees of freedom, both standard (0.52) and Chi-squared (0.50) probabilities of ARCH test supports robustness of the result from Breusch-Pagan-Godfrey test. Hence, the result supports for absence of heteroscedasticity problem.

Furthermore, the above summary table on diagnostic tests confirms normality of the residuals and correct specification of the model. JB statistics (0.26) is much higher than the standard level of significance (0.05), and probability of obtaining this value is 0.87. Since the residuals are normally distributed, we can claim that hypotheses of the coefficients' estimates are validly tested. Besides, the model specification test checked by Ramsey RESET test shows absence of omitted variable(s) because the RESET test p-value (0.33) highly exceeds the standard significance level. Therefore, these evidences lead us to conclude that the model is correctly specified and the result is robust as well.

Model stability test: The most commonly used to test stability of a model are cumulative sum of recursive (CUSUM) test and CUSUM of squares test. The tests are based on the residuals from recursive estimates and presented by Fig. 1.

Null hypothesis H_0: CUSUM distribution is symmetrically centred at 0.

Alternative hypothesis H_1: CUSUM is not symmetrically distributed.

Decision rule: The null hypothesis of normal distribution is failed to be rejected when the graph of CUSUM statistics lies within the bounds of the critical region at 5% level of significance and the alternative hypothesis is accepted otherwise.

From Fig. 1, we fail to reject null hypothesis that cumulative sum of squares of recursive (CUSUM) is symmetrically distributed at 5% level of significance. At the same level of significance, the CUSUM test also confirms similar result, supporting robust stability of the model[1]. Since the model passed all diagnostic and stability tests, we can proceed to examine co-integration test.

4.5 Co-Integration Test and the ARDL Long Run Model

After running the ARDL model, co-integration test is required to identify whether to specify both long run and short run models or the latter alone. To check presence of co-integration in ARDL model, Pesaran et al. (2001) developed the bound test which later improved by

[1]Non-squared version of CUSUM statistics stability test which supports CUSUM of squares result is not included here to avoid redundancy. Its graph is available up on request of the reader.

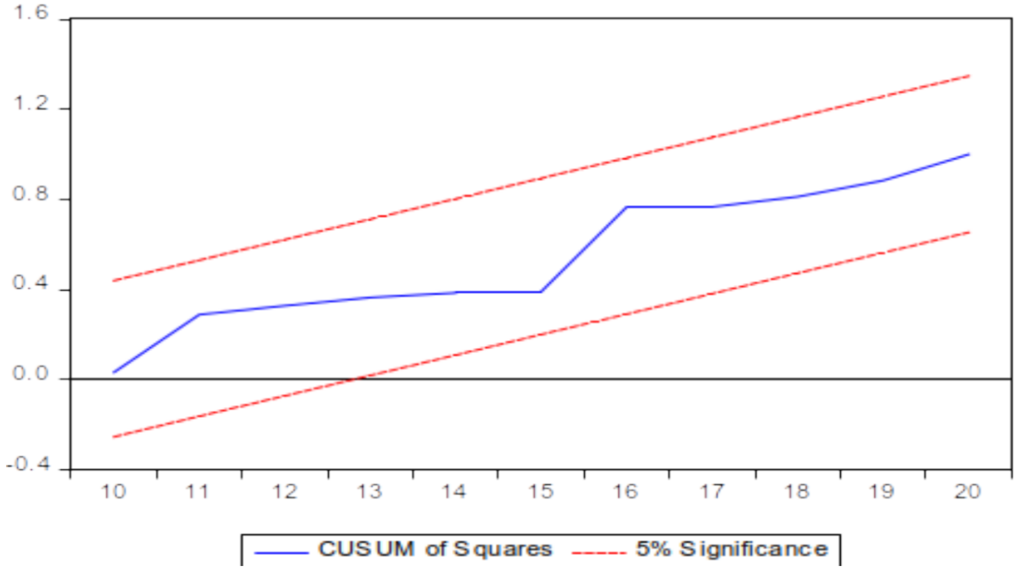

Fig. 1: CUSUM of Squares
Source: Model diagnostics test result using EView 10, 2021.

