

Can an Electronic Money Transaction Raise the Inflation Rate? (Indonesian Pre-Pandemic)

F. Fadli, V. Devia

Brawijaya University, Malang, Indonesia

ABSTRACT

Along with the rapid growth of technology, payment instruments are also changing. Electronic money is slowly but surely replacing the role of paper money and coins. The emergence of electronic money can provide convenience for consumers, it can lead to an increase in the demand for goods and services that ultimately leads to demand-pull inflation. The **purpose** of this study is to determine the impact of electronic money transactions (both in natural and in value terms) on inflation growth. By using the Chow Breakpoint Test, Difference-in-Differences and Propensity Score Matching shows that the inflation trend has tended to decline since the Bank of Indonesia launched its national non-cash campaign. By using the ordinary least squares (OLS) **method** was revealed that an increase in the volume of electronic money transactions in the long-term may affect a decrease in inflation, but not in the short-term. The rate of interest of the Bank of Indonesia, the growth of lending and GDP led to the decline in inflation. It was **concluded** that the Bank of Indonesia could expand the use of electronic money to manipulate inflation levels in the long-term. The policy that can be implemented by Bank Indonesia is to distribute electronic money infrastructure services more evenly and increase the socialization of the use of electronic money, especially in remote areas.

Keywords: electronic money; inflation rate; short-run; long-run; error correction model; propensity score matching; difference in differences; Chow test

For citation: Fadli F., Devia V. Can an electronic money transaction raise the inflation rate? (Indonesian pre-pandemic). *Finance: Theory and Practice*. 2023;27(5):205-218. DOI: 10.26794/2587-5671-2023-27-5-205-218

INTRODUCTION

Technological developments have penetrated all fields, including the transaction activities carried out by the public when carrying out consumption activities. The use of non-cash payment instruments has become a habit of society today. Non-cash payments are more effective and efficient compared to cash because the non-cash payment instruments considered by the community are beneficial. According to Kochergin and Yangirova (2019), the use of electronic money are considered to facilitate transaction activities and they are safe, fast, and convenient to use [1].

Bank Indonesia, in its role to reduce people's dependence on cash, implemented a jargon called the National Non-cash Campaign on August 14th, 2014. The jargon announced by Bank Indonesia is aimed at the public to increase the public's use of non-cash instruments for the creation of a cashless society. The presence of the cashless society is expected to reduce the rate of crime and fraud because the public does not use cash for daily transactions. Apart from that, the government, through Bank Indonesia, wants

to improve its payment systems to catch up with developed countries.

In carrying out its innovations, Bank Indonesia cooperated with three government banks, namely Bank Mandiri, Bank Negara Indonesia, and Bank Rakyat Indonesia, in signing a Memorandum of Understanding regarding the integration of Electronic Data Capture (EDC). Bank Indonesia greatly appreciates the steps taken by the three banks to help improve efficiency in the retail payment system. Bank Indonesia, in achieving its objectives, strongly supports other payment system operators to follow the steps of Bank Indonesia in realizing people who use non-cash instruments.

Some non-cash payment instruments issued by banks in Indonesia to facilitate transaction activities are debit cards, credit cards and electronic money. Debit cards and credit cards are impractical because of their complicated administration and high cost. Electronic money is a solution to the needs of payment instruments because it can make payment processes cheap and fast [2].

The form of electronic money also varies. Some are shaped like cards with a method for replenishing

balances (this form is often used in Indonesia). Another form is the more sophisticated use of applications on smartphones that are connected to a server. The diversity of electronic money types shows that the government, through Bank Indonesia, encourages the use of electronic money. The encouragement has also taken the form of providing an infrastructure suitable for the use of electronic money. The following is data on the provision of electronic money infrastructure (reader machines) in Indonesia.

In achieving its goals, Bank Indonesia tends to focus on the public when conducting small amounts of transactions, thus that the initial step taken by Bank Indonesia is to innovate one of the non-cash instruments, namely electronic money.

As an initial step to introduce the public to non-cash payments, electronic money is very easy to use and has low costs. With the advantages possessed by electronic money, non-bank financial institutions and telecommunications companies have also participated in helping Bank Indonesia to create a cashless society.

The use of electronic money, which is increasing year over year, can also affect the velocity of money [3]. This is because the use of electronic money makes transactions more comfortable and faster. According to the Irving Fisher Money Quantity Theory, the money supply and the velocity of money can affect price. Electronic money cannot affect the amount of money in circulation because it only replaces its role as a medium of exchange [4]. With the amount of money circulating fixed and the velocity of money increases, there will be an increase in prices [5].

After the emergence of a new means of payment, namely electronic money, it is evident that the velocity of money circulation is not constant. Some research resulted that inflation has shown that inflation has decreased drastically in developed countries. It was not caused by monetary policy but by the use of non-cash payment instruments [6].

Several studies have given different results on the relationship between electronic money and inflation. Depending on the case study, some have a negative impact, and some have a positive impact. Therefore, this study analyses the impact of electronic money on inflation in developing countries such as Indonesia. This research focuses on Indonesia because it has wide financial literacy disparities. The use of electronic

money is collected on the island of Java and in the big cities on the islands of Sumatra, Kalimantan and Sulawesi. This is due to the geographical condition of Indonesia which is an archipelago country. The use of the difference-in-differences method as a robustness check is very suitable. This is because there are areas that can be used as control groups and treatment groups.

This research uses the difference-in-difference and the ordinary least squares method as a robustness check that has never been done in other studies. Research on the short-term and long-term impacts of electronic money on inflation using the Error Correction Model in developing countries such as Indonesia has never been carried out. The results of this study will later become input for policymakers in Indonesia to be able to control the inflation caused by electronic money (Bank Indonesia and the Ministry of Finance).

