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Does financial digitalization affect macroeconomic stability in Indonesia? An application of the autoregressive distributed lag (ARDL) model

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ABSTRACT

Digitalization has transformed the monetary system more radical for many years. This study aims to investigate the effect of digital payments on macroeconomic stability. Electronic money is used as a proxy for digital payment. The macroeconomic stability is calibrated using exchange rate volatility and inflation rate. This study uses monthly data ranging from January 2009 to March 2020. Macroeconomic data were collected from the Indonesian Central Bureau of Statistics and the Organisation for Economic Co-operation and Development. Industry and market data from the Central Bank of Indonesia (Statistic of Bank Indonesia) and the Indonesian Stock Exchange (IDX). The data were analyzed using the Autoregressive Distributed Lag (ARDL) to examine the long-run and short-run relationship between the studied variables. This study found that digital payments affect Indonesian macroeconomic stability. Electronic money as a proxy of digitalization has a positive and significant relationship with exchange rate volatility and inflation. Cross-border e-commerce might induce exchange rate volatility due to its convenience as a one-stop shopping service and its lower switching cost of currency. The driver of higher inflation is electronic money, which increases people's spending, thus increasing the velocity of circulation and total consumption.

1. Introduction

Digitalization has already changed the way monetary systems operate for many years, but it has recently begun to change its structure radically. Developed economies are increasingly growing the currency's value and, in some cases, are predicted to become entirely cashless shortly (Fiedler et al., 2019; Rahadi et al., 2021; 2022). Unfortunately, the development of digital payments not only brings benefits such as a greater expansion of financial services and boosted economic growth (Ozili, 2018; Slozko and Pelo, 2014; Tee and Ong, 2016), ease of transaction (Krueger, 2017), alternate for the scarcity of cash (Sivathanu, 2019); but also has drawbacks namely discrimination issue (Ozili, 2018), security problem (Jung, 2014), the incentive for corruption (Park, 2012), large computation and communication cost (Yang and Lin, 2016), rely on the technology applied (de Luna et al., 2019; Yaakop et al., 2021). Moreover, the implication of digital money on macroeconomic stability includes exchange rate stability, disturbance of money supply, and the possible cause of the financial crisis. Considering the divergence results on the impact of digital payment, this study aims to evaluate the effect of digital payment on macroeconomic stability and the implication on the payment system efficiency.

This study differs from the previous study in the following ways. First, we examine digital payment effects on macroeconomic stability indicators, namely inflation and exchange rates. At the same time, most of the literature evaluates the association between cashless payments on Gross Domestic Product (GDP) as a proxy for a country's economic growth (Ozili, 2018; Slozko and Pelo, 2014; Tee and Ong, 2016) or on financial stability and monetary stability. Therefore, investigating the exponential growth of digital payment and macroeconomic indicators will contribute to the literature on macroeconomic stability.

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While other literature uses credit and debit card payment (Immordino and Russo, 2018), the number of new FinTech (financial technology) companies established each year and the total number of FinTech companies (Narayan and Sahminan, 2018) as a proxy of digital payment, we will use electronic transaction both server-based (electronic wallet) and chip-based the economy to better capture changes in digital payment use. Our approach is quite similar to the work of Tee and Ong (2016) and Narayan and Sahminan (2018). We extend these two studies by combining them to evaluate the effect of digital payment by incorporating electronic money transactions for the proxy (Tee and Ong, 2016) to the macroeconomic stability represented by inflation (Narayan and Sahminan, 2018) and exchange rate. By integrating these papers, we expect to explain the exponential growth of electronic money use on the dynamic of country inflation and volatility of exchange rates.

Previous studies revealed that digital payment affects Indonesian macroeconomic stability significantly. Electronic money as a proxy of digitalization has a positive and significant relationship with exchange rate volatility and inflation. Cross-border e-commerce and its ecosystem are possible explanations for the exchange rate volatility due to its convenience as a one-stop shopping service and its lower switching cost of currency. Electronic money can ease transaction and makes people spend money more easily, thus increasing the velocity of circulation and total consumption and boosting the price level. This paper is organized as follows: Section. 2 reviews previous digital payment and macroeconomic stability. Section 3 describes the theoretical framework and empirical strategy used in this study. Section 4 describes the data used to represent the interest and control variables, and Section 5 presents our results and discussion. Section 6 concludes and explains policy implication

2. Literature review

2.1. Digital payment and macroeconomic stability

Charbonneau et al. (2017) stated that digitalization could affect inflation from three channels. First, a lower inflation rate would decrease ICT-related goods and services prices. Decrease in prices of other goods or services due to changes in market structure and level of competition and decrease in production cost due to higher productivity and lower labor requirements. Aligning with that phenomenon, digitalization in the payment system is also evolving. It has become part of the digital finance ecosystem characterized by financial services delivered through mobile phones, personal computers, the Internet, or cards (Ozili, 2018).