Narayan (2005) for small sample sizes. Having lower and upper values, the bound test depends on F-statistics. The value of F-statistics is computed using Wald-test from null hypothesis by making long run coefficients equal to zero. If the computed F-statistics lies below the lower bound, the null hypothesis of no co-integration will be failed to be rejected. Contrarily, if the value is greater than the upper bound of the statistics, the null hypothesis of no co-integration is rejected in conclusion of existence of long run relationship. Tab. 6 presents result from the bound test.

Tab. 6: ARDL Bound test for long run relationship

Test statistic	**Value**	**Level of significance**	$I(0)$	$I(1)$
F-statistic	12.70766	10%	2.13	3.09
K	8	5%	2.38	3.41
		2.5%	2.62	3.7
		1%	2.93	4.06

Notes: F-Bounds Test, null hypothesis: no levels relationship. Asymptotic: $n = 1000$.
Source: own computation using EViews 10, 2021.

F-statistics from Tab. 6 reveals that the F-value (12.71) exceeds the values of upper bound at all levels of significance. Therefore, we can reject the null hypothesis of no level relationship in favour of alternative hypothesis, supporting for the existence of co-integration. This evidence robustly confirms the presence of long run relationship between dependent and right hand variables. Hence, long run and short run models can be reasonably estimated. The estimated parameters' estimates of long run equation of the model are presented by Tab. 7.

Tab. 7 presents long-run result of ARDL model with inflation (CPI) as dependent variable whereas the rest variables: broad money supply (LBMS), real gross domestic product (LRGDP), population size (LPOP), real effective exchange rate (LREER), imports of goods and services (LIM), gross national saving (LGNS), lending interest rate (IR) and dummy variable (DUM) are explanatory variables. As indicated in the preceding section, all variables are expressed in logarithm form except lending interest rate and dummy variable. IR entered in to data processing as it is because the variable itself reported on database in percentage. The last variable (DUM) takes one (1) artificial number for the policy change since 1991 to 2020 and series years before the liberalization (1981 to 1990) take zero (0). Thus, we do not need to express the last two variables in logarithm form. Overall, the incorporated regressors explained the model by 99.7 percent of variation. The long

Tab. 7: The long run ARDL parameter estimates

Variables	Coefficient	Standard error	t-statistic	p-value
LBMS	0.711389	0.514510	1.382655	0.1837
LRGDP	2.911203***	1.047708	2.778641	0.0124
LPOP	0.9199189*	4.691364	1.960877	0.0656
LREER	0.691431***	0.220760	3.132053	0.0058
LIM	−0.438113*	0.214664	−2.040930	0.0562
LGNS	−0.625414*	0.346957	−1.802568	0.0882
IR	0.066100***	0.022061	2.996206	0.0077
DUM	0.258364**	0.111119	2.325117	0.0320
@TREND	−0.300090*	0.169558	−1.769839	0.0937

Sources: own computation using EViews 10, 2021.
Note: The dependent variable is CPI over the sample period 1981–2020. The asterisks ***, ** and * mark statistical significance of coefficients at, 1, 5 and 10 percent level of significance, respectively.

run equation form of the inflation model can mathematically be specified as:

$$\begin{aligned}\mathrm{LCPI} = {} & -0.3 + 0.7\,\mathrm{LBMS} + 2.91\,\mathrm{RGDP} + \\ & + 0.92\,\mathrm{POP} + 0.69\,\mathrm{LREER} - \\ & - 0.44\,\mathrm{LIM} - 0.63\,\mathrm{LGNS} + \\ & + 0.07\,\mathrm{IR} + 0.26\,\mathrm{DUM},\end{aligned} \tag{3}$$

where −1.77, 1.38, 2.77, 1.96, 3.13, −2.04, −1.8, 2.99 and 2.33 are t-values of the corresponding coefficients.

