Essays on the Payment System in Indonesia: Macroeconomics, Behaviour Analysis and Policy Implication

by

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To my beloved wife Sylvi, and the best sons can have, Izhhar and Aidan.

To my parents, parents in law (in Jannah) and grand parents (in Jannah).

To my brothers, sister, brothers in law, sisters in law, cousins, uncles, aunts, nephews, and nieces.

To all my friends.

“Allah does not burden any human being with a responsibility heavier than he can bear. Everyone will enjoy the fruit of the good that one has earned and shall suffer for the evil that one has committed...”

- AL-BAQARAH 286

“Indeed, in the creation of the heavens and the earth and the alternation of the night and the day are signs for those of understanding ...”

- AL-IMRAN 190

"The best of people are those that bring most benefit to the rest of mankind."

- Muhammad SAW

Abstract

The use of non-cash payment instruments in developing nations, particularly Indonesia, has changed significantly compared to conventional payment instruments such as cash and coins. This rapid increase of non-cash payment instruments was made possible not only by the rapid development of the financial and payment system and telecommunications technology but also by government and central bank support, as well as unprecedented events such as pandemics and economic crises. This thesis comprises four articles with intertwined general purposes to present empirical evidence of economic analysis of payment system data, analysis of people's behaviour in adopting a new payment instrument and policy impact analysis, as well as an examination of contemporary methodology to forecast inflation using payment system data. The first essay examines the determinants of money demand in Indonesia. This study examines the stability of money demand by incorporating the payment system innovation variable and the possibility of a structural break related to central bank policies. The second and third essays analyse the behaviour of consumers and merchants in adopting a new payment platform in the presence of a new central bank policy that was hindered by the Covid-19 pandemic. These studies use an online survey with self-administered questionnaires to obtain data from 31 Indonesian provinces. We introduced additional exogenous latent variables embedded inside the unified technology adoption theory; our research successfully unravels and distinguishes the effects of central bank policies and the pandemic. Finally, the fourth study explores payment system data to forecast inflation using various machine learning (ML) techniques and compares it to that of the univariate time series ARIMA and SARIMA models. We also perform various out-of-bag sample periods in each ML model to determine the appropriate data-splitting ratios for the regression case study. The study reveals that the ML models outperformed the ARIMA benchmark in terms of prediction accuracy and discovered that numerous payment system factors were highly predictive of inflation. We demonstrate the interpretation of ML forecast results that complement the causal inference of the more established econometric method.

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Abbreviations, Acronyms, and Symbols

List of Abbreviations and Acronyms

ADT Average daily stock market trading

ARIMA Auto-Regressive-Integrated-Moving-Average

ATMD Automatic Teller Machine and debit cards

AVE average variance extracted

CA Cronbach's alpha

CC Credit cards

CIC Cash in circulation

CR Composite Reliability

CUSUM Cumulative Sum of the recursive residuals test

CUSUMSQ Cumulative Sum of Squares of the recursive residuals test

EE Effort Expectancy

EM Electronic money

ENT Elastic net

FC Facilitating Condition

FM Force Majeure

FTa International outgoing fund transfers

Hb Habit

HM Hedonic motivation

HTMT Heterotrait–Monotrait

IR Interest rates

LE Law Enforcement or Perceived Government's Policy

MAE Mean absolute errors

ML Machine learning

NFCash Cash net flow

PE Performance expectation

PLS Partial Least Squares

PR Perceived risks

PSINV payment system innovation

PV Price value or Perceived value

QRIS Quick Response Code Indonesian Standard

RF Random Forest

RMSE Root mean square error

RMSE Root of the mean squared error

RTGS Real-Time Gross Settlement

SEM Structural equation model

SHAP SHapley Additive exPlanations

SI Social Influence

SKN National clearing

SKNBI Sistem Kliring Nasional Bank Indonesia (The National Clearing System)

SMC Stock market capitalisation

SRMR Standardised Root Mean Residual

SVR Support vector regression

UTAUT The Unified Theory of Acceptability and Use of Technology

XGB Extreme Gradient Boosting

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Chapter 1

Introduction

Payment instruments are vital to the effective operations of modern economies, as they are used daily to transact and move money among diverse economic agents, including households, corporations, retailers, and government organisations.

Numerous academics assert that transitioning from cash-based payment systems to noncash instruments has the potential to yield economic advantages, such as stimulating consumption rates and fostering economic growth. This viewpoint is supported by scholars such as Zandi *et al.* (2013) and Luo *et al.* (2022), who have researched the topic. Additionally, this shift is believed to introduce efficiency into the economy (Varga, 2016). According to previous studies conducted by Pramono *et al.* (2006) and Aristiyowati and Falianty (2018), the use of card payment instruments has been found to have a positive impact on the velocity of money while simultaneously exerting a negative influence on the demand for cash and narrow money. The assertion made by Igamo and Falianty (2018) supports the notion that electronic money has positive long-term effects on both narrow money demand and consumption levels. The positive impact of card, electronic, and mobile payments on the economy has occurred not only in developed countries but also in developing countries, as demonstrated by the studies conducted by Oyelami *et al.* (2020) and Wong *et al.* (2020). However, some researchers have proposed that the introduction of financial or payment system innovation may have certain potential drawbacks. For instance, it could potentially weaken the central bank's ability to control the money supply (Tule and Oduh, 2017) and other monetary aggregates (Bordo and Levin, 2017), as well as reduce seigniorage income (Camera, 2017). Additionally, there are other concerns from the perspective of households, such as the increase in societal risk and the possibility of technology failure. These issues have been explored by de Almeida *et al.* (2018b) and Atzei *et al.* (2017). Understanding how payment systems affect the economy and how certain factors and central bank policy can affect the adoption of noncash payment instruments is crucial in this context.

The measurement of policy impact holds significant importance for organisations, including the central bank, as it serves to enhance stakeholder and public recognition of its significance (Kowalkiewicz and Dootson, 2019). In addition, the evaluation of policy impact assists an organisation in assessing its progress towards achieving its long-term objectives and aims while also identifying and effectively utilising its most important resources. Examining audience behaviour shifts is one approach to researching the impact of public policy; for example, see Coglianese (2012). However, assessing the impact of the central bank's policy on individuals' adoption of a new platform, considering the COVID-19 pandemic outbreak and subsequent containment measures and economic activity restrictions, presents a significant challenge. This question will also be a focal point of my research interest. Causality and impact policy evaluation were the central of attention in the field of economics. The field of economics has placed significant emphasis on the evaluation of causality and the impact of policies. However, in certain economics applications, the focus may not be on causal inference but rather on prediction since it may be more appropriate. For instance, consider the works of Kleinberg *et al.* (2015) and Athey (2019). It is consistent with the increasing complexity and interconnectivity of the global and local economies, driven by digital innovation, coinciding with a future characterised by uncertainty, as global growth slows and inflation rises due to the impact of the pandemic and heightened geopolitical tensions in Europe and other regions. Due to the escalating complexity of the economic framework in conjunction with the rapid increase of digital innovations, certain central banks have initiated the adoption of alternative methodologies to the conventional employment of time-series regression models for the prediction of pivotal macroeconomic indicators. These alternative methodologies encompass Machine Learning (ML) approaches, as discussed by Doerr *et al.* (2021). ML has numerous advantages despite some concerns regarding causal inference and the interpretation of its results. Its adaptability allows them to uncover complex hidden structures that were not expressly stated and to accommodate massive data sets with many regressors without over-fitting; See Lazer *et al.* (2014) and Mullainathan and Spiess (2017) for examples. In addition, Athey and Imbens (2019) suggest that researchers can conduct more advanced empirical and multidisciplinary research by acquiring a comprehensive understanding of these methodologies. This finding has motivated me to examine various machine learning techniques for predicting macroeconomic variables, specifically inflation.

In general, the novel contribution of this thesis consists of providing new empirical evidence on the role of payment system advancement on the money demand and how the central bank's policy affects the economic trend and people's behaviour in using new payment instruments. In addition, our study also contributes to a growing body of literature that successfully compares machine learning (ML) models to the established econometric techniques in economic forecasting, including the interpretability approach and performance comparison of data splitting ratios for ML regression, a topic that is rarely adequately covered. The results obtained in this investigation can support policy evaluation that promotes a more efficient monetary policy related to the payment system landscape and broadens the research horizon on these topics. This thesis consists of four essays that explore payment systems in the context of economic analysis, people's behaviour and policy impact analysis, and the use of the machine learning approach.

Chapter 2 analyses the variables of money demand using quarterly data from 2007Q1 to 2021Q4. This study investigates the stability of the demand for money by combining payment system innovation and the potential for a structural break. The ubiquity of mobile telecommunications and internet access, combined with innovations in Indonesia's financial system, have caused a drastic shift in the nation's payment pattern. During the studied period and the outbreak of the COVID-19 pandemic, a number of government and central bank policies may alter the demand for money and discourage individuals from utilising cash. Little study has been conducted on how previous central bank policies and payment system innovations affect Indonesia's money demand. Despite the fact that according to Hendry and Mizon (2005), the best forecasting model is not necessarily a solid basis for economic-policy research, the failure of the policy to comprehend the anticipated impact would cause harm to society. Since neglecting a structural rupture would be disastrous and lead to a biased and inconsistent conclusion (Pesaran and Timmermann, 2004), evaluating structural ruptures in relation to policymaking has become crucial. This chapter is motivated by these phenomena and seeks to answer the questions of how central bank policy affects money demand stability and how payment system innovation influences money demand. The results indicate the stability of the money demand function in Indonesia, with a suggested structural break that is related to the new policy implemented by the central bank. The study will contribute to a deeper comprehension of the impact of payment system innovation and previous central bank policies on the stability of the money demand, hence providing fresh insights for monetary policy. For instance, confirm previous studies indicating that the development of payment instruments has a significant and negative impact on narrow money demand over the long term (Dunne and Kasekende, 2018; Adil *et al.*, 2020) and address concerns regarding the possibility of a central bank policy weakening as a result of technological advancements in the payment system (Wiafe *et al.*, 2022).

Chapter 3 and Chapter 4 examine the behaviour of consumers and merchants in adopting a new payment platform, namely QRIS, in the presence of a new central bank policy and a pandemic. In late 2019, Bank Indonesia launched a national standard for quick response codes, called the QRIS, that facilitates contactless transactions and interoperability among electronic money and mobile banking providers. Simultaneously with the introduction of QRIS, the COVID-19 pandemic emerged and brought containment and economic activity restrictions, thereby restricting cash transactions. Motivated by these occurrences and a desire to answer the question of the influence of the factors mentioned above, the current study aims to analyse the determinants of user behaviour in adopting QRIS and also to distinguish the policy effect and the pandemic effect. In Chapter 3, I propose new exogenous latent variables, which are force majeure (FM) and perceived government interference or law enforcement (LE), and perceived risk (PR), to be embedded in the conventional Unified Theory of Acceptance and Use of Technology (UTAUT) model proposed by Venkatesh *et al.* (2003). This allows the model to disentangle central bank policy effectiveness from the impact of the pandemic and to separate the pandemic risk from the common risks associated with new technology adoption. In Chapter 4, I applied these variables to the extended Unified Theory of Acceptance and Use of Technology or UTAUT 2 (Venkatesh *et al.*, 2012), with additional survey data in order to assess the consistency of the new proposed variables. In addition, demographic characteristics, specifically age, gender, education, experience, user status, and geography, are also explored as moderating factors on the influence of these variables on behavioural intention to adopt new payment technology. These findings make a valuable contribution to the existing body of knowledge on technology adoption theory; see, for instance, Rogers (1983), Davis (1989), Ajzen (1985), Venkatesh *et al.* (2003, 2012), Williams *et al.* (2015), Aji *et al.* (2020), Zhao and Bacao (2021), and government intervention, for example, see, Carter and Bélanger (2005), Coglianese (2012), Mandari *et al.* (2017), Chong *et al.* (2010), and Chen *et al.* (2019). The findings of this study also make valuable contributions to practical and regulatory improvements within the payment system business. For instance, they help in the assessment of the significance of new policies introduced by the central bank.

