ЕКОНОМИКА ЭЕ
ISSN 0350-137X, EISSN 2334-9190, UDK 338 (497,1)

Vol. 68, january-march 2022, № 1
P. 57-79

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ORIGINAL SCIENTIFIC ARTICLE
DOI: 10.5937/ekonomika2201057E
Received: October 10. 2021.
Accepted: December, 11. 2021.

EFFECTS OF FINANCIAL INCLUSION TO GDP GROWTH – THE CASE OF NORTH MACEDONIA

Abstract

Achieving higher financial inclusion is a target for each government today, committed to build an economy where everyone has easily accessible financial services, leading to higher economic growth. The aim of this paper is examining the relationship between financial inclusion, measured through a selected set of quantitative indicators (encompassing the penetration, availability and usage dimensions) as independent variables, and the economic growth, measured through the GDP per capita, as dependent variable. The research model applied was the multivariate regression model performed through the Ordinary least squares (OLS) method. The data sample consists of several financial inclusion indicators for North Macedonia and GDP per capita for the period 2007-2019. Findings revealed valuable information for the future strategies, institutional arrangements and measures to strengthen national capacities in function of improving the indicators having significant contribution to GDP growth and achieving higher financial inclusion. Also, findings provided theoretical contribution to the current research database for the specific case of North Macedonia.

Key words: *financial inclusion, GDP growth, regression analysis, North Macedonia*

JEL classification: F3, O16, O4

ЕФЕКТИ ФИНАНСИЈСКОГ УКЉУЧИВАЊА НА РАСТ БДП – СЛУЧАЈ СЕВЕРНЕ МАКЕДОНИЈЕ

Апстракт

Постизање веће финансијске инклузије је циљ сваке владе данас, која је посвећена изградњи економије у којој ће сви имати лако доступне финансијске услуге, што доводи до већег економског раста. Циљ овог рада је испитивање односа између финансијске укључености, мерене кроз одабрани скуп квантитативних индикатора

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(који обухватају димензије пенетрације, доступности и употребе) као независних варијабли, и економског раста, мереног кроз БДП по глави становника, као зависне варијабле. Примењени модел истраживања био је мултиваријантни регресиони модел изведен методом обичних најмањих квадрата (ОЛС). Узорак података се састоји од неколико индикатора финансијске инклузије који су везани за Северну Македонију и њен БДП по глави становника за период од 2007. до 2019. године. Налази су открили вредне информације за будуће стратегије, институционалне аранжмане и мере за јачање националних капацитета у функцији побољшања индикатора који значајно доприносе расту БДП-а и постизања веће финансијске укључености. Такође, налази су дали теоријски допринос актуелној истраживачкој бази података за конкретан случај Северне Македоније.

Кључне речи: *финансијска инклузија, раст БДП-а, регресиона анализа, Северна Македонија*

Introduction

Although we live in an era of advanced opportunities thanks to the various innovations and achievements in the financial services market, still “There are an estimated 1.7 billion adults in the World without access to financial services,” according to the statement of the IMF Managing Director Christine Lagarde. Achieving higher financial inclusion is a target for each government today, devoted to build an economy of equal opportunities for every person for easy and affordable access to the financial services, contributing to broader economic and social progress.

North Macedonia, as part of the global economy sets the higher financial inclusion goal as one of its priorities by establishing legal framework in line with European legislation for financial services, as a first step towards creating environment that fosters digitalization and innovation, opens the market for new players in the field of financial services, altogether leading to higher financial inclusiveness resulting in higher economic growth.

The aim of this paper is examining the relationship between financial inclusion, measured through a selected set of quantitative indicators (encompassing the penetration, availability and usage dimensions) as independent variables, and the economic growth, measured through the GDP per capita, as dependent variable, through a multiple regression analysis. The hypothesis of this research is that the financial inclusion positively affects GDP growth in North Macedonia.

Findings revealed that the variable having strongest positive influence on GDP growth is the “Outstanding deposits with commercial banks (% of GDP) and variable “Number of ATM’s per 100,000 adults” is also positively associated with GDP growth. The variables “Outstanding loans from commercial banks (% of GDP)” and “Credit and Debit Cards” are negatively associated with GDP growth, since increasing the indebtedness could lead to decreasing the GDP growth.

Findings provided significant information for financial inclusion indicators that have highest influence on the GDP growth in North Macedonia, being important signals for the future strategies, institutional arrangements and measures to strengthen national capacities in function of improving the most influent indicators to GDP growth and simultaneously achieving higher financial inclusion.

The remaining part of the research is structured as follows: Chapter 2 reviewed the literature, Chapter 3 introduced the methodology used for achieving the research objective, Chapter 4 presented the results from the multiple regression analysis and Chapter 5 provided the conclusions.

Literature review

Financial inclusion provides opportunities for each person to be included in the economy and creates possibilities to reach their life goals, which was the reason why the World Bank Group – the World Bank and IFC have made focused interventions to enable access to a transaction account for 1 billion people t through the Universal Financial Access 2020 initiative. (World Bank, 2020a)

Financial inclusion has wide benefits for each economy, especially through the means of fintech and digital finance.

Digital finance brings benefits to financial inclusion

Digital financial technology promises to transform the payments landscape through the use of mobile phones, computers or cards which connect all parties in the payments infrastructure.

According to studies' results, mobile money services can help improve people's income earning potential and thus reduce poverty. For example, the case study of Kenya showed many benefits from the use of mobile money services, particularly for women, increasing their savings by more than a fifth; allowed 185,000 women to leave farming and develop business or retail activities; and helped reduce extreme poverty among women-headed households by 22 percent (Suri and William, 2016).

In addition, digital financial services can also help people manage financial risk — by making it easier for them to collect money from friends and relatives in times of financial crisis. The research for Kenya discovered that even in situations of lower income, users of mobile money maintained the level of household spending, which was not the case with nonusers and users with limited access to the mobile money network, having reduction in their purchases by 7–10 percent. (William and Suri, 2014).

Financial services provided digitally can also contribute to reduction of costs of receiving payments. As Aker et al. (2016) determined that for governments, replacing cash with digital payments can lead to higher efficiency and decrease the level of corruption, as the case of India, where the leakage of funds for pension payments dropped by 47 percent when the payments were made through biometric smart cards rather than being handed out in cash. Brune et al. (2016) detected that financial services can also help people accumulate savings and increase spending on necessities, like the case with market vendors in Kenya, primarily women, who increased their savings and their business investments after being provided with savings accounts.