Access devices, stored-value cards (SVCs), and network money are the three types of e-money or e-banking (Freedman, 2000). ATMs and home banking via telephone or computer are access devices that enable a bank account holder to withdraw or deposit cash, transfer funds, and pay bills. Though far more convenient than visiting a branch or writing a cheque, these instruments are conceptually identical to the traditional mechanism for making payments, transferring funds, or withdrawing cash. SVCs are prepaid cards with electronic funds deposited on a computer chip (or integrated circuit) inserted in the card. Money deposited in electronic form on devices such as a computer's hard disk and transmitted over a communications network such as the internet is known as network money. These products are in the early stages of production compared to SVCs.

E-money is the newest payment instrument, and according to one broad meaning, it is money exchanged electronically (Popovska-Kamnar, 2014). Specific characteristics of e-money include: (i) lower transaction costs, (ii) higher fixed cost, but necessarily significant due to high usage volume, (iii) can substitute the currency in circulation, (iv) has no value if not used, and less transparent. The impact of e-money on the monetary policy includes (i) a reduction in the central bank's leverage over the money supply., (ii) an increase in the velocity of money, (iii) volatility in the exchange rate, (iv) decreasing the need for printing cash, thus influences the revenues of central banks, (v) lower the transaction cost.

2.2. E-money transmission

On the basis of the Indonesia Government's regulation, the electronic money provider should balance their customer's electronic money value with deposits in commercial banks. This policy maintains the central bank's control over the money supply even if electronic money in Indonesia is increasing. On the other hand, the increase in electronic money usage still increases the velocity of money (Popovska-Kamnar, 2014). The velocity of money can be observed through the exchange equation of Irving Fisher, MV=PY, where: M is the total currency stock, V is the circulating velocity of money, P is the average price amount, and Y is the total output. This equation calculates the velocity of money as the ratio of actual output (GDP) to the money supply. Since the Indonesian government has a policy of maintaining the central bank's control of the money supply, the increase in the velocity of money increased GDP. When a country's GDP increases, the private sector will have more confidence to invest for future economic growth. This condition increases the demand for money in the loanable fund market, thus increasing interest rates. In addition, this condition will attract foreign investors to invest in Indonesia's capital market, thus increasing the demand for the Indonesian Rupiah. In the end, it will make the Indonesian Rupiah to be appreciated relative to other countries' currencies.

On the other hand, the increase in GDP also increases society's income, thus increasing society's purchasing power on imported goods. Therefore, due to the increase in imported goods consumption, the supply of Indonesian Rupiah will increase, making the Indonesian Rupiah depreciate relative to other countries' currencies. The price level (inflation) increase also indicates an increase in GDP. This condition makes Indonesia's products lose competitiveness compared to other countries' products, thus decreasing our exports in the long run. In addition, this condition causes the demand for the Indonesian Rupiah to decrease and makes the Indonesian Rupiah depreciate relative to other countries' currencies in the long run. In conclusion, the impact of electronic money usage increase in Indonesia on inflation and exchange rate is the increase in inflation and volatility of exchange rate (unpredicted). Narayan and Sahminan (2018) investigated how digitalization in the financial services industry has influenced Indonesia's inflation rate. They found that using technology in financial services (measured by the number of financial technology start-ups established each year and the total number of financial technology start-ups each year) affects Indonesian financial stability through the inflation rate.