METHODOLOGY

Error Correction Model (ECM)

The general ECM model according to Engle-Grange is as follows:

$$\Delta Y_t = \alpha_0 + \alpha_1 \Delta X_t + \alpha_2 EC_t + e_t, \quad (1)$$

whereas,

$$EC_t = (Y_t - 1 - \beta_0 - \beta_1 X_t - 1). \quad (2)$$

The EC_t difference value is referred to as a disequilibrium error. The coefficient α_0 is a constant and α_1 is the short-term coefficient. β_1 is the long-term coefficient. The imbalance correction coefficient in the form of an absolute value explains how fast of a time is needed to get the balance value [7].

The ECM model in this study:

$$INF_t = \alpha + \beta_1 EMVO_t + \beta_2 EMVA_t + \gamma EC_t + \varepsilon_t. \quad (3)$$

INF_t is inflation in t period. $EMVO_t$ is an electronic money volume transaction (how many transactions are done) in t period. $EMVA_t$ is the electronic money value transaction (the number of transactions measured in Indonesian currency) in t period. α is constant. β is the coefficient. γ is the speed of adjustment. The coefficient γ is the residual velocity in the previous

period used to correct the change in the coefficient γ to equilibrium in the next period. The coefficient γ must be negative and significant to state whether the ECM model used is valid or not. That is, the p-value $< \alpha$ (5%). EC_t is a residual error in the long-run equation. The ε error in the short-term equation shows that t is the time.

Ordinary Least Square (OLS)

OLS is a method in multiple regression analysis to determine the effect of independent variables on dependent variables [8]. The data scale referred to above is for all variables, especially the dependent variable. The OLS model in this study:

$$INF = \alpha + \beta_1 RATE + \varepsilon, \tag{4}$$

$$INF = \alpha - \beta_1 GDP + \varepsilon, \tag{5}$$

$$INF = \alpha + \beta_1 CRD + \varepsilon. \tag{6}$$

INF is inflation. $RATE$ is a 7-day repo rate of Bank Indonesia. GDP is a GDP real (not nominal) growth rate. The negative relationship between INF and the growth rate of real GDP follows from the Fisher's quantitative money theory equation. CRD is a lending growth. α is constant. β is a Slope or the coefficient estimate. The ε is an error.

The regression results obtained the Best Linear Unbiased Estimator (BLUE). A classic assumption test is needed, we can include Linearity test, Normality test, autocorrelation test, normality test, heteroscedasticity test and a multicollinearity test [9].

Cochrane Orcutt

The Cochrane-Orcutt method is a method used to improve when a regression model is found to be autocorrelated [10]. When the autocorrelation structure is unknown, the $\hat{\rho}$ value (autocorrelation coefficient) can be determined using the following formula:

$$\hat{\rho} = \frac{\sum_i^n e_i e_{i-1}}{\sum_i^n e_i^2}, i = 2, 3, 4, \dots, n, \tag{7}$$

where e_i is the error value in the i -th observation, e_{i-1} is the error value in the $(i - 1)$ -th observation and n is the number of observations. In this method, autocorrelation is removed gradually from its simplest form so that autocorrelation can be overcome.

$$INF_i - \hat{\rho} INF_{i-1} = \beta_0 - \hat{\rho} \beta_0 + \beta_i EMVO_i - \hat{\rho} \beta_i EMVO_{i-1} + \beta_i EMVA_i - \hat{\rho} \beta_i EMVA_{i-1} + \hat{\rho} \varepsilon_i - \hat{\rho} \varepsilon_{i-1} \tag{8}$$

$$= \beta_0 (1 - \hat{\rho}) + \beta_i (EMVO - \hat{\rho} EMVO_{i-1}) + (EMVA - \hat{\rho} EMVA_{i-1}) + \hat{\rho} \varepsilon_i - \hat{\rho} \varepsilon_{i-1}. \tag{9}$$

So that it is obtained

$$INF_i^* = \beta_0^* + \beta_i^* EMVO_i^* + \beta_i^* EMVA_i^* + \varepsilon_i^*, \tag{10}$$

were

$$INF_i^* = INF_i - \hat{\rho} INF_{i-1}, \tag{11}$$

$$\beta_0^* = \beta_0 - \hat{\rho} \beta_0, \tag{12}$$

$$EMVO_i^* = EMVO_i - \hat{\rho} EMVO_{i-1}, \tag{13}$$

$$EMVA_i^* = EMVA_i - \hat{\rho} EMVA_{i-1}, \tag{14}$$

$$\beta_i^* = \beta_i. \tag{15}$$

In this step, it is not known whether the $\hat{\rho}$ value obtained in the first iteration is the best value in overcoming autocorrelation. The value of $\hat{\rho}$ is transformed into Equation the equation in the third step above so that the error value of the new model is obtained. This step needs to be repeated until the convergent $\hat{\rho}$ value is obtained.

Chow Breakpoint Test

The Chow Test is used to test whether two or more regressions are different [11]. The Model Stability Test is conducted to determine within a certain period from the entire range of estimated time periods, whether the model can still be used as a valid prediction. Usually, if there is a policy variable, then the equation model assessment can predict well

from the policy issuance period to the end of the observation period.

$$F = \frac{(RSS^R + RSS^U)/(k+1)}{(RSS^U)/(DoF)}, \quad (16)$$

where RSS^R is the restricted sum of squared residuals, RSS^U is the sum of squared residuals from subsample u, DoF is the Degree of Freedom, and k is the number of parameters in the equation.