Financial capability and financial resilience

The term 'financial capability' which is closely related to financial inclusion, is introduced in the Report of financial inclusion by HM Treasury&Department for Work and

Pensions (2019), explaining that financial inclusion and capability are essential for providing security for consumers against falling in financial difficulty, where the government should be the main actor in helping vulnerable consumers to reduce their debts and achieve financial stability, through continuous guidance and advice for improved management of their finances, increase the financial literacy, and education for adequate budgeting and saving.

Financial inclusion is a means to achieving financial resilience, meaning that people will better manage financial risks when they are able to save money and have access to credit.,. In this regard, the Global Findex survey (World Bank, 2018) examined respondents for their possibilities to get emergency funds in case of need within the next month, as well as what is their main source of funding in such cases. The results from the Global Findex survey (World Bank, 2018) were that globally, 54 percent of adults answered that they could come up with emergency funds, in high-income economies 73 percent, and in developing economies nearly 50 percent. The access to emergency funds is not dependent solely on the income level in an economy, but also the cultural differences and gender aspects across economies.

Economic and social impact of digital financial inclusion

The process of digitalization is also expected to have higher economic growth, living standards and increase in GDP.

The benefits of digitalization will also contribute to achieving the United Nations development goals 2030 (United Nations, 2018):

- Improvement of health care and education, contributing to improvement in human capital.

Human capital is indispensable tool for achieving economic growth. As explained in the McKinzey (2016) report, human capital is improved by continuous investment in education and health care. Additionally, digital payments contribute to improved services in education and health care.

- Reducing the informal economy.

This report (McKinzey, 2016) points out the importance of digital payments to bigger transparency, which leads to reducing the informal economies. It is noted in the report of McKinzey (2016) that there is a high connection between the presence of cash in an economy and the size of its informal sector. Digital payments can help the governments to improve the tax collection and compliance with labor laws if they establish—competitive policies for regulatory and tax issues and strengthen tax collection authorities. According to the findings of one study, if digital payments increase by an average of 10 percent a year, the informal economy could be reduced by up to 5 percent (Schneider, 2013). Reducing the informal economy has significant economic benefits, because formalizing businesses contributes to higher productivity of the entire economy.(McKinsey & Company, 2004; McKinsey Global Institute, 2006; La Porta and Shleifer, 2008)

- Enhancing liquidity.

With increase in digital payments, more transactions and payments are performed leading to higher liquidity.

- Promoting innovation and new business forms.

As already mentioned, digital payments stimulate emergence of new business models, leading to innovation, and possibilities for creation of new jobs, prompting overall growth.

Figure 1 Digital financial inclusion and UN development goals

Digital financial inclusion directly supports ten of the 17 UN Sustainable Development Goals

Goal	Impact from digital financial inclusion
1. No poverty	▪ Poor people and small businesses are able to invest in their future ▪ More government aid reaches the poor as leakage is reduced
2. Zero hunger	▪ Farmers are better able to invest during planting seasons and smooth consumption between harvests ▪ More food aid reaches the poor as leakage is reduced
3. Good health and well-being	▪ Increased government health spending as leakage is reduced ▪ Financial inclusion for women can increase spending on health care
4. Quality education	▪ Digital payments to teachers reduce leakage and absenteeism ▪ Micro tuition payments increase affordability ▪ Financial inclusion for women can increase spending on education
5. Gender equality	▪ Digital reduces women's physical barriers to gaining an account ▪ Women have more control over their finances and their businesses
7. Affordable and clean energy	▪ Mobile pay-as-you-go schemes create access to clean energy ▪ Better targeted subsidies increase use of renewable energy
8. Decent work and economic growth	▪ Greater pool of savings increases lending capacity ▪ Data history of poor and small businesses reduces lending risks
9. Industry, innovation and infrastructure	▪ Digital finance enables new business models and products ▪ More public and private capacity to invest in infrastructure
10. Reduced inequalities	▪ Financial inclusion gives greatest benefit to very poor people ▪ More government aid available as fraud and theft are reduced
16. Peace, justice and strong communities	▪ Digital records of financial transactions increase transparency and enable better monitoring of corruption and trafficking

SOURCE: UN Sustainable Development Goals; McKinsey Global Institute analysis

Source: Adopted from McKinsey (2016)

Financial exclusion

Opposite to financial inclusion is the term financial exclusion. According to the Findex data of World Bank (2018) all unbanked adults live in the developing world, and nearly half live in just seven developing economies: Bangladesh, China, India, Indonesia, Mexico, Nigeria, and Pakistan.

Main reasons for presence of unbanked population as identified under the Global Findex survey (World Bank, 2018) were the *Gender inequality*, *Poverty*, *Low educational attainment* and *Unemployment.* According to the McKinzey Report (McKinzey&Company, 2016), financial exclusion can also affect the middle class population, besides the poor population, especially valid for emerging economies where limited range of financial services are available unlike developed countries, which could result in utilizing informal financial services being more expensive. Additionally, the Report (McKinzey&Company, 2016), recognized that businesses in emerging economies face the problem of lacking access or having insufficient access to credit, blocking their business development. A heavy reliance on cash creates problems for financial institutions, leading to higher costs per customer due to lower pool of customers they can work with, as presented in data from the McKinzey Report (McKinzey&Company, 2016), showing high reliance of cash by individuals and businesses in emerging economies accounting for more than 90 percent of payment transactions by volume. In addition, according to the presented data of the World Payment Report (Capgemini Research Institute, 2019), dominant share of non-cash transactions is present in advanced countries, namely North America and Europe, while developing economies significantly lag behind in their percentage share and volume of non-cash transactions. Dominant use of cash also is a problem for governments since it creates issues with expenditure coverage and collected tax revenues and enables corruption. (Rogoff, 2016) The results of one study found that as much as one-third of government cash payments can be lost this way (Consultative Group to Assist the Poor, 2015). Finally, cash payments reinforce large informal economies.

