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Effect Of Financial Technology On Cash Holding In Indonesia Using Autoregressive Distributed Lag (ARDL)

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Abstract

The rapid proliferation of financial technology (Fintech) has revolutionized the landscape of financial services globally, presenting digital alternatives to conventional banking and payment methods. Indonesia has emerged as a noteworthy adopter of Fintech, driven by the widespread usage of smartphones and government initiatives to foster financial inclusion. Nonetheless, the empirical research concerning the association between Fintech adoption and cash-holding behaviour in Indonesia remains limited. This study explores Fintech's influence on individuals' cash holding patterns in the country, considering direct indicators such as debit cards, credit cards, electronic money, mobile banking, and internet banking. A time-series analysis covering the period from M5 2013 to M3 2023, based on secondary data from the Bank Indonesia Statistic Database, is employed to achieve this research objective. The analytical framework utilizes the Autoregressive Distributed Lag (ARDL) bounds testing approach, accounting for the explanatory variables' concurrent and lagged effects. The empirical findings reveal a significant positive relationship between debit cards, mobile banking, and internet banking usage in short-term cash-holding behaviour. In contrast, credit card usage exhibits a negative and statistically significant association with long-term cash holding. These results contribute to a comprehensive understanding of how Fintech adoption shapes cash-holding behaviour in Indonesia and provide valuable insights into the country's transition toward a cashless society.

Keywords: ARDL; Bound Testing; Cash Holding; Fintech; Indonesia

A. INTRODUCTION

The emergence of financial technology (Fintech) was driven by the limitations of cash transactions, leading to a growing shift toward digital finance (Onah et al., 2020). In Indonesia, the Fintech sector has experienced significant growth in recent years, facilitated by the widespread use of smartphones and government initiatives promoting financial inclusion. Among the various Fintech services available, digital payment services have garnered the highest usage in Indonesia (Pahlevi, 2021).

The Indonesian Financial Literacy Index (SNLIK) 2022 indicates a substantial increase in the financial inclusion index, rising to 85.10 per cent from the previous period's 76.19 per cent (Otoritas Jasa Keuangan, 2022). The surge in Fintech adoption has prompted governments globally, including Indonesia, to implement regulations addressing this transformative financial landscape. Notably, Bank Indonesia introduced Regulation No. 20 of 2018, focusing on Electronic Money, as part of the government's proactive approach to embracing Fintech advancements. Additionally, Indonesia is actively pursuing the goal of a cashless society and developing its Central Bank Digital Currency (CBDC) project, as outlined in the Bank Indonesia roadmap for 2023.

In 2021, (Onah et al., 2020) conducted an ARDL bounds test technique in Nigeria to explore the long-term relationship between four measures: mobile banking, internet banking, automated teller machine (ATM), point of sale transactions, and cash holding. The study revealed an inverse association between cash holding and adopting direct Fintech measures. Similarly, Mlambo & Msosa (2020) conducted a similar study in selected African states, investigating the relationship between automated teller machines (ATM) and mobile subscriptions with money demand, also finding a negative correlation between these variables.

Contrastingly, research on the impact of Fintech on cash holding is limited in Indonesia, despite the country's ongoing preparations for a cashless society and the upcoming launch of its CBDC in 2025 (Bank Indonesia, 2023). As a response, this research aims to investigate the effect of Fintech on individuals' cash holding in Indonesia, following the approach employed by Onah et al. (2020) in Nigeria. The study will also rely on direct

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measurements of Fintech usage, including debit cards, credit cards, electronic money, mobile banking, and internet banking, sourced from data from the Indonesia Central Bank. By addressing this research gap, the study seeks to contribute to understanding Fintech's implications for cash transactions in Indonesia and provide valuable insights for policymakers, financial institutions, and the public.