For several decades, maintaining financial stability has become one of the most important functions of central banks worldwide. Allen and Wood (2006) came up with an approach to observe financial stability and concluded that the best way to define financial stability is through the characteristics of financial instability. They then define financial stability as the absence of financial instability episodes (excessive volatility, stress, or crises) that can lead to unfavorable macroeconomic conditions. Furthermore, technological advancement in financial services is intended to decrease transaction costs, achieve economies of scale by collecting and using big data, lower and secure the transmission of information, and decrease the verification cost (Anjan, 2020). Lower the cost and improve the quality of financial services. Lee and Shin (2018) argued that financial technology creates a more stable financial landscape. Thus, the development of digital payment as a part of financial technology can positively be related to financial stability, i.e., inflation.

2.3. Research framework and hypothesis development

The Diffusion of Innovation Theory (DOI) can investigate the impact of digital payment on an economy. Tee and Ong (2016) studied the impact of cashless payment on economic growth, while Lin (2011) investigated the innovation characteristics' effect on financial transactions under the diffusion innovation theory. Roger first introduced the concept of DOI in 1962, describing how imagination is disseminated to participants of a social system over time (Rogers, 1995). According to DOI theory, the interaction between individuals via interpersonal networks causes the implementation of a new concept or innovation. Diffusion, in this sense, is the spread of digital payment where customers prefer better and easier transactions while companies pursue new profit opportunities. According to the types of innovation adopters and the cycle of innovation-decision, the spread of digital payment would result in accepting cashless transactions within society or culture. Since the effect of cashless payment diffusion depends on how rapidly the organization can implement cashless payment across various stages of innovation processes, the implications of cashless payment adoption vary in different societies.

Gai et al. (2008) examined the relationship between financial innovation and macroeconomic stability using a mathematical model. Their results imply that macroeconomic stability and financial innovation could have minimized the likelihood of a systemic financial crisis in developing countries. Finally, a study in the firm-level analysis by Yao et al. (2018) examined the effect of payment technology advances on China's conventional financial industry. It shows that finding technological innovation in a developing country has promoted the development of the financial industry and accelerated the process of industrial evolution. Duffie (2019) examined the monetary implication and business strategy in the presence of faster payment systems and suggested that larger bank business franchises will most likely be disrupted by financial technology firms, which might affect financial stability.

Furthermore, Genberg (2020) provided conceptual reviews on the implication of digital transformation on financial stability, payment systems, and macroeconomic stability. He denotes that financial technology applied to finance has modest effects on financial stability risk as long as its operations are limited in the payment system. Meanwhile, Tee and Ong (2016) examined the impact of electronic payment on economic growth. They find a significant effect of adopting cashless payment in the economy in the long run. The literature mentioned above leads us to our first hypothesis: The development of digital payment increases macroeconomic stability in the Indonesian economy. To test the developed hypothesis, we estimate using the following model:

$$MS_t = f(Electronic\ money_t + Lag\ of\ dependent\ var\ control + Control\ var_t) \quad (1)$$

where, MS_t is inflation and exchange rate represent macroeconomic stability. Our variable of interest is electronic money payment; this proxy denotes the log value of nominal electronic transactions in the economy. The lag of the dependent variable evaluates the dynamic model, i.e., macroeconomic stability, in the form of an autoregressive model. While the control variables consisted of the debit card transaction (DEBIT), credit card transaction (CREDIT), intrabank transfer (INTRA), interbank transfer (INTER), oil prices (OIL), money supply

(M2), and Jakarta Interbank Offered Rate (JIBOR) (Narayan and Sahminan, 2018; Tee and Ong, 2016).

3. Materials and methods

3.1. Research design

For calibrating the relationship between digital payment on macroeconomic stability and payment efficiency, the Autoregressive Distributed Lag (ARDL) model of Pesaran et al. (2001) is performed. When it comes to analyzing an economic situation, the ARDL model is extremely important. Any changes in an economic variable can cause changes in other economic variables outside the time frame of the economy. This change does not show instantly. Instead, it is distributed over future times. ARDL can calibrate this dynamic, which is the main reason for using the ARDL model in this study. Moreover, the ARDL approach has been widely used since it has many benefits over conventional methodological approaches for assessing cointegration and short/long-run relationships.

Firstly, unlike other time-series approaches like the Engle-Granger causality test (Engle and Granger, 1987), Johansen's tests (Johansen, 1991), and Vector Autoregression (VAR), ARDL used to identify the level relationship for variables, e.g., I(0) or I(1) as well as a combination of I(0) and I(1) variables (Adom et al., 2012; Duasa, 2007). Unfortunately, ARDL does not work with non-stationary variables integrated into order two I(2). However, the opportunity to merge I(0) and I(1) variables is a significant benefit since financial time series are frequently either I(1) or I(0) (0). The benefit can be shown further by contrasting, for example, VAR with ARDL for the robustness check.

