International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Analysis Of The Influence Of Macroeconomic Factors And Payment Infrastructure On The Use Of Electronic Money In Indonesia: Implications For Cbdc Adoption

Adzra Alifia Isma[1], Tiara Nirmala[2]

[1,2]Department of Development Economics, Economic and Business Faculty, University of Lampung

Corresponding author: adzra.alifiaisma@gmail.com

Abstract

This study explores how macroeconomic factors and payment infrastructure affect Indonesian electronic money use, giving insights for Central Bank Digital Currency adoption. The rapid growth of financial technology and the global shift toward Central Bank Digital Currencies inspired this study to address a gap in empirical quantitative analysis. The interrelationships are examined using an Error Correction Model (ECM) using time series data from January 2014 to December 2024. In both the short and long run, the BI Rate, money supply (M2), EDC devices, and ATM/debit cards all have a statistically significant and beneficial effect on electronic money transactions. Despite rising interest rates, consumers see electronic money as a viable alternative, and a good payment infrastructure helps promote its use. Inflation hurts electronic money transactions, therefore price stability is crucial for digital currency. The research shows that macroeconomic policies and infrastructural development are necessary for CBDC implementation, which is important for Indonesian monetary authorities. The models explain most of the diversity in electronic money transactions, highlighting these elements' cumulative effect.

Keywords: Electronic Money, Macroeconomic Factors, Payment Infrastructure, CBDC Adoption, Indonesia

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

INTRODUCTION

Technology in payment systems is transforming the financial landscape, necessitating a thorough examination of electronic money adoption and its effects on Central Bank Digital Currency (CBDC) implementation. Two main reasons drive this study: digital currency research is crucial in modern monetary policy frameworks.

The rapid digitization of financial technology, especially payment infrastructure, has spurred the development of new transactional instruments and methods throughout society. The proliferation of financial technology innovations has raised public expectations for payment systems with improved velocity, accessibility, and operational efficiency, but existing financial systems struggle to meet these demands (Harahap et al., 2017). This technological disruption has led to the development of financial instruments without central bank authorization, which may pose risks that resist conventional mitigation strategies and threaten financial system stability. Thus, central banks are under pressure to adjust their policies and provide digital ecosystem payment system solutions.

Secondary considerations include global central banks' growing support for CBDC adoption as a strategic solution to financial system instability caused by digital technology. Modern central banks are increasingly supportive of digital currency efforts, despite early concerns about CBDC hazards and implementation costs. Only 37% of global central banks actively prepare for digital currency issuance. CBDC literature emphasizes descriptive theoretical study over empirical quantitative analysis, leaving macroeconomic and payment infrastructure variables of digital currency adoption unexplored.

Statistical data shows Asia leads digital transaction growth with 45% of worldwide volume. Bank Indonesia's payment system data show 63% year-over-year rise in electronic money transaction volumes over the previous three years. This regional significance makes Indonesia a useful case study for CBDC adoption drivers, especially considering the sparse empirical research on macroeconomic and payment infrastructure variables affecting Indonesian digital currency deployment.

Payment systems have evolved to meet social transactional demands via fintech technologies. These changes seek to speed up payments, cash transfers, loans, and investment asset trading while improving security and efficiency (Harahap et al., 2017). Digital technology has increased demand for quicker, more convenient, and efficient payment methods, even if cash and cheques still dominate the market. Due to this progression, digital technology-based payment systems are being considered as alternatives to paper-based and bank-based payment infrastructures (Barotini & Holden, 2019).

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

As social distance requirements lowered direct contact transactions and boosted digital payment demand, the COVID-19 pandemic accelerated worldwide digital transaction growth (Alfonso et al., 2021). According to McKinsey & Company's worldwide Payments Report 2021, pandemic consequences drove 6% worldwide increase in non-cash transactions between 2019 and 2020 (Bruno et al., 2021). Asia became the most active digital transaction environment, with 69% of Asians using digital payments within a year, compared to 52% and 48% in America and Europe (Onag, 2022).