In conclusion, the increasing popularity of Fintech has prompted a shift away from traditional cash transactions in favour of digital finance. Indonesia's robust growth in Fintech adoption and the government's endeavours to promote financial inclusion have further facilitated this transition. The absence of extensive research in Indonesia concerning the impact of Fintech on cash holding underscores the significance of this study. By exploring the relationship between Fintech adoption and cash holding in Indonesia, this research aims to enrich the knowledge in this area and contribute to the ongoing efforts in transitioning towards a cashless society.

Banking can be traced back to approximately 1700 BC, with the establishment of the first known bank in the ancient city of Babylon (Bromberg, 1942). Since then, the financial industry has witnessed many innovations and developments, collectively called Fintech (Arner et al., 2015). These innovations have ranged from the introduction of services like Fedwire Funds, ATMs, and Credit Cards in the 1900s (Ahmi et al., 2020) to the current shift towards utilizing cloud-based microservices, analytics tools for market data, and digitized trading processes (O'Reilly et al., 2023).

Indonesia has emerged as one of the countries experiencing rapid growth in the Fintech industry. Starting with only 51 Fintech companies in 2011, the sector has since expanded significantly, driven by the increasing demand for financial services and technological advancements, enabling more efficient and accessible financial transactions. By 2022, the number of Fintech companies in Indonesia had grown sevenfold to 334 (Kumar, 2023).

The advent of financial technology (Fintech) has brought about a significant transformation in individuals' liquidity preferences, with potential implications for money demand (Onah et al., 2020). Empirical studies have shown that individuals retain cash in their wallets when making withdrawals as a safety precaution (Eschelbach & Schmidt, 2013). Additionally, despite the widespread adoption of electronic money, some studies have found that consumers still prefer to carry a minimum amount of cash in their wallets (Fujiki & Tanaka, 2014).

The literature on money demand frequently employs a deterministic time trend methodology to examine the influence of financial innovation. For instance, (Arrau et al. 1991) analyzed quarterly data from 10 developing countries, while (Dekle & Pradhan, 1997) used the time trend technique to assess the impact of financial development on money demand in ASEAN countries. Similarly, in the context of the African continent, Mlambo and Msosa (2020) and Onah et al. (2020) conducted similar research using time series data to investigate the effect of Fintech on cash holding or money demand. Importantly, all these studies consistently found that financial innovation significantly impacts the determination of money demand and cash holding.

Cash holding refers to the amount of money individuals or entities keep readily available for transactions or investment purposes (Gill & Shah, 2011). In macroeconomics, various theories have been developed to explain money demand, which is influenced by the prevailing economic conditions. Early theories, initiated by classical economists, posited that money demand remains unaffected by other factors and is merely a static concept. However, these theories have evolved to incorporate additional considerations (Sriram, 1999; The Institute of Chartered Accountants of India, 2019).

Empirical studies employ different measures to approximate cash holding. For instance, (Fujiki, 2020) utilizes the ratio of cash demands to the sum of financial assets holdings and cash demands (Jiang & Shao, 2019) utilize the ratio of currency in circulation to the gross domestic product (GDP). (Ardizzi et al., 2018) Examine the share of total payments credited to bank accounts. (Grüschow et al.,2016; Xu et al.,2020) consider the currency ratio in circulation to total broad money (M2). These diverse measures enable researchers to capture different aspects of cash holding for their respective analyses.

In the United States during the 1980s, credit card payments reduced cash usage, leading to a decline in cash share from 0.31 to 0.2 (Humphrey, 2004). Additionally, (Reddy S & Kumarasamy D, 2017) utilized an auto-regressive distributed lag model for monthly data and found that currency demand decreased due to credit card usage. Similarly, Yilmazkuday & Yazgan (2009) reached the same conclusion, observing a reduced currency demand with increased credit card usage. Empirical studies have also highlighted a gradual decline in cash circulation outside the banking system, influenced by mobile banking (Muli, 2019). Moreover, (Onah et al., 2020) reported a negative relationship between mobile banking, as a proxy for Fintech, and cash holding.