There are concerns regarding the ability to draw causal inferences from ML results and the interpretability of those results; see Lazer *et al.* (2014), for example. However, ML is an emerging subject in science and finance that is suitable for examining problems with numerous variables and may assist in addressing difficulties that have challenged the established econometric models, see Doerr *et al.* (2021). Numerous studies have been conducted to explore diverse machine-learning approaches for predicting macroeconomic variables, including economic growth. The existing body of research on this subject continues to expand. Yoon (2021) employs ensemble learning techniques, specifically Gradient Boosting and the Random Forest algorithm, to make predictions about the GDP growth in Japan. Conversely, Milačić *et al.* (2017) and Lepetyuk *et al.* (2020) utilise neural networks and deep learning methodologies, employing the dataset from the United States to predict economic growth. Several studies have conducted comparisons of different machine learning techniques for the purpose of forecasting macroeconomic variables. Notable examples are the works of Richardson *et al.* (2021) and Tamara *et al.* (2020). The findings of their study indicate that a considerable number of machine learning techniques exhibited superior performance compared to the conventional econometric methodology. Machine learning techniques have also been employed by numerous researchers to enhance the central bank policy. Chakraborty and Joseph (2017) presented some machine learning models that central banks can utilise within the context of policy implementation. Several machine learning algorithms have been used to predict inflation and optimise central bank policy; for example, Medeiros *et al.* (2021) and Rodríguez-Vargas (2020). Lu (2020) also explores financial market risk indicators that can improve macro-control monetary policy adoption using a neural network method.

This literature drives the fifth chapter. It attempts to employ machine learning techniques as an alternative to the more established econometric model for forecasting inflation using payment system data. In addition to macroeconomics and financial statistics, our work examines payment system data to estimate inflation using machine learning techniques as opposed to the univariate time series econometric models ARIMA. We also examine the importance of individual variables in machine learning model outcomes by utilising global and local SHAP values. Our approach follows Lundberg *et al.* (2020), who propose the integration of both local and global explanations through SHAP values for interpreting machine learning results in the field of health science for the case of mortality risk and risk factors among patients with chronic kidney disease. In addition, for each ML model, we evaluated the effect of data splitting ratios on forecast accuracy using out-of-bag sample periods, a topic that is seldom addressed in regression ML research but frequently explored in classification ML.

We expect the contribution to be twofold. First, we expand and compare alternate tools of machine learning models for economic prediction that will contribute significantly to the academic community, particularly in the field of regression machine learning and multidisciplinary economic-related topics. Our findings will also be advantageous for the central bank and other policymaking organisations. Second, we use unconventional data in predicting inflation, namely payment system data and stock market data, that represent the economic activity such as consumption, investment and even government expenditure that was absent in the previous studies. The contribution of the chapter is to bridge two strands of literature: inflation forecasting using machine learning, particularly in Indonesia (Medeiros *et al.*, 2021; Rodríguez-Vargas, 2020; Zahara and Ilmiddaviq, 2000; Savitri *et al.*, 2021) and the use of payment systems data to forecast macroeconomic (Aprigliano *et al.*, 2019; Galbraith and Tkacz, 2018; Chapman and Desai, 2020). Therefore, this study makes a valuable contribution to the advancement of interdisciplinary research in the fields of applied economics and machine learning. Such interdisciplinary research has the potential to provide more practical and applicable knowledge to the field compared to research that focuses solely on a single subject. The results of our study support the need to incorporate machine learning algorithms as supplementary tools to aid the central bank in forecasting future conditions and comprehending its primary objective of maintaining price stability.

This thesis is composed of six chapters. The remaining sections of this thesis are organised as follows: The second chapter investigates the stability of money demand, the role of payment system innovation and the possibility of a structural break that represents policy impact. Chapters 3 and 4 investigate the adoption of a new payment platform, QRIS, by consumers and merchants in the presence of a central bank policy and the Covid-19 pandemic. Using payment system data, Chapter 5 examines machine learning models as an alternative to the more established econometric model for predicting inflation. Chapter 6 summarises the essential findings, implications, and limitations of the study.

Chapter 2

Money Demand Stability with Endogenous Structural Breaks and the Role of Payment System Innovation in Indonesia

Chapter Abstract

This study analyses money demand and its fundamental variables in Indonesia using quarterly data from 2007Q1 to 2021Q4 using Gregory-Hansen's (1996b) cointegration test and Hendry's General to Specific approaches. We examine the stability of the long-run demand for money function during the observed period, taking into account central bank policies, the COVID-19 pandemic, and payment instrument advancement. The Gregory and Hansen (1996b) test found a cointegrating relationship between money demand variables with a structural break in 2011Q2, which refers to the central bank's new minimum reserve policy. The cointegration and error correction models show a causal relationship between money demand and its conventional determinants, as well as payment system innovation. As evidence of the stability test results of the short-run equations, we confirm the stable narrow money and currency demand in Indonesia. The paper advises that the central bank should comprehensively understand how technological advancement in the payment system affects money demand and how prior central bank policy may induce a structural break to maintain the optimality of monetary policy.

2.1 Introduction

Payment instruments are an important catalyst in the daily interactions of economic participants, such as households, businesses, retailers, and governments, particularly in the modern economy. According to Kokkola (2010), a *payment instrument* is defined as a device or a set of operations that allows the transferring or receiving of funds from payer to payee. Due to technological innovation in payment systems, people can now pay for transactions using various alternative instruments, including paper-based payment, card payment, or more advanced digital payment instruments, in addition to traditional banknotes and coins. These payment instruments may also act as a store of value in addition to their traditional functions as a medium of exchange and a means of payment. Consequently, the use of noncash payment methods becomes paramount.

Many scholars claim that altering payment methods from cash to noncash was claimed would benefit the economy by boosting consumption rate and economic growth, for example, see Zandi *et al.* (2013) and Luo *et al.* (2022), and initiate efficiency in the economy (Varga, 2016). This favourable effect of card, electronic, and mobile payments on the economy occurs not just in industrialised nations but also in developing nations, as evidenced by Oyelami *et al.* (2020) and Wong *et al.* (2020). However, some potential drawbacks may approach, such as weakening the ability of the central bank to control the money supply (Tule and Oduh, 2017) or other monetary aggregates (Bordo and Levin, 2017) and subside the seigniorage income (Camera, 2017); and other pitfalls forms that might arise from the perspective of the households, such as the increase of societal risk and technology failure, for example, see de Almeida *et al.* (2018a) and Atzei *et al.* (2017).

In recent decades, the ubiquity of mobile telecommunications, internet connectivity and payment system innovation in Indonesia has resulted in a drastic shift in the country's payment patterns, which may influence the consumer habits and economic activities of the populace.

According to Pramono *et al.* (2006) and Aristiyowati and Falianty (2018), card payment instruments have a favourable effect on the velocity of money and a negative effect on the demand for cash and narrow money. This finding is corroborated by Igamo and Falianty (2018), who concludes that electronic money has favourable long-term impacts on narrow money demand as well as the level of consumption.

Macroeconomic theory suggests that stable money demand is essential for central banks to implement monetary policy since it ensures that shifts in monetary aggregates caused by a policy will have predictable impacts on economic growth and price stability. According to the study of Simorangkir (2004), Hossain (2011), and Leong *et al.* (2021), there is a stable relationship between narrow money demand and income regardless of the ongoing financial reforms and innovation in Indonesia, particularly after the financial crises in the late 1990s, whereas Lestano *et al.* (2011) conclude that demand for broad money in Indonesia is not stable.

Motivated by previous empirical studies, we aim to examine the dynamic interaction between the money demand and its conventional drivers, interest rate and income, with the inclusion of payment instruments innovation and the existence of structural break. This research will focus on Indonesia, a G20 developing middle-income country with the world's fourth-largest population, using quarterly data from 2007Q1 through 2021Q4. In addition, there are a number of policies issued by the central bank and the government, as well as the existence of a crisis and other unanticipated events that could cause a structural break in the economy, for example, see Galati *et al.* (2018) and Karavias *et al.* (2022). According to Hendry and Mizon (2005), it is necessary for policymakers to comprehend the cause and existence of the structural break in the economy to evaluate their policies and enhance their projections. Gregory and Hansen (1996b) cointegration approach with structural break is used to help determine the presence of cointegration among the variables while capturing the possible structural break endogenously. The GH test is then followed by an error correction model to estimate the coefficients of the short-run and long-run explanatory variables of the demand for narrow money and currency demand equations, specifically income, interest rate, and payment instrument innovation. Finally, we analyse the parameter stability of the money demand equation in the short term using the CUSUMSQ stability test of Brown *et al.* (1975).

The remaining sections of this chapter are structured as follows. The next section provides the relevant works of literature and some of the measures that may affect the demand for money, and section 2.3 presents the methodology. Section 2.4 outlines the data and model specification, and the empirical results are presented in section 2.5. Finally, the concluding remarks are presented in section 2.6.

2.2 Literature review

Modelling the influence of payment instrument innovation on money demand in relation to the quantity theory for money has become popular in practice and applied in many studies. This section presents a literature overview on money demand, the role of financial innovation in the economy, and measures that may influence money demand.

2.2.1 Theoretical review

John Maynard Keynes (1936) theorised that money demand is affected by transaction motive and precaution motive based on income level and speculative motives that consider the current interest rate (r) and the wealth level. This concept influenced many later theories, such as those developed by Friedman (1970), who pointed out that the opportunity cost of retaining cash consists of the potential gain from owning bonds, stocks, and other interest-bearing assets. Therefore, a higher return on other assets will cause a decrease in the demand for money because of the principle of diminishing marginal rate of substitution between money and other assets (Laidler, 1993). In addition, Fender (2012) provides a detailed explanation of the idea that, traditionally, money demand has been driven by interest rate and income, which can be expressed as follows:

$$\left[\frac{M_t}{P_t}\right] = L(y_t, R_t) \tag{2.1}$$

Where M_t/P_t is the real money demand of the household during period t, y is the household's consumption during period t, and R is the interest rate of some asset. However, does money demand still matter? Instability in the relationship between nominal income and broad money, as noted by Alamsyah *et al.* (2001), makes it challenging for the central bank to control the money base. In addition, according to Fender (2012), giving the central bank a responsibility to maximise societal welfare was doubtful, and determining how to quantify the central bank's success was a further concern.

Many countries widely regarded the Inflation Targeting Framework (ITF) as the "state of the art formula" for monetary policy, see Gillitzer and Simon (2018), and in Indonesia, the ITF has been successfully performed since it was first implemented in mid-2005 (Juhro and Goeltom, 2015). However, the ITF has a potential shortcoming that should be taken into account. Woodford (2005) and Gonçalves and Salles (2008), for instance, are of the opinion that there are no compelling arguments to consider the idea of money growth playing a significant role in the central bank, and many scholars also support the idea of avoiding theoretical and practical ignorance of "money" in monetary policy discourse, see Kahn and Benolkin (2007).

Issing (1997, 2011) argued that monetary policy applying ITF based only on interest rate targeting as a medium objective could be suboptimal. In addition, according to Blinder (2010) and Mishkin (2010), the development of money and credit are critical components of a medium-term objective to be examined by monetary authorities as it is crucial to forecast financial imbalances in the long term. Hence, the stability of the demand for money is still essential for the central bank to achieve a credible monetary policy.

Differences in empirical background explain why the Federal Reserve and the European Central Bank view money and monetary policy differently, as pointed out by Kahn and Benolkin (2007). When compared to the United States, money growth in the Euro area is more highly connected to inflation over the medium and long term and is viewed as a more accurate forecast of inflation. In this regard, Issing (2011) explained that the ECB's strategy is distinct from that of other central banks due to the central bank's view of money as a crucial element. Consequently, it is essential to comprehend the linkages between money demand and its traditional variables, such as income, interest rate, and other factors, such as technological advancement, from the standpoint of the quantity theory of money.

