Do Digital Payments Matters?

The Effects of Digitalization impact on Payment Efficiency and Macroeconomic Stability-

This project between some master student and lecturer from SBM-ITB with Central Bank of Indonesia, Analyzing the effect of digital payment on payment system efficiency and macroeconomic stability towards financial system stability.

This study has two aims:

- to evaluate the effect of digital payment on macroeconomic stability
- to investigate the implication of digital payment on the payment system efficiency.

In the model examination, we use electronic money transaction as the proxy for the digitalization. Meanwhile for the first objective, the macroeconomic indicators namely inflation and exchange rate volatility are used as the proxy. Inflation represent the internal stability while the exchange rate volatility represent the external stability. For the second objective, we use ticket sizing of digital payment and private consumption as the proxy for payment system efficiency.

Data

In this study we use secondary data for analyzing the model. The secondary data related to the transaction of electronic money, debit card, credit card and bank transfer from the Payment Statistic of Central Bank of Indonesia (Statistic Pembayaran Bank Indonesia), Macroeconomic will be collected from Indonesian Central Bureau of Statistic (BPS), world bank data (https://data.worldbank.org/) and OECD. Industry and market data from Central Bank of Indonesia (Statistic of Bank Indonesia), Indonesian Stock Exchange (IDX). The following are overall data sets and their sources. The descriptive statistics for the data are shown in Table 2:

Table 1. Data Sources

No	Variables	Proxy	Source
1	Credit	Credit Card Transaction Nominal to Credit Card Transaction Volume	Statistik sistem Pembayaran APMK (BI)
2	Debit	Debit Card Transaction Nominal to Debit Card Transaction Volume	Statistik sistem Pembayaran APMK (BI)
3	Intra	Intra bank transfer nominal to Intra bank transfer volume	Statistik sistem Pembayaran APMK (BI)
4	Inter	Interbank transfer nominal to Interbank transfer volume	Statistik sistem Pembayaran APMK (BI)
5	Elmon	Electronic money transaction nominal to Electronic money transaction volume	Statistik sistem Pembayaran Uang Elektronik (BI)
6	CPI	Log of CPI	BPS
7	BI Rate	Monthly BI rate	BPS
8	Exchange Rate	Exchange rate volatility	BPS
9	IPI	Industry Productivity Index	BPS
10	IHSG	IDX Composite Index	IDX
11	Inflation	Inflation rate	BPS
12	Oil Price	Log of oil price	OECD
13	M2	Log of oil M2	BPS
14	JIBOR	Jakarta Interbank Offered Rate	BI
15	Import Price	Log of oil price	Worldbank, Trading Economic
16	Consumption	Log of oil private consumption	OECD

Table 2. Descriptive Statistics of the Variables

Variables	**Mean**	**min**	**max**	**std dev**	**skewness**	**kurtosis**
Credit	0.906	0.673	1.038	0.077	-0.723	3.246
Debit	0.574	0.389	0.655	0.051	-1.044	3.452
Intra	2.144	1.704	2.876	0.301	0.642	2.144
Inter	1.942	1.52	2.239	0.155	-0.269	2.308
Elmon	0.019	0.0324	0.054	0.0083	0.734	4.087
CPI (in ln)	4.836	4.647	4.989	0.07	-0.274	2.545
BI Rate	6.211	4.25	8.75	1.065	-1.177	2.136
Exchange Rate (in ln)	9.356	9.05	9.672	0.184	-0.261	1.491
IPI(in ln)	4.876	4.612	5.439	0.137	1.811	9.42
IHSG(in ln)	8.39	7.158	8.795	0.337	-1.467	5.271
Inflation	0.36	-0.45	3.29	0.491	2.277	12.873
Oil Price(in ln)	4.2	2.806	4.696	0.343	-0.674	3.658

