**Do Digital Payments Matters?**

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

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# Introduction

Digitalization has already changed the way monetary systems operate for many years, but it has recently begun to make a more radical change in its structure. Developed economies are increasingly growing the value of currency, and in some cases are predicted to become fully cashless in the near future (Fielder, Gern, & Stolzenburg, 2019).

Unfortunately, the development of digital payments not only bring benefits such as greater expansion of financial services and boost economic growth (Ozili, 2018; Slozko & Pelo, 2014; Tee & Ong, 2016; Zandi et al, 2016), ease of transaction (Krueger, 2017), alternate for the scarcity of cash (Sivathanu, 2019); but also has drawbacks namely discrimination issue (Ozili, 2018), security problem (Jung, 2015), incentive for corruption (J. Park, 2012), large computation and communication cost (Yang & Lin, 2015), rely on the technology applied (De Luna et al., 2018). Considering the divergence results on the impact of digital payment in the former research, this study aims to evaluate the effect of digital payment on macroeconomic stability as well as the implication on the payment system efficiency.

This study differs from the previous study in the following ways. First, we examine digital payment effects on the macroeconomic stability indicators namely inflation rate, while most of the literature are evaluating the association between cashless payment on Gross Domestic Product (GDP) as a proxy of country’s economic growth (Ozili, 2018; Slozko, 2014; Tee and Ong 2016, Zandi et al., 2013) or on financial stability and monetary stability (Manning & Russo, 2007). Investigation on the exponential growth of digital payment and macroeconomic indicators will provide contribution to the literature of macroeconomic stability. Furthermore, the literature suggests a strong relationship between macroeconomic stability with the financial stability (Blot, Creel, Hubert, Labondance, & Saraceno, 2015; Bordo & Wheelock,

1998; Fazio, Silva, Tabak, & Cajueiro, 2018; Fouejieu, 2017; Fouejieu, Popescu, & Villieu, 2019). It means that macroeconomic stability might be a transmission channel for financial stability.

Second, while other literature use credit and debit card payment (Immordino & Russo, 2018) or number of new fintech company established each year and total number of fintech company (Narayan & Sahminan, 2018) as a proxy of digital payment, we will use the log value of nominal electronic transaction in the economy to better capture changes in digital payment use.

Third, most of the studies performed for payment efficiency very much relies on perception analysis from primary data collection (APEC, 2016; Grüschow, Kemper, & Brettel, 2016; Y.

S. Park, 2006). Due to the measurement of time and cost relies on primary data collection, the analysis that can be performed is limited to a specific period. This research proposed a novelty approach to calculate the payment efficiency for digital payment, using aggregate of secondary data available from credit card volatility for calibrating the payment efficiency. With this approach, we can utilize the secondary data available to measure the payment efficiency of digital payment in Indonesia.

Fourth, other research analysing payment efficiency in the firm level by evaluating Check processing, Automated Clearinghouse services, and Fedwire (Bauer & Ferreier, 1996) or real- time gross settlement (RTGS) adoption (Berger, Hancock, & Marquardt, 1996). While in this study, we relate electronic money transactions with efficiency measures for investigating its behaviour. The exponential use of electronic money transactions and its relationship to payment efficiency will provide a new landscape of study.

In this study we use digital payment data from Indonesia, however, the analysis can be extended to broader developing countries which have relatively similar characteristics with Indonesia. The use of cashless payment has increased exponentially in Indonesia, the country has a rapidly growing mobile market which leads to one of the largest social media user in the world (Azali, 2016). The shift to electronic payment is also evidence in Thailand (Khiaonarong, 2000). Therefore, this research could contribute in explaining the landscape of digital payment in the developing countries.

Our approach is quite similar with the work of Tee & Ong (2016) and Narayan & Sahminan, (2018), in fact, this study extend these two studies by combining them to evaluate the effect of digital payment by incorporating electronic money transaction for the proxy (Tee & Ong, 2016) to the macroeconomic stability represented by the inflation (Narayan & Sahminan, 2018). By integrating these papers we expect to have more explanation in the exponential growth of electronic money use on the dynamic of country inflation rate.

To calibrate the relationship between digital payment on macroeconomic stability as well as on the payment efficiency auto regressive distributed lag (ARDL) model of (Pesaran et al., 2001) is performed. The ARDL method combines the short-run impact of the given variables with a long-run equilibrium using a term for error correction without dropping long-run information. Moreover, while most techniques of cointegration are sensitive to sample size, the ARDL method provides robust and consistent results for small sample sizes (Adom, Bekoe, Kutri, & Akoena, 2012; Pesaran & Shin, 1995; Pesaran et al., 2001) which is suitable for our setting as we have small sample sizes.

In this study, we expect that our findings show a significant and positive relationship between digital payment on macroeconomic stability as well as increasing payment system efficiency. Should we find the evidence, we can encourage the regulator to provide policy and infrastructure that support the development of digital transformation.

# Literature Review

## Digital Payment and Macroeconomic Stability

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

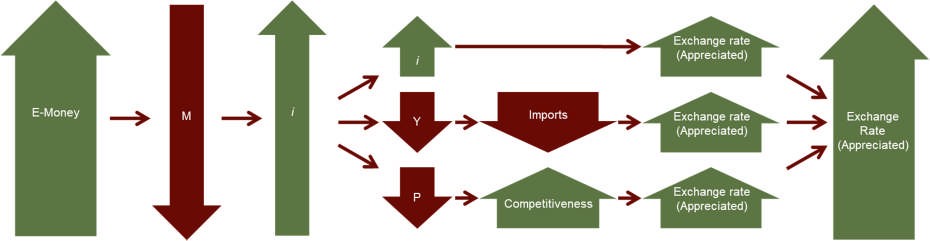
E-money or e-banking can be divided into three groups: access devices, stored-value cards (SVCs), and network money (Freedman, 2000). Access devices include ATMs and home banking by telephone or computer, which allow the holder of an account at a bank to withdraw or deposit cash, transfer funds, and pay bills. While much more convenient than visiting a branch or writing a cheque, these types of instruments do not differ conceptually from traditional mechanism for making payments, transferring funds, or withdrawing cash. SVCs are prepaid cards in which funds are stored in electronic form on a computer chip (or integrated circuit) embedded in the card. Network money are money stored in electronic form on devices such as the hard disk of a computer and are transferred over communications network such as the internet. These products are at a far earlier stage development than the SVCs.