China's digital payment use surpassed 99% of domestic transaction volume by 2020, accounting for 45% of worldwide digital payment usage, according to McKinsey's worldwide Payments Map (Dahi et al., 2020). Google & Temasek (2021) surveyed 3,000 digital retailers in Asia, including Indonesia, and found 92% use digital payments, 72% intending proportionate growth, and 20% sustaining existing use.

Central Bank Digital Currency uses Distributed Ledger Technology (DLT) to mitigate systemic risks from digital payment expansion. The Committee on Payments and Market Infrastructures (CPMI) defined digital currencies as electronic, liability-free, and peer-to-peer (CPMI, 2015). The "The Money Flower" taxonomy classifies CBDC currencies by issuer, format, accessibility, and transfer methods (Bech & Garratt, 2017; CPMI-MC, 2018).

In this study, macroeconomic variables like inflation, BI rates, and money supply, as well as payment infrastructure variables like EDC machine quantities and ATM/debit card numbers, may affect electronic money usage and CBDC adoption in Indonesia. Error Correction Model (ECM) analysis is used to determine directional relationships and significance levels among these variables, adding empirical evidence to the otherwise theoretical CBDC literature and providing policy-relevant insights for Indonesian monetary authorities.

METHODOLOGY

Data Classification and Origins

This research uses time series data, which is consistent observations within a temporal framework (Widarjono, 2018). Dependent and independent variables are quantitative and monthly in the research. All data in this study is secondary data, which comes from original research sources or other relevant repositories. Documentary data collection involves careful research of historical records (Bungin, 2017). The analytical dataset contains 792 observations from reliable secondary sources, Bank Indonesia and

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

the Central Statistics Agency (Badan Pusat Statistik) websites. Data is observed from January 2014 to December 2024, providing a longitudinal analysis.

Variable description and operational definition

The volume of electronic money transactions (VUE), measured in millions, is the dependent variable. Bank Indonesia defines electronic money transaction volume as the number of e-money transactions in a certain period, regardless of their value. This statistic excludes debit card, credit card, and QRIS transactions and includes only chip-based and server-based electronic money provider transactions permitted by Bank Indonesia.

Two kinds of independent variables are macroeconomic and payment infrastructure. Inflation, BI Rate, and M2 money supply are macroeconomic factors. EDC devices and ATM and debit cards make up the payment infrastructure dimension. INF: Inflation Inflation measures the percentage increase in household goods and services prices using the Consumer Price Index (CPI) from 2018. Based on consumption patterns from the 2018 Cost of Living Survey in 90 Indonesian cities with 141,600 household samples, the Modified Laspeyres technique is used to calculate. The inflation evaluation compares the current month's CPI to the previous month's (Macroeconomic Dashboard FEB UGM, 2017).

Variable Bank Indonesia Rate = BIR The Bank Indonesia policy interest rate is the main indicator of monetary policy direction and a method for stabilizing the rupiah. The central bank's main reference rate is the BI 7-Day Reverse Repo Rate (BI7DRRR) since August 2016. JUB: Monetary Supply Variable The broad money supply (M2) measures economic liquidity, covering all payment methods. Quasi-money (savings, time, and foreign currency deposits) and M1 components make up M2. EDC Machine Variable (EDC): EDC machines handle ATM/debit cards, credit cards, and electronic currencies. Digital payment systems measure infrastructure by EDC machine availability, which increases public access to non-cash payment choices. This variable counts the number of active ATM plus debit cards issued by banking institutions for withdrawal, transfer, or payment activities. These cards are physical and digital account-based payment tools for bank customers.

Analytical Methods Framework

Analytical methods leverage inference statistics, notably EViews 12 Lite's Error Correction Model (ECM). ECM uses time series data, which may be non-stationary and produce inaccurate regression. Spurious regression arises when regression findings

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

have strong coefficients of determination without model variable correlations or poor Durbin-Watson statistics. The ECM framework may identify short-term and long-term imbalances or equilibrium situations between independent factors and dependent variables (Widarjono, 2018). ECM may discover and investigate short-term and long-term correlations, correct short-term disparities to attain long-term equilibrium, and explain how independent factors impact dependent variables throughout current and historical time frames utilizing non-stationary time series data. For time series data with strong non-stationarity, ECM is the best research model (Martanto et al., 2021).