Difference in Difference

The Difference-in-Differences (DID) is a statistical technique used in econometrics and quantitative research in the social sciences that attempts to mimic an experimental research design using observational data by studying the differential effect of a treatment on a “treatment group” versus a “control group” in a natural experiment [12]. This research used Jakarta as a state capital of Indonesia for treatment group and Jayapura as the capital and largest city of the Indonesian province of Papua.

$$INF_{it} = \beta_i + \beta_t + \gamma Treated_i X Post_t + u_{it}, \quad (17)$$

where the dependent variable is the inflation rate of city i at date t ; β_i are city-specific, time-invariant fixed effects and β_t are the time-specific, city-invariant fixed effects. $Treated_i$ denotes a vector of the dummy variables: $Treated_i = 1$ for the treatment group, and $Treated_i = 0$ for the control group. $Post_t$ denotes a vector of dummy variables: $Post_t = 1$ in the post-treatment periods when the application of the jargon of the non-cash national movements by Bank Indonesia was announced at date $t \geq 0$, and $Treated_i = 0$ otherwise. u_{it} are the error terms. γ is the coefficient of enthusiasm for Specification. This research utilizes two sources of variation to distinguish γ . Initially, γ is recognized utilizing the variety between the treatment group and the control group. Second, γ is likewise distinguished utilizing the variety inside each group before and after the application of the jargon of the non-cash national movements by Bank Indonesia is announced.

Propensity Score Matching (PSM)

Propensity Score Matching (PSM) method is used to minimize the possibility of selection bias. PSM can reduce to a one-dimensional score of various multidimensional matching variables [13].

The first order in applying the PSM method is to use logistic regression models as this distribution is often approximately normal. Given the observed covariate vectors (x_i), as conditional probabilities for specifying certain treatments ($w_i = 1$) versus non-treatment ($w_i = 0$), PSM will define the trend scores for individuals. The covariates in vector X are called matching variables.

$$P(x_i) = pr(w_i = 1 | X = x_i). \quad (18)$$

The second-order matches treated subjects to non-treated subjects which supports the calculable propensity scores. The main matching methods are nearest neighbour matching, radius matching, kernel matching, and stratification matching.

The third order is balance assessment, which checks whether the propensity scores are balanced across treatment and matched groups and whether the matching variables are balanced across treatment and matched teams among the strata of the propensity scores.

RESEARCH RESULTS

Error Correction Model

The first step in the ECM method is to perform a unit root test using the ADF method. The unit root test results using ADF are as follows.

Based on *Table 1*, the ADF Unit Root test results show that the electronic money transaction volume variable and the electronic money transaction value are not stationary at the degree level. Only the variable of inflation is stationary at the degree level. Therefore, it is necessary to test the degree of integration to see if the data will be stationary in the first difference or second difference degree. The reason for the transformation of variables into natural logarithms is to smooth the data due to the different units of measurement of each different variable.

After the first difference, the results of the degree of integration test using the ADF show that all the stationary data is in the first-degree difference. This is

Table 1

Unit Root Testing Results

Level Difference			1 st Difference		
Variable	Prob.	Results	Variable	Prob.	Results
INF	0.0317	Stationary	INF	0.0000	Stationary
LN_EMVO	0.9847	Not stationary	LN_EMVO	0.0000	Stationary
LN_EMVA	0.8749	Not stationary	LN_EMVA	0.0000	Stationary

Source: Compiled by the authors.

Table 2

Cointegration Test Results

Variable	Prob.	Result
RES(-1)	0.0077	There is Cointegration

Source: Compiled by the authors.

evidenced by the probability value being smaller than the α of 5% or 0.05. Therefore, it can be concluded that all the variables of this study were stationary at the first difference degree. After the integration requirements are met, it can enter the next stage.

Table 2 explains that the residuals tested by the ADF method show there to be a cointegration between the research variables. The probability value is smaller than α , thus it can be concluded that there is cointegration between the research variables. Before proceeding to the next step, the classic assumption test must be run to produce a BLUE-regression.

The linearity test is carried out to check whether the independent variables are linearly related to the dependent variable. The linearity test in this study using the Ramsey RESET test as shown in Table 3. The result of this test was 0.5512, which is > 0.05 . Thus, it can be concluded that the independent variables are linearly related to the dependent variable.

The Breusch-Pagan Godfrey Test as shown in Table 4 was carried out to check whether heteroscedasticity occurred. The p-value is indicated by the value of the probability, which is equal to 0.2757. This is > 0.05 . This means that the regression model shows homoscedasticity. In other words, there is no problem with the assumption of non-heteroscedasticity.

Table 3

Ramsey RESET Test

	Value	Df	Probability
t-statistic	0.597719	116	0.5512
F-statistic	0.357268	(1,116)	0.5512
Likelihood ratio	0.369020	1	0.5435

Source: Compiled by the authors.

Table 4

Breusch Pagan Godfrey Test Results

F-statistic	1.306652
Obs*R-Squared	3.922595
Scaled explained SS	8.869701
Probability F(3,115)	0.2757
Prob. Chi-Square(3)	0.2699
Prob. Chi-Square(3)	0.0311

Source: Compiled by the authors.

Table 5

VIF Results

Variable	Centred VIF	Uncentered VIF	Coefficient Variance
LNEMVO	0.008549	2763.831	26.06883
LNEMVA	0.012392	2290.884	26.06883
C	0.102260	119.8602	NA

Source: Compiled by the authors.

Table 6

Normality Test

Jarque-Bera	Probability
0.563623	0.754416

Source: Compiled by the authors.

Table 7

Short-run ECM Estimation Results

Dependent Variable: Inflation (Y)			
Variable	Coefficient	Prob.	Results
D(LN_EMVO)	0.058921	0.4523	not significant
D(LN_EMVA)	-0.012317	0.8568	not significant
RES(-1)	-0.086002	0.0193	significant negative

Source: Compiled by the authors.