E-money is the newest instrument in the payment system, and according to one broader definition this is the money that is transferred electronically (Popovska-Kamnar,2014). Specific characteristics of e-money includes: (i) lower transaction costs, (ii) higher fixed cost, but necessarily significant due to high usage volume, (iii) can substitute the currency in circulation, (iv) has no value if not used and less transparent.

Impact of e-money on monetary policy includes: (i) decrease in the control of central bank over money supply, (ii) increase in the velocity of money, (iii) volatility in exchange rate, (iv) decreasing the need of printing cash, thus influences the revenues of central banks, (v) lower the transaction cost.

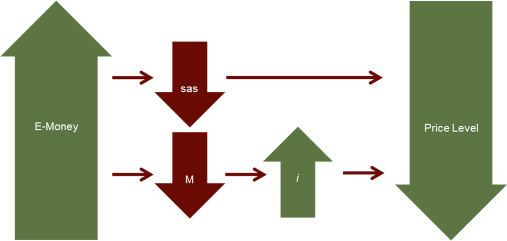
We can see from Figure 1, Money stored in e-money are not included in the monetary multiplier process, thus decrease the money supply. Decrease in money supply can increase interest rates, resulting in the increase of foreign capital inflow, thus affecting exchange rate (appreciated).

At the same time, increase in interest rates reduces private sectors’ investment, thus reduces society’s income. Less society’s income reduces society’s purchasing power on imported goods, thus affecting exchange rate (appreciated).

At the same time, decrease in private sectors’ investment reduces country’s real output, thus lowers the price level. Lower price level increases national product price competitiveness compared to other foreign products, thus increases export. Increase in export affects exchange rate (appreciated).

**Figure 1 E-Money Transmission to Exchange Rate**

Then Figure 2 show by using e-money, society will be exposed to lower transaction cost. Central bank’s cost will also be lower due to the decreasing needs of printing cash. Although the fixed cost of providing e-money is higher, but this per unit fixed cost is expected to be lower than the decrease of transaction and printing money cost, thus, in overall, the use of e-money will reduce overall costs. Having lower cost, will reduce the short-run aggregate supply curve, thus lowers the price level.

Another transmission happened through the interest rate channel. Money stored in e-money are not included in the monetary multiplier process, thus decrease the money supply. Decrease in money supply can increase interest rates. Increase in interest rates reduces private sectors’ investment. Decrease in private sectors’ investment reduces country’s real output, thus lowers the price level.

**Figure 2 E-Money Transmission to Inflation**

Narayan & Sahminan, (2018) investigates how digitalization in the financial services industry has influenced Indonesia’s inflation rate. They found out that the use of technology in financial services (measured by the number of financial technology start-ups established each year and

the total number of financial technology start-ups each year) affects Indonesian financial stability through inflation rate.

For several decades, maintaining financial stability has become one of the most important functions of central banks around the world. Allen & Wood (2006) come up with an approach to observe financial stability and conclude that the best way to define financial stability is through the characteristics of financial instability. They then define financial stability as the absence of financial instability episodes (excessive volatility, stress, or crises) that can lead to unfavorable macro-economic conditions. Technological advancement in financial services is intended to decrease transaction costs, achieve economies of scale by collecting and using big data, lower and secure the transmission of information, and decrease the verification cost (Thakor, 2020). Not only lowering the cost and improving the quality of financial services, (Lee & Shin, 2018) argued that financial technology also creates a more stable financial landscape. Thus, the development of digital payment as a part of financial technology can have a positive relation with financial stability i.e. inflation.

## Digital Payment and Macroeconomic Efficiency

Digital payment is an efficient, hassle-free method of payment that is profitable for consumers and businesses. They allow businesses to create accounts and gift programs that are easy to use, creating customer incentives for future visits. Also, for businesses, cellular payments eliminate the need to rent or buy payment processing equipment.

Customers will enjoy an efficient transaction process too. All their info will be stored digitally, making checkout a fast and painless experience. Plus, it's safer to carry your cellphone than cash or credit cards. In today's environment of identity theft and fraud, consolidation of financial information is good news for those who care about financial data and security.

This efficiency acts like two double-edged swords. On one hand, the payment efficiency makes transactions easier, with notions that digital payment will replace future cash money in the future (Duffie, 2019; Yanagawa and Yamaoka, 2019), and it is proven through research survey that digital payment transactions through cashless process will be faster compared to credit card and even regular cash money transactions (Polasik et al., 2013). On the other hand, the payment efficiency can also lead to more undetectable transactions and source of funding due to its efficiencies. As postulated by Park ( 2012) and Rato et al (2020), the presence of digital payment systems due to its convenience can lead to higher corruption activity due to the high level of anynonymousity presented. Another drawback from the presence of digital payment is the increasing level of nonperforming loans (NPL). Due to low level of credit checking, and the increased promotion of so called PayLater schemes, more and more consumers are spending their money through the digital payment system, and in the end if not governed well, can lead to high level of NPL.