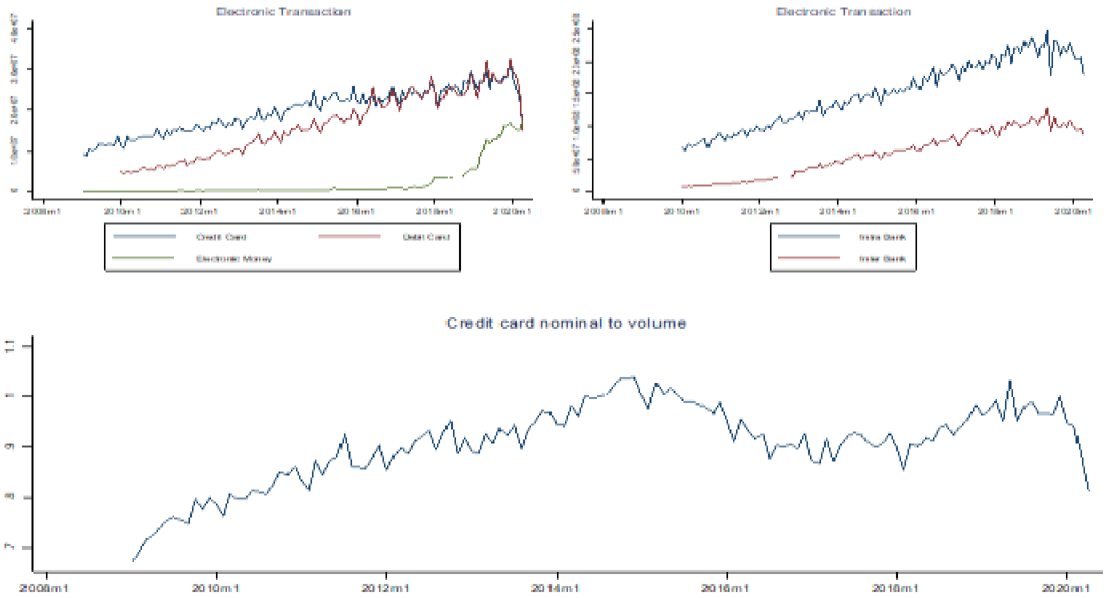

Figure 1. Electronic Transaction

Results and Discussion

Test of Order Integration

This paper will use ARDL bounds testing of Pesaran et al. (2001) to estimate the long-run cointegration between the variables. The advantages using bound testing compared to other econometric models: it gives valid results of cointegration test whether the underlying series are I(1) or I(0), or a combination of both. The test is reliable for the case that involves structural breaks. Third, it can be used for small-sample size. In order to use the ARDL bounds test cointegration approach, we need to ensure that the stationarity of all variables is not I(2) and from Table 3 all variables stationary at I(0) or I(1).

To test the stationary of the operational variables we use some test stationary test namely: Augmented Dickey-Fuller (ADF) Test (**J.** Econometrica, 1981), Phillips-Perron Test (**J.** Econometrica, 1987), and DF-GLS test of Elliott, Rothenberg, Stock (**J.** Econometrica,1996). The following are unit root test for checking the stationary of the data:

Table 3. Unit Root Test for the Variables

Variables	ADF Test		Phillips-Perron Test	DF-GLS Test
	Trend	Drift	Trend	
Credit	-2.686	-3.165***(0)	-18.901***(1)	-8.703***(1)
Debit	-18.476***(1)	-18.289***(1)	-24.299***(1)	-8.495***(1)
Intra	-14.343(1)	-14.415(1)	-15.626***(1)	-7.585***(1)
Inter	-12.13(1)	-12.147(1)	-12.654***(1)	-6.724***(1)
Elmon	-2.53	-2.965***(0)	-15.177***(1)	-4.565***(1)
CPI	-2.122	-2.39***(0)	-11.649***(1)	-7.887***(1)
BI Rate	-7.271***(1)	-7.309***(1)	-7.281***(1)	-3.218**(1)

Variables	ADF Test		Phillips-Perron Test	DF-GLS Test
	Trend	Drift	Trend	
Exchange Rate	-8.61***(1)	-8.3***(1)	-8.651***(1)	-3.777***(1)
IPI	-4.349***(0)	-4.284***(0)	-4.398***(0)	-4.352***(0)
IHSG	-2.853***(0)	_1.362	-10.303***(1)	-6.618***(1)
Inflation	-8.029***(0)	-7.957	-7.529***(0)	-8.667***(0)
Oil Price	-6.23***(0)	-5.872***	-6.206***(1)	-6.464***(1)
JIBOR	-2.32***(0)	-2.321	-10.849***(1)	-7.302***(1)
M2	-2.889	-1.73**(0)	-15.599***(1)	-8.766***(0)
Import Price	-1.795**(0)	-1.21	-5.748***(1)	-5.189***(1)