The ARDL approach also integrates the short-run effect of the given variables with a long-run equilibrium using an error correction without sacrificing long-run data. As a result, it is possible to evaluate both the short-term and long-term relationships between the factors simultaneously. Furthermore, unlike traditional cointegration tests, it is possible to set different lags for each element in the analysis, making it more versatile (Pesaran et al., 2001). Lastly, although most cointegration approaches are susceptible to sample size, the ARDL approach produces stable and reliable findings for small sample sizes (Adom et al., 2012; Pesaran and Shin, 1998; Pesaran et al., 2001), which is ideal for our situation because we have small sample sizes. Following Pesaran and Shin (1995), the following general ARDL (p; q) model:

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} \phi_i y_{t-i} + \beta' x_t + \sum_{i=0}^{q-1} \beta_i^{*\prime} \Delta x_{t-i} + u_t \quad (2)$$

where, p≥1, q≥0, for simplicity, assume that the lag order q is the same for all variables in the K×1 vector x.

3.2. Data sources and variable measurements

This study uses monthly data ranging from January 2009 to March 2020. The secondary data are related to electronic money, debit cards, credit cards, and bank transfers from the Payment Statistic of the Central Bank of Indonesia (Table 1). Macroeconomic data were collected from the Indonesian Central Bureau of Statistics (BPS) and OECD. Industry and market data from the Central Bank of Indonesia (Statistic of Bank Indonesia) and the Indonesian Stock Exchange (IDX).

Table 1: Data sources and measurements

No.	Variable(s)	Measurement/proxy	Source(s)
1	ELMON	Electronic money transaction nominal to Electronic money transaction volume	Payment system statistics central bank of Indonesia
2	ER	Exchange rate volatility	Central bureau of statistics (BPS)
3	INFLATION	Inflation rate	Central bureau of statistics (BPS)
4	ELMON	Electronic money transaction nominal to Electronic money transaction volume	Payment system statistics central bank of Indonesia
5	DEBIT	Debit card transaction nominal to debit card Transaction volume	Payment system statistics central bank of Indonesia
6	INTRA	Intra bank transfer nominal to Intra bank transfer volume	Payment system statistics central bank of Indonesia
7	INTER	Interbank transfer nominal to Interbank transfer volume	Payment system statistics central bank of Indonesia
8	OIL	Log of oil price	Organization for economic co-operation and development (OECD)
9	M2	Log of oil M2	Central bureau of statistics (BPS)
10	JIBOR	Jakarta Interbank Offered Rate	Payment system statistics central bank of Indonesia

4. Results and discussion

4.1. Test of stationary data

We use the ARDL bounds testing of Pesaran et al. (2001) to estimate the long-run cointegration between the variables. In applying ARDL bounds test cointegration, it is necessary to ensure that the stationarity of all variables is not I(2). Table 2 showed that all variables were stationary at I(0) or I(1). To test the stationary of the operational variables, we use some test stationary tests, namely: The Augmented Dickey-Fuller (ADF) Test, the Phillips-Perron Test, and the DF-GLS test of Elliott (1998). In addition, the following are unit root tests for checking the stationary of the data.

Table 2 indicates that 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.

Table 2: Result of stationary data (unit-root test)

Variable(s)	ADF		Phillips-Perron	DF-GLS test
	Trend	Drift	Trend	
ELMON	-2.53	-2.965***(0)	-15.177***(1)	-4.565***(1)
ER	-8.61***(1)	-8.3***(1)	-8.651***(1)	-3.777***(1)
INFLATION	-8.029***(0)	-7.957	-7.529***(0)	-8.667***(0)
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)
OIL	-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)

** and ***: Significant at α= 5% and 1%, respectively

4.2. ARDL bounds testing for long-rung cointegration

The bounds test of cointegration can be used to evaluate the long-run relationship between the variables after the unit root properties of the variables have been checked. According to Pesaran et al. (2001), the bound test is used to validate the impact of the long-run equation, and the F test is used to check the existence of cointegration. A statistical value greater than the bound tests upper value I(1) means that the null hypothesis "there is no cointegration" is rejected, resulting in the acceptance of the alternative hypothesis "there is cointegration" condition. The F test is used to verify the joint significance of lagged variables to check for cointegration. Two asymptotic critical values were introduced by Pesaran et al. (2001), with a lower bound assuming that variables are less than I(0) levels and an upper bound assuming that values are I(1). An F statistic greater than the upper bound critical value I(1) indicates a cointegration effect. For example, suppose the probability of ECM_{t-1} less than the alpha 5% indicates a cointegration effect.