In terms of efficiency, we can also see that for payment itself, we can categorize the terms of efficiency into two categories: time and cost efficiency. For the perspective of time efficiency, digital payment promotes faster transactions compared with other regular payment methods. As seen in the study by Park (2006) which suggests that cross-border payments are slow,

inefficient and costly for banks and businesses. Deloitte (2018) presents a report that mentions why digital/card-based payments represent an increasingly important opportunity for SMEs to improve the operation of their businesses. Polasik et al. (2012) conducted a study in Poland on comparison between a wide range of payment methods from cash and standard cards to contactless cards, RFID stickers and mobile payments (NFC and remote). Transactions were timed by means of digital chronography of video material recorded in the biggest chain of convenience stores in Poland. The results confirm that cash is a significantly faster payment method than traditional payment cards with a magnetic stripe or EMV chip. However, the innovative payment methods, such as contactless cards and NFC mobile payments, are competitive to cash in terms of time efficiency.

The second category is the cost efficiency. As seen by the study performed by Bijwaard & Franses (2009), cash payment has its own disadvantages, where cash payment leaves rounding issues, that although seems small in nominal terms, however, when combined produced significantly high numbers of rounding which leads to inefficiency. Grüschow et al. (2016) identify that Electronic payments in terms of both credit card and PayPal cause higher payment costs, and do not show scale efficiency in e-commerce. Furthermore, this research illustrates differences in the collection time of accounts receivable across payment methods, implying the cost of capital that arises for the retailer. The results lead to the conclusion that prepayments and PayPal payments are associated with the lowest cost of capital. Leinonen (2007) posits that even small cost savings per transaction and efficient choice of payment instrument will amount to large total savings due to the very large retail payment volumes. The right economic incentives would promote and speed up these changes towards more efficient payment habits. Another study worth cited is the work by Igamo and Falianty (2018) which suggest the following findings: electronic money increases private consumption expenditures as a proxy for the efficiency. On the other hand, the result showed that electronic money decreases narrow money (M1). Based on their study, an increase of 1 percent in electronic money will reduce narrow money (M1) by 0.102659 percent and the increase of electronic money by 1 percent will increase the consumption level by 0.5336 percent.

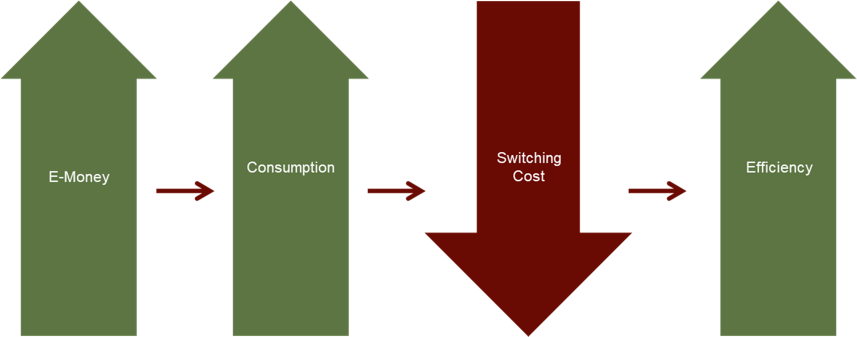
The other aspect that also related with cost efficiency is the lower switching cost. As stated in the study by Brunnermeier and James (2019), in the traditional condition switching cost generates network externalities, as the use of currencies traditionally exhibits strong network externalities. Switching costs, which severely impair traditional currency competition, are likely to be much lower in a digital environment. The ability to exchange value peer-to-peer within networks eliminates the need for a third party, and thus any fee that party would charge, in an exchange of currencies. Users could set up their mobile devices to execute currency exchanges automatically whenever needed. The reduction in switching costs brought about by mobile networks will lead to one of the most salient features of digital currency competition: an unbundling of the roles of money. When switching costs are low, there is no longer a strong incentive to use one currency as both a store of value, medium of exchange, and unit of account. Instead, users of the network can seamlessly switch among currencies and convert units when needed.

Overall, then, the unbundling of the roles of money reduces the need for coordination on a single currency. It does so by allowing users to obtain the distinct services provided by money from multiple different assets and by mitigating the importance of coordination on a common asset across users. The unbundling of money can lead to increased competition among currencies. In Hayek’s view (1976), currencies would compete primarily as stores of value, but historically this type of competition has been limited due to switching costs and network externalities. With unbundled money, currencies are free to specialize to a certain role. Currencies that act as stores of value may compete with one another while others that act as exchange media compete separately. Reduced frictions and network externalities make this competition along specialized dimensions much fiercer than Hayek’s currency competition.

Digital Payment as a replacement of currency could benefit issuers, consumers, and merchants. Issuers would benefit from the interest-free debt financing provided by digital money balances. Consumers would benefit from the convenience. For merchants, accepting digital money would reduce costs if bits and bytes replaced physical coins and notes. The estimated annual costs of handling central bank currency by U.S. retailers and banks are $60 billion, which includes costs of processing and accounting of money, storage, transport, and security (Hayes et al. 1996). Hayes et al. (1996) also suggests that the cost of an electronic payment ranges between one-third and one-half of a paper check or paper giro payment. An indication of the low cost per transaction are the several money schemes under development that will allow (online) payment of transaction for as little as one cent (micropayments) (Berensten, 1997).

While digital money products based on smart cards would mainly reduce the demand for currency, software-based digital money products could also affect the demand for transaction deposits due to reduced transaction cost and learning spillovers. Software-based digital money products could facilitate and reduce the cost of transferring value among different types of accounts, banks, and countries (Berentsen, 1997). The second reason -- learning spillovers -- refers to the notion that using software-based digital money products will improve the skills and knowledge of their users regarding the use of personal finance software and telecommunication technologies to optimize their finance. Personal finance software products keep track of account information and monetary transactions and help in creating budgets, managing investments, and filling out tax forms. They also provide access to electronic banking and electronic bill payment services (Berensten, 1997).

All in all, from all the studies presented above, we can conclude that the introduction of digital payment can influence the payment efficiency, in this case it will influence the system in two ways: time and cost efficiency. This study proposes a new approach to calculating payment efficiency for digital payments, using available secondary data. With this approach, we can use secondary data available to measure the efficiency of digital payment payments in Indonesia.