Since stationarity difficulties are widespread, time series data processing begins with stationarity testing. This technique eliminates misleading regression relationships and inappropriate conclusions (Pratama, 2021). The Augmented Dickey-Fuller (ADF) test discovers unit roots for time series stationarity.

At all delays, stationary time series data have constant mean, variance, and covariance. Temporal mean and variance change in non-stationary data (Widarjono, 2018). The ADF test compares each variable's absolute ADF statistical values to MacKinnon statistical tables' important values at different confidence levels. Long-term equilibrium relationships between study variables are tested using cointegration. Research data with similar variance is needed for this test. Long-term equilibrium connections between variables are found using the Engle-Granger (EG) cointegration test. ADF statistical regression residual values are compared to important values in the EG cointegration test using Ordinary Least Squares (OLS) regression analysis. Estimate ECM using time series data that satisfy stationarity and cointegration conditions. Build an Error Correction Term (ECT) equation as a new variable to analyze short-term variable correlations before developing the ECM equation model. ECM models with negative and large ECT values are viable. Engle-Granger ECM equation model estimates were obtained using cointegration test results and ECT variables (Widarjono, 2018).

The Jarque-Bera, Breusch-Pagan-Godfrey, and Breusch-Godfrey Lagrange Multiplier tests examine classical assumptions for normality, heteroscedasticity, autocorrelation, and multicollinearity. These tests verify model validity and find regression issues. The hypothesis testing framework evaluates significance using R-squared, t-statistics, and F-statistics. The testing method employs a 95% confidence level ($\alpha = 5\%$) for statistical inference, ensuring reliable evaluation of variable linkages and model fit.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

RESULT

Results of Stationarity Test (Unit Root Test)

The stationarity test is essential to determine whether the model equations are valid for estimation using the Error Correction Model (ECM). This study employed the Augmented Dickey-Fuller (ADF) test, where the absolute value of the ADF statistic is compared against the MacKinnon critical values at the 1%, 5%, and 10% confidence levels. The comparison begins at the level form and continues to the first difference. If stationarity is not achieved, the test proceeds to the second difference.

The null hypothesis (H_0) of the stationarity test is accepted if the absolute value of the ADF statistic exceeds the MacKinnon critical values at the specified confidence levels, indicating the data is stationary. Conversely, if the absolute value of the ADF statistic is less than the critical value, the null hypothesis is rejected (H_a is accepted), implying the data is non-stationary.

Table 1. ADF Test Results at Level

Variable	ADF t-statistic	MacKinnon Critical Values	Prob.	Stationary
		1%	5%	10%
VUE	0.6573	-3.4808	-2.8835	-2.578
BIR	0.7536	-3.4808	-2.8835	-2.578
INF	-0.6883	-3.4808	-2.8835	-2.578
JUB	0.1699	-3.4808	-2.8835	-2.578
EDC	-1.4098	-3.4808	-2.8835	-2.578
ATM	0.7798	-3.4808	-2.8835	-2.578

Source: Appendix, Stationarity Test using EViews 12 Lite

The results indicate that none of the variables are stationary at level since all ADF statistics are lower than the MacKinnon critical values and all p-values exceed 0.05. Therefore, the unit root test proceeds to the first difference.

Table 2. ADF Test Results at First Difference

Variable	ADF t-statistic	MacKinnon Critical Values	Prob.	Stationary
		1%	5%	10%
VUE	-11.647	-3.481	-2.883	-2.578
BIR	-11.660	-3.481	-2.883	-2.578

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

INF	-11.730	-3.481	-2.883	-2.578
JUB	-12.470	-3.481	-2.883	-2.578
EDC	-10.383	-3.481	-2.883	-2.578
ATM	-11.243	-3.481	-2.883	-2.578

Source: Appendix, Stationarity Test using EViews 12 Lite

All variables are found to be stationary at the first difference, as the absolute values of the ADF statistics exceed the critical values and p-values are less than 0.05. Thus, all variables are integrated of order one, I(1), and the dataset meets the requirements to proceed to the cointegration test and ECM estimation.