*,**,*** significant at α=10%,5%,1%

Based on the preliminary test, in which we find that the variables are stationary at order integration I(0) and I(1) therefore we can proceed to perform Autoregressive Distributed Lag (ARDL) for the estimation model.

ARDL Bounds Testing for Long-Rung Cointegration

After verifying the unit root properties of the variables, the bounds test of cointegration can be implemented to analyze the long-run relationship between the variables. Following Pesaran et al. (2001), to validate the effect of long-run relation in the equation, we use the bound test and apply the F test to verify the presence of cointegration. A statistical value above the upper value I(1) of the bound test indicates that the null hypothesis "there is no cointegration" is rejected, leading to accepting the alternative hypothesis "there is cointegration" condition. To check for cointegration, the F test is applied to validate the joint significance of lagged variables. As noted in Pesaran et al. (2001), two asymptotic critical values are proposed, with a lower bound assuming that variables are below I(0) levels, and an upper bound assuming that values are I(1). An F statistic above the upper bound critical value I(1) means that there is cointegration effect. A probability of ECM_{t-1} below the alpha 5% means there is cointegration effect. Once testing for cointegration, the ARDL model could be implemented to estimate the short run and the long-run effects among the variables that present significant cointegration.

As an additional diagnostic check, the Breusch-Godfrey Lagrange Multiplier (LM) test of residual serial correlation is applied, indicating a null hypothesis of "no serial correlation." The LM follows a $\chi 2$ distribution with one degree of freedom (first-order). Breusch-Pagan / Cook-Weisberg test for heteroskedasticity is performed to make sure that the models have constant variance. Furthermore, Ramsey's RESET test for misspecification model is proposed with the null hypothesis of "no misspecification." The RESET is distributed as $\chi 2$ with one degree of freedom. The Jarque-Bera (J-B) test for normality is also applied to test the distribution of residual with the null hypothesis of "residual has a normal distribution."

Relationship between Electronic Money and Macroeconomic Stability

In this study, volatility of exchange rate and inflation rate are used as proxies for macroeconomic stability. On the other side of the equation is the explanatory variables with electronic money as proxy for digitalization, the others electronic transaction are used for the control variables as well as some industry and country level data.

Exchange Rate Volatility

The exchange rate volatility is estimated using ARCH method. The following are the steps for calculating the exchange rate volatility. We want to check if there is ARCH effect on the model, first we test arch effect on exchange rate. The result shows in following tables. We have tested the null of 'no ARCH effects' against four separate alternative, the result we reject the null hypothesis. So there is ARCH effects in the model.

Table 4. LM Test for ARCH

Lags	chi2	df	Prob>chi2
1	123.688	1	0
2	123.93	2	0
3	122.911	3	0
4	121.976	4	0

After that we want to create a new dependent variable by estimating the arch model on variable exchange rate, so we see the ACF and PACF for exchange rate volatility