**Figure 3 E-Money Transmission to Efficiency**

# Theoretical Framework and Empirical Strategy

## Theoretical Framework and Hypothesis Development

The Diffusion of Innovation Theory (DOI), DOI can be used for investigating the impact of digital payment on an economy. Tee and Ong (2016) study cashless payment on economic growth while Lin (2011) study the effect of existing innovation characteristics on the use of online financial transactions under the diffusion innovation theory. Roger first introduced the concept of DOI in 1962 where he explained how creativity is disseminated over time to members of a social system (Rogers, 1995). According to DOI, interaction between individuals via interpersonal networks is causing the adoption of a new idea or innovations. Diffusion in this sense is the spread of digital payment where customers prefer better and easier transactions while companies pursue new opportunities for profit. The spread of digital payment would result in the acceptance of cashless transactions within society or culture, according to the types of innovation adopters and the cycle of innovation-decision. Since the effect of cashless payment diffusion depends on how rapidly the organization is able to implement cashless payment across various stages of innovation processes, the implications of cashless payment adoption vary in different societies .

Gai et al. (2008) using a mathematical model analyze the impact of financial innovation and macroeconomic stability. Their findings suggest that macroeconomic stability and financial innovation may have reduced the probability of systemic financial crisis in the developed countries. Study in the firm level analysis from Meifang et al (2018) who investigate the impact of payment technology innovations on the traditional financial industry in China, shows that finding technological innovation in the developing country has promoted the development of the financial industry and accelerated the process of industrial evolution.

The seminal works from Darrel Duffie (2019) which examine the monetary implication and business strategy in the presence of faster payment systems also suggest that larger bank business franchises will most likely be disrupted by the financial technology firms which

might affect the financial stability. Furthermore, Genberg (2020) provides conceptual reviews on the implication of digital transformation on financial stability, payment system and macroeconomic stability. He denotes financial technology that applied to finance has modest effects in affecting financial stability risk as long as their operations are limited in the payment system. Meanwhile, Zandi et al (2016) and Tee and Ong (2016) examine the impact of electronic payment on economic growth. They find that there is a significant effect of adopting cashless payment in the economy in the long run. The aforementioned literature lead us to our first hypothesis:

*The development of digital payment increases macroeconomic stability in the Indonesian economy.*

To test the developed hypothesis, we estimate using the following model:

𝑀𝑆𝑡 = ݂(𝐸𝑙𝑒𝑐𝑡𝑟݋𝑘݅𝑐 𝑚݋𝑘𝑒𝑦𝑡 + 𝐿𝑎𝑔 ݂݋ 𝑑𝑒𝑝𝑒𝑘𝑑𝑒𝑘𝑡 𝑣𝑎𝑟 𝑐݋𝑘𝑡𝑟݋𝑙 + 𝐶݋𝑘𝑡𝑟݋𝑙 𝑣𝑎𝑟𝑡) (1)

Where 𝑀𝑆𝑡 is the macroeconomic stability represented by inflation (Narayan & Sahminan, 2018). Our variable of interest is the electronic money payment, this proxy denotes the log value of nominal electronic transactions in the economy. The dynamic of the model is

evaluated by the lag of the dependent variable in which the macroeconomic stability in the form of the autoregressive model. While the control variables consisting of debit card transaction, credit card transaction, bank transfer, inflation lags for inflation expectations of backward-looking agents, import prices, oil prices, and unemployment rate (Narayan & Sahminan, 2018; Tee & Ong, 2016).

The second hypothesis of this research is related to the association between digital payment and payment efficiency. This efficiency acts like two double-edged swords. On one hand, the payment efficiency makes transactions easier, with notions that digital payment will replace future cash money in the future (Duffie, 2019; Yanagawa & Yamaoka, 2019), and it is proven through research survey that digital payment transactions through cashless process will be faster compared to credit card and even regular cash money transactions (Polasik,, et al., 2012). On the other hand, the payment efficiency can also lead to more undetectable transactions and source of funding due to its efficiencies. As postulated by Park (2012), the presence of digital payment systems due to its convenience can lead to higher corruption activity due to the high level of anynonymousity presented. Another drawback from the presence of digital payment is the increasing level of nonperforming loans (NPL). Due to low level of credit checking, and the increased promotion of so called PayLater schemes, more and more consumers are spending their money through the digital payment system, and in the end if not governed well, can lead to high level of NPL.

Based on the preceding explanation, one main issue in the digital payment drawback is the transaction security, however we believe that technological development can suppress the disadvantages and make the benefit of digital payment more prominent. This lead to the second hypothesis of this study:

*The evolution of digital payment induces payment system efficiency.*

To test the developed hypothesis, we calibrate using the following model:

𝑃𝐸𝑡 = ݂(𝐸𝑙𝑒𝑐𝑡𝑟݋𝑘݅𝑐 𝑚݋𝑘𝑒𝑦𝑡 + 𝐿𝑎𝑔 ݂݋ 𝑑𝑒𝑝𝑒𝑘𝑑 𝑣𝑎𝑟 𝑐݋𝑘𝑡𝑟݋𝑙𝑡 + 𝐶݋𝑘𝑡𝑟݋𝑙 𝑣𝑎𝑟݅𝑎𝑏𝑙𝑒𝑠𝑡) (2)

In this model 𝑃𝐸𝑡 is the payment efficiency represented by the volatility of credit card transactions. Higher volatility in credit card transactions implies higher inefficiency in the payment system.

In this model, our variable of interest is the electronic money payment, this proxy denotes the log value of nominal electronic money transactions in the economy. The dynamic of the model is evaluated by the lag of the dependent variable in which the cost efficiency of electronic payment activities in the form of autoregressive model. While the control variables consisting Consumer Prices Index (CPI), BI Rate (BIR), IDR Exchange Rate against US Dollar (EXH), Industrial Production Index (IPI), and Jakarta Stock Price Index (IHSG) (Achsan et al., 2020), number of transaction and value of transaction (Carbó-valverde & Kahn, 2016), consumption level, real GDP, interest rate, and consumer price index (Igamo & Falianty, 2018).