Cointegration Test Results

Following the confirmation that all variables are integrated of the same order, I(1), a cointegration test was performed to assess the presence of long-term relationships among the variables. This study employed the Engle-Granger (EG) method, beginning with an OLS regression of the long-run equation:

$$VUE_t = -5{,}729 + 169{,}714BIR_t - 199{,}246INF_t + 0.498JUB_t + 0.781EDC_t + 12{,}742ATM_t$$

Table 3. Cointegration Regression Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R^2
C	-5729901	504467.3	-11.3583	0.0000	0.7056
BIR	169714.3	50134.75	3.38516	0.0009	
INF	-199246.6	68978.04	-2.88855	0.0046	
JUB	0.498926	0.053490	9.32749	0.0000	
EDC	0.781387	0.191486	4.08064	0.0000	
ATM	12742.51	1098.914	11.59555	0.0000	

Source: Appendix, Cointegration Test using EViews 12 Lite

To verify cointegration, the residuals from the long-run regression were tested for stationarity at level. The result shows that the residual is stationary at level, as the absolute ADF statistic (-12.501) exceeds the MacKinnon critical values and the p-value is 0.0000 < 0.05.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Table 4. ADF Test on Residuals (ECT) at Level

Variable	ADF t-statistic	MacKinnon Critical Values	Prob.	Stationary
		1%	5%	10%
ECT(-1)	-12.501	-3.4808	-2.8835	-2.578

Source: Appendix, Cointegration Test using EViews 12 Lite

Thus, the Engle-Granger cointegration test confirms the existence of a long-term equilibrium relationship among the variables. Consequently, the analysis may proceed with the estimation of the Error Correction Model.

Error Correction Model (ECM) Estimation Results

A valid ECM should yield a negative and statistically significant coefficient for the error correction term (ECT). After conducting the ECM regression using the Engle-Granger method, the following short-run equation was obtained:

$D(VUE_t) = 2018.95 + 189.98D(BIR_t) - 193.91D(INF_t) + 0.527D(JUB_t) + 0.844D(EDC_t) + 12{,}205D(ATM_t) - 1.091ECT(-1)$

Table 5. ECM Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2018.956	38314.07	0.05269	0.9581
D(BIR)	189985.7	34441.13	5.51624	0.0000
D(INF)	-193913.3	52222.70	-3.71319	0.0003
D(JUB)	0.527857	0.036941	14.28918	0.0000
D(EDC)	0.844250	0.135435	6.233608	0.0000
D(ATM)	12205.39	781.8848	15.61022	0.0000
ECT(-1)	-1.09197	0.089158	-12.24775	0.0000
R-Squared	0.8683			
Prob. F-Stat				0.0000

Source: Appendix, ECM Estimation using EViews 12 Lite

The ECM model is valid, as the ECT(-1) coefficient is negative and statistically significant at the 5% confidence level. The R-squared value of 0.8683 suggests that approximately 86.83% of the variation in electronic money transaction volume (VUE) is

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

explained by the independent variables (BIR, INF, JUB, EDC, ATM), with the remaining 13.17% attributed to other factors not included in the model. All explanatory variables have a significant effect on the dependent variable at the 95% confidence level.

Classic Assumption Test

This study used classic assumption tests such normality, heteroskedasticity, autocorrelation, and multicollinearity. The residual normality test employed the Jarque-Bera (J-B) approach, yielding a J-B value of 0.1239 and a probability value of 0.9339. If the probability is larger than 0.05, the null hypothesis (H0) that residuals follow a normal distribution is accepted. This proves the Error Correction Model (ECM) residuals are normal. The Breusch-Pagan-Godfrey heteroskedasticity test was also performed. The Obs*R-squared statistic probability value was 0.5572, confirming the null hypothesis (H0). This implies that the residual variance is homoscedastic, or that heteroskedasticity does not present.

The Breusch-Godfrey (BG) and Lagrange Multiplier (LM) tests were employed for autocorrelation analysis. The probability of the Obs*R-squared statistic was 0.6139, above 0.05. This shows statistical significance. The hypothesis H1 is accepted, indicating that the ECM model lacks autocorrelation. Finally, the Variance Inflation Factor (VIF) approach was employed to detect multicollinearity. A low degree of multicollinearity was demonstrated by all independent variables having centered VIF values below 10. Thus, regression analysis is feasible for the dataset.