Table 8

Long-run ECM Estimation Results

Dependent Variable: Inflation (INF)			
Variable	Coefficient	Prob.	Results
D(LN_EMVO)	0.191657	0.0404	Significant positive
D(LN_EMVA)	-0.316882	0.0052	Significant negative
C	-2.266917	0.0000	Significant negative

Source: Compiled by the authors.

Table 9

Long-run ECM Estimation Results (Cochrane Orcutt)

Dependent Variable: Inflation (INF)			
Variable	Coefficient	Prob.	Results
D(LN_EMVO)	-0.156377	0.0063	Significant negative
D(LN_EMVA)	-0.024433	0.7343	Not Significant
AR(1)	-0.947936	0.0000	Significant negative

Source: Compiled by the authors.

The results of the multicollinearity test, as shown in Table 5, indicate that the Centered VIF value for all variables is below 10. It can be stated that there is no multicollinearity problem present in the prediction model.

The normality test, as shown in Table 6 in this study, used the Jarque-Bera Test. All the significant values of the test are < 0.05 . It results in the acceptance of H_0 which means the residual is normally distributed.

The Durbin-Watson Stat value in the model of this study was 0.186876 (details are in the appendix). This value is the value of the Durbin-Watson (DW) test. The Durbin-Watson test table has the critical values of $d_l = 1.68531$ (Durbin-Watson test table for lower critical values) and $d_u = 1.71889$ (Durbin-Watson test table

for upper critical values). The results are $DW < d_u$ and value $(4 - DW) > d_u$, indicating that there is a negative autocorrelation problem. To eliminate the symptoms of autocorrelation, one can use Cochrane Orcutt (the results of the calculations are in the appendix). After transforming the model using Cochrane Orcutt, a DW value of 1.878212 was obtained. Moreover, this research also conducted a robustness check using OLS against other factors that could affect inflation to accommodate the possibility of errors in the model specification, for example, significant explanatory variables are missing because the Durbin-Watson test rejected the hypothesis of no autocorrelation in a random perturbation.

The results of the short-run ECM estimation in Table 7 shows that in the short-run, the variables

Table 10

Chow Breakpoint Test Results

Chow Breakpoint Test: 2014M08				
Null Hypothesis: No breaks at specified breakpoints				
Varying regressors: All equation variables				
Equation Sample: 2009M01 2019M12				
F-statistic	23.68388		Prob. F(1,130)	0.0000
Log likelihood ratio	22.09196		Prob. Chi-Square(1)	0.0000
Wald Statistic	23.68388		Prob. Chi-Square(1)	0.0000

Source: Compiled by the authors.

of electronic money transaction volume (EMVO) and electronic money transaction value (EMVA) cannot affect inflation (INF). According to Keynes (1937), prices are sticky in the short-term [14]. Wage rigidity causes the prices to change in the long-run [15].

The results of the ECM analysis in the long-term in *Table 8* show that the variable volume of electronic money transactions (EMVO) can affect inflation positively. The value of electronic money transactions (EMVA) can negatively affect inflation (INF). However, the results of the long-run regression analysis experience symptoms of autocorrelation (the test results are present in the discussion of the classic assumption test), meaning that they must be transformed using Cochrane Orcutt.

The ECM results in the long-term in *Table 9* indicate that only the volume of the electronic money transaction (EMVO) can affect the inflation variable (INF). This is consistent with the theory of the velocity of money proposed by Fisher. This states that the velocity of money can affect prices [5]. The volume of electronic money transactions (EMVO) illustrates how much electronic money is used for transactions. This means describing how quickly electronic money can change hands. The value of electronic money transactions (EMVA) only illustrates the nominal amount of electronic money transactions.

Chow Breakpoint Test

Table 10 shows the Chow Breakpoint Test gives an F statistical value of $23.683 > F$ table 3.91 with a probability of 0.000. The conclusions obtained accept the hypothesis that the parameters are unstable for both periods before August 2014 and after August 2014 at the 5% significance level. These results indicate that for both periods, the parameters change significantly, or that the application of the jargon of the non-cash national movements by Bank Indonesia has an impact on the inflation movement.

Difference in Difference (DID)

This research also applied the Difference in Difference (DID) method for robustness checking. The use of the DID method is to find out whether the period of the application of the jargon of the non-cash national movements by Bank Indonesia has an impact on the inflation movement. Before applying the DID method, a common trend assumption test was performed. The common trend assumption is the assumption set where no treatment results from the treatment group and the control group has the same trend [16]. Common trend assumptions usually use pre-treatment data to show the same trend.

Based on *Fig. 1*, it shows that in the period before the implementation of the jargon of the non-cash national movement in August 2014, inflation in the Jakarta and