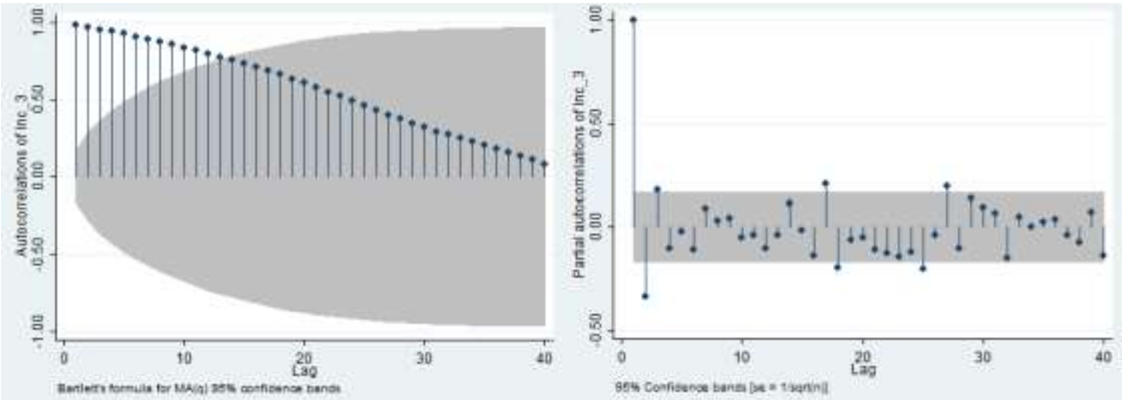

Figure 2. ACF and PACF for Exchange Rate

From the graph acf and pacf above, we can see the model for exchange rate are AR(1), or AR(2). After that we combine the following models into ARCH/GARCH model and the result are in the table.

Table 5. BIC Score ARIMA Models

ARIMA	ARCH	GARCH	BIC
1,0,0	1	0	-6.51E+02
1,0,0	1	1	-6.63E+02
1,1,0	1	0	-6.68E+02
1,1,0	1	1	-6.72E+02
2,0,0	1	0	-6.68E+02
2,0,0	1	1	-6.70E+02
2,1,0	1	0	-6.65E+02
2,1,0	1	1	-6.69E+02

We choose the model with the smallest BIC score (ARIMA (1,1,0) with arch (1) garch(1)) . Then we estimating the new dependent variable with the model that we choose, we define it 'variance'. The next step, we must check whether long-run relationship between the variables exists. This is undertaken by testing the null hypothesis of 'no long-run relationship' using an F-test for the joint significance of the lagged levels of the variables. The resulted F-statistics is compared to the critical values specified by Pesaran et al. (2001). The Bound Test results for the model of exchange rate volatility as dependent variable is presented in Table 6.

Table 6. Bound Test for Dependent Exchange Rate

	10%		5%		1%	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F	2.009	3.176	2.317	3.573	2.991	4.426

The F critical values is 2.009 for ɑ = 10%, 2.317 for ɑ = 5%, and 2991.3 for ɑ = 1% (Pesaran et al. 2001, p. 300). The resulted F-stat is 5.785, or larger than critical value of ɑ = 1%. Thus, do reject the null hypothesis. So, there is long-run relationship among the variables. Then we estimate the long-run and short-run relationships between the variables based according to the selected ARDL with error correction model models. The results are shown in Table 7.

Table 7. Estimates of Long-Run and Short-Run Coefficients

Speed Adjustment		
Variable	Coefficient	Std Error
Volatility Exchange Rate	-0.4499***	0.12
Estimates of Long-Run Coefficients		
Variable	Coefficients	Std Error
Credit	-0.0051	0.0045
Debit	0.00103	0.006
Intra	-0.00346*	0.0019
Inter	-0.00179	0.002
Elmon	0.0678**	0.0377
Lnoil	0.0007177	0.0009
lnm2	-0.0017788	0.002
JIBOR	0.00012	0.00015
Estimates of Short-Run Coefficients		
Variable	Coefficients	Std Error
d(Lnoil)	-0.0009485	0.0007
Ld(Lnoil)	-0.002**	0.0008
Intercept	0.019	0.014

Tables 7 shows that, in the long run relationship, the electronic money transaction has a positive and statistically significant at 5% significant level. Meanwhile the intra bank transaction has a negative and statistically significant in 10% significant level. This results reveal that the electronic money transaction and intra bank transaction converges on its long-run equilibrium by 6.7% and 0.3% consecutively. Accordingly, for the former variable, any increase in electronic money transaction associated with the increase in the volatility of the exchange rate. While for the latter variable, indicate that the increase in intra bank transaction will lead to the decrease of exchange rate volatility.

In the short-run relationship, oil price coefficient is negative and statistically significant. So in short-run, when oil price is increasing, the exchange rate will decline. Our first finding confirm the theory that the increase of electronic money will increase the volatility in exchange rates (Neda, 2014). In this case, the change of the monetary multiplier is an important indicator. This indicator shows the share of currency in the money supply. As a result of e-money the currency decreases producing effects to multiplier.