When speaking of financial exclusion, it is worth mentioning that besides involuntary financial exclusion that was elaborated above, there are also cases of voluntary financial exclusion, as recognized in the World Bank Policy Research Report, World Bank and IMF (2008), belonging to some categories of wealthy customers or some older categories of individuals or households in advanced economies who don't use financial services. Moreover, voluntary financial exclusion could be due to ethical, cultural or religious reasons. From a policy point of view, the category of voluntary nonusers of financial services is not a problem for an economy.

Research Task and Methodology

The aim of this paper is examining the relationship between financial inclusion, measured through a selected set of quantitative data on indicators (encompassing the penetration, availability and usage dimensions) as independent variables, and the economic growth, measured through the GDP per capita, as dependent variable.

Research design

For examining the correlation between financial inclusion indicators and economic growth, the research model applied was the *Causal research,* more specifically "the cause and effect relationship" elaborated by Saunders et.al (2003). The aim of this research objective is determining the strength of relationship or dependence of the economic growth, (GDP per capita), as dependent variable, from each of the independent variables of financial inclusion influencing positively/or negatively/or having no influence to economic growth. For this purpose, a multiple regression analysis was performed.

The quantitative indicators representing the "financial inclusion" used as independent variables in the regression analysis were selected by taking care to reflect on all aspects of financial inclusion, namely the penetration, availability and usage of the financial services, There is growing literature elaborating the question on how to accurately measure the financial inclusion, where some studies suggested it could be done by measuring the proportion of adults or households possessing a bank account (See, e.g., Honohan, 2008). The disadvantage of this approach is that it measures only one aspect of financial inclusion while ignoring other equally important aspects that should represent one inclusive financial system.

The approach suggested by Sarma (2015) also used by many policy makers involves the use of a several indicators determining different aspects of financial inclusion in terms of penetration, availability and usage dimension, such as: Automated teller machines per 100,000 adults and % of branches of commercial banks per 1,000 km2 which were used as proxies of Access, % of deposit accounts with commercial banks per 1,000 adults were used as proxy of penetration and Outstanding deposits with commercial banks (% of GDP) along with Outstanding loans with commercial banks (% of GDP) were used as proxies of usage, while GDP was used as a proxy of economic growth. This approach was also adopted for the subject research.

The following quantitative indicators as determinants for financial inclusion were applied for our research: 1) Number of commercial bank branches per 100,000 adults and 2) Number of ATMs per 100,000 adults, as proxies of "Access" indicators, 3) Outstanding deposits with commercial banks (% of GDP) and 4) Outstanding loans from commercial banks (% of GDP) as proxies of "Usage" indicators, 5) Number of deposit accounts with commercial banks per 1,000 adults, 6) Number of credit cards per 1,000 adults and 7) Number of debit cards per 1,000 adults, as proxies for "Usage – penetration of financial services" indicators. The GDP, or per capita income, was used as a proxy for "Economic growth", representing the dependent variable in the regression analysis. The selection of this specific set of quantitative indicators acting as the most representative indicators for each dimension of financial inclusion is also in line with the IMF Financial Access Survey (IMF, 2019) also identifying these indicators as "Key FAS indicators". Also, the additional indicators selected in our dataset which are not part of the "Key FAS indicators" - the indicators for number of debit and credit cards per 1,000 adults were also included aiming to examine the influence of the digitalization process in North Macedonia on the economic growth, which is recognized in many research studies as a substantial precondition for increasing financial inclusion and positively affecting the economic growth. The indicators on mobile money which are part of the "Key FAS indicators" were excluded from our dataset since North Macedonia still does not have mobile money services.

As regards selection of the measure for economic growth, there are several measures such as: National income levels, physical capital allocation, Gross Domestic Products (GDP) of the nation etc. GDP measures the value of production of activities that fall within the boundary of the national accounts system. Although the measures for GDP could sometime create uncertainties especially when measuring production by the government sector, however GDP is best suited measure for the total value of the economic resources that affect well-being of one economy. For the purpose of this study, GDP per capita was used as proxy for economic growth.

Data sample

The dataset for which regression analysis was performed consists of the financial inclusion indicators and economic growth for North Macedonia for the period 2007-2019 because of the limited data availability for the full set of financial inclusion indicators for the years preceding 2007. The data source for the financial inclusion indicators were secondary data available from the IMF Financial Access Survey (IMF, 2019), while data source for GDP (per capita) was the World Bank database on GDP by countries and income groups (World Bank, 2020b). The original raw data are presented in Table no. 1.

Table no.1 Original time series raw data of GDP and financial inclusion indicators

		X1	X2	X3	X4	X5		X6	X7	Y
Economy	**Year**	**No. of commercial bank branches per 100,000 adults**	**No. of ATMs per 100,000 adults**	**Outstanding deposits with commercial banks (% of GDP) in USD**	**Outstanding loans from commercial banks (% of GDP) in USD**	**No. of deposit accounts with commercial banks per 1,000 adults**	**No. of debit and credit cards per 1,000 adults**	**No. of credit cards per 1,000 adults**	**No. of debit cards per 1,000 adults**	**GDP in USD**
North Macedonia Republic of	2007	19.97110	31.72587	43.01039	33.49630	1276.127	319	101	218	12283.53
	2008	24.34928	45.30514	43.60505	40.47049	1761.834	404	118	287	12943.86
	2009	25.31325	49.20707	45.31236	41.89599	1947.802	489	112	378	12886.68
	2010	25.64760	51.11873	48.77017	42.65875	2007.342	837	178	658	13308.57
	2011	24.16125	51.24758	50.44556	43.60436	1977.841	848	170	678	13608.50
	2012	24.64955	49.64873	52.57580	46.33029	2049.318	878	172	706	13534.72
	2013	24.75643	54.04573	51.66441	45.85298	2089.657	905	182	723	13918.64
	2014	24.87130	55.59807	54.39009	47.94392	2157.926	928	184	744	14411.91
	2015	24.69380	60.66463	54.77906	49.65225	2207.901	966	190	777	14956.44
	2016	25.00528	60.00113	54.27026	47.23683	2232.273	1050	217	833	15371.95
	2017	25.64679	59.41986	54.89045	48.14315	2223.861	1050	216	834	15528.91
	2018	24.15298	59.80737	56.42911	48.64126	2273.077	1047	214	833	15971.86
	2019	24.11153	61.54182	58.14487	48.69918	2276.494	1061	214	846	16479.00