In this section, we describe each variable in terms of sign and statistical significance, but explanations of interpretations and relative findings are left for the discussion part. In long run, broad money supply (LBMS) is not statistically significant, but coefficients of real gross domestic product (RGDP), real effective exchange rate (LREER) and interest rate (IR) are positive and found to be highly significant at 1% level of significance. In addition, import of goods and services (LIM) and dummy variable coefficients are significant at 5%; however, each variable has inverse and direct association with growth of consumer price index (CPI), respectively. On the other hand, variables such as: population size (LPOP), gross national saving (LGNS) and time trend (T) are weakly significant (at 10 percent), but population coefficient is positive while coefficients of the latter variables are negative. Short run relationship of these variables with the dependent variable is examined in the next section.

4.6 The Short Run ARDL Model Estimation Result

Estimating an error correction model would be imperative once the presence of long-run relationship between the variables is confirmed by co-integration test. The re-parameterized short-run relationship between inflation and macroeconomic variables was scrutinized with the Error Correction Model (ECM). From the regression output, we find out that one year lagged coefficient of ECT is negative, and it is also statistically significant. Further, the coefficient (−0.53) lies between 0 and −1 as expected, indicating monotonic convergence of the error correction toward the equilibrium. It implies almost more than 50 percent of the short run dynamics get adjusted toward the long run equilibrium. Tab. 8 reports regression result obtained from ARDL error correction model.

Result from error correction model (ECM) in table 8 shows that except imports of goods and services (DLIM), all variables are statistically significant although their statistical significance varies. At 1% level of significance, macroeconomic variables like growth of broad money supply and its one-year lag, population size, one year lagged of both gross national saving and imports are found to be statistically significant in short run. On the other hand, real GDP and gross national saving are statistically significant at 5%, but the dummy variable found to be significant only at 10 percent. Regarding direction of these variables' effect on inflation coefficients

Tab. 8: ECM Regression

Variable	Coefficient	Std. error	t-Statistic	Prob.
C	−34.07132***	2.464803	−13.82314	0.0000
D(LBMS)	0.576537***	0.090086	6.399814	0.0000
D(LBMS (−1))	−0.326507***	0.087660	−3.724684	0.0016
D(LRGDP)	0.379384**	0.160539	2.363199	0.0296
D(LPOP)	0.91631***	1.262939	7.255380	0.0000
D(LIM)	0.021306	0.047122	0.452149	0.6566
D(LIM (−1))	0.324808***	0.054228	5.989696	0.0000
D(LGNS)	−0.091353**	0.033298	−2.743513	0.0134
D(LGNS (−1))	0.126656***	0.029487	4.295372	0.0004
D(DUM)	−0.050070*	0.029156	−1.717352	0.1031
Coint. Eq. (−1)	−0.534348***	0.038703	−13.80634	0.0000
R-squared = 0.909402		F-statistic = 27.10205		Prob. (F-statistic) = 0.000000
Adjusted R-squared = 0.87584				Durbin-Watson statistics = 2.246313

Sources: own computation using EViews 10, 2021.
Note: The dependent variable is DCPI over the sample period 1981–2020. The asterisks ***, ** and * mark statistical significance of coefficients at, 1, 5 and 10 percent level of significance, respectively.

of one year lagged broad money supply, gross national saving and the dummy show their negative correlation with inflation while the remaining variables have positive association with the variable of interest. Overall, short run regressors jointly explained the variation of the regressand variable by 87%, as signified by the ECM adjusted coefficient of determination.

5 DISCUSSION

Broad money supply (LBMS): As expected, each coefficient estimates of short run and long run found to be positive, but the long run is insignificant. Nevertheless, the ECM version of ARDL model reveals that both current and one year lagged growth of broad money supply has strong impact on inflationary situation in Ethiopia. Estimate of the short run elasticity of money supply is 0.58. It can be inferred as; other things remain the same, one-unit percentage increase in money supply leads to raise inflation growth by about 0.58%. This finding is consistent with empirical studies conducted in Ethiopia such as Gebremeskel (2020) and Kahssay (2017), who suggested that monetary growth is instantly inflationary phenomenon without any long run adjustment toward the equilibrium. Further, the finding partially supports the QTM and monetarist view, but contradicts the reformulated QTM (Keynes's Version) theory, which claims no effect of money expansion on general price level prior to attainment of full employment.