After checking for cointegration, the ARDL model could be used to estimate the short-run and the long-run effects of the variables with substantial cointegration. The Breusch-Godfrey Lagrange Multiplier (LM) test of residual serial correlation is used as an additional diagnostic check, showing a null hypothesis of "no serial correlation." The LM has one degree of freedom (first-order) and follows a $\chi 2$ distribution. In addition, the Breusch-Pagan/ Cook-Weisberg test for heteroskedasticity is conducted to ensure that the models have constant variance. Finally, the Jarque-Bera (J-B) test for normality is often used to test the distribution of residual with the null hypothesis of "residual has a normal distribution" (Thadewald and Büning, 2007).

4.3. Relationship between e-money and macroeconomic stability

This study uses exchange rate volatility and inflation rate as proxies for macroeconomic stability. The explanatory variables with electronic money as a proxy for digitalization are on the other side of the equation. The other electronic transaction is used for the control variables and some industry and country-level data.

4.3.1. Exchange rate volatility

The exchange rate volatility is estimated using the Autoregressive Conditional Heteroscedasticity (ARCH) method. The following are the steps for calculating the exchange rate volatility. We want to check if there is an ARCH effect on the model. First, we test the ARCH effect on the exchange rate. The result is shown in Table 3. We have tested the null of 'no ARCH effects' against four different alternatives, and the result is that we reject the null hypothesis. So, there are ARCH effects in the model.

Table 3: Result of Lagrange multiplier testing

Lags	Chi-square	df	Prob.>chi2
1	123.688	1	0.000
2	123.93	2	0.000
3	122.911	3	0.000
4	121.976	4	0.000

Note: Autoregressive conditional heteroscedasticity model

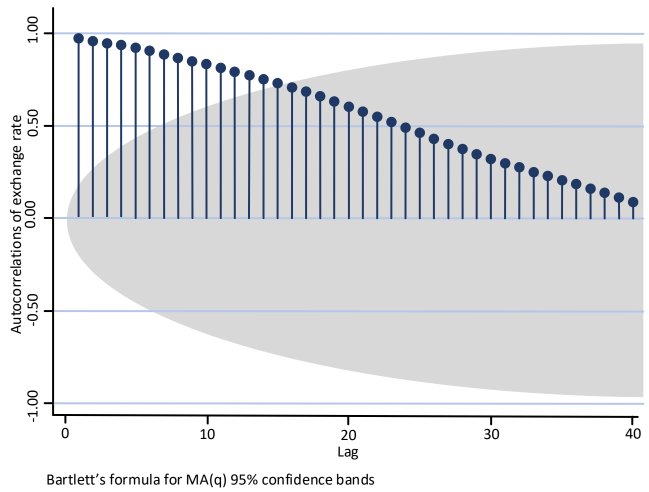
After that, we want to create a new dependent variable by estimating the arch model on the variable exchange rate, so we see the exchange rate volatility ACF and exchange rate volatility PACF.

Fig. 1 displays the ACF and PACF models for exchange rates AR(1) or AR(2). After that, we combine the following models into the ARCH/GARCH model, and the result is in Table 4.

We choose the model with the smallest BIC score (ARIMA (1,1,0) with ARCH (1) GARCH(1)). Then, we estimate the new dependent variable with the model we choose and define it as "variance." The long-run relationship between the variables is checked in the next step. To check the joint significance of the lagged levels of the variables F-test is used under the null hypothesis of "no long-run relationship." The resulting F-statistic is compared to the critical values Pesaran et al. (2001) specified. The Bound Test result for the model with exchange rate volatility as a dependent variable is presented in Table 5.