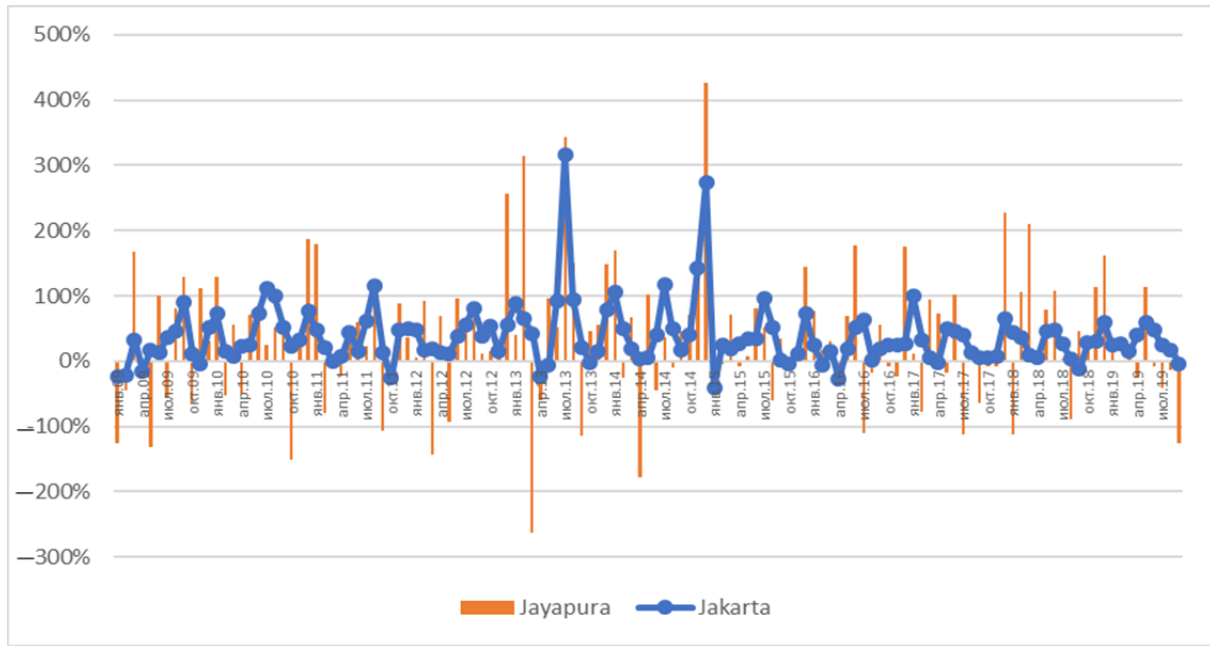


Fig. 1. Common Trend Inspection Source: Compiled by Author

Source: Compiled by the authors.

Table 11

Difference in Differences Results

Test	Coef.	Std. Err	T	P > t	95% Conf. Interval	
DID	-0.9308841	0.1938362	-4.80	0.000	-1.313156	-0.5486118
Placebo	-0.0511369	0.0781356	-0.65	0.515	-0.2064914	0.1042177

Source: Compiled by the authors.

Jayapura regions had the same trend. The choice of the city of Jakarta as the treatment group is due to the very frequent use of electronic money. This is because Jakarta is the capital of Indonesia. The selection of Jayapura city as a control group is due to the almost non-use of electronic money in the city. This is because the city of Jayapura is a remote area that does not have the infrastructure to support the use of electronic money.

The results of the Difference in Differences method on the Table 11 show a similarity to the Multiple Linear Regression method. The coefficient value shows negative and significant results. As shown in the results of Table 10, the coefficient value of -0.9308841 with a probability value ($P > t$) below 5%. These results indicate that in the period after the implementation of the jargon of the non-cash national movement, the inflation movement has decreased.

A second way to test the assumption of equal trends would be to perform what is known as a “placebo” test

Matching Methods Results

Table 12

Matching Methods	ATT	t
Nearest Neighbor	-0.543	-5.432
Radius	-0.543	-5.432
Stratification	-0.543	-5.432

Source: Compiled by the authors.

[16]. The placebo test performs additional difference-in-difference estimates using a “sham” treatment group, that is, the group not affected by the program [12]. This research uses inflation data from Singapore as a treatment group and Brunei Darussalam as a control group for the same period as the DID test. Singapore and Brunei Darussalam are used because they are neighboring countries, have direct borders

Table 13

Other Factors Multiple Linear Regression Estimation Results 1

Dependent Variable: Inflation (INF)				
Var.	Coeff.	t-Stat.	Prob.	Results
RATE	-0.003528	-3.778618	0.0005	Significant negative
C	0.051118	10.71255	0.0000	Significant positive
R-squared	0.267990			
F-statistic	14.27795			
Prob(F-statistic)	0.000528			
Linearity	0.3330			
Normality	0.193816			

Source: Compiled by the authors.

Table 14

Other Factors Multiple Linear Regression Estimation Results 2

Dependent Variable: Inflation (INF)				
Var.	Coeff.	t-Stat.	Prob.	Results
CRDT	0.212780	6.450438	0.0000	Significant positive
C	1.756366	2.900618	0.0055	Not Significant
R-squared	0.454197			
F-statistic	41.60815			
Prob(F-statistic)	0.000000			
Linearity	0.0509			
Normality	0.464029			

Source: Compiled by the authors.

with Indonesia and are included in ASEAN countries. The inequality of the results from the placebo test also strengthens the results of the analysis. The application of the jargon of the non-cash national movement only has an impact on the inflation rate in Indonesia (Placebo test probability above 5%).

Propensity Score Matching (PSM)

Table 12 shows the results of the estimation of the Average Treatment of Treated Effect (ATT) with 3 matching methods (Nearest Neighbor, Radius, and Stratification). The ATT value shows conformity with the DID results (-0.543) and the t-test shows

Other Factors Multiple Linear Regression Estimation Results 2

Dependent Variable: Inflation (LINF)				
Var.	Coeffi.	t-Stat.	Prob.	Results
LGDP	1.531864	2.744967	0.0078	Significant positive
C	-0.850147	-0.905328	0.3686	Not Significant
R-squared	0.102466			
F-statistic	7.534845			
Prob(F-statistic)	0.007788			
Linearity	0.6603			
Normality	0.192873			

Source: Compiled by author.

significant results ($> t$ table). This means that when the jargon of the non-cash national movement is applied, there is a decrease in the inflation rate, showing the same result as DID coefficient. These results indicate that it is appropriate to use Jakarta as the treatment group and Jayapura as the control group.