Understanding the role of technological advancement in the payment system, which promotes the use of noncash payment instruments, on the money demand can be evaluated using the shopping time model (McCallum and Goodfriend, 1989), which was initially introduced by Saving (1977). In this study, money is an asset held only for transaction purposes and assumed in a closed economy, as previously demonstrated by Hueng (1998). The shopping-time model allows us to evaluate the role of technological advancement in payment instruments that would potentially substitute traditional money functions. The accommodation of payment instrument innovation in the demand for money equation is explained in the model adopted from Dias (2001). In a close economy, consider a hypothetical household tries to maximise their expected welfare at time t from the utility function over an infinite period: Many countries widely regarded the Inflation Targeting Framework (ITF) as the "state of the art formula" for monetary policy, see Gillitzer and Simon (2018), and in Indonesia, the ITF has been successfully performed since it was first implemented in mid-2005 (Juhro and Goeltom, 2015). However, the ITF has a potential shortcoming that should be taken into account. Woodford (2005) and Gonçalves and Salles (2008), for instance, are of the opinion that there are no compelling arguments to consider the idea of money growth playing a significant role in the central bank, and many scholars also support the idea of avoiding theoretical and practical ignorance of "money" in monetary policy discourse, see Kahn and Benolkin (2007).

Issing (1997, 2011) argued that monetary policy applying ITF based only on interest rate targeting as a medium objective could be suboptimal. In addition, according to Blinder (2010) and Mishkin (2010), the development of money and credit are critical components of a medium-term objective to be examined by monetary authorities as it is crucial to forecast financial imbalances in the long term. Hence, the stability of the demand for money is still essential for the central bank to achieve a credible monetary policy.

Differences in empirical background explain why the Federal Reserve and the European Central Bank view money and monetary policy differently, as pointed out by Kahn and Benolkin (2007). When compared to the United States, money growth in the Euro area is more highly connected to inflation over the medium and long term and is viewed as a more accurate forecast of inflation. In this regard, Issing (2011) explained that the ECB's strategy is distinct from that of other central banks due to the central bank's view of money as a crucial element. The findings extend beyond highly developed nations, such as those in Europe and the US, and are also observable in emerging countries, including Indonesia (Mahatir *et al.*, 2020) and many sub-Saharan countries (Mlambo and Msosa, 2020). Consequently, it is essential to comprehend the relationship between money demand and its traditional variables, such as income, interest rate, and other factors, such as technological advancement, from the standpoint of the quantity theory of money.

Understanding the role of technological advancement in the payment system, which promotes the use of noncash payment instruments, on the money demand can be evaluated using the shopping time model (McCallum and Goodfriend, 1989), which was initially introduced by Saving (1977). In this study, money is an asset held only for transaction purposes and assumed in a closed economy, as previously demonstrated by Hueng (1998). The shopping-time model allows us to evaluate the role of technological advancement in payment instruments that would potentially substitute traditional money functions. The accommodation of payment instrument innovation in the demand for money equation is explained in the model adopted from Dias (2001). In a close economy, consider a hypothetical household tries to maximise their expected welfare at time t from the utility function over an infinite period:

$$U(c_t, l_t) + \sum_{j=1}^{\infty} \beta^j \, E_t \left[U\left(c_{j+t}, l_{j+t}\right) \right] \tag{2.2}$$

where c_t, is the household's consumption during period t, l_t, is the leisure of the household, β, is the constant discount factor that is positive but smaller than 1, and E_t, denotes the expectation conditional on information at time t. At time t, it is assumed that the household is concerned about their consumption of goods and leisure not only in the present but also in future periods. They know the current values of all relevant variables when making decisions. According to the shopping time model, the more time (and energy) spent on shopping, the less time is available for leisure. The relationship can be expressed in terms of a function, ψ, as follows:

$$l_t = \psi(s_t, m_t) \tag{2.3}$$

where s_t is the transaction cost, $0 < s < 1$ at period t, that accommodates payment system innovation such as card and digital money that allows noncash transactions and $m_t = M_t/P_t$, is the real money holding. So that the lower the transaction cost, s_t, the more transactions can be carried out with the same amount of money hold, m_t. The household is then moderated by a budget constraint. The household receives real income in the amount y_t, which this amount is unaffected by their choices, then divides his wealth between money and bonds. Let M_t and B_t be the nominal money balances and the nominal quantity of bonds purchased by the household in period t (which expire in $t+1$) at the interest rate R_t. That is, the household begins period t with assets in the amount $M_{(t-1)}$ and $B_{(t-1)}$. The household's budget constraint for period t can be written as follows:

$$P_t\, y + M_{(t-1)} + (1+R_t)B_{(t-1)} = P_t c_t + M_t + B_t \tag{2.4}$$

where P_t is the price index at time t, M_t is the nominal holding of money, and B_t is the nominal holding of bonds. The objective of the household at period t is then to choose the value of consumption c_t, money holding M_t, and bonds B_t in equation (2.2) and equation (2.3), subject to the constraint (2.4). Formulation of a Lagrangian expression, L_t, to maximise the problem can be formulated as follows:

$$\begin{gathered} L_t = U[c_t, \psi(s_t, \frac{M_t}{P_t})] + \beta U[c_{(t+j)}, \psi(s_{(t+j)}, \frac{M_{(t+j)}}{P_{(t+j)}})] + \\ \lambda_t(1+R_{(t-1)})B_{(t-1)} - [P_t(c_t - y) + (M_t - M_{(t-1)})] - B_t \end{gathered} \tag{2.5}$$

Then we maximise the equation with respect to λ_t, as well as the appointed variables and impose the budget constraint 2.4 by following the first-order condition $\vartheta L_t \,/\, \vartheta\lambda_t = 0$. In obtaining the money demand function, however, we need to find the first order of $\vartheta L_t \,/\, \vartheta c_t$ and $\vartheta L_t \,/\, \vartheta M_t$, and set the resulting equations equal to zero.

$$\frac{\vartheta L_t}{\vartheta c_t} = U_1[c_t, \psi(s_t, m_t)] + U_2[c_t, \psi(s_t, m_t)]\psi_1(s_t, m_t) - \lambda_t P_t = 0 \tag{2.6}$$

$$\frac{\vartheta L_t}{\vartheta M_t} = \frac{U_2[c_t, \psi(s_t, m_t)]\psi_2(s_t, m_t)}{P_t} - \lambda_t + \lambda_t(1+R_t)^{-1} = 0 \tag{2.7}$$

Then by eliminating $\lambda_t P_t$ from equation (2.6) and (2.7), we have

$$\begin{aligned} U_2[c_t, \psi(s_t, m_t)]\psi_2(s_t, m_t) = \\ [1-(1+R_t)^{-1}]\left\{U_1[c_t, \psi(s_t, m_t)] + U_2[c_t, \psi(s_t, m_t)]\psi_1(s_t, m_t)\right\} \end{aligned} \tag{2.8}$$

We can assume the welfare function takes a Cobb-Douglas form:

$$U(c_t, l_t) = c_t^{(1-\alpha)} l_t^{\alpha} \tag{2.9}$$

and

$$l_t = \psi(s_t, m_t) = s_t^{-a} m_t^{a} \tag{2.10}$$

where α and a are positive fractions $(0 < \alpha < 1, 0 < a < 1)$. Then the partial derivatives will be

$$U_1 = \frac{\vartheta U}{\vartheta c} = (1-\alpha)c_t^{-\alpha}(s_t^{-a} m_t^{a})^{\alpha} \tag{2.11}$$

$$U_2 = \frac{\vartheta U}{\vartheta l} = \alpha c_t^{1-\alpha}(s_t^{-a} m_t^{a})^{(\alpha-1)} \tag{2.12}$$

$$\psi_1 = \frac{\vartheta \psi}{\vartheta s} = -a\, s_t^{-(a+1)}\, m_t^{a} \tag{2.13}$$

$$\psi_2 = \frac{\vartheta \psi}{\vartheta m} = a\, s_t^{-a}\, m_t^{a-1} \tag{2.14}$$

Using these, we find that equation (2.8) becomes

$$\begin{aligned} \alpha c_t^{1-\alpha}(s_t^{-a} m_t^{a})^{\alpha-1} . a s_t^{-a} m_t^{a-1} = \\ \left[1-(1+R_t)^{-1}\right]\left\{(1-\alpha)c_t^{-\alpha}(s_t^{-a} m_t^{a})^{\alpha} + \alpha c_t^{1-\alpha}(s_t^{-a} m_t^{a})^{\alpha-1} . - a s_t^{-(a+1)} m_t^{a}\right\} \end{aligned} \tag{2.15}$$

After simplification and solving for λ_t, we find

$$m_t = \left[1 + \frac{1}{R_t}\right] \frac{a\alpha c_t}{1-\alpha-a\alpha\frac{c_t}{s_t}} \tag{2.16}$$

The above result shows a positive sign of positive partial derivative w.r.t c_t, negative partial w.r.t R_t and s_t, that demonstrates payment instrument innovation exerts influence in increasing overall money demand due to a reduction in the cost of the transaction. Based on this result, the general form of money demand function that accommodates payment instrument innovation may be written as follows:

$$m_t = L(c_t, R_t, s_t) \tag{2.17}$$

This equation shows that consumption positively influences the demand for money, while the interest rate and financial innovation has a negative impact on money held by household. Advancement of financial product reduces the cost of the transaction, which finally increase the opportunity for overall money demand usage. In addition, the use of traditional money (notes and coins) will be substituted by other forms of money that allow for a noncash transaction. This is confirmed by Lippi and Secchi (2009), who pointed out, based on the framework of Ba umol (1952) and Tobin (1956), that the advancement of technology in the payment system negatively impacts the demand for currency.

2.2.2 Empirical literature

Several empirical studies have examined research on money demand and associated topics in industrialised and developing countries, including Indonesia. Studies on Indonesian money demand have used a variety of variables, econometric techniques, and tests. Arintoko (2011) used both the narrow money (M1) and broad money (M2) definitions of money in his study and found that there was a cointegration relationship between money and real output in Indonesia. This finding is further supported by Doguwa *et al.* (2014) research, which confirms the presence of a similar relationship in Nigeria. The long-rung relationship of the money demand function (real narrow money and real broad money) in Indonesia was also corroborated by Zams (2018) with the existence of a structural break. This conclusion is similar to the findings of Anglingkusumo (2005), Mahatir *et al.* (2020) and Lubis *et al.* (2019), which demonstrated a cointegration relationship between currency demand in Indonesia and its determinants.

These findings are consistent with the studies in other countries; for example, Lucas Jr and Nicolini (2015) reveals the stability of money demand and its cointegration relationship with interest rate and income using US data, and Nepal and Paija (2020) examines the money stability of seven countries in South Asia. These findings were further validated by Teles and

Zhou (2005) with an alternative monetary aggregate is known as money zero maturity (MZM), which is calculated by adding together M2 and institutional money market mutual funds minus small-denomination time deposits.

Many studies found that financial innovation has a significant impact on money demand. According to Dekle and Pradhan (1997), the influence of financial innovation could have either a positive or negative impact. It depends on whether it was an institutional reform, such as a rise in the number of banks and technological advancement (a negative influence), or an increase in the monetisation of the economy and financial deepening that allows for shifts between various types of money (a positive impact). In the study conducted by Dunne and Kasekende (2018) using panel data analysis in 34 African nations, it was found that financial technology development had a negative influence on money demand (MD), which is consistent with Mlambo and Msosa (2020). According to Aliha *et al.* (2017) in their study of 230 nations, financial innovation has a negative influence on money demand (MD), both in the long-run and the short-run, which is similar to the findings of Adil *et al.* (2020) for India-based study. In contrast, Ahad (2017) demonstrates a different positive effect of financial development on money demand, that financial development is defined as real domestic credit to the private sector per capita.

Many scholars also pointed out that the usage of electronic payment will decrease the usage of cash payment (Humphrey, 2004; Guariglia and Loke, 2004), and the substitute effect is more significant for smaller denominations for the retail transaction (Amromin and Chakravorti, 2007). However, some scholars suggested that the role of cash in many countries, including in developed countries, will still remain and will not entirely be replaced by cards or electronic payment instruments in the near future, see Liao and Handa (2010) and Tee and Ong (2016). These findings are consistent with those of Fung *et al.* (2014), who found that many people still continue to maintain cash as a store of value and for precautionary purposes in comparison to other payment methods. According to Bech *et al.* (2018), this state is also supported by relatively low and constant inflation, which reduces the cost of storing cash and may be prompted by the financial crisis. The behaviour of individuals in deciding to adopt payment instruments was also relatively unchanged with an unwritten convention “first, decide the share of cash, then other alternatives of payment instruments are the rest" (Von Kalckreuth *et al.*, 2014).