Diagnostic and the stability tests are conducted in order to ascertain the robustness of the ARDL model. The results (Table 8) show that, the R^2 for dependent exchange small and for the inflation sufficiently high. The p-values of the serial correlation using Breusch-Godfrey LM test is 0.895, which imply that there are no autocorrelation problems. The results of the heteroscedasticity tests of Breusch-Pagan-Godfrey also show that there is no heteroscedasticity issues in dependent exchange rate volatility, for exchange rate we use robustness estimation and the result there is no heteroscedasticity.

Table 8. Goodness of Fit, Diagnostic Test and Stability Test

Goodness of Fit, Diagnostic Tests and Stability Test	
	Dependent exchange rate ARCH GARCH
Goodness of Fit	
R2	0.4303
Adjusted R2	0.369
Diagnostic tests	
Serial Correlation	0.845[0.3579]
Heteroscedasticity	242.61[0]
Stability test	
Ramsey RESET	51.98[0]

Inflation Rate

In the next part we examine the ARDL with ECM model for inflation rate as dependent variable. First we must check whether long-run relationship between the variables exists using Bound Test. The result is shown in following table.

Table 9. Bound Test for Dependent Inflation

	10%		5%		1%	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F	2.010	3.188	2.321	3.592	3.004	4.463

The F critical values is 2.01 for α = 10%, 2.321 for α = 5%, and 3.004 for α = 1% (Pesaran et al. 2001, p. 300). The resulted F-stat is 16.731, or higher than critical value of α = 1%. Thus, reject the null hypothesis. So, there is long-run relationship between the variables. Then estimate the long-run and short-run relationships between the variables based according to the selected ARDL models. The results are shown in the following tables.

Table 10. Estimates of Long-Run and Short-Run Coefficients

Speed Adjustment		
Variable	Coefficient	Std Error
INFL	-0.9997***	0.09
Estimates of Long-Run Coefficients		
Variable	Coefficients	Std Error
Credit	1.599	1.439
Debit	4.98***	1.454
Intra	0.89*	0.452
Inter	0.7627	0.4266
Elmon	29.48**	12.33
oil price	-0.255	0.243
lnimp	2.16**	0.953
BIR	0.002	0.065
Estimates of Short-Run Coefficients		
Variable	Coefficients	Std Error
d(Debit)	-8.66***	1.734
d(Intra)	1.873***	0.685
Intercept	-17.17***	5.2

Table 10 show that, in the long-run equilibrium, the Debit, Intrabank, Electric Money ratio, and Import Price coefficients are positive and statistically significant. Accordingly, in the long-run any increase in Debit, Interbank, Electronic Money and Import Price will cause the inflation to increase. In the short-run, Debit ratio coefficient is negative and statistically significant, while the Intrabank ratio is positive and statistically significant. So in short-run, when debit ratio is increasing, the inflation will decline. In contrast, any increase in Intrabank ratio will cause the inflation to increase.

Diagnostic and the stability tests are conducted in order to ascertain the robustness of the ARDL model. The results (Table 11) show that, the R2 for dependent exchange small and for the inflation sufficiently high. The p-values of the serial correlation using Breusch-Godfrey LM test is 0.2141, which imply that there are no autocorrelation problems. The results of the heteroscedasticity tests of Breusch-Pagan-Godfrey also show that there is no heteroscedasticity issues in dependent inflation, for exchange rate we use robustness estimation and the result there is no heteroscedasticity.

Table 11. Goodness of Fit, Diagnostic Tests and Stability Test

Goodness of Fit, Diagnostic Tests and Stability Test	
	Inflation
Goodness of Fit	
R2	0.6625
Adjusted R2	0.6119
Diagnostic tests	
Serial Correlation	0.042[0.8381]
Heteroscedasticity	0.00[0.9551]
Stability test	
Ramsey RESET	4.38[0.0063]

A. Relationship between Electronic Money and Payment Efficiency

In the investigation of payment between electronic money and payment efficiency nexus we use three different proxies for payment efficiency namely: credit card volatility, electronic money growth and private consumption.