In conclusion, the evolution of banking and financial technology has been marked by transformative innovations throughout history. Indonesia's Fintech industry has experienced significant growth, fuelled by technological advancements and growing demand for convenient financial services. Research conducted in various countries consistently reveals a negative relationship between adopting digital payment methods, including debit cards, credit cards, mobile banking, and cash holding. This suggests a gradual transition from traditional cash transactions toward the increasing prevalence of digital finance.

B. RESEARCH METHODS

When conducting regression analysis with time series data, Gujarati (1978) explains that a distributed-lag model is utilized when the regression model incorporates both present and past values of the explanatory variables. Additionally, an autoregressive model is employed when the model includes one or more lagged values of the dependent variable as explanatory variables. Building on this, (Pesaran et al., 2001) introduced the concept of cointegration called ARDL (Autoregressive Distributed Lag), also known as bounds testing. This approach is used interchangeably with cointegration and helps avoid spurious regression by considering the inclusion of lagged values that may be missing. It serves as an alternative to other cointegration concepts. The application of ARDL is particularly useful in cases where the pace of cash reduction due to Fintech varies across different regions, with emerging markets and developing economies displaying slower trends (Fujiki, 2020; Jiang & Shao, 2019). (Achsani et al., 2010) further assert that ARDL is the most appropriate model for determining money demand in Indonesia.

By employing ARDL and considering the modified proxy for cash holding, this study aims to comprehensively analyze the impact of Fintech on money demand, particularly in the context of the Indonesian economy. We adopt the proxy for cash holding used by (Onah et al., 2020), which is the ratio of currency in circulation to total broad money (M2). This approach allows for a robust examination of the relationship between financial technology and cash usage, considering both present and lagged variables and accounting for the unique characteristics. However, we modify the proxy by including currency outside commercial and rural banks' data due to data availability constraints. (Onah et al., 2020) justify this choice by arguing that Fintech is expected to reduce this ratio, as it diminishes the incentive for individuals to hold cash. Nonetheless, it is essential to acknowledge that cash transactions will continue to persist in the economy, despite the influence of Fintech.

In developing his model (Onah et al., 2020) start by determining the money demand following (Ben-Salha & Jaidi's, 2014) function, which can be written as:

$$\left(\frac{M}{P}\right) = f\,(y, i)$$

Where (M/P) represents real monetary aggregates, M represents nominal monetary aggregates, and p represents the price level. Equation 1 explains that Real demand for money is a function of real income (y) and the opportunity cost of holding money (i), which are the inflation and exchange rates. Then (Onah et al. 2020) adopt the adjustment of the money demand function by Fujiki & Tanaka (2014) in order to find the effect of financial technology on cash holding, which can be written as:

$$M = \ln D\alpha(U) + X'\beta(U)$$

Equation (2) posits that variable D, a direct measure of financial technology, determines cash holding M. X is a vector of explanatory variables. At the same time, U is a scalar random variable that combines all unobserved factors influencing the structural results of Eqn (1). Following (Onah et al., 2020), variable D, specifically in this research, can be rewritten as:

$$\ln D = \delta(DC, CC, EM, MB, IB)$$

An unknown function influences variable D, which depends on the values of transactions from DC, CC, EM, MB, and IB, which are used as indicators of financial technology. From this specification, we can rewrite Eqn (2) as:

$$\frac{COB}{M2_t} = \delta_1\, lnD_t^i + \delta_2\, lny_t + \delta_3\, ifr_t + \delta_4 lnreer_t + \varepsilon_t$$

As seen in Equation (3), including superscripts in Equation (4) implies we examine diverse financial technology. The variable COB/M2 reflects the amount of cash on hand, while the other variable explains financial technology and other factors that can impact money demand.