## Empirical Strategy

To calibrate the relationship between digital payment on macroeconomic stability as well as on the payment efficiency auto regressive distributed lag (ARDL) model of Pesaran (2001) is performed. Auto regressive Distributed Lag Models (ARDL) model plays a vital role when it comes to the need to analyse an economic scenario. In an economy, change in any economic variables may bring change in other economic variables beyond the time. This change in a variable is not what reflects immediately, but it distributes over future periods. ARDL can calibrate this dynamics and this is the main reason for using the ARDL model in this study. Moreover, the ARDL method has been extensively utilized as it provides several advantages over traditional statistical methods for assessment of cointegration and short/long-run relationships.

Firstly, un likely to other time series methods such as Johansen’s tests (Johansen, 1991), Granger/Enger causality test (Engle & Granger, 1987) and Vector Autoregression (VAR), ARDL can be performed to test for a level relationship for variables that are either I(0) or I(1) as well as for a combination of I(0) and I(1) variables (Duasa 2007, Adom et al. 2012). Unfortunately, ARDL does not work with non-stationary variables integrated of order two I(2). However, the ability to combine I(0) and I(1) variables is a great advantage as financial times series often are either I(1) or I(0). The advantage can be further clarified by comparing

e.g. VAR with ARDL for the robustness check.

The ARDL method additionally combines the short-run impact of the given variables with a long-run equilibrium using a term for error correction without dropping long-run information. One may therefore assess the short-term and long-term relationship between the variables at the same time. Furthermore, unlike traditional cointegration tests, it is possible to establish different lags for each variable in the analysis (Pesaran et al., 2001) which makes it more versatile. Lastly, most techniques of cointegration are sensitive to sample size, while the ARDL method provides robust and consistent results for small sample sizes (Pesaran & Shin 1998; Pesaran et al., 2001; Adom et al., 2012) which is good for our setting as we have small sample sizes.

Most linear distributed lag models discussed in the literature belong to the class of rational distributed lag models. Early examples of this type of models include the polynomial and geometric distributed lag models. The rational distributed lag model can also be written in the form of the autoregressive distributed lag (ARDL) models.

Following Pesaran and Shin (1995), the following general ARDL(p; q) model:

𝑦𝑡 = 𝛼଴ + 𝛼ଵ𝑡 + ∑𝑝 ߶௜𝑦𝑡ି௜ + 𝛽ᇱ𝑥𝑡 + ∑𝑞ିଵ 𝛽∗ᇱ∆𝑥𝑡ି௜ + 𝑢𝑡 (3)

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p ≥ 1, q ≥ 0, for simplicity assuming that the lag order q is the same for all variables in the K

× 1 vector x.

There are many popular cointegration models in literature. Usually, in different situations researchers use their cointegration model. Engle and Granger (1987) found the first cointegration method. They said that in I(1) order the method was applicable for two variables. Johansen and Juselius (1990) is the second method of cointegration that is used for large size of data and all series have the same order of integration. These two methods have some limitation that all series should be integrated at the same level. Researchers urged to introduce a novel technique that treats the variables with different series of I(0) and I(1). At last Pesaran et al. (2001) developed Autoregressive Distributed Lag (ARDL) cointegration model to solve the issue. The ARDL method is applied to deal with the variables having stationary series mixture of I(0) and I(1). The ARDL model is superior to the other cointegration model and provides reliable results for small sample size. Autoregressive Distributed Lag (ARDL) model having problem of endogeneity during estimations. Endogeneity problems can be solved by taking lags of variables and make the model dynamic as in Pesaran et al. (2001), while Engle-Granger cointegration and Johansen cointegration are not able to apply different lags of variables. (Nkoro & Uko, 2016) found ARDL cointegration technique cannot be applied when the underlying variables are integrated of order I(2), when there are multiple long-run relationships, ARDL approach cannot be applied.

The advantage of ARDL lies in its ability to generate sufficient lags for variables in the model and its superiority to sufficiently provide for the means to ascertain residual correlation. It is also capable of providing the short-run and long-run at the same time. The dynamism is based

on the transformation of the variable at the period of one lag in the model using the optimal lag length. When there is a single long run relationship, the ARDL procedure can distinguish between dependent and explanatory variables.

In applied econometrics, the Granger (1981) and, Engle and Granger (1987), Autoregressive Distributed Lag (ARDL) cointegration technique or bound test of cointegration(Pesaran and Shin 1999 and Pesaran et al. 2001) and, Johansen and Juselius (1990) cointegration techniques have become the solution to determining the long run relationship between series that are non-stationary, as well as reparameterizing them to the Error Correction Model (ECM). The reparameterized result gives the short-run dynamics and long run relationship of the underlying variables. Long-run relationship means that there is cointegration between the dependent variable and the independent variable. Cointegration is an econometric concept that mimics the existence of a long-run equilibrium among underlying economic time series that converges over time. Cointegration test examines how time series, which though may be individually non-stationary and drift extensively away from equilibrium can be paired such that the workings of equilibrium forces will ensure they do not drift too far apart. Thus, cointegration establishes a stronger statistical and economic basis for empirical error correction model, which brings together short and long-run information in modeling variables.

The first problem concerns the time series dependent variables are not at level, however we can still use the ARDL model following Fitriani (2017), Sugiharti et al (2020) and Lin et al (2019). Fitrianti (2017) and Sugiharti et al (2020) use exchange rate volatility to see the long run and short run impacts on Indonesia real exports to other countries. Lin et al (2019) investigates the linear/nonlinear long-run and short-run dynamic relationships between oil prices and two implied volatilities, oil price volatility index (OVX) and stock index options volatility index (VIX), representing panic gauges. The idea is that as long as the volatility data in the stationary process of I(0), I(1) or combination of I(0) and I(1) the ARDL model can be performed to estimate the model (Dehay & Leskow, 1996; Leskow, 2001).