In addition, Tee and Ong (2016) suggested that policy in boosting economic growth through promoting noncash payments should not be set as a short-term target. It is due to the effect of the usage of noncash payments on economic growth will only be notable for an extended period. For a specific payment instrument which is electronic money, Igamo and Falianty (2018) has found that electronic money positively affects the level of consumption in the long-run. However, the growth of electronic money has a negative and significant impact on the growth of narrow money (Aristiyowati and Falianty, 2018; Igamo and Falianty, 2018).

2.2.3 Outline some of the measures adopted that may have an impact on the demand for money

The Central Bank of Indonesia and the government have actively promoted less-cash payment methods, such as electronic money, card payment, and mobile payment, to boost the economy's efficiency. Since the adoption of inflation targeting in Indonesia in January 2005, the central bank and the government have announced a number of policies that are regarded as significant milestones that may affect the demand for money in Indonesia, such as:

1. Electronic money regulation. Electronic money, or e-money, is another form of cash whose monetary value is stored electronically on cards, devices, or servers (Halpin and Moore, 2009). Electronic money has been circulating in Indonesia since 2007, but Bank Indonesia first regulated it in April 2009. Banks and nonbanks licensed by BI can issue electronic money and will be supervised periodically. E-money is separated into two types: registered e-money, which requires customer identity data, and unregistered e-money, with a maximum amount of monetary value that can be stored.

2. Tightening of the reserve requirement. In March 2011, the Central Bank of Indonesia (Bank Indonesia) implemented a new policy that increased the minimum statutory reserves (giro wajib minimum, GWM) for conventional banks dealing in foreign-denominated currencies. Reserve requirements for foreign currency funds increased from 1% in 2010

to 5% in March 2011 and 8% in June 2011. The minimum reserve requirement for Rupiah remains the same for both primary and secondary reserves. Banks that break GWM obligations will be penalised in Rupiah using the central bank's middle rate on the day of violation.

3. National initiatives of less cash movements. Bank Indonesia officially launched "The National Noncash Movement" (GNNT) in August 2014, aimed to build awareness and promote noncash payment instruments among the public, business and government institutions. Gradually fostering a less cash society will reduce the cost of money printing and distribution and provide a more effective and accountable transaction in the economy.

4. Changing the manner of transactions at toll gates from cash to noncash. In September 2017, the Ministry of Public Works and Public Housing launched Regulation No. 16/PRT/M/2017 on Noncash Toll Transactions on Toll Roads, which was effectively implemented in October 2017 to limit car users in paying tolls in cash. This regulation aims to increase the efficiency of transactions at tollgates that were previously segregated among card issuers (Joewono *et al.*, 2017).

5. Substituting a noncash instrument for the cash payment of social support or subsidy. In July 2017, the government released Presidential Regulation No. 63/2017 on Cashless Social Assistance Distribution to promote financial inclusion and improve efficiency, transparency, and accountability in distributing financial support to low-income citizens $(Kartu\ Keluarga\ Sejahtera, KKS)$. After the new regulation, KKS recipients are now linked to a bank account and receive government social support electronically.

6. Implementation of QRIS (Quick Response Code Indonesian Standard). In late 2019, Bank Indonesia launched a national standard for quick response in the payment system called the QRIS. It aims to promote interoperability and enhance efficiency by allowing consumers to transfer funds to their counterparts who use different payment services (Indonesia, 2019b)). QRIS enables contactless payment transactions among server-based e-money or digital wallets and mobile banking users among different providers.

7. The Covid-19 epidemic. Since the World Health Organization proclaimed COVID-19 a global pandemic in March 2020, the pandemic has had a significant impact on lives, livelihoods, and the global economy. In March 2020, it was confirmed by the government that the virus had spread to Indonesia.

   In this study, the technological advancement of payment instruments (PSINV) is represented by the usage of retail payment instruments, namely electronic money, ATM/Debit card and credit card payments relative to cash holding. Based on the mentioned above, the hypothesis built and will be tested in this study comprised as follows:

   (a) Increase in consumption will lead to a rise in the demand for money, both in terms of cash and narrow money.

   (b) Increase in interest rate will lead to a decline in currency and narrow money demand.

   (c) Technological advancement of payment instruments has a substitution relationship with conventional money; therefore, the use of noncash payment instruments will lead to a decrease in the use of cash and demand for money, and vice versa.

   (d) There is a structural break in the money demand function related to the policy issued by the central bank or the government, as mentioned above.

2.3 Methodology

To ensure stationarity and the order of integration of the series, each variable is examined using the Augmented Dickey-Fuller (ADF) and Phillip-Perron's (PP) unit root tests. Then, in order to account for the possibility of a structural break, a residual-based test for cointegration developed by Gregory and Hansen (1996b), which permits a structural break among the observed variables, is undertaken in the second phase. Gregory and Hansen (1996b) present three distinct models to account for the structural break in the alternative cointegrating relationship. Given the observed data is Y_t and X_t, where Y_t is a scalar variable, X_t is a vector of explanatory variables. The standard model of cointegration with no structural change is defined as follows:

$$Y_t = \alpha_1 + \beta X_t + \varepsilon_t \tag{2.18}$$

where the dependent variable Y_t and the explanatory variables X_t are supposed to be I (1) and the error ε_t term is *I(0)*.

Considering the parameters α and β as time-invariant, Gregory and Hansen (1996b) defined the structural break as a shifting of a new 'long-run' relationship from cointegration that was held in the previous period of time, with the timing of shift as unknown. Then, the structural change will be reflected in changes in the intercept (α) and/or changes in slopes (β). To capture a structural change, the dummy variable D_t is defined as: $D_t = 1$, if $t > T_b$ and $D_t = 0$, if $t \leq T_b$. **The first model** is a level shift (C) model, defined as:

$$Y_t = \alpha_1 + \alpha_2 D_t + \beta X_t + \varepsilon_t \tag{2.19}$$

This basic model from Gregory and Hansen describes a level shift in the cointegrating relationship, represented by a change in the intercept while holding the slope coefficients constant. Parameter (α_1) measures the intercept before the break in T_b and (α_2) represents the shift that occurred after the break. **The second model** is the level shift with trend (C/T) model:

$$Y_t = \alpha_1 + \alpha_2 D_t + \gamma_t + \beta X_t + \varepsilon_t \tag{2.20}$$

where γ is the coefficient of the time trend term, t. **The third model** is the intercept and slope shifts (C/S) model or regime shift:

$$Y_t = \alpha_1 + \alpha_2 D_t + \beta X_t + \delta X_t D_t + \varepsilon_t \tag{2.21}$$

Where δ measures the change in the cointegrating vector after the regime shift. As an extension to these three models, Gregory and Hansen (1996a) introduced **a fourth model** in which both the regime and trend shifts are permitted, denoted as C/S/T. Due to software limitations, we have not employed the fourth Gregory-Hansen model to test for the presence of cointegration.

$$Y_t = \alpha_1 + \alpha_2 D_t + \gamma_t + \beta X_t + \delta X_t D_t + \varepsilon_t \tag{2.22}$$

All the GH models are residual-based tests that use ADF test statistics to examine the null hypothesis of no cointegration compared to the alternative hypothesis of cointegration in the presence of a possible break in various models of C, C/T, C/S and C/S/T. The cointegration breakpoint is determined by the minimal value of the t-statistic. If evidence of cointegration with structural breaks is present, we adopt an adequate error correction model. Then, we apply the London School of Economics (LSE)/Hendry's general-to-specific approach (GETS) to develop a parsimonious short-run regression model, see Campos *et al.* (2005). In the final step, the Cumulative Sum of Squares (CUSUMQ) of the recursive residuals test of Brown *et al.* (1975) is used to assess the stability of the model parameters of the short-run equations.

2.4 Data description and model specification

In this section, we show a brief description of both the analysed variables and model specifications.

2.4.1 The data

The study uses quarterly data covering the period of the first quarter of 2007 to the fourth quarter of 2021 due to e-money data only being available since that year. Data are gathered from the Indonesian Financial Statistics of Bank Indonesia and the Indonesian Bureau of Statistics, which is available at https://www.bi.go.id/id/statistik/ekonomi-keuangan/spip/Pages/SPIP-Mei-2022.aspx. As described in the previous section, variables used in this research to investigate the determinants of money demand in Indonesia comprise as follows: M1 is narrow money, COB is total cash outside the bank or currency demand, CONS is consumption, IR is an interest rate (bank rate), and PSINV is payment instrument innovation which refers to the value of the transaction of card payment and digital payment divided by cash outside the bank. The descriptive statistics of the data included in this study are shown in Table 2.1 below.

Table 2.1: Summary of the variable included in the study

VARIABLE *)	MEAN	MEDIAN	MAXIMUM	MINIMUM	STD. DEV.	OBS.
RCOB	3,510.25	3,408.45	5,768.95	1,757.63	975.20	60
RM1	8,573.95	8,251.66	15,839.51	4,509.12	2,600.63	60
RCONS	12,223.03	12,206.34	13,173.63	11,358.35	460.10	60
IR	6.30	6.50	11.02	3.50	1.64	60
PSINV	0.26	0.26	0.35	0.16	0.04	60

$*$) *RM1, RCOB, and RCONS in Billions Rupiah*

Source: Bank Indonesia

2.4.2 Empirical model specification and description of the variables

Based on the classic money demand theory and empirical studies, the purpose of this study is to investigate the dynamic relationship between the demand for money, namely narrow money (M1) and currency demand (COB), with its traditional determinants (income, interest rate, and price), and payment instrument innovation, following Pramono *et al.* (2006) who modified the basic money demand model for Indonesia to enable the assessment of payment instrument innovation influence. We use two alternative measures of money demand which are narrow money demand (M1) and currency demand (COB). The functional form with respective money demand is as follows:

$$\frac{M}{P} = f(RCONS, IR, PSINV) \tag{2.23}$$

where M is money demand, $RCONS$ is real consumption, P is a consumer price index, IR is the nominal interest rate (bank rate), and $PSINV$ is payment system innovation. Components in equation (2.23) were transformed into a natural log, except for interest rate and the ratio of payment instruments innovation, which are expressed in two models as follows: Specification (1):

$$LRM1_t = \alpha_1 + \beta_1 LRCONS_t + \beta_2 IR_t + \beta_3 PSINV_t + \varepsilon_t \tag{2.24}$$

Specification (2):

$$LRCOB_t = \alpha_3 + \beta_4 LRCONS_t + \beta_5 IR_t + \beta_6 PSINV_t + \varepsilon_t \tag{2.25}$$

Dependent variables in specifications (1) and (2) are defined as follows: $LRM1$ is the natural logarithm of real narrow money $M1$ deflated by the natural logarithm of the CPI, $LRCOB$ is the natural logarithm of cash outside the bank subtracted by the natural logarithm of the CPI. Both specifications have the independent variables of real consumption $(LRCONS)$, interest rate (IR), and payment instruments innovation $(PSINV)$, and ε_t is the error term in the model.

2.5 Empirical result

The macroeconomic time series data is often not stationary; hence, the regression based on nonstationary data might produce spurious and meaningless economic results (Enders, 2015). In the first stage, we evaluate the data using the unit root tests. This test is employed to see the stationarity conditions of the data to be observed. The unit root testing method used in this study is Augmented Dickey-Fuller (ADF) and Phillips-Perron Test (PP). The result of unit root tests is shown in table 2.2 below. Based on visual evaluation at the level of the series and the result of the Augmented Dickey-Fuller test and Phillips-Perron Test, the unit root tests result indicates that the observed variables are stationary at the first difference.