Before running the model, following the type of data that is time series, it is crucial to conduct tests to test the data's stationary properties. (Onah et al., 2020) used the NG-Perron test to test the variable's stationary properties. This test is used because NG-Perron has been tested to be more reliable than Augmented Dickey-Fuller and Philip-Perron Tests (Folarin & Asongu, 2017). This research follows the (Onah et al. 2020) testing approach, which is Autoregressive Distributed Lag (ARDL) by (Pesaran et al., 2001). The ARDL model can be written as below:

$$\Delta\left(\frac{COB}{M2}\right)_t = \delta_0 + \delta_1\left(\frac{COB}{M2}\right)_{t-1} + \delta_2 lnD_{t-1}^i + \delta_3 lny_{t-1} + \delta_4 ifr_{t-1} + \delta_5 lnreer_{t-1} + \delta_6 Trend + \sum_{j=1}^{l}\tau_{1j}\,\Delta\left(ln\left(\frac{COB}{M2}\right)_{t-1}\right) + \sum_{j=1}^{m}\tau_{2j}\,\Delta lnD_{t-1}^i + \sum_{j=1}^{n}\tau_{3j}\,\Delta lny_{t-1} + \sum_{j=1}^{o}\tau_{3j}\,\Delta ifr_{t-1} + \sum_{j=1}^{p}\tau_{1j}\,\Delta lnreer_{t-1\varepsilon t}$$

Onah et al. (2020) used Wald Restrictions to estimate the F-statistics for all the level series in Equation (5), as advised by Onah et al. (2020). The F-statistics value was used to determine if the variables had a long-run connection. When the null hypothesis for the Wald Restriction is applied to Equation (5) and the F-statistics values are $\delta2 = \delta3 = \delta4 = \delta5 = 0$, it suggests that no long-run association exists.

The estimated F-statistics value was compared to the upper and lower critical values supplied by (Pesaran et al., 2001). If the estimated F-statistics value exceeds the upper critical value, we reject the null hypothesis of no cointegration, suggesting the presence of a long-run connection according to the decision criteria for the cointegration test. If the F-statistics value is less than the lower critical value, it indicates the lack of a long-run link. However, there could be a situation where findings are equivocal when the F-statistics value falls between the upper and lower crucial thresholds.

To analyze the impact of financial technology, income, inflation rate, and exchange rate on cash holding, as well as the speed of adjustment back to long-run equilibrium after a short-run shock, (Onah et al., 2020) proceed with the estimation of the error correction model (ECM). In determining the ECM, they involve two main steps. The first step is to conduct a regression where they regress the independent variables on the dependent variable. We then subtract the actual value of the dependent variable from the estimated value, which can be represented as:

$$ECT = \left(\frac{COB}{M2}\right)_t - (\,\vartheta_0 + \vartheta_1 T + \vartheta_2 lnD_t^i + \vartheta_3 lny_t + \vartheta_4 ifr_t + \vartheta_5 lnreer_t$$

This step aims to capture the differences between the actual and predicted values of the dependent variable. The second step involves analyzing the speed of adjustment back to the long-run equilibrium after a short-run shock. This helps us understand how quickly the system returns to its long-term balance after experiencing a temporary disturbance.

Considering the variables' trending nature and significance in the regression results, (Onah et al., 2020) included a trend component in the analysis. This trend component helps account for the long-term behaviour and patterns observed in the variables. To incorporate the error correction term (ECT) obtained from Equation (6) into the dynamic form of Equation (4), we arrive at Equation (7). Equation (7) is then used to estimate the error correction model (ECM).

$$\Delta\left(\frac{COB}{M2}\right)_t = (\,\gamma_0 + \gamma_1 T + \gamma_2 lnD_t^i + \gamma_3 lny_t + \gamma_4 ifr_t + \gamma_5 lnreer_t + \tau ECT_{t-1} + \varepsilon_t$$

By incorporating the ECT and the dynamic relationship between the variables, Equation (7) allows us to capture the short-term adjustments toward the long-run equilibrium. This dynamic approach provides a more comprehensive understanding of the relationships among the variables and their adjustments over time. After an external shock, τ is expected to be negative and significant, showing complete adjustment after a shock.