Robustness Check

Other factors that influence inflation

$$INF = 0.051118 - 0.003528RATE + \varepsilon \quad (19)$$

The regression results of the inflation variable with the 7-day repo rate of Bank Indonesia in *Table 13* show negative results, this is in accordance with the explanation in the previous paragraph. The results of *Table 13* show that any increase in interest rate in 2009–2019 (monthly) in Indonesia by 1% will have an impact on reducing the inflation rate by 0.003%. The increase in the Volume of Electronic Money for the

Transaction was accompanied by an increase in the interest rate. The volume of transactions on electronic money increased due to changes in the use of cash into electronic money [17]. Therefore, the transaction remains the same.

$$INF = 1.756366 + 0.212780CRDT + \varepsilon \quad (20)$$

The policy of increasing the interest rate by Bank Indonesia resulted in lowering demand for credit, thereby reducing the price level (deflation). The regression results of the credit growth variable with inflation in *Table 14* also show a positive relationship. The results of *Table 14* show that any decrease in credit growth in 2005–2019 (quarterly) in Indonesia by 1% will have an impact on reducing the inflation rate by 0.21%. This indicates that the decline in credit growth due to an increase in interest rates will lead to a decrease in the inflation rate [18].

$$INF = -0.850147 + 1.531864GDP + \varepsilon \quad (21)$$

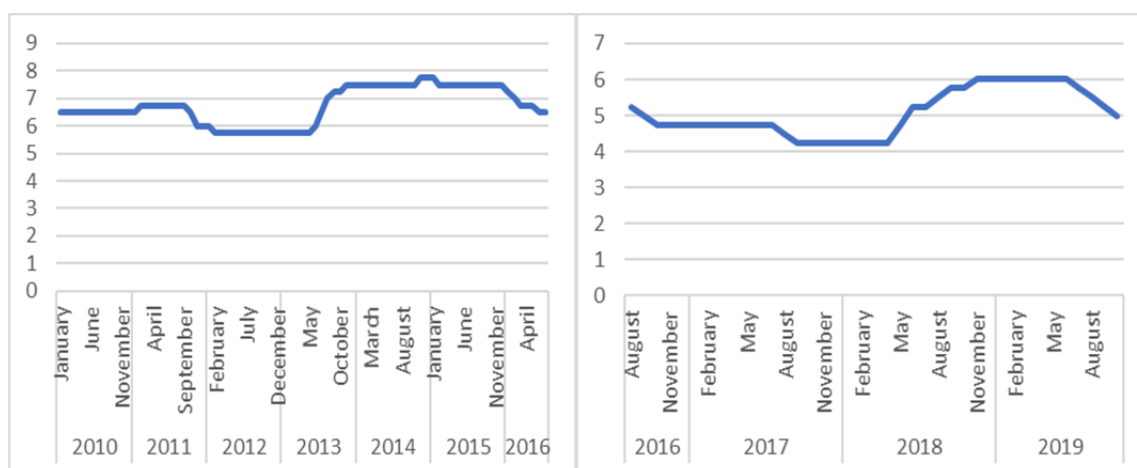


Fig. 2. BI Rate % and 7-Day Repo Rate, %

Source: Bank Indonesia.

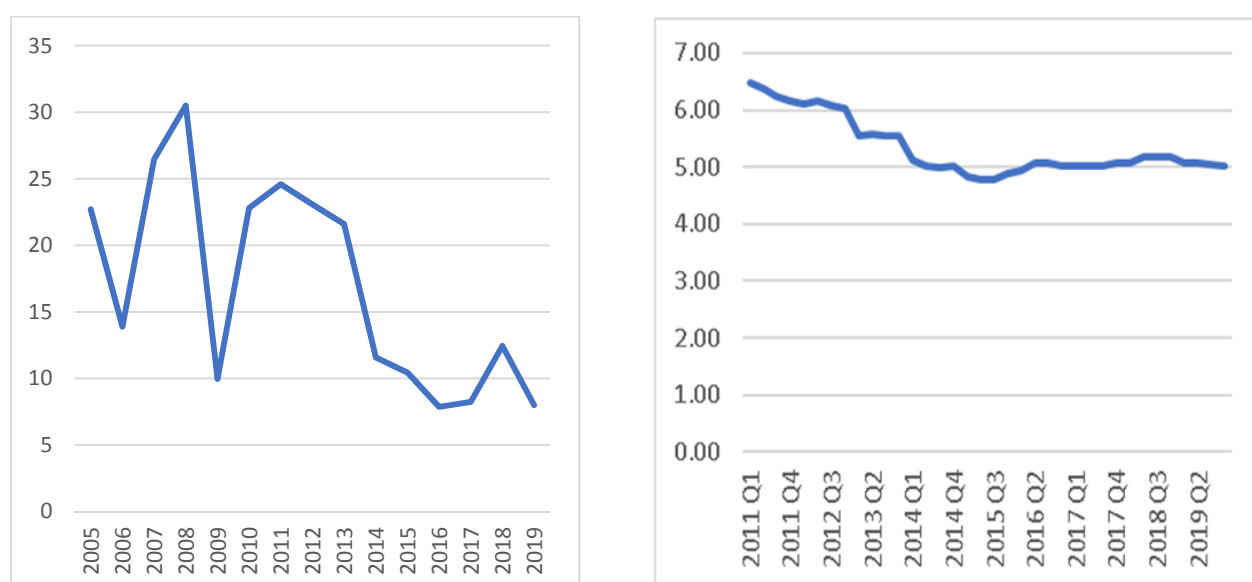


Fig. 3. Credit Growth, %

Source: Bank Indonesia.

Fig. 4. Indonesia GDP Real Growth, %

Source: Statistic Indonesia.