Table 2.2: Result of Unit Root Test

VARIABLE	ADF TEST		PHILLIPS-PERRON TEST	
	LEVEL	1ST DIFFERENCE	LEVEL	1ST DIFFERENCE
LRM1	1.065 (4)	-2.680* (3)	0.453	-13.947***
LRCOB	-0.264 (4)	-3.839*** (3)	-1.384	-25.289***
LRCONS	-2.035 (4)	-2.953** (3)	-1.73	-15.515***
IR	-1.899 (1)	-5.131*** (0)	-1.656	-4.758***
PSINV	-2.389 (0)	-9.255*** (0)	-2.059	-10.781***

Notes:
*) Entries in ***, **, * represent significance at 1%, 5% and 10% level, respectively.
**) ADF test for variables at level and 1st differences are in constant

2.5.1 Cointegration

Following the result of the stationarity test that the variables follow the same order of integration and are stationary at the first difference or I (1), we can conduct a cointegration test to determine whether cointegration exists. From equation 2.23, we estimate the equation of money demand functions for both specifications (1) and (2) without the structural break and conduct the Engle and Granger (1987) residual test to examine the existence of cointegration in the proposed model that Table 2.3 reports below.

Table 2.3: Estimation Result for money demand function without structural break

Independent Variables	**Dependent variables**	
	LRM1	**LRCOB**
C	14.478***	13.479***
	(-22.929)	(-19.796)
LRCONS	-1.060***	-1.059896***
	(-8.949)	(-8.300)
IR	-0.058***	-0.043***
	(-5.504)	(-3.749)
PSINV	-0.414	-0.358
	(-0.818)	(-0.655)

*Note: ***, **, * denote significance at 1%, 5% and 10% level, respectively.*

Table 2.4: Unit Root Tests on the Residual of equation (2.24) and (2.25)

Dependent variables	**LRM1**	**LRCOB**
Augmented Dickey-Fuller test statistic	-1.804	-2.78
Test critical values:		
1% level	-3.557	
5% level	-2.917	

**MacKinnon (1996) one-sided p-values.*

All parameters of both equations are statistically significant at the 1% level, with the exception of payment instrument innovation. The unit root tests on the residuals from equations (2.24) and (2.25) in Table 2.4 indicates that there is no evidence of a cointegration relationship among the variables, and the signs of some of the dependent variables were different from economic theory and most empirical studies. This condition could be the result of a structural break that might exist in the cointegration relationship between the variables.

In light of this, we will use the Gregory and Hansen (1996b) test for cointegration with an uncertain break date to determine the potential breakpoint. Specification (1) and (2) are then applied to the three GH equations with a structural break in order to examine the cointegration relationship of the money demand function in Indonesia. The implied specifications of Gregory and Hansen for narrow money demand equation (2.24) are as follows:

$$LRM1 = \alpha_1 + \alpha_2\phi_{tb} + \beta_1 LRCONS_t + \beta_2 IR_t + \beta_3 PSINV_t + \varepsilon_t \tag{2.26}$$

$$LRM1 = \alpha_1 + \alpha_2\phi_{tb} + \gamma_1 t + \beta_1 LRCONS_t + \beta_2 IR_t + \beta_3 PSINV_t + \varepsilon_t \tag{2.27}$$

$$\begin{aligned} LRM1 = \alpha_1 + \alpha_2\phi_{tb} + \beta_1 LRCONS_t + \delta_{11}\phi_{tb} LRCONS_t + \beta_2 IR_t + \delta_{12}\phi_{tb} IR_t + \\ \beta_3 PSINV_t + \delta_{13}\phi_{tb} PSINV_t + \varepsilon_t \end{aligned} \tag{2.28}$$

Specification (2) is then applied to the three GH equations containing a structural break to examine the stability of the demand function of currency demand in Indonesia. The following are the implied Gregory and Hansen specifications from equation (2.25):

$$LRCOB = \alpha_3 + \alpha_4\phi_{tb} + \beta_4 LRCONS_t + \beta_5 IR_t + \beta_6 PSINV_t + \varepsilon_t \tag{2.29}$$

$$LRCOB = \alpha_3 + \alpha_4\phi_{tb} + \gamma_2 t + \beta_4 LRCONS_t + \beta_5 IR_t + \beta_6 PSINV_t + \varepsilon_t \tag{2.30}$$

$$\begin{aligned} LRCOB = \alpha_3 + \alpha_4\phi_{tb} + \beta_4 LRCONS_t + \delta_{24}\phi_{tb} LRCONS_t + \beta_5 IR_t + \\ \delta_{25}\phi_{tb} IR_t + \beta_6 PSINV_t + \delta_{26}\phi_{tb} PSINV_t + \varepsilon_t \end{aligned} \tag{2.31}$$

Table 2.5 shows the outcomes of the residual-based test on the null hypothesis of no cointegration of Gregory and Hansen (1996) for the 1(1) series in the presence of a structural break, for specifications (1) and (2) with different break dates for all three GH models.

The Gregory and Hansen cointegration test revealed a long-term relationship between the variables of the demand for narrow money function or specification (1) with several possible break dates. The break dates suggested by the three models of the GH test are 2017Q2, 2011Q2, and 2013Q1, with the recommended breakpoint occurring in 2011Q2, assuming level and slope shifts (GH-2). Similar GH test outcomes were seen for the currency demand equation or specification (2), with alternative breakpoints at 2017Q3, 2011Q2, and 2013Q1; and the occurrence of a structural break in the series at 2011Q2 is recommended based on the assumption of level and slope shifts (GH-2).

Table 2.5: Gregory-Hansen Cointegration Test Result for money demand

MONEY AGGREGATES	Model	ADF	Breakpoint	5% CV	Existence of Cointegration
LRM1	GH-1	-3.96	2017q2	-5.28	NO
	GH-2	-6.33***	2011q2	-5.57	YES
	GH-3	-4.55	2013q1	-6.00	NO
LRCOB	GH-1	-4.84	2017q2	-5.28	NO
	GH-2	-6.74***	2011q2	-5.57	YES
	GH-3	-4.84	2013q1	-6.00	NO

∗) *Entries in ***, indicates rejection of the null hypothesis at the 1% significance level.*
Source: Author computation

These findings suggest that long-run cointegration is formed under the assumption of level and slope shifts (GH-2), with all the estimates being statistically significant, valid based on the data, and consistent with the theory. Table 2.5 of the GH-2 cointegration test findings suggest the existence of a long-run relationship between real money demand (narrow money and currency demand), real income, interest rate, and payment instrument innovation, as the null hypothesis is rejected at the 1% significance level.

According to Pesaran and Timmermann (2004), ignoring structural break exposes the estimator to risks of inefficiency, resulting in biased inferences. Based on the GH test result that a structural break occurred in 2011Q2, the dummy variable is formed with indicator function = 0 for periods 2007Q1 to 2011Q1 and the indicator function = 1 for periods 2011Q2 and forward. Table 2.6 displays the results of the estimation of the implied Gregory and Hansen (C/T) equation 2.20. Evidently, the structural break that happened in 2011Q2 corresponds to the year in which the central bank implemented the new regulation regarding reserve requirements, particularly in March 2011, which was applied in stages.

This study follows Zams (2018), who found a structural break in the Indonesia money demand function and Bathaluddin *et al.* (2015), who found that a change in reserve requirement policy by the central bank may be responsible for the changing of banks' behaviour of maintaining excess liquidity for precautionary purposes. The impact of this quantitative strategy of the central bank on money demand can also be explained by its effect on liquidity and credit channels; for example, see Tovar Mora *et al.* (2012) and Warjiyo and Juhro (2022).

2.5.2 Cointegrating equation and error correction estimates

The structural break identified to occur in 2011Q2 reflects the impact of the central bank's new regulation that increased the minimum statutory reserves, particularly for deposits in foreign currency. This regulation was effectively implemented in two stages, in March 2011 and June 2011, corresponding to the central bank's policy to halt the influx of capital and moderate the appreciation of the exchange rate, thereby neutralising its impact on domestic liquidity, see Warjiyo (2017). As part of the policy mix approach, this reserve requirement policy was linked to a loan-to-funding ratio (LFR) policy to anticipate procyclicality in liquidity with the ultimate goal of promoting stable GDP growth and inflation, for example, see Oktiyanto *et al.* (2013). Consequently, the reserve requirement policy successfully boosted the credit rate, see Purnawan and Nasir (2015), which subsequently had an expansionary effect on the demand for money.

Real consumption (LRCONS) estimates are correctly signed and statistically significant at the 1 per cent level in both the narrow money demand and currency demand equation, while interest rate (IR) parameter estimates are statistically significant only for the narrow money demand equation. The GH-2 cointegration estimates presented in Table 2.6 indicate that the consumption elasticity is less than unity with a positive and statistically significant in affecting real money demand, both the narrow money demand and currency demand, indicating that real money demand is inelastic with respect to consumption. The result indicates the argument that money is essential and more sensitive to changes in consumption than changes in the interest rate. These findings follow of Pramono *et al.* (2006) and Huntington *et al.* (2019).

Table 2.6: Long Run Parameters for Demand for Money Functions with Intercept and Regime Shifts (GH2)

INDEPENDENT VARIABLE	MONEY AGREGATES	
	LRM1	LRCOB
C	6.568*** (11.622)	5.719*** (7.085)
LRCONS	0.419*** (3.971)	0.393** (2.606)
IR	-0.015*** (-2.749)	-0.001 (-0.099)
PSINV	-0.450** (-2.075)	-0.419 (-1.353)
trend	0.020*** (14.874)	0.019*** (10.022)
Dum11Q2	0.104*** (5.421)	0.120*** (4.393)
Adjusted R2	0.983	0.963
Serial Correlation LM Test	2.613	2.486

*Note: ***, **, * denote significance at 1%, 5% and 10% level, respectively.*

As anticipated, our study indicates that the interest rate (IR) has a negative and statistically significant relationship with long-term real narrow money demand. The negative estimate may reflect the opportunity cost of holding money over the long term and imply that money and financial assets are substitutes. This is consistent with the findings of Riyandi (2012) and Zams (2018) and in accordance with economic rationale. On the other hand, it was discovered that interest rates have no long-term effect on the currency demand.

In the long term, the advancement of payment instruments (PSINV) has a significant and negative impact on the narrow money demand. Our findings confirm previous studies; for example, Dunne and Kasekende (2018) and Adil *et al.* (2020). This result is consistent with expectations, given that the innovation of payment instruments was closely tied to technological advancements that substituted the function of conventional money and facilitated economic transactions. In the case of specification (2), we discovered that the advancement of payment instruments does not have a long-term impact on the amount of cash in circulation, which follows Aristiyowati and Falianty (2018).

The time trend and dummy break date have positive and significant coefficients for specifications (1) and (2). Further evidence indicates that the endogenous change was a level shift with a time trend, as suggested by the selection of the GH-2 equation. A statistically significant and positive upward trend over time indicates an increase in real money demand. This result is consistent with those of Zams (2018) and Adil *et al.* (2020).