# Data

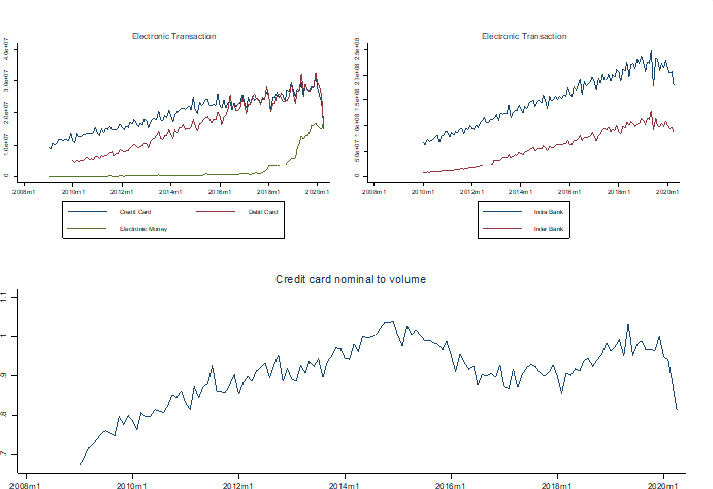
In this study we use secondary data for analyzing the model. The secondary data related to the transaction of electronic money, debit card, credit card and bank transfer from the Payment Statistic of Central Bank of Indonesia (Statistic Pembayaran Bank Indonesia), Macroeconomic will be collected from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

**Table 1. Data Sources**

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

**Table 2. Descriptive Statistics of the Variables**

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



**Figure 4. Electronic Transaction**

# Results and Discussion

## Test of Order Integration

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

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

**Table 3. Unit Root Test for the Variables**

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

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

\*,\*\*,\*\*\* significant at α=10%,5%,1%

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

## ARDL Bounds Testing for Long-Rung Cointegration

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

As an additional diagnostic check, the Breusch-Godfrey Lagrange Multiplier (LM) test of residual serial correlation is applied, indicating a null hypothesis of “no serial correlation.” The LM follows a χ2 distribution with one degree of freedom (first-order). Breusch-Pagan / Cook-Weisberg test for heteroskedasticity is performed to make sure that the models have constant variance. Furthermore, Ramsey's RESET test for misspecification model is proposed with the null hypothesis of “no misspecification.” The RESET is distributed as χ2 with one degree of freedom. The Jarque-Bera (J-B) test for normality is also applied to test the distribution of residual with the null hypothesis of “residual has a normal distribution.”

### Relationship between Electronic Money and Macroeconomic Stability

In this study, volatility of exchange rate and inflation rate are used as proxies for macroeconomic stability. On the other side of the equation is the explanatory variables with

electronic money as proxy for digitalization, the others electronic transaction are used for the control variables as well as some industry and country level data.

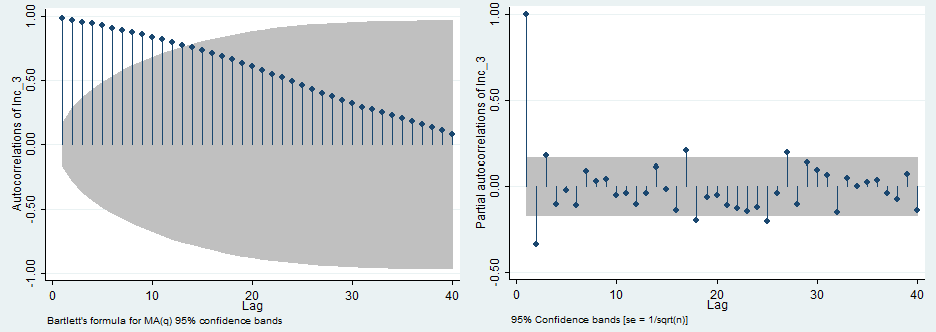
### Exchange Rate Volatility

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

**Table 4. LM Test for ARCH**

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

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



**Figure 5. ACF and PACF for Exchange Rate**

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

**Table 5. BIC Score ARIMA Models**

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

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

**Table 6. Bound Test for Dependent Exchange Rate**

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

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

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

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

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

exchange rate. While for the latter variable, indicate that the increase in intra bank transaction will lead to the decrease of exchange rate volatility.

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

Diagnostic and the stability tests are conducted in order to ascertain the robustness of the ARDL model. The results (Table 8) show that, the R2 for dependent exchange small and for the inflation sufficiently high. The p-values of the serial correlation using Breusch-Godfrey LM test is 0.895, which imply that there are no autocorrelation problems. The results of the heteroscedasticity tests of Breusch-Pagan-Godfrey also show that there is no heteroscedasticity issues in dependent exchange rate volatility, for exchange rate we use robustness estimation and the result there is no heteroscedasticity.

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

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

### Inflation Rate

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

**Table 9. Bound Test for Dependent Inflation**

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

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

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

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

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

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

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

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

### Relationship between Electronic Money and Payment Efficiency

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

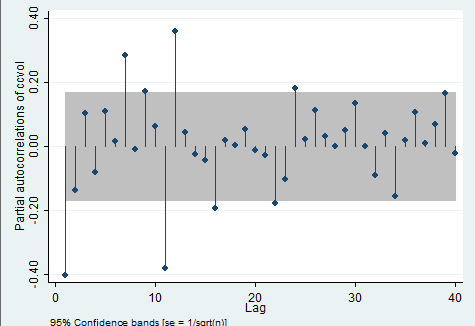
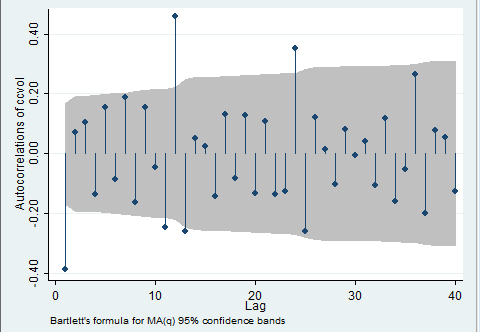
### Credit Card Volatility