To ensure the consistency of the results, (Onah et al., 2020) also employed cumulative sum (CUSUM) tests as consistency parameter checks. These tests help assess whether the estimated model exhibits stable and consistent relationships over time. Additionally, they also conducted several diagnostic tests to evaluate the ECM results. These tests include the autoregressive conditional heteroscedasticity (ARCH) test, which examines the presence of conditional heteroscedasticity in the error term. The Breusch-Godfrey (BG) test detected serial correlation in the model's residuals. Conducting these additional diagnostic tests helps ensure the reliability and robustness of the ECM results obtained.

C. RESULTS AND ANALYSIS

a. Descriptive Result

The descriptive results of the variables are presented in Table 1. Among all the Fintech proxies, Internet Banking shows the highest mean value of transactions, while credit card transactions have the lowest mean value. The author also includes Skewness and Kurtosis tests in the descriptive statistics to assess the data distribution for normality. According to Hair et al. (2010), a data set can pass the skewness test if the results fall within the range of -2 to 2 and the kurtosis test if the results fall within the range of -7 to 7. Furthermore, since the dataset used consists of more than 100 data points, the normality of the data can generally be accepted (Gujarati, 1978).

Table 1. Descriptive Statistics

	Mean	Median	Max	Min	Std. Dev	Skewness	Kurtosis
M2 in Billion (IDR)	5,610,000	5,420,000	8,530,000	3,410,000	1,410,000	0.3467	2.0757
COCARB in Billion (IDR)	571,000	570,000	898,000	334,000	153,000	0.3253	1.9356
EM in Billion (IDR)	29,700	737	144,000	480	37,700	1.3116	3.9530
DC in Billion (IDR)	526,000	550,000	739,000	306,000	115,000	-0.2566	1.9421
CC in Billion (IDR)	16,500	21,400	34,400	446	10,800	-0.6050	1.7467
MB in Billion (IDR)	301,000	170,000	993,000	34,300	281,000	1.0438	2.7674
IB in Billion (IDR)	1,780,000	1,460,000	4,460,000	715,000	916,000	0.9998	2.9938
GDP in Billion (IDR)	843,000	863,000	996,000	679,000	93,800	-0.1583	1.8421
INF in %	4.08%	3.47%	8.79%	0.03%	2.06%	0.6556	2.5778
JISDOR (IDR)	13,653	13,901	16,367	9,802	1,193	-0.9289	4.0491

Source: Stata Output, 2023

b. Unit Root Test Result

The NG Perron Test is employed as a unit root test to assess the stationarity of the data. Table 2 and 3 displays the results of this test. According to the findings, all variables demonstrate stationarity at both the level and the first difference since their respective p-values are below the predetermined significance level. Specifically, COB/M2 and IB are stationary at the level, while the remaining variables exhibit stationarity at the first difference. These results meet the requirement of an ARDL model, which necessitates that all variables be stationary at either I(0) or (I(1)). Before conducting the NG Perron Test, the most optimal lag for each variable was chosen by Schwarz Information Criteria.

Table 2. NG - Perron Test Result (Level)

	Level I(0)			
	SIC	NG Perron Tau	5%	Conclusion
COB/M2	1	-5.12	-2.952	Stationer
EM	3	-1.749	-2.969	Non-Stationer
DC	5	-1.067	-2.934	Non-Stationer
CC	1	-1.416	-2.997	Non-Stationer
MB	3	-1.943	-2.969	Non-Stationer

Level I(0)				
	SIC	**NG Perron Tau**	**5%**	**Conclusion**
IB	3	-3.08	-2.969	Stationer
GDP	1	-2.73	-2.997	Non-Stationer
INF	1	-2.48	-2.997	Non-Stationer
REER	1	-1.529	-2.997	Non-Stationer