Table 2.7: Short-run Parameters for Demand for Money Functions with Intercept and Regime Shifts (GH2)

INDEPENDENT Variable	Money Agregates	
	LRM1	LRCOB
C	0.035*** (10.268)	0.0303*** (7.702)
D(LRM1(-1))	-0.355*** (-4.561)	
D(LRM1(-6))	-0.355*** (-5.585)	
D(LRCOB(-1))		-0.157** (-2.493)
D(LRCOB(-3))		-0.181*** (-3.32)
D(LRCONS)	0.427*** (7.898)	0.534*** (6.323)
D(IR(-1))	-0.021*** (-3.974)	0.015** (2.090)
D(IR(-6))	-0.012** (-2.385)	-0.017** (-2.514)
D(PSINV)	-0.383*** (-2.954)	-0.570*** (-2.995)
D(PSINV(-2))	-0.502*** (-3.611)	
D(PSINV(-6))	-1.014*** (-6.984)	
ECT_RM1(-1)	-0.406*** (-3.570)	
ECT_RCOB(-1)		-0.770*** (-6.620)
Adjusted R2	0.867	0.887
Serial Correlation LM Test	4.142	1.880

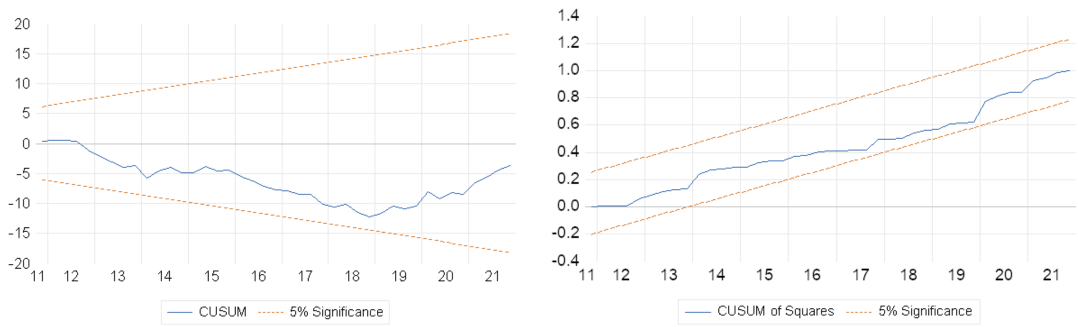
*Note: ***, **, * denote significance at 1%, 5% and 10% level.*

Based on the selected GH-2 model, we estimate an error correction model with the suggested optimal lag length of 6 based on the Lag Length Selection using Information Criteria presented in the Appendix, Table A.2 and Table A.3. Table 2.7 demonstrates the outcome of a parsimonious short-run regression model derived from Hendry's general-to-specific technique (GETS); for detail, see Campos *et al.* (2005). The short-run regression results show that in addition to actual consumption, policy rates, payment instrument innovation, and previous values of real money demand are all robust determinants of the demand for money.

Table 2.7 demonstrates that a rise in the use of cards and digital payment compared to cash usage decreases the demand for money for both the narrow money and currency demand, which may also indicate a rise in the efficiency of transaction costs. This finding implies that the monetary authority should support the innovation of payment instruments and encourage economic agents to adopt them widely all over the country. The error correction term coefficient for specification (1) is negative (-0.406) and very significant, which also implies that real narrow money demand is cointegrated into its determinants in the pre and post-the new reserve requirement regulation periods. The ECM estimate indicates that approximately 40.6% of the disequilibrium in real narrow money demand caused by shocks in the previous period will return to the long-run equilibrium within one quarter. Furthermore, the error correction term coefficient for specification (2) is negative (-0.770) and very significant, implying that real currency demand is cointegrated with its determinants, considering the structural break that may result from the central bank's new reserve requirement policy. The currency demand adjustment speed is higher than the narrow money demand. In addition to the model's diagnostic test, we employ other potential measures of financial innovation, such as the ratio of the use of ATM/Debit cards to cash holding, as well as an additional control variable, namely the CPI (consumer price index), to test the model's robustness, as reported in Appendix Table A.4. The results appear to be consistent and align with the financial innovation and money demand literature.

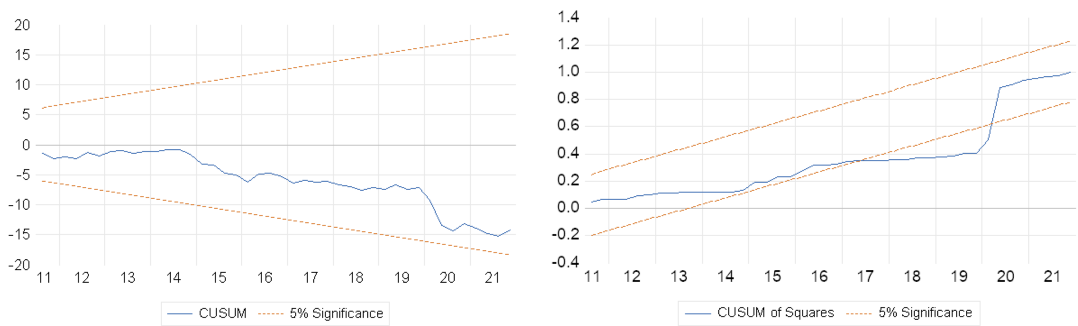
2.5.3 Parameter stability test

We then use Brown *et al.* (1975)'s CUSUM and CUSUMSQ tests to determine if Indonesia's short-run money demand function, as reported in Table 2.7, is stable during the observed period. If the recursive residual of the expected money demand equation lies outside the two critical lines, the parameter is considered unstable. The CUSUM and CUSUMSQ test results of the short-run equation confirm the stability of the money demand equation for both Specification (1) and Specification (2), as evidenced by the fact that the recursive residual of the estimated narrow money demand equation lies within the critical bounds of 5 per cent significance level, as depicted in Figure 2.1 and 2.2.



(a) CUSUM Test for LRM1 (b) CUSUMSQ for LRM1

Figure 2.1: Stability Test for Short-run Narrow Money Demand (CUSUM and CUSUMSQ Tests)



(a) CUSUM Test for LRCOB (b) CUSUMSQ for LRCOB

Figure 2.2: Stability Test for Short-run Narrow Money Demand (CUSUM and CUSUMSQ Tests)

2.6 Conclusion

This study analyses the impact of technological advancements in the retail payment system on the demand for money and their implications for Indonesian monetary policy. We also examine the stability of the money demand and the occurrence of structural breaks related to the central policies using data from 2007Q1 to 2021Q4. The findings of our study indicate that real money demand is cointegrated with real consumption, policy rate, and payment instrument innovation, with a suggested break in 2011Q2 under the assumption of intercept and trend shift (C/T). The identified break date corresponds to the release of a new policy regarding the minimum statutory reserves of foreign deposits and a loan-to-funding ratio (LFR) policy by the central bank in 2011 to limit the influx of capital and neutralise its effect on domestic liquidity as explained by Warjiyo (2017).

The results of the cointegration equation and error correction models indicate a causal relationship between real money demand, specifically narrow money and currency demand, and its traditional determinants (income and interest rate), as well as the technological advancement of the payment instrument. This study validates the shopping-time model of money demand theory, which posits that the demand for money is impacted not only by its traditional drivers but also by the advancement of payment technology. The error correction term (ECT) coefficient of one period lag revealed that approximately 40.6 per cent of the disequilibrium in the narrow money demand equation (M1) is rectified after one quarter. In comparison, the ECT of the currency demand equation is expected to correct around 77.0 per cent of the disequilibrium after one quarter. The CUSUM and CUSUMSQ tests give evidence for a stable demand function in Indonesia both before and after the new reserve requirement policy was introduced since the recursive residual plots of the narrow money demand and the currency demand are within the 5% critical lines.

In conclusion, the long-run and short-run estimates of the narrow money demand and currency demand equations shown in this analysis are novel for the subject area in Indonesia; they highlight the dynamic interaction among the variables under consideration and capture the structural break that reflects the influence of central bank policy. This result implicitly addresses worries over the prospect of a central bank policy weakening as a result of technological advancements in the payment system; for example, see Wiafe *et al.* (2022). Despite the fact that the ITF has been in place since 2006, considering the Indonesia Payment System Blueprint initiated by the central bank and the rapid development of payment system innovation, see Indonesia (2019a), the central bank must have a comprehensive understanding of how technological advancements in the payment system affect money demand and other monetary aggregates. As a result, our analysis suggests that central banks should monitor and anticipate the effects of payment system advancement on monetary aggregates to maintain the effectiveness of the monetary policy and consider the payment system in its policy mix framework.

Finally, we propose expanding future research on the payment system to include policy impact analysis based on primary data and examining how people respond to central bank policies. In addition, it would be advantageous to apply more contemporary techniques, such as a machine learning approach that encompasses both structured and unstructured data, to examine policy-related issues in more depth.

Chapter 3

Measuring Central Bank's Policy Effectiveness in Affecting Intention to Use New Payment Platform during COVID-19 Pandemic

Chapter Abstract

This study aims to evaluate the adoption of the central bank's payment system policy, QRIS (Quick Response code Indonesian Standard). The evaluation is hindered by the contemporaneous emergence of the COVID-19 pandemic, which acts as a confounding factor in adopting the new payment instrument. To disentangle the impact of central bank policy from the pandemic, a novel extension of the model of the Unified Theory of Acceptance and Use of Technology (UTAUT) is proposed and is estimated using purposive sampling from an online survey with 572 respondents during the pandemic in Indonesia. The data were analysed using the Structural Equation Model with SmartPLS, and seven hypotheses were assessed. The result of the study successfully disentangles the policy impact from the pandemic effect and separates the pandemic risk from common risks (PR) and other technology adoption determinants. The results indicate that perceived central bank policy and pandemic risk are the most influential variables affecting the intention to use QRIS. The findings suggest that this measurement approach can be appropriately used as a complementary tool to examine the effectiveness of the central bank's policy in influencing people's behaviour.

3.1 Introduction

Measuring policy impact is critical for an organisation; it helps increase stakeholder and public awareness of its relevance (Commission *et al.*, 2016). Furthermore, policy impact evaluation helps an organisation determine whether or not it is accomplishing its long-term objectives and goals, as well as identify and utilise its most valuable resources. One way of studying the impact of regulatory policy is by examining behavioural changes in the audience; see, for example, Coglianese (2012). In addition to its principal role as a monetary authority, Bank Indonesia is mandated by the Indonesian constitution to implement macroprudential and payment system policies. The impact of a macroprudential policy has been studied extensively; for example, see Tressel and Zhang (2016). However, research on payment system policies is surprisingly limited, both in terms of understanding their transmission channels and evaluating their effectiveness, as Gogoski (2012) mentioned.

In late 2019, Bank Indonesia launched a national standard for quick response codes in the payment system called the QRIS. QRIS refers to an advanced QR pattern for payments that allows contactless transactions and interoperability among electronic money and mobile banking providers. Previously, consumers had to subscribe to multiple payment service providers or platforms to settle their online transactions, while merchants had to apply multiple QR codes from various service providers and install multiple cashless payment infrastructures, such as an electronic data capture (EDC) machine or an electronic funds transfer at the point of sale (EFT-POS) terminal, in order to accept cashless payments. The purpose of QRIS was to integrate a variety of distinct payment platforms into a single, efficient system through which all online transactions would be conducted.

Evaluation of the QRIS policy's impact on people's behaviour in adopting this new platform, which subsequently will increase the number of non-cash transactions, is therefore vital. However, policy impact evaluation is a challenging task as, concurrently with the introduction of QRIS, the COVID-19 pandemic emerged and brought containments and economic activity restrictions, and therefore, it is difficult to separate the effect of central bank policy from the impact of the pandemic. People were encouraged to spend more time at home during the pandemic due to government-enforced lockdowns, avoiding shopping and dining in crowded spaces. Cashless payments were promoted to limit the risk of infection (WHO, 2020), despite the fact that these payment instruments are still not widely available in many countries (Auer *et al.*, 2020). As a result, the usage of fintech products and services, such as digital payments and remittances, increased significantly during the COVID-19 pandemic (Rowan *et al.*, 2020) and is often higher in countries with more stringent COVID-19 containment measures.

The effect of the COVID-19 pandemic on people's intention to adopt new technology, such as the digital wallet and mobile payment, has been studied, e.g. Aji *et al.* (2020) and Zhao and Bacao (2021). Also, previous research has emphasised the impact of government policies on people's intentions to use new technologies. For example, Chong *et al.* (2010) discovered that government endorsement, such as a clear regulation, substantially influences the intention to use internet banking; and government support significantly impacts farmers to adopt new technology initiated by the government (Mandari *et al.*, 2017). However, to the best of our knowledge, no previous study has evaluated and distinguished the influence of government (central bank) policy and the COVID-19 pandemic on people's behavioural intention in using a new payment instrument, particularly in the Asian country region.

Accordingly, this research aims to conduct an empirical examination of the effectiveness of Bank Indonesia's policy in influencing people's behaviour intention toward the adoption of QRIS in the context of the COVID-19 pandemic. Policy effectiveness refers to the degree to which QRIS impacted the targeted behaviour, as in Coglianese (2012), and is measured using a novel model of the Unified Theory of Acceptance and Use of Technology (UTAUT) originally proposed by Venkatesh *et al.* (2003). The novelty in this paper is that new additional latent variables are introduced, namely perceived risk (PR), force majeure (FM), and perceived government role or law enforcement (LE), which allow the model to disentangle central bank policy effectiveness from the impact of the pandemic. The model development and the specific interest of the study will be considered the novelty of this research.