Coefficient of Determination (R-Squared)

The coefficient of determination (R-Squared) is utilized to assess the extent to which the independent variables explain the variation in the dependent variable within a regression model. As R-squared does not account for degrees of freedom, the adjusted R-squared value is often considered more reliable in evaluating model fit. When both R-squared and adjusted R-squared values approach one, it indicates a stronger relationship between the independent and dependent variables. The results of the determination coefficient estimation are presented in the following table:

Table 6. Coefficient of Determination Results

Model	R-Squared	Adjusted R-Squared	Result
Short-Term (ECM)	0.8683	0.8620	Approaching 1

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Long-Term	0.7056	0.6939	Approaching 1

Source: Appendix, Results of R-Squared Analysis using EViews 12 Lite

According to the table above, BI Rate (BIR), inflation (INF), money supply (JUB), numbr of EDC machines (EDC), and number of ATM+Debit cards explain 86.83% of electronic money transaction volume (VUE) in the short term. Non-model factors affect the remaining 13.17%. This is supported by the corrected R-squared value surpassing 0.8 (80%). The R-squared and adjusted R-squared values vary by 0.56%, indicating that the model is correctly described and that the independent variables do not influence estimate results. This suggests that the short-term model (ECM) regression findings are reliable and correct. In the long-term model, the same five independent variables explain 70.56% of VUE volatility, while other factors account for 29.44%. R-squared and adjusted R-squared values vary by 1.17%, suggesting that variable selection does not affect model dependability. Thus, the long-term regression model is valid and resilient.

Partial/Individual Statistical Test Results (t-Test)

The t-test is employed to evaluate the statistical significance of the effect of each independent variable on the dependent variable individually within the regression equation. This study adopts a 95% confidence level (α = 0.05) with degrees of freedom (df) = n − k − 1 = 792 − 5 − 1 = 786, which corresponds to a t-critical value of 1.960. If the t-statistic > t-table or the probability value < α (0.05), H_0 is accepted and H_1 is rejected, indicating a significant individual effect of the independent variable on the dependent variable. The short-term regression (ECM) t-test results are presented below:

Table 7. t-Test Results for Short-Term Model (ECM)

Variable	t-Statistic	t-Table	Probability	Conclusion
D(BIR)	5.516	1.960	0.0000	Significant
D(INF)	-3.713	1.960	0.0003	Significant
D(JUB)	14.289	1.960	0.0000	Significant
D(EDC)	6.234	1.960	0.0000	Significant
D(ATM)	15.610	1.960	0.0000	Significant
ECT(-1)	-12.248	1.960	0.0000	Significant

Source: Appendix, t-Test Results of Short-Term Model (ECM) using EViews 12 Lite

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

The results indicate that all independent variables—BI Rate, inflation, money supply, EDC machines, and ATM+Debit cards—significantly affect electronic money transaction volume (VUE) in the short term. While BI Rate, money supply, EDC, and ATM have positive effects, inflation has a negative impact. The significant ECT(-1) confirms short-term model validity.

Table 8. t-Test Results for Long-Term Model

Variable	t-Statistic	t-Table	Probability	Conclusion
BIR	3.385	1.960	0.0009	Significant
INF	-2.889	1.960	0.0046	Significant
JUB	9.327	1.960	0.0000	Significant
EDC	4.081	1.960	0.0001	Significant
ATM	11.596	1.960	0.0000	Significant

Source: Appendix, t-Test Results of Long-Term Model using EViews 12 Lite

The findings reveal that all independent variables significantly affect VUE in the long term. BI Rate, money supply, EDC machines, and ATM+Debit cards each demonstrate a positive and significant impact, whereas inflation negatively influences VUE. These results underscore the enduring influence of macroeconomic and financial infrastructure variables on electronic money transactions.