Source: IMF (2019), Word Bank (2020b)

Research method

For conducting the multivariate regression model, Ordinary least squares (OLS) method was utilized. Before running the multiple regression analysis, first, some of variables were log transformed in order to reduce skewness of original data and conform to normal distribution. For this purpose, our regression model used the log transformed dependent variable Y (LNGDP), log transformed X5 (LNACC-Number of deposit accounts with commercial banks per 1,000 adults), log transformed X6 (LNCC - Number of credit cards per 1,000 adults) and log transformed X7 (LNDC - Number of debit cards per 1,000 adults). For the remaining variables X1 (Number of commercial bank branches per 100,000 adults), X2 (Number of ATMs per 100,000 adults), the model used the original data without log transformation, because their values are in similar range with the remaining log values of independent variables and the log dependent variable and there is no need for their log transformation, since transformed data will not significantly change the results of the regression model. For X3 (Outstanding deposits with commercial banks (% of GDP) and X4 **(**Outstanding loans from commercial banks (% of GDP), log transformation couldn't be applied because they are expressed as percentage values. Summarized dataset with log transformation of some variables is presented in Table no.2.

Table no. 2 Time series dataset of log transformed GDP and some log transformed financial inclusion indicators

		X1	X2	X3	X4	X5	X6	X7	Y
	Year	**No. of commercial bank branches per 100,000 adults**	**No. of ATMs per 100,000 adults**	**Outstanding deposits with commercial banks (% of GDP)**	**Outstanding loans from commercial banks (% of GDP)**	**LNACC per 1,000 adults**	**LNCC**	**LNDC**	**LNGDP**
North Macedonia, Republic of	2007	19.97110	31.72587	43.01039	33.49630	7.151585	4.617734	5.384046	9.41601
	2008	24.34928	45.30514	43.60505	40.47049	7.474111	4.768325	5.658231	9.46837
	2009	25.31325	49.20707	45.31236	41.89599	7.574457	4.714482	5.933963	9.46395
	2010	25.64760	51.11873	48.77017	42.65875	7.604567	5.183647	6.489748	9.49616
	2011	24.16125	51.24758	50.44556	43.60436	7.589761	5.135966	6.519806	9.51845
	2012	24.64955	49.64873	52.57580	46.33029	7.625262	5.149706	6.559443	9.51301
	2013	24.75643	54.04573	51.66441	45.85298	7.644755	5.2046	6.583091	9.54098
	2014	24.87130	55.59807	54.39009	47.94392	7.676903	5.216734	6.612185	9.57581
	2015	24.69380	60.66463	54.77906	49.65225	7.699798	5.245251	6.654868	9.61289
	2016	25.00528	60.00113	54.27026	47.23683	7.710776	5.379603	6.725429	9.64030
	2017	25.64679	59.41986	54.89045	48.14315	7.707000	5.374713	6.726471	9.65045
	2018	24.15298	59.80737	56.42911	48.64126	7.728890	5.366282	6.725533	9.67858
	2019	24.11153	61.54182	58.14487	48.69918	7.730392	5.366521	6.741043	9.70984

Source: IMF (2019), Word Bank (2020) and author's own calculation

For building the one best-fitting regression model, the "Backward elimination method" was chosen, that begins with full model containing all independent variables. Before choosing the best-fitting model, several aspects were examined:

- The potential risk of overfitting by examining the correlation between each independent variable and dependent variable set through conducting simple linear regressions between each independent and dependent variable set, then by comparing the p-value for each independent variable in the full multiple regression model (which should be below 0.05 according to the set 95% confidence level), and validating results through the Redundant Variable Test.
- The potential risk of multi-collinearity appears in cases when two or more of the independent variables are highly correlated with each other, leading to the risk for not being sure which of the independent variables determines

the variation in the dependent variable. (David, M.L. et. al, 2017), measured through the Variance Inflation Factors (VIF's), which should be less than 5.0 according to the criteria developed by Snee, R.D (1973).

- The potential existence of autocorrelation of residuals (or serial correlation) especially important when dataset is a time-series data. The autocorrelation is the similarity of a time series over successive time intervals which can lead to the risk of underestimating the standard errors and can cause misleading conclusions that the predictors are significant when they are not.

The autocorrelation of residuals was measured through the Durbin-Watson stat and Breusch-Godfrey Serial Correlation LM Test. The Durbin Watson statistics (limited to detecting first order auto regression) assumes value between 0 and 4, where DW=2 indicates that there is no autocorrelation and errors and normally distributed with a mean of 0, if DW is below 2, there is positive correlation (which is more common for time series data), and if DW is above 2, it indicates negative correlation (less common for time series data). The Breusch-Godfrey Serial Correlation LM Test, or Lagrange Multiplier (LM) Test, also testing the autocorrelation of residuals, is used for detecting autocorrelation up to any predesignated order p.

- The potential risk of heteroscedasticity, as a systematic change in the spread of residuals over the range of measured values, which could lead to inefficient regression predictions (Astivia et al, 2019), is being measured through the Breusch-Pagan-Godfrey heteroscedasticity test and the Jarque-Berra probability coefficient.

The ideal situation would be for all independent variables to be correlated with the dependent variable but not with each other, the errors to be normally distributed with a mean of 0 which would mean non-existence of autocorrelation and to have homoscedasticity, or homogeneity of variance of variables. If redundant variable is determined that does not contribute to the regression equation, or a variable that is highly correlated with other variables, it is removed from the model, up to the stage where all remaining variables are statistically significant to the model, under satisfying other preconditions of nonexistence of autocorrelation and heteroscedasticity.

Research results and discussion

In order to examine the relationship between the variables determining financial inclusion and economic growth, a multiple regression analysis was performed by using E-views tool.

First, the potential overfitting risk was examined by assessing the correlation between each independent variable and dependent variable and eliminate independent variables that have weak or no correlation, by performing simple linear regressions between each independent and dependent variable set.