The research is based on a purposive sample of 572 observations of consumers and vendors in many cities in Indonesia. Based on the data set, the extended UTAUT model is estimated using the methods of a partial least squares (PLS) method to structural equation modelling (SEM). The findings show and disentangle the role of the central bank's policy and the influence of the COVID-19 pandemic on people's intention to adopt QRIS. As a result, this study provides an alternative method for policy evaluation for central banks or government institutions, as well as input for players in the payment system industry to focus on the elements that will increase the adoption of new payment instruments.

3.2 Literature review and hypotheses development

3.2.1 QRIS (Quick response code indonesian standard)

As part of the Indonesian payment system blueprint, Bank Indonesia and the payment system association developed a standardised QR code for all payment service providers in Indonesia called QRIS. It aims to promote interoperability and enhance efficiency by allowing individuals to transfer funds to their counterparts who use different payment services (Bank Indonesia, 2019). In addition, QRIS enables contactless payment among server-based e-money or digital wallets and mobile banking from diverse providers. Accordingly, QRIS refers to a QR code payment standard for Indonesian payment instruments that allows a user of one payment service to transfer funds to their counterpart who uses a different payment service provider. The central bank also implemented a stringent licensing procedure for QRIS membership, requiring a recommendation from the standard agency, followed by surveillance and sanction imposition.

Despite a few cases of the ineffectiveness of QRIS implementation among merchants, six million subscribers were registered in 2020 throughout 34 provinces and 480 districts, connecting users of 50 digital wallets and more than 20 mobile banking brands throughout the country (Indonesia, 2020). According to Donovan (2012), mobile banking or digital wallets have a number of advantages over card payment (debit and credit cards or electronic money) and cash, including being significantly more cost-effective, safer, and convenient than cash or card-based e-money, as well as increasing financial access for the poor.

Regardless of its merits, Camner (2013) argued that a segregated and isolated payment environment is unlikely to sustain significant usage and may even result in a monopolistic market. This finding is corroborated by Banda *et al.* (2015), who reveals that high concentration levels in a specific industry may lessen the incentive to innovate and lead to high prices. As a result, the authority needs to promote fair competition that fosters innovation and consider the likelihood of anti-competitive behaviour that results in economic inefficiency (Macmillan *et al.*, 2016), which supports the QRIS initiation. Additionally, this form of initiation is typically accounted for as part of a central bank's policy; for example, see Khiaonarong (2003).

3.2.2 Behavioural Economics on the Payment Instrument

The rationality assumption, which states that economic agents are fully rational, calculate and maximise utility with perfect foresight of the future and the possible rewards of each economic choice, underpins conventional economics theory, such as neoclassical economics. Due to cognitive and time constraints, people cannot collect all relevant knowledge and evaluate all possible options to get the optimal results; Herbert Simon called this "bounded rationality" (Wilson, 2020). Consequently, it is essential to comprehend how human psychological tendencies influence economic decision-making, which is the focus within the field of behavioural economics.

When it comes to financial decision-making, individuals may not always exhibit rational behaviour and fully evaluate all the facts at hand. This phenomenon can be attributed to the presence of behavioural biases that exert an impact on their decision-making process. Behavioural biases can be classified into two main categories: cognitive errors and emotional biases. These biases can negatively impact financial decision-making by influencing individuals to make suboptimal decisions. Cognitive biases can result in poor investment decisions, market inefficiency, and lower returns overall. According to Elliehausen (2019), another financial decision-making-related bias that is occasionally observed is temporal inconsistency behaviour; it refers to the tendency of individuals to have a "present bias," in which they attribute greater importance or value to the present moment than to future events or outcomes. It can cause individuals to make decisions that are contrary to their long-term financial plan. This behavioural bias is difficult to avoid and leads to irrational decisions, such as following a popular investment trend or selling securities during a market decline. According to the findings of Rasool and Ullah (2020), there is evidence to suggest that financial literacy may mitigate the impact of behavioural bias in financial decision-making. However, Chairunnisa and Dalimunthe (2021) arrived at a different conclusion, asserting that financial knowledge does not appear to exert a substantial impact in this regard.

Similar to financial instruments, individuals, in choosing an appropriate payment instrument to settle their transaction, also consider economic variables; for example, see McCallum and Goodfriend (1989) with his shopping time model. However, not all alternative payment instruments were appropriately accepted by consumers, although it was introduced by an established worldwide company, for example, Chase Pay (standalone version), Amazon Local Register, and Google Wallet 1.0. Another example is the recent introduction of central bank digital currencies (CBDCs) in various countries, such as the e-Naira in Nigeria, the Sand Dollar in the Bahamas, and the Jam-Dex in Jamaica. However, these CBDCs have not witnessed widespread public adoption since their introduction. The relatively slow rate of adoption, which cannot be labelled as a complete failure, of new payment instruments cannot be primarily attributed to economic factors. Many non-economic factors may also influence this outcome. Thus, it is crucial to comprehend the behavioural variables of individuals that impact their adoption of a particular payment instrument.

3.2.3 COVID-19 and transaction behaviour

COVID-19 has profoundly impacted lives, livelihoods and the global economy since it was declared as a global pandemic by the World Health Organization in March 2020. According to the World Health Organization Organization (2020), COVID-19 can be transmitted directly or indirectly through contact with sick individuals or contaminated goods or surfaces. As a result, many governments have responded by introducing social distancing regulations, temporary workplace and school closures, and social lockdowns to combat COVID-19's harmful health consequences.

These containment policies had severely impacted society and shifted consumer behaviour.

As a result, people were forced to spend more time at home, could not directly contact coworkers, and do more online. Consequently, demand for digital financial services and mobile money surged (Agur *et al.*, 2020) while demand for conventional currency decreased (Cevik, 2020). In this context, shifting consumer behaviour in response to COVID-19 has boosted the growth of contactless instruments like mobile payment and digital wallets while limiting COVID-19 transmission (Pal and Bhadada, 2020).

In Indonesia, the government has encouraged businesses, food vendors, transportation providers, and traditional marketplaces to use non-cash transactions (Indonesia, 2020). Additionally, the central bank has initiated numerous programmes to accelerate the transition to a cashless economy and to foster interoperability of contactless payment instruments (i.e. e-wallet and mobile payment) between the fintech industry and banking by establishing the QRIS, as recommended by the Bank for International Settlements Borio *et al.* (2020).

Several econometric techniques have been used to study policy impact analysis in economics utilising secondary data, such as the time series analysis (Sharma *et al.*, 2018; Gortz *et al.*, 2020) or difference-in-differences method (Lechner *et al.*, 2011; Fredriksson and Oliveira, 2019). However, the emergence of the pandemic has made it difficult for researchers to evaluate the impact of policies that were introduced contemporaneously near the starting period of the pandemic. Therefore, to avoid this difficulty, we examine people's behaviour in adopting a new payment platform considering the central bank's intervention and the Covid-19 pandemic using the UTAUT model developed by Venkatesh *et al.* (2003), which is capable of separating policy from the pandemic.

3.2.4 Research framework

This study examines how central bank policy influences people's intention to use QRIS during the COVID-19 outbreak using the UTAUT model. Venkatesh *et al.* (2003) established the Unified Theory of Acceptability and Use of Technology (UTAUT), which provides measurement methods for assessing user acceptance of new technology products. UTAUT emerged from earlier theories defining user acceptance of information technologies and has been empirically validated, albeit the outcome may vary by field of research and country (Attuquayefio and Addo, 2014). According to the UTAUT model, four latent factors influence behaviour intention (BI) in adopting new technology: performance expectation (PE), effort expectation (EE), social influence (SI), and facilitating condition (FC). For that reason, UTAUT is the appropriate theory for studying QRIS acceptability since it enables the examination of variables affecting the information technology (IT) surrounding the QRIS while also taking social issues into account. Additionally, the UTAUT model has been empirically validated in numerous research relating to information technology in many countries, see, e.g. (Williams *et al.*, 2015). We extend the original UTAUT model in this study to account for the impact of the COVID-19 pandemic and the central bank policy on people's behaviour towards adopting new technology, specifically QRIS. We also include variable perceived risk (PR) to distinguish risks associated with the COVID-19 pandemic from common risks related to the introduction of new technology. The conventional UTAUT constructs, namely performance expectancy, effort expectancy, social influence, and facilitating condition, were combined with new latent variables, including perceived risks (PR), the COVID-19 pandemic or other unprecedented events referred to as force majeure (FM), and perceived government (central bank) policy referred to as law enforcement (LE). As a result, as illustrated in Figure 1, the proposed research model is developed.

Performance expectation (PE)

The term Performance Expectation refers to the extent to which users anticipate that adopting new technology would enable them to perform their jobs more effectively (Venkatesh *et al.*, 2003). PE has been shown empirically to be a significant predictor of behavioural intention to adopt new mobile payment technologies (Morosan and DeFranco, 2016), particularly for organisational users (Venkatesh *et al.*, 2012). Additionally, its significance in influencing the intention to adopt new technology, such as a digital wallet or mobile payment, also appeared during the COVID-19 pandemic, e.g. Aji *et al.* (2020) and Zhao and Bacao (2021). As a result, a rise in PE will have an effect on the user's behaviour intention and, ultimately, on the new technology's acceptability. Therefore, the following hypotheses were formed:

Hypothesis 1 (H1): Performance expectancy positively affects behavioural intention (BI) in using QRIS.

Effort Expectancy (EE)

The term Effort Expectancy refers to the easiness level associated with individuals operating the new technology (Venkatesh *et al.*, 2003). EE approximates the perceived ease of use in the technology acceptance model (TAM) proposed by Davis (1989) or the adverse value of complexity in innovation diffusion theory (IDT) proposed by Rogers (1983), which both explain people's belief that using a given technology will be effortless. This variable has been consistently publicised as a critical predictor in explaining intention behaviour, see, e.g. (Venkatesh *et al.*, 2016). In the context of Indonesia, the ease of use factor emerges as a prominent determinant influencing individuals' intention to use new financial instruments. For instance, Riza (2021) examines the impact of ease of use on the adoption of digital services in Islamic banking, while Kadim and Sunardi (2023) explores the relationship between ease of use and the adoption of the QRIS payment platform. According to Aydin and Burnaz (2016), ease of use appears to be the most significant predictor of consumers' mobile wallet usage. As a result, we hypothesised as follows:
Hypothesis 2 (H2): Effort Expectancy (EE) positively affects behavioural intention (BI) in using QRIS.

Social Influence (SI)

Venkatesh *et al.* (2003) defined Social Influence as the extent to which users believe that people surrounding them think they should use new technology. According to the theory of reasoned action (TRA) (Fishbein *et al.*, 1980) and the theory of planned behaviour (TPB) proposed by Ajzen (1985), it is represented as a Subjective Norm and has been empirically shown to have a direct influence on behavioural intention (Venkatesh *et al.*, 2012). Social influence or subjective norms were also found to have a direct effect on people's intention to use near-field communication mobile payments (NFC-MP) and internet banking; see, for example, Morosan

and DeFranco (2016) and Lee (2009). According to Lin et al. (2019), social influence has a greater impact on the behavioural intention to use mobile payment in Korea than in China due to the differences in demographic characteristics and payment patterns between the two countries; whereas Sun et al. (2012) confirm the effect of subjective norms on the intention to adopt new technology in relation to religious affiliation. Therefore, the hypothesis is proposed as follows:
Hypothesis 3 (H3): Social Influence (SI) positively affects behavioural intention (BI) in using QRIS

Facilitating Condition (FC)

Facilitating Condition refers to the stage at which a person has confidence in the resources and technical assistance available to support them using the new technology (Venkatesh *et al.*, 2003). Using mobile banking or a digital wallet properly, for example, requires a number of apparatus and supporting ecosystems, such as a server, legal aspects or licences, a network of agents and merchants, easy access for user assistance, payment protocol, and security, among others (Gupta, 2013). Numerous further studies have established that the facilitating condition plays a significant role in the behavioural intention to use new technology; see, for example, Morosan and DeFranco (2016) in the case of NFC mobile payment in hotels, and Widodo *et al.* (2019) for the adoption of the digital wallet, among other studies. The greater the number of facilities made available by the service provider, the higher the likelihood of adopting new technology. As a result, the following hypothesis is proposed:
Hypothesis 4 (H4): Facilitating Condition (FC) has a positive relationship with the behavioural intention (BI) in using QRIS.