Real gross domestic product (RGDP): The result from both short run and long run dynamics suggests positive and significant effect of real output on aggregated price growth in Ethiopia. The coefficients of long run and short run are 2.91 and 0.37 respectively. In the long run, percentage change impact of real GDP exceeds a unit elasticity ($e > 1$), implying strong association between the variable with price dynamics in Ethiopia. This can be interpreted as: ceteris paribus, a percentage change in long run real output causes the consumer price index to be changed by 2.91 percentages. In opposite to the prior expectation, the direction of correlation between output sector and inflation suggested to be positive. In fact, sign of the coefficient is one of the study's gaps of inconsistency, which aimed to examine the literature contradiction on the effect of this variable. This finding is not limited to the current study, because researchers such as Gashe (2017) have come up with similar conclusion.

Justification of the positive effect of real GDP on inflation could be explained on grounds of following reasons. During the past two decades, Ethiopia's economy has experienced the fastest growth performance with double digits growth rate in some years. At the same time significant prices evolution and volatilities have been observed. Better real GDP performance could be due to increase in relative share of industrial and service sector along with their productivity improvement, enhancement in factor accumulation and factor productivity, and considerable growth in infrastructural development. More specifically, the positive association of real GDP growth with inflation can be reasoned in three ways. Firstly, by reducing households' propensities to save, moderate price increase can induce growth. Similarly, when price of products rises, the nominal rates of return on capital relative to the cost could be increased and thereby reallocate profit share of firms through rising propensity to save and invest. Secondly, price growth could redistribute money volume from money holders to the central authority which commonly known as inflation tax. The reallocated money can serve the government to initiate new investment or expand the existing one and therefore enhance output growth. The third one is that substantial improvement of total investment as a share of real GDP was observed since 2004 when inflation begun to hike. Thus, the positive link between inflation and real GDP can be explained through households' propensity to save, redistribution of money holdings in the economic system and the improved share of investment.

Population size (LPOP): In short run, this variable found to be highly significant at 1% level of significance and its sign is positive as expected. Other things remain the constant, the elasticity coefficient (0.92) implies that a percentage increase in population size leads inflation rate to be grown by 0.92 percentages. The elasticity is almost the same in the long run case, but its weakly affects price growth. The result suggests the importance of population size in explaining inflationary situation in Ethiopia. The role of this variable has not been explicitly considered in previously conducted researchers, which makes the current study peculiar. Nevertheless, studies conducted in developing countries such as Ghana, Pakistan and Rwanda by Enu and Havi (2014); Furrukh et al. (2016), and Ruzima and Veerachamy (2015) respectively, revealed importance of population growth in explaining inflation in context of these countries though its impact in relation to direction and time dimension is different. This study implies the effect of population on price increase is robust in short run than the long run. Therefore, population size is among short run drivers of price growth in Ethiopia.

Real effective exchange rate (LREER): As theoretically expected, the result from long run model shows that coefficient of real effective exchange rate is positive and highly significant too. The coefficient shows, in long run, effective exchange rate induces 0.69 percent of inflation, other things remain the same. This finding could be due to the influence of progressive currency devaluation undertaken in Ethiopia since 1992. It also supports the conclusions drawn by IMF (2020) and Abate (2020). During the study period therefore exchange rate has been important long run sources inflation in Ethiopia.

Imports of goods and services (LIM): The short run re-parameterized current year coefficient of import is insignificant, but one year lagged coefficient of import is highly significant and also positively affects the growth of consumer price index. A percent increase in previous year import causes inflation to be grown by 0.32 percent, holding other things constant. This result is consistent with the finding got by Kahssay (2017). Unexpected according to theoretical hypothesis, its long run coefficient is negative and statistically significant at 10%, showing that import of goods and services is less important in driving long run price dynamics in Ethiopia.