Table no.3 Summary data of simple linear regressions

	F	p-value	S t a n d . error	R Square (adj)	X1	X2	X3	X4	X5	X6	X7
BNCH	1.70982	0.21767	0.089106	0.055849	X						
ATM	44.1307	3.64E-05	0.042784	0.782335		OK					
DEP	72.6814	3.55E-06	0.034727	0.856599			OK				
CRED	29.5691	0.000205	0.049875	0.704209				OK			
LNACC	18.8299	0.001176	0.058164	0.597719					OK		
LNCC	36.8449	8.08E-05	0.045926	0.74919						OK	
LNDC	20.6308	0.000841	0.056484	0.620623							OK

Source: Author's own calculations

The summary of simple linear regressions presented in Table no.3 show that the Number of commercial bank branches per 100,000 adults has very weak correlation with GDP, evidenced through the very low value of R square (adj) which is only 0.0558, explaining very low contribution of the predictor X1 to Y of only 5,6%, the lowest value of F (1.71) and p-value (0.217) above the threshold of 0,05 which altogether shows that the independent variable X1 does not contribute to the regression model and is not statistically significant:

- **LNGDP (y) does not appear highly correlated with Number of commercial bank branches per 100,000 adults (x1)**
- LNGDP (y) appears highly correlated with ATM - Number of ATMs per 100,000 adults (x2)
- LNGDP (y) appears highly correlated with DEP - Outstanding deposits with commercial banks (% of GDP) (x3)
- LNGDP (y) appears highly correlated with CRED - Outstanding loans from commercial banks (% of GDP) (x4)
- LNGDP (y) appears highly correlated with LNACC - Number of deposit accounts with commercial banks per 1,000 adults- (x5)
- LNGDP (y) appears highly correlated with CC - Number of credit cards per 1,000 adults (x6)
- LNGDP (y) appears highly correlated with DC - Number of debit cards per 1,000 adults (x7)

Therefore, maybe it would be best to exclude the independent variable (x1) from the multiple regression model as potential redundant variable because it did not contribute to the variation of dependent variable.

However, at this stage the multivariate regression analysis was performed for the full model containing all independent variables, in order to check the results of overall model and validate the above stated assumption.

The results of a multiple regression analysis conducted for the full model of Y (LNGDP) versus all independent variables X1 (BNCH), X2 (ATM), X3 (CRED), X4 (DEP), X5 (LNACC), X6 (LNCC), X7 (LNDC), and the summary of results are presented in Table no. 4.

Table no.4 Least Squares multiple regression analysis of Y vs. X1, X2, X3, X4, X5, X6, X7

Dependent Variable: LNGDP
Method: Least Squares
Sample: 2007 2019
Included observations: 13

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNDC	-0.243585	0.044704	-5.448873	0.0028
LNCC	0.212478	0.067564	3.144832	0.0255
LNACC	0.206578	0.200640	1.029593	0.3504
DEP	0.020339	0.005005	4.063838	0.0097
CRED	-0.012033	0.004377	-2.749086	0.0404
BNCH	-0.003264	0.010151	-0.321598	0.7608
ATM	0.008110	0.002319	3.497058	0.0173
C	7.604263	1.206275	6.303921	0.0015

R-squared	0.993856	Mean dependent var	9.560373
Adjusted R-squared	0.985254	S.D. dependent var	0.091704
S.E. of regression	0.011136	Akaike info criterion	-5.882048
Sum squared resid	0.000620	Schwarz criterion	-5.534387
Log likelihood	46.23331	Hannan-Quinn criter.	-5.953508
F-statistic	115.5417	Durbin-Watson stat	1.930622
Prob(F-statistic)	0.000032		

Source: Author's own calculations

Table no.4 results showed very high R square (adj) = 0.985 and high F confirming very high contribution of the predictor variables to Y of high 98,5% and the p-value of the overall model (0.0015) showed statistically significant model. However, two independent variables have p-values above the threshold and individually are not statistically significant for the model. The variable X1 (BNCH - Number of commercial bank branches per 100,000 adults) has p-value of 0.76 and validates the previous assumption that this variable is redundant, while the p-value for variable X5 (LNACC - Number of deposit accounts with commercial banks per 1,000 adults) is 0.35 which also showed that this variable is not statistically significant for the model and maybe redundant.

The results of this table also show that the Durbin-Watson stat examining the presence of autocorrelation in residuals of the regression model evidences that there was no serial correlation over time since the DW value is close to 2 (DW=1.93). Also, the results of the Table no. 5 show that the p-value is 0.596 (which should be above the threshold of 0.05) validating the assumption that the multiple regression model did not have autocorrelation (serial correlation) of residuals.

Table no.5 Breusch-Godfrey Serial Correlation LM Test:

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.150670	Prob. F(4,1)	0.5960
Obs*R-squared	10.67968	Prob. Chi-Square(4)	0.0304

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 01/22/21 Time: 14:34
Sample: 2007 2019
Included observations: 13
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNDC	0.002770	0.068628	0.040357	0.9743
LNCC	-0.046361	0.088557	-0.523514	0.6930
LNACC	0.092017	0.320456	0.287142	0.8220
DEP	0.001948	0.005950	0.327306	0.7986
CRED	-0.000880	0.005248	-0.167629	0.8943
BNCH	-0.002363	0.010189	-0.231935	0.8549
ATM	-0.000976	0.003910	-0.249632	0.8443
C	-0.433370	2.012771	-0.215310	0.8650
RESID(-1)	-0.405514	0.874816	-0.463542	0.7237
RESID(-2)	-0.726725	0.577962	-1.257394	0.4277
RESID(-3)	-1.609993	0.809714	-1.988348	0.2967
RESID(-4)	-0.472533	1.047436	-0.451132	0.7302

R-squared	0.821514	Mean dependent var	2.05E-16
Adjusted R-squared	-1.141832	S.D. dependent var	0.007188
S.E. of regression	0.010520	Akaike info criterion	-6.989909
Sum squared resid.	0.000111	Schwarz criterion	-6.468417
Log likelihood	57.43441	Hannan-Quinn criter.	-7.097099
F-statistic	0.418425	Durbin-Watson stat	2.019538
Prob(F-statistic)	0.849611		

Source: Author's own calculations

As regards the heteroscedasticity risk measured through the Breusch-Pagan-Godfrey test, examining whether the variance in errors from regression is dependent on the values of the independent variable. With the Breusch-Pagan-Godfrey test, the Chi-square value (along with associated p-value) is tested and indicates whether the variance are all equal if the p-value is above 0.05, when then the null hypothesis is accepted and there is homoscedasticity. In contrary, if the null hypothesis is rejected, there is heteroscedasticity. In our model, results from Table no.6 show that the p-value (0.3362) is above 0.05 and it can be concluded that there was no heteroscedasticity of errors in regression, or the variance of errors is homogeneous.