Table 15 shows the positive relationship between inflation and GDP. An increase in GDP growth will lead to an increase in the inflation rate [19]. The results of Table 12 show that a decrease in GDP growth in 2003–2019 (quarterly) in Indonesia by 1% will have an impact on reducing the inflation rate by 1.53%.

DISCUSSION

The results obtained from the study show there to be a negative relationship between the volumes of electronic money transactions (EMVO) and inflation (INF). This means that the higher the volume

of electronic money transactions, the lower the inflation. The results of this study are in line with the research results of Frida Calson-Öhman and Ramon Marimon which have been described in the literature review above.

Moreover, the results of the study are in line with the theories of Baumol and Tobin. The higher the interest rate that occurs in society, the greater the costs borne by someone who holds cash [20, 21]. The increase in volume of electronic money transactions (EMVO) is a result of a shift in payment methods that previously used cash to now use electronic money.

Apart from encouragement from the government, such as using electronic money to pay for toll road use, the public would prefer to use electronic money as a transaction tool compared to cash because, by using electronic money, the public does not need to bear the costs of losing to the interest rate, as stated by Baumol and Tobin. The easy top-up process (transferring the nominal money from a bank account to electronic money) causes people to tend to use electronic money only for current transaction needs and prefer to keep most of their money in a bank account. Therefore, when the interest rate is high, people will be reluctant to make transactions.

Apart from that, electronic money providers being in competition to attract people is also a factor causing there to be a negative relationship between electronic money transaction volume and inflation. Almost all electronic money providers cooperate with e-commerce companies using the “burn money” marketing strategy by giving cashback and discounted prices [6]. This marketing strategy can drive a large volume of electronic money transactions, accompanied by lower prices for goods.

Figure 2 shows the interest rates in Indonesia during the period 2010–2019. From 2010 to 2016, Bank Indonesia still used the BI rate. From 2016 until now, Bank Indonesia has used 7-day repo rates. Based on this data, during the period 2010–2019, interest rates experienced a positive trend. When interest rates increase, the amount of money held for transactions decreases. In other words, the transaction component of the demand for money is negatively related to the interest rate [16, 22].

Figure 3 shows that Indonesia experienced a decline in credit growth from 2005 to 2019. The decline in credit growth was the result of the increase in the interest rate. Meanwhile, a decrease in credit growth can cause a decrease in the inflation rate [13, 23, 24].

Figure 4 shows Indonesia’s real GDP growth which is experiencing a downward trend. This indicates that the growth in the use of electronic money is not accompanied by a growth in GDP. Meanwhile, GDP is influenced by the inflation rate [19, 25]. Hence, the decline in Indonesia’s GDP causes deflation. GDP growth in Indonesia based on the figure above has experienced a downward trend from 2011–2019

although the use of electronic money has increased. Besides, higher inflation expectations were reported by individuals who focused more on how to cover their future expenses and on prices they pay (rather than on the inflation rate) and by individuals with lower financial literacy [26]. Therefore, the low level of financial literacy in Indonesia has resulted in lower inflation.

CONCLUSIONS

Based on the research results above, it can be concluded that electronic money has no impact on inflation in the short-term. In the long-term, electronic money has a negative effect on inflation. The increase in the use of electronic money as a transaction is a result of changes in the payment method, which previously paid used cash and is now using electronic money, so that it does not affect the price level. The marketing strategy of electronic money service providers, in collaboration with e-commerce companies, is competing to provide massive discounts on their merchandise prices if buyers use electronic money as a means of payment that can trigger a price decline. Another cause is the positive trend of interest rates implemented by Bank Indonesia, declining credit growth, declining GDP growth, and low financial literacy rate. Moreover, in the period after Bank Indonesia implemented the jargon of the national non-cash campaign, the inflation rate has decreased.

This research can be used as an input for the government to increase cooperation and coordination when supporting the electronic money infrastructure in various regions with Bank Indonesia under the national non-cash campaign program. To avoid inequality, only a few large cities in Indonesia tend to use electronic money. Nevertheless, it should be more evenly distributed across all regions in Indonesia. In addition, increasing the level of financial literacy of the Indonesian people also needs to be done.

The limitation of this research is that it only uses the variable transaction volume and the electronic money transaction value to see its effect on inflation. This is because there were limitations regarding the availability of the data.

ACKNOWLEDGMENTS

Thank you to the Department of Economics, Faculty of Economics and Business, Brawijaya University for supporting us in completing this research.