Gross national saving (LGNS): In short run, both the current year gross national saving and its one year lagged coefficients show significant influence of the variable on consumer price index. Keeping other things constant, a unit increase in percentage of gross national saving reduces consumers price index by 0.066 percent, while its previous year accumulation encourages variable of interest by 0.13 percent, indicating stronger effect of national saving inertial than its current year influence. In long run process, a percent rise in gross national saving diminishes consumer price index by 0.63 percent, other thing remains the same. Nevertheless, the long run statistical significance is weak (at 10 percent level of significance), which reveals strength of national saving in determining short run inflation growth than in the long run process. This finding highly supports econometric evidences found from Ethiopia by Gashe (2017) and Kahssay (2017). Generally, we can conclude that gross national saving is among significant determinants of inflation both short run and long run model though it is statistically weak in the latter case.

Lending interest rate (IR): In contrast to theoretical expectation (based on the Monetarists hypothesis), an increase in the lending interest rate by a percent induces consumer price index by 0.07 percent, other things remain constant. This finding suggests positive relationship between lending interest rate and growth of price level though the magnitude is too small. Thus, it would be vital to conclude that Monetarist theory (see Friedman and Schwartz, 1963), of interest rate do not work in the context of Ethiopian economy. Yet, the finding supports the works of Haile and Megerssa (2020), in argument for less effectiveness of interest rate in affecting inflation in the long run. As to their explanation, the rise of demand for non-financial assets and future expectation of inflation by the public due to past experience of money growth and inflation are among the provided justifications. Low financial development and less inclusiveness of financial system in the country may also moderately elucidate the less importance of the monetary instrument to contain inflation.

Dummy variable: It is a created variable to capture effect of changed policy from socialism to liberal capitalism occurred during 1991/92. The result shows that in the long run, the price policy during the market based economic system has positively affected inflation rate with 0.26 percent contribution. However, effect of the policy change is weak in short run both in magnitude (−0.05) and statistical significance (10%). This may lead us to conclude that the impact of change in price policy undertaken when Ethiopian People Democratic Republic Front (EPDRF) seized power is not forgotten, and it is stronger in long run than short run process.

6 CONCLUSIONS AND POLICY IMPLICATIONS

6.1 Conclusions

Even though historically inflationary situation in Ethiopia is relatively low with exceptional years of shocks resulted from drought and civil war, recently inflation has been persistently growing with double digit in contrary to the NBE single digit target. As a developing country, although sustainable economic growth is expected to be accompanied by justifiable inflation rate, the trend for Ethiopia indicates outstrip of the phenomenon beyond the threshold that favourable to functioning of the economy. Various theoretical and empirical literatures, which were conducted mostly in developing countries including Ethiopia, have been reviewed. Most of the empirical papers devoted to consider monetary instrumental variables such as money supply, interest rate and effective exchange rate, while fiscal instruments: GDP, government expenditure and budget deficit were deliberated as source of price growth. However, the impact of population size was not yet explicitly scrutinized even though the country's population number being grown is clear to cause inflationary tendency especially through the demand side. In addition, the inconsistency in the direction of impact of

RGDP and effective exchange rate on inflation growth is also another aspect that motivated the researchers.

Focusing on the reality of controversy in the literature on the effect of these two variables and influence of population size, the study aimed to empirically examine macroeconomic determinants of inflation in Ethiopia using time series database spanning over the years 1981 to 2020. To realize the objective, the ARDL Bound test, which was employed to check whether con-integration exist between the inflation proxy variable and the right-hand side variables included by the model. Then both long run and short run (ECM) version of the model were regressed after checking all diagnostic tests. The bound test of co-integration shows the existence of long run relationship between the dependent and independent variables. Additionally, the empirical result reveals that in the long run: real GDP, real effective exchange rate and lending interest rate are found to be dominant determinants of inflationary situation in Ethiopia. All of these variables positively affected CPI rate. The magnitude of real output elasticity is greater than a unit, whereas effective exchange rate and interest rate are considered to have moderate and weak effect on the variable of interest, respectively. Broad money supply has insignificant role in stimulating price in the long run.