Table no.6 Heteroscedasticity Test

Heteroscedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.509113	Prob. F(7,5)	0.3362
Obs*R-squared	8.823639	Prob. Chi-Square(7)	0.2656
Scaled explained SS	1.181744	Prob. Chi-Square(7)	0.9913

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/22/21 Time: 14:35
Sample: 2007 2019
Included observations: 13

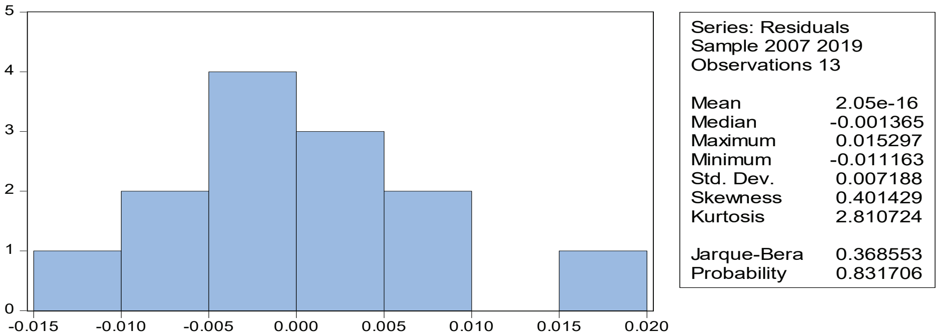
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.009004	0.006354	1.417094	0.2156
LNDC	-0.000181	0.000235	-0.769772	0.4762
LNCC	4.98E-06	0.000356	0.013991	0.9894
LNACC	-0.001830	0.001057	-1.731535	0.1439
DEP	5.58E-05	2.64E-05	2.117139	0.0878
CRED	-1.50E-05	2.31E-05	-0.650896	0.5438
BNCH	0.000149	5.35E-05	2.783424	0.0387
ATM	5.22E-06	1.22E-05	0.427710	0.6867

R-squared	0.678741	Mean dependent var	4.77E-05
Adjusted R-squared	0.228979	S.D. dependent var	6.68E-05
S.E. of regression	5.87E-05	Akaike info criterion	-16.37453
Sum squared resid	1.72E-08	Schwarz criterion	-16.02686
Log likelihood	114.4344	Hannan-Quinn criter.	-16.44599
F-statistic	1.509113	Durbin-Watson stat	2.424978
Prob(F-statistic)	0.336184		

Source: Author's own calculations

To confirm whether the residuals were normally distributed, a Jarque-Bera test was conducted. Jarque-Bera test examines whether sample data have the skewness and kurtosis that match normal distribution. The results of the histogram of the observations for residuals showed that the Jarque-Bera probability is above 0.05, demonstrating that data were normally distributed.

Figure no. 2 Jarque-Bera test



Source: Author's own calculations

The multi-collinearity risk examining if two or more of the independent variables are highly correlated with each other is tested through the VIF for each independent variable summarized in Table no.7. Results showed very high VIF's which leads to potential multi-collinearity amongst independent variables, but the multiple regression analysis was conducted again by eliminating 2 variables identified as redundant and then results of the reduced regression analysis were checked, including the multi-collinearity issues.

Table no.7 Variance Inflation Factors

Variance Inflation Factors
Date: 01/22/21 Time: 14:37
Sample: 2007 2019
Included observations: 13

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
LNDC	0.001998	8643.802	39.07511
LNCC	0.004565	12637.33	30.53279
LNACC	0.040257	244440.8	94.94804
DEP	2.50E-05	6997.689	58.38566
CRED	1.92E-05	4099.601	37.77934
BNCH	0.000103	6456.862	20.46311
ATM	5.38E-06	1620.744	35.56752
C	1.455099	152543.7	NA

Source: Author's own calculations

In order to examine the overfitting risk and validate previously identified redundant variables, the Redundant Variables Test was conducted, which also confirmed that two variables are redundant in the model (variable X1 -BNCH - Number of commercial bank branches per 100,000 adults and variable X5 -LNACC - Number of deposit accounts with commercial banks per 1,000 adults) and should be excluded. The test shows that the p-value of these two variables is 0.5511 which evidenced not statistically significant variables.

Table no. 8 Redundant Variables Test

Redundant Variables Test
Equation: EQ01
Specification: LNGDP LNDC LNCC LNACC DEP CRED BNCH ATM C
Redundant Variables: LNACC BNCH

	Value	df	Probability
F-statistic	0.672807	(2, 5)	0.5511
Likelihood ratio	3.098238	2	0.2124

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.000167	2	8.34E-05
Restricted SSR	0.000787	7	0.000112
Unrestricted SSR	0.000620	5	0.000124
Unrestricted SSR	0.000620	5	0.000124

LR test summary:

	Value	df
Restricted LogL	44.68419	7
Unrestricted LogL	46.23331	5

Restricted Test Equation:
Dependent Variable: LNGDP
Method: Least Squares
Date: 01/22/21 Time: 14:44
Sample: 2007 2019
Included observations: 13

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNDC	-0.214270	0.033220	-6.450123	0.0004
LNCC	0.185396	0.058935	3.145785	0.0162
DEP	0.019514	0.002320	8.412677	0.0001
CRED	-0.009876	0.003406	-2.899919	0.0230
ATM	0.010114	0.001470	6.878378	0.0002
C	8.886713	0.131966	67.34085	0.0000

R-squared	0.992202	Mean dependent var	9.560373
Adjusted R-squared	0.986633	S.D. dependent var	0.091704
S.E. of regression	0.010603	Akaike info criterion	-5.951415
Sum squared resid	0.000787	Schwarz criterion	-5.690669
Log likelihood	44.68419	Hannan-Quinn criter.	-6.005010
F-statistic	178.1427	Durbin-Watson stat	1.474597
Prob(F-statistic)	0.000000		

Source: Author's own calculations

Having in mind the overfitting risk, the independent variables identified as redundant (X1 -BNCH - Number of commercial bank branches per 100,000 adults and X5 -LNACC - Number of deposit accounts with commercial banks per 1,000 adults) were excluded from the model, and the regression analysis was conducted again for the reduced model. Also, in order to reduce the VIF's and due to relatively low number of observations, we tried to merge the independent variables X6 (LNCC - Number of credit cards per 1,000 adults) and X7 (LNDC - Number of debit cards per 1,000 adults), due to the fact that these two variables are indeed highly correlated, determining number of bank cards per 1,000 adults (credit or debit) - LNCDC. If we merge these two variables in one, it was expected to achieve the similar results from examining the relationship between usage of bank cards and GDP, and use this one predictor variable in predicting GDP growth.