Credit Card Volatility

In the first part we calibrate the ARDL model with credit card volatility as the dependent variable. The credit card volatility is derived using ARCH model. First we test arch effect on credit card volatility. The result shows in following tables. We have tested the null of 'no ARCH effects' against four separate alternative, the result we reject the null hypothesis. So there is ARCH effects in the model.

Table 12. LM Test for ARCH credit card volatility

Lags	chi2	df	Prob>chi2
1	11.255	1	0.0008
2	12.607	2	0.0018
3	13.216	3	0.0042
4	13.057	4	0.011

After that we want to create a new dependent variable by estimating the arch model on variable credit card volatility, so we see the ACF and PACF for credit card volatility using visual inspection in Figure 6.

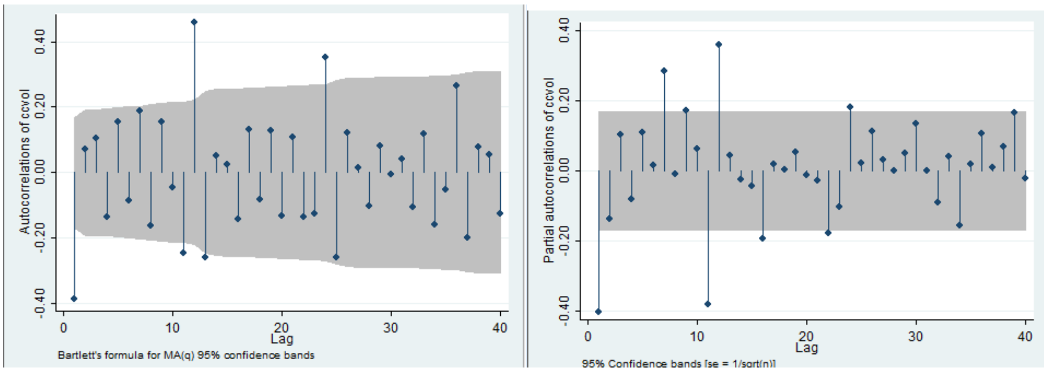

Figure 3. ACF and PACF for credit card volatility

The acf graph significant at lag 1,12 so this model is AR (1),AR(12) and the pacf side lag 1,7,11 are significant so this model MA (1),MA(7),MA(11). After that we combine the following models into ARCH/GARCH model and the result are in the table.

Table 13. BIC Score ARIMA Models

ARIMA	ARCH	GARCH	BIC
1,0,0	1	0	-5.64E+02
0,0,1	1	0	-5.53E+02
1,0,0	1	1	-5.60E+02
0,0,1	1	1	-5.58E+02
1,1,1	1	0	-5.50E+02
1,1,1	1	1	-5.46E+02
1,1,0	1	0	-4.70E+02
1,1,0	1	1	-4.65E+02
0,1,1	1	0	-5.62E+02
0,1,1	1	1	-5.21E+02

We choose the model with the smallest BIC score (ARIMA (1,0,0) with arch (1)) . Then we estimating the new dependent variable, we define it 'variance'. Then we must check whether long-run relationship between the variables exists. The result is shown in following table.

Table 14. BIC Score ARIMA Models

	10%		5%		1%	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F	2.194	3.334	2.555	3.785	3.349	4.756

The F critical values is 2.19 for ɑ = 10%, 2.555 for ɑ = 5%, and 3.349 for ɑ = 1%. The resulted F-stat is 11.743, or higher than critical value of ɑ = 1%. Thus, reject the null hypothesis. So, there is long-run relationship between the variables. Then estimate the long-run and short-run relationships between the variables based according to the selected ARDL models. The results are shown in the following table. In short-run any increase in BI rate, will increasing the variance.