In support of recent empirical researches, it would be important to note that the growth of RGDP has a leading role in influencing long run inflation in Ethiopia. Therefore, this finding is in a position of supporting positive effect of real GDP on inflationary growth in the context of Ethiopia. The slight effect of interest rate may have resulted from underdevelopment and low inclusiveness of financial sector in Ethiopia. On the other hand, the speed of error correction measure obtained from ECM indicated the existence of fast adjustment of the disequilibrium toward long run equilibrium. It implies almost more than 50% of the error annually gets adjusted to achieve the equilibrium. Furthermore, from the ECM result the main determinants: one year lagged and current year coefficients of gross national saving and broad money supply, current real GDP and current population size found to be important factors driving the price dynamic in short run. RGDP is the only variable affected general price growth both in short run and long run. Besides, imports have only inertial effect on short run inflation dynamic. Relative to other macroeconomic variables, elasticity of population size found to have greater effect on short run dynamics of price growth, which may reflect high influence of population size in pushing up the consumer price index. Hence, the implication of this finding is either the amount of aggregate demand force of the public has grown beyond the production level or supply side has not grown to meet the prevailing demand.

6.2 Policy Implications

Based on the obtained results this research forwards the following policy implications. The current finding stresses the importance of real effective exchange rate in driving long run inflation in Ethiopia. It is believed that devaluation promotes import substitution and encourages export by making the domestic goods cheaper at international markets than domestic markets. In Ethiopia, enormous capital, intermediate and consumer's goods are imported because of limited supply of industrial manufacturing capacity to satisfy the domestic demands. Since exports' share of GDP is very low relative to imports, persistently devaluating the domestic currency leads not only to inflation but also exhaust foreign exchange reserves because of inelastic nature of imports to devaluation in Ethiopia.

Thus, rather than relying on birr devaluation to encourage export, the next two alternatives could mitigate the inflation problems related to the rising foreign exchange rate. The first one is enhancing export performance through diversifying export items along with their productivity. The second alternative is substituting the imported commodities through establishing new manufacturing industries and expanding the current industrial sectors for commodities that the economy largely accesses by importing them from foreign trade partners. If stable and optimum exchange rate is combined with above two measures, essential capital goods will be imported relatively with cheap cost which in turn helps to build import substitution industries.

In short run dynamics, broad money supply found to be dominant sources of inflation rate in Ethiopia, partly in support of monetarist view. This implies either reducing money supply through tight monetary policy or directing the increased money supply in to productive development infrastructures can play a role in controlling persistent price growth. Since the main reason behind soaring general price is food inflation, consumers who earn fixed income are the primary victim of the phenomenon because price hike deteriorates purchasing power of their income. This situation in turn reduces propensity to save and thereby to invest, discouraging sustainable economic growth. Thus, the government ought to respond by utilizing the circulating money on productive investment by supplementing it with flexible wage.

Population size also found to have high effect on consumer price index growth primarily in the short run. This could be through stimulating demand for commodities. One of the measures taken to make supply side balance with the growing demand which arose from the pressure of high population number is boosting production capacity of the government as well as creating conducive environment to the private producers. If tight monetary policy is opted to curb price rise, again it should be integrated with supply-side policy because it adversely affects economic growth. As the major component of general inflation comes from food price, government expenditure should be target to enhance production and supply of food related items. In addition, applying fixed price policy on basic materials and food items can have significant role in price stabilization.

Finally, the study revealed positive association between real GDP and inflation. This finding does not imply that the rising inflation in Ethiopia is favourable for output growth because the country's economy has experienced high growth rate especially during the last two decades. Thus, further research needs to be conducted by explicitly identifying supply and demand side models of inflation along with their relative importance and thereby analysing how the growing real output linked with the increasing price level in Ethiopia.

7 ACKNOWLEDGEMENT

The authors would like to extend their gratitude to National Bank of Ethiopia (NBE), World Economic Outlook (WEO) of IMF, World Development Indicators (WDI) of the World Bank (WB) and Jimma University staffs for the secondary data and unreserved support they provided to successful accomplishment of the study.

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Journal information

- ISSN 2336-6494 (Print)
- ISSN 2694-7161 (Online)
- Online submission, open access, double blind referred
- Free of charge submission and no publication fees
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