Therefore, a reduced log-log multiple regression model was conducted of Y versus X2, X3, X4, (X6+X7) and summary of results are presented in Table no.9.

Table no.9 Least Squares multiple regression analysis of Y vs.X2, X3, X4, (X6+X7)

Dependent Variable: LNGDP
Method: Least Squares
Date: 01/22/21 Time: 14:51
Sample: 2007 2019
Included observations: 13

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNCDC	-0.145773	0.039606	-3.680539	0.0062
DEP	0.024423	0.003190	7.656753	0.0001
CRED	-0.016465	0.004761	-3.458341	0.0086
ATM	0.012085	0.002221	5.440268	0.0006
C	9.375147	0.141762	66.13308	0.0000

R-squared	0.976317	Mean dependent var	9.560373
Adjusted R-squared	0.964475	S.D. dependent var	0.091704
S.E. of regression	0.017284	Akaike info criterion	-4.994315
Sum squared resid	0.002390	Schwarz criterion	-4.777027
Log likelihood	37.46305	Hannan-Quinn criter.	-5.038978
F-statistic	82.44854	Durbin-Watson stat	1.859646
Prob(F-statistic)	0.000002		

Source: Author's own calculations

The coefficients of this multiple regression model showed very high significance of the overall model (R square (adj) =0.9645, p-value=0.0000) and high value of F (82.448) as well as high statistical significance of each independent variables to Y (p-values are below 0,05). The B coefficients of LNCDC and CRED are negative values which can be argumented with the fact that by increase of the percentage share of loans in GDP (CRED), the indebtedness is increased which can lead to decreasing the GDP growth. Also, the LNCDC which variable is a sum of number of debit and credit cards is a negative value due to the similar logic as with loans, i.e an increase in number of cards (where credit cards participate in the overall increase in number of cards) could mean increasing the indebtedness of adults which might lead to decreasing the GDP growth.

Also, values of the Durbin-Watson stat =1.85 (value is around 2) and the Breusch-Godfrey Serial Correlation LM Test having p-value of 0.55 (above 0.05) measuring the existence of autocorrelation confirm that the multiple regression model does not have autocorrelation (serial correlation) of residuals over time.

Table no.10 Breusch-Godfrey Serial Correlation LM Test:

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.854927	Prob. F(4,4)	0.5585
Obs*R-squared	5.991639	Prob. Chi-Square(4)	0.1998

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 01/24/21 Time: 11:43
Sample: 2007 2019
Included observations: 13
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNCDC	-0.013277	0.050572	-0.262547	0.8059
DEP	0.001348	0.003866	0.348831	0.7448
CRED	-0.005454	0.005943	-0.917788	0.4107
ATM	0.002625	0.002928	0.896631	0.4206
C	0.122543	0.184463	0.664325	0.5428
RESID(-1)	-0.169573	0.522444	-0.324576	0.7618
RESID(-2)	-0.454203	0.445600	-1.019306	0.3657
RESID(-3)	-1.035918	0.630176	-1.643856	0.1756
RESID(-4)	-0.111456	0.688733	-0.161828	0.8793

R-squared	0.460895	Mean dependent var	-9.56E-16
Adjusted R-squared	-0.617314	S.D. dependent var	0.014113
S.E. of regression	0.017947	Akaike info criterion	-4.996776
Sum squared resid	0.001288	Schwarz criterion	-4.605657
Log likelihood	41.47905	Hannan-Quinn criter.	-5.077169
F-statistic	0.427464	Durbin-Watson stat	2.495367
Prob(F-statistic)	0.857569		

Source: Author's own calculations

As regards heteroscedasticity issue, the Breusch-Pagan-Godfrey test (Table no.11) showed that the p-value (0.1448) is above 0.05 and it can be concluded that there was no heteroscedasticity of errors in regression, or the variance of errors is homogeneous.

Table no.11 Heteroscedasticity Test: Breusch-Pagan-Godfrey

Heteroscedasticity Test: Breusch-Pagan-Godfrey

F-statistic	2.318639	Prob. F(4,8)	0.1448
Obs*R-squared	6.979585	Prob. Chi-Square(4)	0.1370
Scaled explained SS	1.331051	Prob. Chi-Square(4)	0.8561

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/24/21 Time: 11:44
Sample: 2007 2019
Included observations: 13

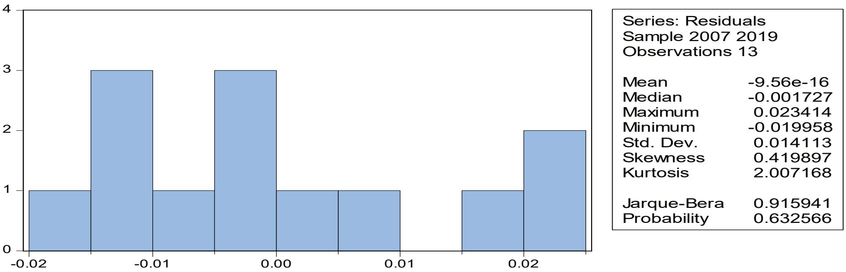
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002997	0.001313	2.283143	0.0518
LNCDC	-0.000781	0.000367	-2.130107	0.0658
DEP	-1.21E-05	2.95E-05	-0.410637	0.6921
CRED	3.69E-05	4.41E-05	0.836665	0.4271
ATM	2.55E-05	2.06E-05	1.240707	0.2499

R-squared	0.536891	Mean dependent var	0.000184
Adjusted R-squared	0.305337	S.D. dependent var	0.000192
S.E. of regression	0.000160	Akaike info criterion	-14.35839
Sum squared resid	2.05E-07	Schwarz criterion	-14.14110
Log likelihood	98.32953	Hannan-Quinn criter.	-14.40305
F-statistic	2.318639	Durbin-Watson stat	2.015687
Prob(F-statistic)	0.144779		

Source: Author's own calculations

Also, the results of the histogram of the observations for residuals showed that the Jarque-Bera probability is above 0.05, demonstrating that the data is normally distributed.