Table 4: Result of BIC scores

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



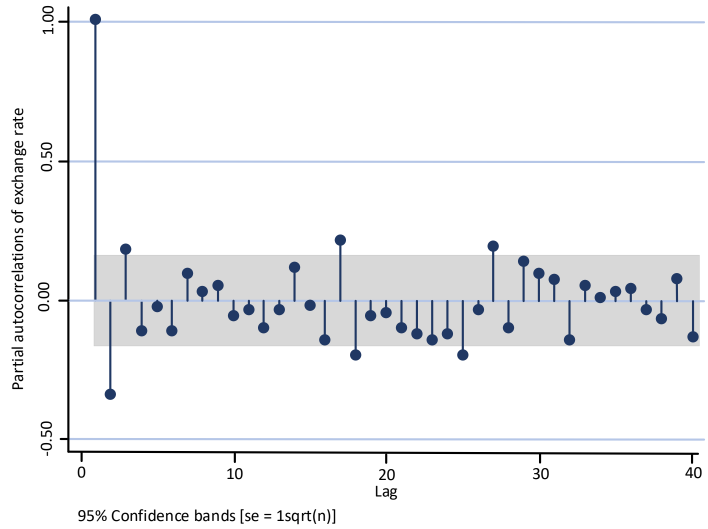


Fig. 1: ACF and PACF (exchange rate volatility)

Table 5: Result of bound testing for exchange rate volatility

	10%		5%		1%	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
Fstat =11.149 Sig. =0.000	2.009	3.176	2.317	3.573	2.991	4.426

Note: Dependent variable: Exchange rate volatility

The F critical value is 2.009 for α=10%, 2.317 for α=5%, and 2991.3 for α=1%. The resulting F-stat is 11.149, or larger than the critical value of α=1%. Thus, do reject the null hypothesis. So, there is a long-run relationship among the variables. Then we estimate the long-run and short-run relationships between the variables based on the selected ARDL with error correction model models. The result is shown in Table 6.

Table 6: Result of long-run and short-run estimates for exchange rate volatility

Variable	Coefficient	Std. error
Speed adjustment		
Exchange rate volatility	-0.52922***	0.110000
Long-run coefficients		
ELMON	0.000983***	0.000289
CREDIT	-0.013***	0.004000
DEBIT	-0.005268***	0.002010
INTRA	-0.00275	0.002730
INTER	0.0672***	0.001545
OIL	-0.0018672***	0.000570
M2	0.0002553**	0.000110
JIBOR	-0.0011	0.003300
Short-run coefficients		
d(CREDIT)	0.0044***	0.001350
Ld(CREDIT)	-0.0024***	0.000900
Intercept	0.138***	0.025000

** and ***: Significant at α= 5% and 1%, respectively

Table 6 shows the long-run and short-run estimates for exchange rate volatility. Electronic and interbank transactions and money supply are positive and statistically significant. Meanwhile, credit card transactions, debit card transactions, and oil prices are negative and statistically significant. Accordingly, any increase in electronic money transactions is associated with exchange rate volatility for the former variable. It can be explained by cross-border e-commerce, which facilitates cross-border transactions with different currencies. So, one can buy a product from a broad without import tax as long as it is less than 75 USD and sometimes with a free delivery cost.

Moreover, it is common that cross-border e-commerce has e-money as part of its ecosystem to provide one-stop services, making currency exchange no longer a big problem. The ease of cross-border transactions and low switching costs will increase the domestic currency exchange rate volatility. In this case, people will buy cross-border product instead of domestic products because it is less expensive and lower the domestic currency because the domestic money supply increases. Our results are consistent with the findings of Popovska-Kamnar (2014). Meanwhile, the negative association between electronic payments using credit cards and debit cards shows that using credit and debit cards mainly for domestic transactions strengthens the currency exchange rate. In the short-run relationship, credit card transaction is positive and statistically significant. At the same time, the first lag of credit card transactions has a negative and significant coefficient. We conduct diagnostic and stability tests to ascertain the ARDL model's robustness.

Table 7 shows the p-values of the serial correlation using the Breusch-Godfrey LM test is 0.9995, implying that no autocorrelation problems exist. On the other hand, the Breusch-Pagan-Godfrey test showed heteroscedasticity issues in the model. Therefore, we use robustness estimation to deal with heteroscedasticity.

4.3.2. Inflation rate

Next, we examine the ARDL with the ECM model for the inflation rate. But, first, we must check whether the long-run relationship between the variables exists using Bound Test. The result is shown in Table 8.