Table 15. Estimates of Long-Run and Short-Run Coefficients for variance

Speed Adjustment		
Variable	Coefficient	Std Error
Volatility Credit Card	-0.874***	0.107
Estimates of Long-Run Coefficients		
Variable	Coefficients	Std Error
CPI	0.00122	0.097
BI Rate	0.00047	0.000065
Exchange Rate	-0.0004892	0.0004511
IPI	0.0001269	0.00044
IHSG	0.000191	0.00033
Elmon	0.00098	0.0094
Estimates of Short-Run Coefficients		
Variable	Coefficients	Std Error
Intercept	-0.00267	0.00555
d(BI Rate)	-0.00064***	0.00024

Consumption

We change our time set from monthly into quarterly for this dependent variable first we look the stationary for all variables.

Table 18. Unit root test for quarterly data

Variables	ADF Test		Phillips-Perron Test	DF-GLS Test
	Trend	Drift	Trend	
Consumption	-11.934***(1)	-11.558***(1)	-16.987***(1)	-8.998***(1)
BI Rate	-2.127	-2.23**(0)	-4.68***(0)	-3.73***(1)
Exchange Rate	-4.544***(1)	-4.570***(1)	-4.424***(1)	-4.223***(1)
CPI	-2.141	-2.526***(0)	-4.283***(1)	-3.87***(1)
IPI	-4.889***(0)	-4.766***(0)	-4.869***(0)	-4.565***(0)
IHSG	-5.429***(0)	-5.714***(0)	-6.165***(0)	-5.63***(0)

*,**,*** significant at ɑ=10%,5%,1%

Based on the preliminary test, in which we find that the variables are stationary at order integration I(0) and I(1) therefore we can proceed to perform Autoregressive Distributed Lag (ARDL) for the estimation model. First we must check whether long-run relationship between the variables exists. The result is shown in following table.

Table 19. Bound Test for private consumption variable

	10%		5%		1%	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F	2.475	3.749	2.983	4.423	4.195	6.014

The F critical values is 2.475 for ɑ = 10%, 2.983 for ɑ = 5%, and 4.195 for ɑ = 1%. The resulted F-stat is 4.376, or higher than critical value of ɑ = 1%. Thus, reject the null hypothesis. So, there is long-run relationship between the variables. Then estimate the long-run and short-run relationships between the variables based according to the selected ARDL models. The results are shown in the following table.

Table 20. Estimates of Long-Run and Short-Run Coefficients for Private Consumption

Speed Adjustment		
Variable	Coeffisient	Std Error
Private Consumption	-0.1339**	0.09
Estimates of Long-Run Coefficients		
Variable	Coefficients	Std Error
CPI	0.1334	0.3436
Exchange Rate	0.4022	0.3884
IHSG	0.6777***	0.2260
Elmon	4.9800*	2.916
Estimates of Short-Run Coefficients		
Variable	Coefficients	Std Error
Intercept	3.3718**	1.262
d(Private Consumption)	-0. 9567***	0.1248
Ld(Private Consumption)	-0.7196***	0.1236

Table 20 shows that, in the long run relationship, the electronic money transaction has a positive and statistically significant in 10% significant level. IHSG has a positive and statistically significant in 1% significant level. This results reveal that the electronic money transaction and IHSG converges on its long-run equilibrium by 497% and 67.7% consecutively. Accordingly, for the former variable, any increase in electronic money, IHSG transaction associated with the increase in the private consumption. Our finding confirm the theory that the increase of electronic money will increase private consumption (Igamo & Falianty, 2018). When IHSG increase, investors will invest large amounts of their capital in hope they will get bigger return. By switching traditional to electronic money will reducing the switching cost (Brunnermeier and James, 2019) and because of that the payment efficiency will increase.

Diagnostic and the stability tests are conducted in order to ascertain the robustness of the ARDL model.

Table 21. Goodness of Fit, Diagnostic Tests and Stability Test

Goodness of Fit, Diagnostic Tests and Stability Test		
	Credit card volatility	consumption
Goodness of Fit		
R2	0.3986	0.7326
Adjusted R2	0.351	0.6758
Diagnostic tests		
Serial Correlation	3.705[0.0543]	0.902[0.3423]
Heteroscedasticity	350.92[0]	0.39[0.5338]
Stability test		
Ramsey RESET	48.47[0]	0.83[0.4863]

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