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

**Table 12. LM Test for ARCH credit card volatility**

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

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



**Figure 6. ACF and PACF for credit card volatility**

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

**Table 13. BIC Score ARIMA Models**

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

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

**Table 14. BIC Score ARIMA Models**

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

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

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

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

### Consumption

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

**Table 18. Unit root test for quarterly data**

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

\*,\*\*,\*\*\* significant at α=10%,5%,1%

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

**Table 19. Bound Test for private consumption variable**

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

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

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

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

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

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

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

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

# References

Achsan, W., Achsani, N. A., & Bandono, B. (2020). Impact of Macroeconomic Condition on Credit Card Default in Emerging Economy : Empirical Evidence from Indonesia.

*International Journal of Finance and Banking Research*, *6*(18), 37–43. https://doi.org/10.11648/j.ijfbr.20200603.11

Adom, K. P., Bekoe, W., Kutri, S., & Akoena, K. (2012). Modelling aggregate domestic electricity demand in Ghana : An autoregressive distributed lag bounds cointegration approach. *Energy Policy*, *42*, 530–537. https://doi.org/10.1016/j.enpol.2011.12.019

Allen, W. A., & Wood, G. (2006). Defining and achieving financial stability. *Journal of Financial Stability*, *2*(2006), 152–172. https://doi.org/10.1016/j.jfs.2005.10.001

APEC. (2016). *APEC Fintech E-payment Readiness Index Ecosystem Assessment and Status Report supported by PayPal*.

Azali, K. (2016). Cashless in Indonesia Gelling Mobile E-frictions ? *Journal of Southeast Asian Economies*, *33*(3), 364–387. https://doi.org/10.1355/ae33-3e

Bauer, P. W., & Ferreier, G. D. (1996). Scale economies , cost efficiencies , and technological change in Federal Reserve paymemts processing. *Journal of Money, Credit and Banking*, *28*(4), 1004–10038.

Berger, A. N., Hancock, D., & Marquardt, J. C. (1996). A Framework for Analyzing Efficiency , Risks , Costs , and Innovations in the Payments System. *Journal of Money, Credit, and Banking*, *28*(4), 696–732.

Bijwaard, G. E., & Franses, P. H. (2009). The effect of rounding on payment efficiency.

*Computational Statistics and Data Analysis*, *53*(4), 1449–1461. https://doi.org/10.1016/j.csda.2008.09.034

Blot, C., Creel, J., Hubert, P., Labondance, F., & Saraceno, F. (2015). Assessing the link between price and financial stability ଝ. *Journal of Financial Stability*, *16*, 71–88. https://doi.org/10.1016/j.jfs.2014.12.003

Bordo, M. D., & Wheelock, D. C. (1998). *Michael D. Bordo David C. Wheelock*. Carbó-valverde, S., & Kahn, C. M. (2016). *Payment Systems in the US and Europe:*

*Efficiency, Soundess and Challanges*. *REVISTA DE ESTABILIDAD FINANCIERA*

(Vol. 30).

Charbonneau, K., Evans, A., Sarker, S., & Suchanek, L. (2017). *Digitalization and Inflation : A Review of the Literature*.

Daniels, K. N., & Murphy, N. B. (1994). The Impact of Technological Change on Household Transactions Account Balances : an Empirical Cross-Section Study. *Journal of Financial Services Research*, 113–119.

De Luna, I. R., Liébana-cabanillas, F., Sánchez-fernández, J., & Muñoz-leiva, F. (2018).

Technological Forecasting & Social Change Mobile payment is not all the same : The

adoption of mobile payment systems depending on the technology applied. *Technological Forecasting & Social Change*, (August), 1–14. https://doi.org/10.1016/j.techfore.2018.09.018

Dehay, D., & Leskow, J. (1996). Testing stationarity for stock market data. *Economic Letters*, *50*(October 1987), 205–212.

Deloitte. (2018). *SME Digital Payments New opportunities to optimise*.

Duffie, D. (2019). *Digital Currencies and Fast Payment Systems : Disruption is Coming*.

Fazio, M. D., Silva, C. T., Tabak, M. B., & Cajueiro, O. D. (2018). In fl ation targeting and fi nancial stability : Does the quality of institutions matter ? ☆. *Economic Modelling*, *71*(March 2017), 1–15. https://doi.org/10.1016/j.econmod.2017.09.011

Fielder, S., Gern, K.-J., & Stolzenburg, U. (2019). The Impact of Digitalization on the

Monetary System. In S. and Q. of L. P. Policy Department for Economic (Ed.), *The Future of Money*. European Parliament.

Fitriani, S. (2017). The Exchange Rate Volatility and Export Performance : The Case of

Indonesia ’ s exports to Japan AND US. *Bulletin of Monetary Economics and Banking*, *20*(1), 49–70.

Fouejieu, A. (2017). In fl ation targeting and fi nancial stability in emerging markets.

*Economic Modelling*, *60*, 51–70. https://doi.org/10.1016/j.econmod.2016.08.020 Fouejieu, A., Popescu, A., & Villieu, P. (2019). Trade-offs between macroeconomic and

financial stability objectives. *Economic Modelling*, *81*(November 2018), 621–639. https://doi.org/10.1016/j.econmod.2019.02.006

Freedman, C. (2000). Monetary policy implementation: Past, present, and future – Will electronic money lead to the eventual demise of central banking? *International Finance, 3 (2), 211-227*.

Gai, P., Kapadia, S., Millard, S., & Perez, A. (2008). Financial Innovation, Macroeconomic Stability and Systemic Crises. *The Economic Journal*, *118*(2007), 401–426.