Figure no.3 Jarque-Bera test



Source: Author's own calculations

Table no.12 Variance Inflation Factors of the regression model Y vs. X2, X3, X4, (X6+X7)

Variance Inflation Factors
Date: 01/24/21 Time: 11:45
Sample: 2007 2019
Included observations: 13

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
LNCDC	0.001569	3036.512	10.13579
DEP	1.02E-05	1179.891	9.844497
CRED	2.27E-05	2013.398	18.55421
ATM	4.93E-06	617.2554	13.54578
C	0.020096	874.4989	NA

Source: Author's own calculations

Table no.12 results testing the multi-collinearity issues showed reduced values of VIF's in comparison with the full model, although still above the suggested level of 5. The multi-collinearity was the only issue with this model, but having in mind that the Beta coefficients with the reduced model remained at approximately similar values (were not distorted), it can be considered that the multi-collinearity should not be a significant issue. Otherwise, if we continue to furtherly exclude independent variables to additionally reduce the VIF's, the p-values of independent variables of the model are distorted and become insignificant, and therefore we face the risk of reducing the model's quality or even lead to statistically non- significant model.

Therefore, the log-log regression model of Y vs.X2, X3, X4, (X6+X7) shall be used for further predictions, which formula is:

$$\mathbf{LN(GDP) = b_{0\,+}\, b_{1\,X}\, ATM_{\,+}\, b_{2\,X}\, CRED_{\,+}\, b_{3\,X}\, DEP_{\,+}\, b_{4\,X}\, LN\,(CDC)}$$

LN (GDP) = 9.3751 + 0.0121 x ATM + 0.0244 x DEP - 0.0164 x CRED - 0.1457 x LN (CDC)

Before using the regression equation for making predictions, first the regression model has to be validated by using the cross-validation method, by splitting the existing data in two parts, and using the first part of data for developing a multiple regression model and the second part of data for evaluating the predictive ability of the model. (David, M.L et. Al,2017) The first part of data were the time series variables for the period 2007-2016, while the second part of data where the regression equation was evaluated were data for 2017, 2018 and 2019. The regression equation replaced the actual values of the independent variables for the years 2017, 2018 and 2019, and if the results for GDP (after calculating the exponent of LNGDP) were close to the known values of GDP, then the equation is confirmed as correct and can be used for predicting the GDP growth for the future period.

The regression equation for 10 observations was the following:

LN (GDP) = 9.3712 + 0.0113 x ATM + 0.0227 x DEP - 0.0151 x CRED - 0.1357 x LN (CDC)

The results of the formula are presented in the column LNGDP forecast presented in Table no.13.

Table no.13 Validation of the multiple regression model for prediction

Year	Number of ATMs per 100,000 adults	Outstanding deposits with commercial banks (% of GDP)	Outstanding loans from commercial banks (% of GDP)	LNCDC	LNGDP	LNGDP forecast
2007	31.72587	43.01039	33.4963	6	9.416015	
2008	45.30514	43.60505	40.47049	6	9.468377	
2009	49.20707	45.31236	41.89599	6	9.46395	
2010	51.11873	48.77017	42.65875	7	9.496164	
2011	51.24758	50.44556	43.60436	7	9.51845	
2012	49.64873	52.5758	46.33029	7	9.513014	
2013	54.04573	51.66441	45.85298	7	9.540985	
2014	55.59807	54.39009	47.94392	7	9.575811	
2015	60.66463	54.77906	49.65225	7	9.612897	
2016	60.00113	54.27026	47.23683	7	9.6403	
2017	59.41986	54.89045	48.14315	7	9.650459	9.6187447
2018	59.80737	56.42911	48.64126	7	9.678584	9.6508544
2019	61.54182	58.14487	48.69918	7	9.709842	9.7069145

Source: Author's own calculations

As it can be noted from the predicted results for LN (GDP) for 2017-2019 by using the regression equation provided as result of the multiple regression model for the time series data from 2007 to 2016, the LN (GDP) values are very close to the real LN (GDP) values for 2017-2019 and close to the GDP values after calculating the exponents of LN (GDP), which is a proof that the regression model was valid and can be used for prediction purposes.

Conclusion

The final regression equation results uncovered the following relationships:

For 1 unit increase of number of ATM's per 100,000 adults, it is expected to see about 1,2% increase in GDP, holding other variables constant, since exp (0.0120845)= 1.012. For 1 unit increase of Outstanding deposits with commercial banks (% of GDP), it is expected about 2,5% increase In GDP holding other variables constant, since exp (0.024423) = 1.0247, and for 1 unit increase of Outstanding loans from commercial banks (% of GDP), it is expected about 1,7 % decrease in GDP, holding other variables constant, since exp (-0.1457728) = 0.983. As regards the log transformed variable LN (CDC), 1% increase in CDC is associated with 1.4% decrease in GDP, holding other variables constant. Therefore, results have shown that the research hypothesis is approved, i.e the financial inclusion positively affects GDP growth in North Macedonia.

The regression equation can be utilized for predicting the growth of GDP based on improvement or deterioration of the financial inclusion indicators, being a valuable information for government' and regulator' authorities, providing guidelines for the future directions in improving the variables having most significant positive contribution to GDP growth, as well as undertaking additional efforts to improve variables having negative influence on GDP growth, leading to increasing the financial inclusion. Also, findings give significant theoretical contribution to the current research database for the specific case of North Macedonia.

Recommendations for future research could refer to using the selected dataset of quantitative financial inclusion indicators for calculating a single Index for Financial Inclusion (IFI). Also, the selected proxy for the dependent variable "Economic growth" - "GDP per capita" could also be expanded to include more control variables which are also determining the economic growth (despite only GDP per capita), such as the productivity, physical capital and labour.

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