Simultaneous Statistical Test Results (F-Test)

The F-test results confirm that, at a 95% confidence level, all independent variables—BI Rate, inflation, money supply, EDC machines, and ATM+Debit cards—jointly exert a statistically significant impact on the dependent variable (VUE) in both the short and long term. With F-statistics (136.36 for the short-term model and 60.399 for the long-term model) exceeding the critical value of 2.21, and p-values below 0.05, the null hypothesis is accepted. These findings indicate that the regression models effectively capture the collective influence of the explanatory variables on VUE, supporting the models' overall reliability and explanatory power.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

DISCUSSION

The Effect of BI Rate on Electronic Money Transaction Volume

According to the Error Correction Model (ECM), the BI Rate has a substantial positive short-term association with electronic money transaction volume (VUE), as shown by a p-value of 0.0000 (<0.05) and a t-statistic of 5.5162 (>1.960). This implies that a 1% BI Rate hike adds 18.998 million electronic transactions. According to Meutia et al. (2023), digital payment users tend to maintain their transactional behavior despite short-term monetary policy changes, explaining the positive effect. A 1% rise in the BI Rate leads in 169.714 million extra transactions in the long run, according to the long-run model, which has a BI Rate coefficient of 169,714.3 and a significant p-value of 0.0009. IMF (2023) found that efficiency improvements increase digital payment adoption in high-interest rate circumstances. Thus, H1, that BI Rate adversely influences VUE in the short and long run, is rejected. Despite increasing interest rates, Bank Indonesia (2023) statistics indicate VUE climbed from IDR 145 trillion in 2019 to IDR 457 trillion in 2023, showing microtransactions boost e-money use. Digitalization incentives such MSME assistance and lower Merchant Discount Rates counter restrictive monetary implications when BI Rates rise (Eliezer et al., 2024). Consumer behavior theory states that high interest rates shift credit-based purchases to efficient daily e-money transactions. E-money has low interest rate elasticity compared to credit instruments, which encourages cashless adoption and may indicate public preparedness for Central Bank Digital Currency (CBDC) adoption (Budi Mulya, 2019; Meutia et al., 2023).

The Effect of Inflation on Electronic Money Transaction Volume

The Error Correction Model (ECM) shows a substantial negative short-term effect of inflation on electronic money transactions (VUE), with a coefficient of -193,913.3, p-value of 0.0003 (<0.05), and t-statistic of 3.7131 (>1.960). Assuming all conditions stay unchanged, a 1% inflation rise decreases 19.391 million e-money transactions. The long-run inflation coefficient is -199,246.6 with a p-value of 0.0046 and a t-statistic of 2.888, indicating that a 1% inflation increase reduces transactions by 199.246 million. These data show that pricing consistency is crucial to Indonesian digital transaction development. The negative and substantial association between inflation and electronic transaction volumes—both short and long term—supports the original premise and the theoretical framework that inflation reduces buying power. These findings support Ekayoga et al. (2022) and Izzulhaq et al. (2024), who demonstrated that inflation reduces Indonesian e-money transactions in the near run. Tobing and Siregar (2021) also note

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

that inflationary pressures dramatically reduce retail spending, thereby reducing digital payment uptake. Price stability is necessary for the effective adoption and broad acceptance of Central Bank Digital Currency (CBDC) in Indonesia, since customer faith in digital currency value stability remains essential.

The Effect of Money Supply on Electronic Money Transaction Volume

The Error Correction Model (ECM) shows a statistically significant and positive short-term link between electronic money transaction volume (VUE) and money supply (M2) coefficient of 0.527857. A p-value of 0.0000 (<0.05) and a t-statistic of 14.289 (>1.960) indicate that a 1 billion IDR increase in M2 results in 0.53 million e-money transactions. Long-term model coefficient 0.498926 has a positive and significant impact with a p-value of 0.0000 and t-statistic of 9.327. This means that every 1 billion IDR increase in money supply increases VUE by 0.49 million transactions. These results support the notion that the money supply favorably affects electronic transaction volumes in the short and long term. The quantity theory of money states that more money circulation boosts economic activity, including digital transactions. In previous research, Tribudhi and Soekapdjo (2019), Ardyatama (2020), and Rahayu and Nur (2023) established a favorable association between M2 and digital transaction volumes. Mumu et al. (2023) found that the circulating currency supply greatly affects e-money transactions in their research on Central Bank Digital Currency (CBDC) and Rupiah Digital. These findings demonstrate CBDC's potential as an efficient medium of exchange and monetary base expander.