Source: Stata Output, 2023

Table 3. NG - Perron Test Result (First Difference)

First Difference I(1)				
	SIC	**NG Perron Tau**	**5%**	**Conclusion**
COB/M2	1	-4.041	-2.953	Stationer
EM	3	-5.21	-2.97	Stationer
DC	5	-3.76	-2.935	Stationer
CC	1	-7.348	-2.999	Stationer
MB	3	-7.518	-2.97	Stationer
IB	3	-7.906	-2.97	Stationer
GDP	1	-7.845	-2.999	Stationer
INF	1	-6.746	-2.999	Stationer
REER	1	-8.965	-2.999	Stationer

Source: Stata Output, 2023

c. Cointegration Bounds Test

Since the unit root test shows most of the variable is stationary in I(1) and the variable COB/M2 and Internet Banking is already stationary in I(0), this indicates the requirements to do an ARDL model are met. After the unit root test, the next step is to do the Cointegration Bound Test by Pesaran et al. (2001) to assess whether the model has a long-term relationship and needs an ECM. Table 4 shows the result of the bounds test and several other tests. All models show a long-term relationship between the variables after a short-run shock. Furthermore, diagnostic tests conducted on the residuals reveal no evidence of serial correlation (as the null hypothesis of the Breusch-Godfrey test cannot be rejected) and no evidence of autoregressive conditional heteroskedasticity (as the null hypothesis of the ARCH test cannot be rejected).

Table 4. Bound Test Result

Model	**ARDL**	**Bound Test F-Statistic**	**Relationship**	**BG LM Test**	**ARCH Test**
COB/M2, LNEM, LNGDP, LNREER, IFR	(1,3,1,1,1)	9.267	Long-term Relationship	0.7257	0.9898
COB/M2, LNEM, LNGDP, LNREER, IFR	(1,5,1,1,1)	6.853	Long-term Relationship	0.2503	0.7251
COB/M2, LNEM, LNGDP, LNREER, IFR	(1,1,1,1,1)	11.973	Long-term Relationship	0.9922	0.7331
COB/M2, LNEM, LNGDP, LNREER, IFR	(1,3,1,1,1)	8.744	Long-term Relationship	0.5794	0.7116
COB/M2, LNEM, LNGDP, LNREER, IFR	(1,3,1,1,1)	10.203	Long-term Relationship	0.6207	0.9644

Source: Stata Output, 2023

d. Regression Result

The ARDL model estimator was employed to assess the impact of Fintech, income, exchange rate, and inflation rate on cash holdings in Indonesia. The findings are presented in Tables 5 and 6, revealing diverse results for the five Fintech measures: EM, DC, CC, MB, and IB. Table 5 demonstrates that three financial technologies significantly influence cash holdings in Indonesia in the short run. Specifically, Debit Card and Mobile Banking exhibit a significant impact at 99%, while Internet Banking shows significance at 90%. When a 1% increase occurs in the value of a debit card transaction, cash holdings increase by 2.46%. Similarly, a 1% increase in the value of mobile and internet banking transactions results in a 1.09% and 0.62% incline in cash holdings, respectively.

Moreover, the short-run model indicates no primary predictor for money demand in Indonesia, as the other variables yield widely varied results. Even if they are significant, their effects are considered relatively small. Interestingly, Ln REER emerges as the most influential determinant of money demand or cash holdings in this model, as it exhibits significance in the two models.