Table 7: Result of goodness of fit and diagnostic testing for exchange rate volatility

	Dependent variable: Exchange rate volatility
Goodness of fit	
R squared	0.5842
Adj. R squared	0.5398
Diagnostic tests	
Serial Correlation	0.845 [0.9995]
Heteroscedasticity	143.51 [0.0000]

Table 8: Result of bound testing for inflation rate

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

The F critical value is 2.01 for α=10%, 2.321 for α=5%, and 3.004 for α=1% (Pesaran et al., 2001). The result of the F-stat is 13.127, and it is higher than the critical value of α=1%. Thus, reject the null hypothesis. So, there is a long-run relationship between the variables. In the next step, based on the selected ARDL model, the long-run and short-run relationships between the variables are estimated. The result is shown in Table 9.

Table 9: Result of long-run and short-run estimates for inflation rate

Variable(s)	Coefficient(s)	Std. error
Speed adjustment		
Inflation rate	-0.8872***	0.10
Long-run coefficients		
ELMON	0.1439*	0.0812
CREDIT	0.499	0.87
DEBIT	0.3787	0.80
INTRA	-3.544***	1.35
INTER	0.8455*	0.434
OIL	-0.00021	0.157
Short-run coefficients		
Ld(INFLATION)	0.334***	0.09
d(INTRA)	3.452***	0.9454
Ld(INTRA)	3.58***	1.06
L2d(INTRA)	2.683***	0.928
L3d(INTRA)	1.909***	0.625
Intercept	31.39***	15.08

* and ***: Significant at α=10% and 1%, respectively

Table 9 shows that in the long-run equilibrium, the electronic money interbank transaction has a positive and is statistically significant at a 10% significant level. Meanwhile, the intra-bank transaction is negative and statistically significant at a 1% significant level. Accordingly, any increase in electronic money and interbank transactions is associated with the inflation rate for the former variable. While for the latter variable indicated that the increase in intra-bank will lead to a decrease in the inflation rate.

The possible explanation for why electronic money drives higher inflation is that using electronic money eases consumers to spend money, thus increasing the velocity of circulation and total consumption (Kipkemboi and Bahia, 2019). Meanwhile, in the short-run, intra-bank transactions, the first lag of inflation and intra-bank transactions, second and third lag of intra-bank transactions have a positive and significant relationship with the inflation rate. The p-values of the serial correlation using the Breusch-Godfrey LM test is 0.44, implying no autocorrelation issues exist. Table 10 shows the results of the goodness of fit and diagnostic testing for the inflation rate.

Table 10: Results of the goodness of fit and diagnostic testing for inflation rate

	Dependent variable: Inflation rate
Goodness of fit	
R-square	0.5696
Adjusted R-square	0.5214
Diagnostic tests	
Serial correlation	3.887 [0.440]
Heteroscedasticity	335.76 [0.000]

5. Conclusion

In summary, this research underscores the profound impact of digitalization on macroeconomic stability. Specifically, electronic money, serving as a representative facet of digitalization, exhibits a discernible and positive correlation with both exchange rate volatility and inflation. The interplay between exchange rate volatility and the adjustment of the monetary multiplier assumes a pivotal role in this regard, shedding light on the proportion of currency within the money supply. The introduction of electronic money precipitates a decline in the currency component, thereby influencing the multiplier. Furthermore, the escalation of inflation can be attributed to electronic money's capacity to diminish transaction costs and facilitate a surge in economic transactions. Our findings emphasize that the proliferation of electronic transactions contributes to heightened macroeconomic instability. This phenomenon is underpinned by the cost-efficiency of electronic money, which stimulates an increased volume of transactions and augments the velocity of money. The full utilization of this augmented velocity hinges on the central bank's ability to effectively regulate and measure monetary aggregates. Failure to do so may entail an escalation in economic volatility. To mitigate these adverse effects, financial authorities should proactively address the enduring relationship between electronic money and macroeconomic instability. Consequently, it is advisable for the central bank to uphold its fiscal equilibrium by imposing a minimum issuer requirement for electronic money. The imposition of a reserve requirement on electronic money serves as a counterbalancing mechanism, ensuring that any increase in electronic money is offset by an equivalent decrease in currency circulation.

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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