Grüschow, R. M., Kemper, J., & Brettel, M. (2016). How do different payment methods deliver cost and credit efficiency in electronic commerce? *Electronic Commerce Research and Applications*. https://doi.org/10.1016/j.elerap.2016.06.001

Igamo, A. M., & Falianty, T. A. (2018). The Impact of Electronic Money on The Efficiency of The Payment System And The Substitution of Cash In Indonesia. *Sriwijaya International Journal of Dynamic Economics and Business*, *2*(3), 237–254.

Immordino, G., & Russo, F. F. (2018). Cashless Payments and Tax Evasion Giovanni.

*European Journal of Political Economy*, *55*, 36–43. https://doi.org/10.1016/j.ejpoleco.2017.11.001

Jung, M. S. (2015). A Study on Electronic-Money Technology Using Near Field Communication, *7*, 1–14. https://doi.org/10.3390/sym7010001

Khiaonarong, T. (2000). Electronic payment systems development in Thailand. *International Journal of Information Management*, *20*.

Krueger, M. (2017). The introduction of cashless wage payments and the spread of branch banking in post-war. *Financial History Review*, *24*(2), 185–207.

Lee, I., & Shin, J. Y. (2018). Fintech : Ecosystem , business models , investment decisions , and challenges. *Business Horizons*, *61*(1), 35–46. https://doi.org/10.1016/j.bushor.2017.09.003

Leinonen, H. (2007). *On the efficiency of multilateral interchange fees ( MIFs ) to promote payment efficiency ?*

Leskow, J. (2001). The Impact of Stationarity Assessment on Studies of Volatility and Value-at-Risk. *Mathematical and Computer Modelling*, *34*, 1213–1222.

Lin, H. (2011). International Journal of Information Management An empirical investigation of mobile banking adoption : The effect of innovation attributes and knowledge-based trust. *International Journal of Information Management*, *31*(3), 252– 260. https://doi.org/10.1016/j.ijinfomgt.2010.07.006

Lin, J., Liang, C., & Tsai, W. (2019). Nonlinear Relationships between Oil Prices and Implied Volatilities : Providing More Valuable Information. *Sustainability*, *11*, 1–15.

Manning, M., & Russo, D. (2007). Payments and monetary and financial stability. In

*Payment and Monetary and Financial Stability*. European Central Bank.

Narayan, S., & Sahminan, S. (2018). Has FinTech Influencced Indonesia’s Exchange Rate and Inflation? *Bulletin of Monetary Economics and Banking*, *21*(2), 177–190.

Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag ( ARDL ) cointegration technique : application and interpretation, *5*(4), 63–91.

Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review*, *18*(4), 329–340. https://doi.org/10.1016/j.bir.2017.12.003

Park, J. (2012). Journal of International Money Corruption , soundness of the banking sector

, and economic growth : A cross-country study. *Journal of International Money and Finance*, *31*(5), 907–929. https://doi.org/10.1016/j.jimonfin.2011.07.007

Park, Y. S. (2006). *The Inefficiencies of Cross-Border Payments : How Current Forces Are*

*Shaping the Future*.

Pesaran, M. H., & Shin, Y. (1995). *An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis ¤*.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds Testing Approaches to the Analysis of Level Relationship. *Journal of Applied Econometrics*, *326*(February 1999), 289–326. https://doi.org/10.1002/jae.616

Polasik, M., Gorka, J., Wilczewski, G., Kunkowski, J., Przenajkowska, K., & Tetkowska, N. (2013). Time Efficiency of Point-of-Sale Payment Methods : Empirical Results for Time Efficiency of Point-Of-Sale Payment Methods : Empirical Results for Cash , Cards , and Mobile Payments. https://doi.org/10.1007/978-3-642-40654-6

Popovska-Kamnar, N. (2014). The use of electronic money and its impact on monetary policy. *Journal of Contemporary Economic and Business Issues, 1 (2), 79-92.*

Rato, F., Gugus, R., & Imam, I. (2020). Cashless Transaction Policy : The Strategy of Fraud Prevention in Jakarta Province , Indonesia. *Advances in Economics, Business and Management Research*, *144*(Afbe 2019), 149–153.

Rogers, E. M. (1995). *Diffusion of Innovations*. New York: Free Press.

Sivathanu, B. (2019). Adoption of digital payment systems in the era of demonetization in India An empirical study. *Journal of Science and Technology Policy Management*, *10*(1), 143–171. https://doi.org/10.1108/JSTPM-07-2017-0033

Slozko, O., & Pelo, A. (2014). The electronic payments as a major factor for futher economic development. *Economics and Sociology*, *7*(3), 130–141. https://doi.org/10.14254/2071- 789X.2014/7-3/13

Sugiharti, L., Esquivias, M. A., & Setyorani, B. (2020). Heliyon The impact of exchange rate volatility on Indonesia ’ s top exports to the fi ve main export markets. *Heliyon*, *6*(September 2019), e03141. https://doi.org/10.1016/j.heliyon.2019.e03141

Tee, H., & Ong, H. (2016). Cashless payment and economic growth. *Financial Innovation*, *2*(4), 1–9. https://doi.org/10.1186/s40854-016-0023-z

Thakor, A. V. (n.d.). Fintech and banking : What do we know ? *Journal of Financial Intermediation*. https://doi.org/10.1016/j.jfi.2019.100833

Yanagawa, N., & Yamaoka, H. (2019). *Digital Innovation , Data Revolution and Central Bank Digital Currency Digital Innovation , Data Revolution and Central Bank Digital Currency \**. *Bank of Japan Working Seriess* (Vol. 19-E-2).

Yang, J., & Lin, P. (2015). A mobile payment mechanism with anonymity for cloud computing. *The Journal of Systems & Software*. https://doi.org/10.1016/j.jss.2015.07.023

Zandi, M., Koropeckyj, S., Singh, V., & Matsiras, P. (2016). The Impact of Electronic Payments on Economic Growth. *Moody’s Analytics*.

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