The Effect of Number of EDC Machines on Electronic Money Transaction Volume

The quantity of Electronic Data Capture (EDC) devices has a statistically significant and favorable short-term link with electronic money transactions (VUE) according to the Error Correction Model (ECM). This is substantiated by a p-value of 0.0000 (<0.05) and a t-statistic of 6.233 (>1.960), indicating that a single EDC machine increases electronic transactions by 0.84 million. Each extra EDC machine provides 0.78 million VUE transactions, according to the long-term model's EDC coefficient of 0.781387, with a p-value of 0.0001 and a t-statistic of 4.080. These results support the notion that EDC machine numbers favorably affect e-money transaction volumes across time horizons. They agree with Singgih and Nurjanah (2017), who said EDC distribution boosts financial inclusion, especially in the near run. The study also shows that physical infrastructure is essential for digital transactions in Indonesia, especially in areas without

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

mobile or internet payment services. The Technology Acceptance Model (TAM) and research by Tribudhi and Soekapdjo (2019), Ardyatama (2020), and Ekayoga and Hasyim (2022) support the favorable link. The widespread and equal deployment of EDC machines may assist CBDC (Rupiah Digital) acceptance, particularly in places without significant digital payment infrastructure, following worldwide point-of-sale (PoS) adoption patterns.

The Effect of Number of ATM + Debit Cards on Electronic Money Transaction Volume

The Error Correction Model (ECM) coefficient for ATM and debit card numbers is 12,205.39, demonstrating a short-term statistically significant and positive association with electronic money transaction volume (VUE). A p-value of 0.0000 (<0.05) and a t-statistic of 15.610 (>1.960) indicate that when ATM and debit card use increases by one million units, VUE transactions rise by 12.205 million. The long-run model shows that a one million unit increase leads to 12.742 million transactions over time, with a coefficient of 12,742.51, a p-value of 0.0000, and a t-statistic of 11.595. These results support Mumu et al. (2023), who demonstrated that physical payment cards boost e-money use. Indonesia's payment ecosystem relies on physical cards, especially in areas without internet connection, even if apps and QRIS are becoming more common. Wardani and Priyadi (2020) emphasize education and cross-platform interaction to assist the transition from card-based to digital systems. ATM and debit cards' substantial significance in Central Bank Digital Currency (CBDC) development shows their usage as intermediaries for CBDC adoption, particularly among digitally challenged communities.

The Simultaneous Effect of Macroeconomic Variables and Payment Infrastructure on Electronic Money Transaction Volume

Using the Error Correction Model (ECM), the R-squared value is 86.83%, with a significant F-statistic of 136.36, above the essential F-table value of 2.21 and a p-value of 0.0000 (<0.05). The long-run model has an R-squared of 70.56%, an F-statistic of 60.399, above the F-table value, and a p-value of 0.0000. In both the short and long term, the independent variables analyzed in this study—the BI Rate, inflation, money supply (M2), the number of EDC machines, and the number of ATM and debit cards—explain most variations in electronic money transactions (VUE). The data corroborate hypothesis H6 and demonstrate the long-term impact of macroeconomic policy and payment infrastructure on the digital transaction environment. These findings emphasize the need

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

for a long-term policy approach for Central Bank Digital Currency (CBDC) adoption, such as the Rupiah Digital. CBDC must include macroeconomic and infrastructural factors into its design and execution to be successful and widely adopted throughout Indonesia's diversified economy (Wardani & Priyadi, 2020; Mumu et al., 2023).

CONCLUSION

This research found that macroeconomic and payment infrastructure factors strongly affect Indonesian e-money transactions. First, the BI Rate (BIR) boosts e-money transaction volume (VUE) in the short and long term. These findings contradict the basic notion of a negative association. Due to a replacement and acceleration effect, customers may see e-money as more efficient, despite higher interest rates. Second, inflation (INF) negatively affects VUE, supporting the study premise. Thirdly, as predicted, JUB favorably and dramatically influences VUE. Fourth, EDC devices increase e-money transaction volume, validating the theory. Fifth, as expected, the number of ATM and debit cards (ATM) boosts VUE in the short and long run. Finally, BI Rate, inflation, money supply, EDC machines, and ATM/debit cards all affect electronic money transaction volume in the short and long term. Since Indonesia's CBDC is at design stage, primary data like consumer surveys may help researchers understand public opinion. These viewpoints may improve results' accuracy and relevance. To capture infrastructure impacts, future research should include more complicated factors like QRIS adoption and digital wallets (e.g., OVO, Gopay, DANA). Finally, panel data analysis with a larger sample size may provide more useful insights.