REFERENCES

1. Kochergin D.A., Yangirova A.I. Central Bank digital currencies: Key characteristics and directions of influence on monetary and credit and payment systems. *Finance: Theory and Practice*. 2019;23(4):80–98. DOI: 10.26794/2587–5671–2019–23–4–80–98
2. Gunawan H., Sinaga B.L., Purnomo W.P.S. Assessment of the readiness of micro, small and medium enterprises in using e-money using the Unified Theory of Acceptance and Use of Technology (UTAUT) method. *Procedia Computer Science*. 2019;161:316–323. DOI: 10.1016/j.procs.2019.11.129
3. Kartika V.T., Nugroho A.A.B. Analysis on electronic money transactions on velocity of money in ASEAN-5 countries. *Journal of Business and Management*. 2015;4(9):44–56.
4. Luo S., Zhou G., Zhou J. The impact of electronic money on monetary policy: Based on DSGE model simulations. *Mathematics*. 2021;9(20):2614. DOI: 10.3390/math9202614
5. Mele A., Stefanski R. Velocity in the long run: Money and structural transformation. *Review of Economic Dynamics*. 2019;31:393–410. DOI: 10.1016/j.red.2018.09.004
6. Calson-Öhman F. The effect of increased e-commerce on inflation. Master degree thesis. Stockholm: Institution for Social Sciences; 2018. 31 p. URL: <https://sh.diva-portal.org/smash/get/diva2:1214628/FULLTEXT01.pdf>
7. Ren X., Shao Q., Zhong R. Nexus between green finance, non-fossil energy use, and carbon intensity: Empirical evidence from China based on a vector error correction model. *Journal of Cleaner Production*. 2020;277:122844. DOI: 10.1016/j.jclepro.2020.122844
8. Wang L., Hou H., Weng J. Ordinary least squares modelling of urban heat island intensity based on landscape composition and configuration: A comparative study among three megacities along the Yangtze River. *Sustainable Cities and Society*. 2020;62:102381. DOI: 10.1016/j.scs.2020.102381
9. Simamora R.H. Socialization of information technology utilization and knowledge of information system effectiveness at Hospital Nurses in Medan, North Sumatra. *International Journal of Advanced Computer Science and Applications*. 2019;10(9):117–121. DOI: 10.14569/IJACSA.2019.0100916
10. Ayinde K., Lukman A.F., Rauf R.I., Alabi O.O., Okon C.E., Ayinde O.E. Modeling Nigerian COVID-19 cases: A comparative analysis of models and estimators. *Chaos, Solitons & Fractals*. 2020;138:109911. DOI: 10.1016/j.chaos.2020.109911
11. Petrevska B. Predicting tourism demand by A.R.I.M.A. models. *Ekonomiska Istraživanja = Economic Research*. 2017;30(1):939–950. DOI: 10.1080/1331677X.2017.1314822
12. Fadli F., Maski G., Sumantri V.D.S. Earmarking tax: Can it increase public trust in the Indonesian government? *Institutions and Economies*. 2020;12(2):1–40. URL: <https://ijie.um.edu.my/index.php/ijie/article/view/17016/11582>
13. Yan Y., Hongbing O. Effects of house-sale restrictions in China: A difference-in-difference approach. *Applied Economic Letters*. 2018;25(15):1051–1057. DOI: 10.1080/13504851.2017.1394968
14. Bhattarai S., Eggertsson G.B., Schoenle R. Is increased price flexibility stabilizing? Redux. *Journal of Monetary Economics*. 2018;100:66–82. DOI: 10.1016/j.jmoneco.2018.07.006
15. Rhee H.J., Song J. Wage rigidities and unemployment fluctuations in a small open economy. *Economic Modelling*. 2020;88:244–262. DOI: 10.1016/j.econmod.2019.09.033
16. Shu Y., Cai J. “Alcohol bans”: Can they reveal the effect of Xi Jinping’s anti-corruption campaign? *European Journal of Political Economy*. 2017;50:37–51. DOI: 10.1016/j.ejpoleco.2017.09.004
17. Brown M., Hentschel N., Mettler H., Stix H. The convenience of electronic payments and consumer cash demand. *Journal of Monetary Economics*. 2022;130:86–102. DOI: 10.1016/j.jmoneco.2022.06.001

18. Eo Y., Lie D. Average inflation targeting and interest-rate smoothing. *Economics Letters*. 2020;189:109005. DOI: 10.1016/j.econlet.2020.109005
19. Chen H. Nominal GDP targeting, real economic activity and inflation stabilization in a new Keynesian framework. *The Quarterly Review of Economics and Finance*. 2020;78:53–63. DOI: 10.1016/j.qref.2020.01.002
20. Alvarez F., Lippi F. Cash burns: An inventory model with a cash-credit choice. *Journal of Monetary Economics*. 2017;90:99–112. DOI: 10.1016/j.jmoneco.2017.07.001
21. Alvarez F., Lippi F., Robatto R. Cost of inflation in inventory theoretical models. *Review of Economic Dynamics*. 2019;32:206–226. DOI: 10.1016/j.red.2018.11.001
22. Švigir M., Miloš J. Relationship between inflation and economic growth; comparative experience of Italy and Austria. *FIP: Financije i pravo*. 2017;5(2):91–101. URL: <https://hrcak.srce.hr/file/285035>
23. Alberola E., Urrutia C. Does informality facilitate inflation stability? *Journal of Development Economics*. 2020;146:102505. DOI: 10.1016/j.jdeveco.2020.102505
24. Kumar A., Dash P. Changing transmission of monetary policy on disaggregate inflation in India. *Economic Modelling*. 2020;92:109–125. DOI: 10.1016/j.econmod.2020.07.016
25. Balima H. W., Kilama E. G., Tapsoba R. Inflation targeting: Genuine effects or publication selection bias? *European Economic Review*. 2020;128:103520. DOI: 10.1016/j.eurocorev.2020.103520
26. Davoli M., Rodríguez-Planas N. Culture and adult financial literacy: Evidence from the United States. *Economics of Education Review*. 2020;78:102013. DOI: 10.1016/j.econedurev.2020.102013

ABOUT THE AUTHORS



Faishal Fadli — PhD in Econ., Head of International Undergraduate Program Economics Department; Lecturer, School of Economics and Business, Brawijaya University, Malang, Indonesia
<https://orcid.org/0000-0001-9478-0316>
faishalfadli@ub.ac.id



Vietha Devia — PhD in Finance, Head of Quality Assurance Unit Economics Department Brawijaya University, Malang, Indonesia; Lecturer, School of Economics and Business Brawijaya University, Malang, Indonesia
<https://orcid.org/0000-0001-7340-1911>
Corresponding author:
vietha.devia@ub.ac.id

Conflicts of Interest Statement: The authors have no conflicts of interest to declare.

The authors read and approved the final version of the manuscript.

The article was submitted on 23.08.2022; revised on 15.09.2022 and accepted for publication on 26.10.2022.