Table 5. ARDL Result (Short-Run)

Independent Variable	EM	DC	CC	MB	IB
Ln EM	0.0017 (0.321)				
Ln DC		0.0246 (0.008)			
Ln CC			0.0009 (0.221)		
Ln MB				0.0109 (0.008)	
Ln IB					0.0062 (0.079)
Ln GDP	0.0419 (0.116)	-0.0086 (0.748)	0.3018 (0.220)	0.0275 (0.282)	0.0283 (0.270)
Ln REER	-0.0179 (0.116)	-0.0237 (0.075)	-0.1902 (0.164)	-0.0198 (0.152)	0.0262 (0.066)
Inf	-0.0025 (0.207)	-0.0387 (0.475)	0.0079 (0.885)	0.0257 (0.152)	-0.0436 (0.451)
Constant	-0.0025 (0.965)	-0.1605 (0.581)	-0.5222 (0.011)	-0.2737 (0.508)	-0.2065 (0573)
R Squared	0.3780	0.5376	0.3985	0.4147	0.4207
Adj. R Squared	0.3122	0.4775	0.3484	0.3528	0.3595
CUSUM	Stable	Stable	Stable	Stable	Stable

Source: Stata Output, 2023

On the other hand, the long-run effect of Fintech on cash holding in Indonesia has a different result. Credit Cards become a variable with a significant negative relationship with cash holding, with a 1% increase in the value of transactions of credit cards resulting in a 0.09% decline in cash holding. While the variable Electronic Money is not significantly related to cash holding. The model also ranges from 31-47% of adjusted r-squared, indicating there is more to the money demand function than the variables used in this research.

Table 6. ARDL and EC Result (Long-Run)

Independent Variable	EM	DC	CC	MB	IB
Ln EM	0.0016 (0.129)				
Ln DC		0.0188 (0.328)			
Ln CC			-0.0009 (0.009)		
Ln MB				0.0009 (0.682)	
Ln IB					0.0034 (0.368)
Ln GDP	0.0044 (0.836)	-0.0004 (0.989)	0.0366 (0.001)	0.0235 (0.329)	0.0181 (0.410)
Ln REER	-0.0310 (0.048)	-0.0209 (0.278)	-0.0397 (0.001)	-0.0282 (0.086)	-0.0334 (0.026)
Inf	-0.0189 (0.630)	0.0259 (0.640)	0.0167 (0.649)	0.0012 (0.976)	-0.0236 (0.570)

Source: Stata Output, 2023

The results from this research differ from past literature, but the nature of different economic variables and Indonesia's economic condition affect the result of this research (Cheong and Tang, 2007). This research follows (Onah et al.'s, 2020) model with several modifications but with a different result. While (Onah et al.,2020) found a significant negative relationship in the long term among the Fintech proxies. On the other hand, this research found that only several proxies are significant, and only Credit Cards give a significant negative correlation in the long term, while others have a positive relationship.

Positive short-run relationships in debit cards, Mobile Banking, and Internet Banking indicate that in Indonesia, the role of Fintech is complementary, not a substitute to currency. Several reasons that can influence this result are the community's behaviour (Chen et al., 2019) and the policy and regulations in Indonesia. Another reason that can affect this is that the security of carrying cash in Nigeria is riskier than in Indonesia.

D. CONCLUSIONS

The research findings indicate that Debit cards, Mobile Banking, and Internet Banking have a significantly positive relationship with cash holding in the short run, while Electronic Money and Credit cards show non-significant results. However, in the long run, Credit Cards are the only variable with a significantly negative relationship to cash holding. On the other hand, Electronic Money, Debit cards, Mobile Banking, and Internet Banking are not significantly related to cash holding in the long run. Specifically, Electronic Money is the only variable not significantly related to cash holding in the short or long run.

Based on the conclusions drawn from the analysis, several key recommendations can be made. Governments should actively encourage the development and adoption of Fintech innovations within their financial systems. However, it is crucial to carefully assess certain policies, such as the recent Indonesian government's admin fee on QRIS transactions, as they might impact users' choice of alternative payment methods. Furthermore, governments should prioritize improving and expanding digital payment infrastructure, including investing in secure and reliable electronic payment systems, promoting interoperability among various payment platforms, and educating the public about the benefits and usage of digital payment methods. Countries can embrace the ongoing transition towards a more efficient and cashless financial ecosystem by fostering a conducive environment for Fintech growth and enhancing digital payment options.

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