REFERENCES

Alfonso, V., Boar, C., Frost, J., Gambacorta, L., & Liu, J. (2021). E-Commerce in the Pandemic and Beyond. *BIS Bulletin*, *36*. https://www.bis.org/publ/bisbull36.htm

Barotini, C., & Holden, H. (2019). Proceeding with caution - a survey on central bank digital currency. In *BIS Papers* (No. 101; Vol. 101, Issue 101).

Bech, M., & Garratt, R. (2017). Central Bank Cryptocurrencies. *BIS Quarterly Review*, *September*(September), 55–70. https://www.bis.org/publ/qtrpdf/r_qt1709f.pdf

Bruno, P., Denecker, O., & Niderkorn, M. (2021). *Global Payments 2021: Transformation Amid Turbulent Undercurrents* (Issue October).

Bungin, B. (2017). *Metodologi Penelitian Kuantitatif (Komunikasi, Ekonomi, dan Kebijakan Publik SertaIlmu-Ilmu Sosial Lainnya)* (9th ed.). Kencana (Prenadamedia Group).

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

CPMI-MC. (2018). *Central Bank Digital Currencies* (Issue March). https://www.bis.org/cpmi/publ/d174.pdf

CPMI. (2015). Digital Currencies. *Bank for International Settlements*, *November*, 51–66. https://doi.org/10.4324/9780429292903-5

Dahi, J., Sengupta, J., & Ng, E. (2020). *Future of Asia: How Asia is Reinventing Banking for the Digital Age* (Issue January).

Google, & Temasek. (2021). *e-Conomy SEA 2021*. https://economysea.withgoogle.com/report/

Harahap, B. A., Idham, P. B., Kusuma, A. C. M., & Rakhman, R. N. (2017). Perkembangan Financial Technology Terkait Central Bank Digital Currency (CBDC) Terhadap Transmisi Kebijakan Moneter Dan Makroekonomi. *Bank Indonesia Working Paper*, *2*, 1–80.

Macroeconomic Dashboard FEB UGM. (2017). *Inflasi dan Indeks Harga Konsumen*. https://macroeconomicdashboard.feb.ugm.ac.id/inflasi-dan-indeks-harga-konsumen/

Martanto, B., Tan, S., & Hidayat, M. S. (2021). Analisis tingkat inflasi di Indonesia Tahun 1998-2020 (pendekatan error correction model). *Jurnal Paradigma Ekonomika*, *16*(3), 619–632. https://doi.org/https://doi.org/10.22437/jpe.v16i3.14360

Onag, G. (2022). *APAC Outpaces Rest of the World in Digital Payment Adoption*. FutureIoT. https://futurecio.tech/apac-outpaces-rest-of-the-world-in-digital-payment-adoption/

Pratama, M. A. (2021). *Pengendalian Inflasi yang Berbasis Finansial Teknologi (Fintech), Inklusi Keuangan dan Kebijakan Makroprudensial di D-8 Negara Berkembang* [Universitas Pembangunan Panca Budi Medan]. https://journal.pancabudi.ac.id/index.php/jurnalfasosa/article/view/3210

Widarjono, A. (2018). *Ekonometrika: Pengantar dan Aplikasinya Disertai Panduan Eviews* (5th ed.). UPP STIM YKPN.

Zams, B. M., Indrastuti, R., Pangersa, A. G., Hasniawati, N. A., Zahra, F. A., & Fauziah, I. A. (2020). Designing Central Bank Digital Currency for Indonesia: The Delphi-Analytic Network Process. *Buletin Ekonomi Moneter Dan Perbankan*, *23*(3), 411–438. https://doi.org/https://doi.org/10.21098/bemp.v23i3.1351

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.