Perceived risks (PR)

Perceived Risk refers to an individual's perceptions of potential losses associated with pursuing the desired outcome through the use of technology, following Featherman and Pavlou (2003). They classified perceived risk into seven dimensions: performance, financial, time, psychological, and social, as well as privacy and overall risk. For the purposes of this study, we measure perceived risks in accordance with Lee (2009), who pointed out that the amount of intention to use mobile banking is mostly driven by security or privacy risk as well as financial risk.

Financial risk, or the possibility of losing money, is a critical matter to consider in the payment sector. Concerns about the possibility of losing money when conducting transactions using mobile banking remains a major concern in developing countries, particularly in Africa and Asia; see, for example, Achieng and Ingari (2015) and Bansal and Bagadia (2018). Concerns about privacy security have been raised as a result of the development of mobile money and its rapid adoption (Harris *et al.*, 2012), which should be of concern to issuers and regulators. This statement is consistent with Hoffman *et al.* (1999) assertion that the elevation of negative perceptions concerning privacy threats emerges with the increase in online users' competence.

In general, perceived risk has an adverse influence on the intention to use mobile banking (Bansal and Bagadia, 2018), mobile payment (Yang et al., 2015), and digital wallet (Liébana-Cabanillas *et al.*, 2020), among other financial services. As a result, we proposed the following hypotheses:

Hypothesis 5 (H5): Perceived risk negatively influences behavioural intentions to use QRIS.

Force Majeure (FM)

In this study, the role of the COVID-19 pandemic is captured by adding a new external factor representing the pandemic, namely, Force Majeure (FM). Various studies on technology acceptance were conducted during the COVID-19 pandemic in numerous fields, such as Riza (2021) in Islamic mobile banking and Sukendro *et al.* (2020) in e-learning platforms among students of sports science education, both of which have been published recently. However, it is arduous to find discourses that explain the impact of the COVID-19 pandemic on the behavioural intention to use technology. In the study of e-wallet usage conducted by Aji *et al.* (2020), the COVID-19 pandemic is represented as a perceived risk factor that positively affects the intention to use an e-wallet, both directly and indirectly. However, this finding contradicts other studies that indicate that perceived risk had no effect on people's intention to adopt FinTech applications during the COVID-19 epidemic, e.g., Nawayseh (2020)

Taking into account the preceding findings, this study attempts to differentiate between common risk factors associated with the acceptance of new technology, as represented by the perceived risk (PR), and risks associated with the COVID-19 pandemic or a situation in which the research was conducted in the manner used in previous studies, by treating the COVID-19 pandemic as an exogenous latent variable, namely force majeure (FM). Thus, *force majeure* is defined as the user's belief about the possibility of avoiding the negative impact of unprecedented events, namely the COVID-19 pandemic (or any disaster), through the application of new technology. Hence, the hypothesis is proposed as follows:

Hypothesis 6 (H6): There is a positive relationship between Force Majeure (FM) and behavioural intention (BI) in using QRIS.

Law Enforcement or Perceived Government Policy (LE)

A study conducted by Chong *et al.* (2010) found that government support significantly influences the intention to use internet banking. In the case of Fintech services, this finding is verified by Chen et al. (2019), who stated that government endorsement of legitimacy and reliability would help to increase public awareness of their new technology. Carter and Bélanger (2005) found that, in the case of new technology introduced by the government, such as e-government, the perceived trustworthiness of the government has a considerable impact on the user's intention to adopt the state's e-government services. Janssen et al. (2018) considered it to be the ultimate predictor, particularly faith in the government, rather than the technology under observation, namely e-government. This finding is consistent with Teo *et al.* (2008), who argue that individuals' impressions of the quality of an e-government website are influenced by their trust in the government, not its technology.

In the study conducted by Mandari *et al.* (2017) regarding farmers' behavioural intention towards using m-government services, government support was discovered as a significant factor influencing the intention to use such new technology. Farmers are more likely to accept m-government if they believe the government would deliver benefits related to the latest technology being used. The findings were corroborated by Aji *et al.* (2020), who explicates that government support indirectly influences the intention to use e-wallets and that the perceived usefulness factor fully mediates this relationship. Thus, without the sense of benefits, government assistance will have no effect on the intention to utilise such technologies. In this study, *law enforcement* is defined as the public's belief and trust in the government's or central bank's new policy, in this case, the introduction of QRIS with any regulations attached to it. As a result, we propose the following hypothesis:

Hypothesis 7 (H7): There is a positive relationship between perceived government's (central bank) policy or law enforcement (LE) and behavioural intention (BI) in using QRIS.

3.3 Research method

3.3.1 Data collection and sampling technique

This is a cross-sectional study conducted in Indonesia from February to March 2021 using an online Qualtrics survey with self-administered questions. The online survey method was chosen to minimise measurement errors caused by the interviewers and to avoid the risk of coronavirus infection. Regarding the ethical consideration of the study, the research was approved by the University of Birmingham's Humanities and Social Sciences Ethical Review Committee. Prior to the main data collection, a pilot test was conducted to ascertain the clarity of the questionnaire, as suggested by Pickard (2013). It is to ensure that the questionnaire was accurately translated from its original source and did not cause misinterpretation, all questions were easily answered by respondents, and the results were comfortably recorded. Considering Saunders *et al.* (2009), a non-probability sampling method employing the purposive sampling technique with judgmental sampling was utilized in this study to ensure that only relevant respondents who had experience using QRIS participated in the research.

3.3.2 Items measurement

The questionnaire was structured in three sections. The first section informed the respondent about the topic and purpose of the research, followed by request for electronic consent. The second segment begins with a screening question to determine respondents' relevance, followed by closed-ended questions concerning respondents' sociodemographic factors, such as gender, age, education, and QRIS experience. The third and final section contains close questions that represent indicators of latent variables developed by Venkatesh *et al.* (2003, 2012) and the aforementioned extended factors to address the stated research objectives. It consists of 23 measurement items that serve as an indicator for eight latent variables: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating condition (FC), perceived risk (PR), perceived COVID-19 pandemic or force majeure (FM), perceived government (central bank) policy or law enforcement (LE), and behavioural intention (BI). All questions use a five-point Likert scale (from 1 to 5, representing "strongly disagree" to "strongly agree"). Appendix B.1 shows a description of variable operationalisation, while Figure 3.1 illustrates the study model and proposed hypothesis previously addressed.

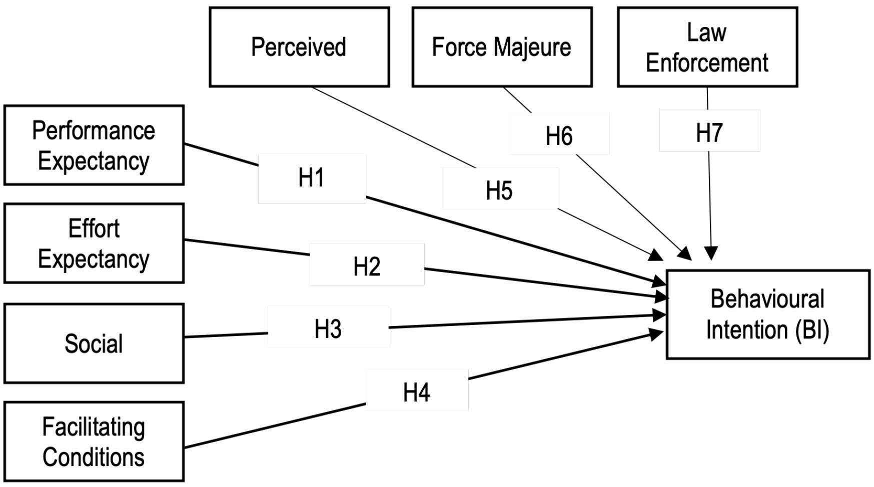


Figure 3.1: Research Model
Source: Author, developed from Venkatesh et al. (2003)

3.3.3 Partial least squares (PLS)

For various reasons, a partial least squares (PLS) method for structural equation modelling (SEM) was used with SmartPLS 3.3 to conduct data analysis in this study, see Ringle *et al.* (2015). To begin, the primary objective of this research was to explore the determinant factors that influence the intention towards the adoption of QRIS in the context of the Covid-19 pandemic and the government-initiated technology innovation, utilising the technology adoption theory known as UTAUT.

Hair Jr *et al.* (2016) pointed out that the variance-based PLS approach to structural equation model (SEM) offers an alternative to covariance-based SEM that is mainly used for exploratory research and theory development, and it is also suggested for a confirmatory study, see, for example, Afthanorhan (2013). Second, according to Ali *et al.* (2018), the causal-predictive aspect of PLS-SEM imposes minimal requirements on distribution normality and sample size. Hair Jr *et al.* (2017) also affirm that the PLS prediction-oriented approach to SEM provides a prominent predictive accuracy that validates the proposed model and verifies a well-developed causal relationship, even when the data is not normally distributed. In short, PLS-SEM estimates coefficients that maximise the R Square values and minimise the error terms of the endogenous constructs (Hair Jr *et al.*, 2016).

3.4 Result

3.4.1 Respondent's demographic profile

The survey obtained 849 responses via a web-based online Qualtrics survey; nevertheless, some respondents did not complete the survey (78), eight respondents did not consent, and a significant number of respondents failed the screening question (277 participants). As a result, this study can analyse only 572 valid data points representing 31 Indonesian provinces. It consists of 239 males (41.78%) and 333 females (58.22%), with an average age of 26 to 35 years and a majority of participants holding a bachelor's degree (364 or 63.64 per cent). The respondents predominantly live in the capital city of a province (207 or 36.19%), followed by the district area and Jakarta-surrounding (Jabodetabek), which accounted for 34.44% and 29.37%, respectively. Most respondents reported having internet access in their premises (475 or 83.04%), while only 97 respondents (16,96%) do not have internet access. Additionally, the majority of respondents indicated that they had used QRIS for more than one year (50.70%). Table 3.1

shows the demographics of the participants in this study.

Table 3.1: Respondent's Demographic Profile

Variable	Description	N	(%)
Gender	Male	239	41.78%
	Female	333	58.22%
Age	18 – 25	165	28.85%
	26 – 35	171	29.90%
	36 – 45	150	26.22%
	46 – 55	81	14.16%
	>55	5	0.87%
Educational Level	Junior High school/Primary Edu	4	0.70%
	High school/equivalent	105	18.36%
	Diploma	35	6.12%
	S1	364	63.64%
	S2/S3	64	11.19%
Marital status	single (unmarried)	226	39.51%
	married	335	58.57%
	divorced	9	1.57%
	widowed	2	0.35%
Location	Jakarta capital city and surrounding (Jabodetabek)	168	29.37%
	Province Capital City	207	36.19%
	Outside province cap.city	197	34.44%
Internet access	Available	475	83.04%
	Not available	97	16.96%
Duration of Use QRIS	<3 Months	87	15.21%
	3 – 6 Months	84	14.69%
	6 Months – 1 Year	111	19.41%
	>1 Years	290	50.70%

Source: Data processing

3.4.2 Measurement model assessment

The first stage in evaluating PLS-SEM results is testing the measurement models that consist of reliability (or internal consistency), convergence and discriminant validity (Hair Jr et al., 2016). The reliability test addresses the consistency level of research measurements. Cronbach's alpha (CA) and composite reliability (CR) were used to assess the construct's reliability; the higher values mainly represent higher levels of reliability with a minimum threshold value of 0.7 (Kline, 2015). As shown in Table 2, all Cronbach's alpha and composite reliability values of latent variables exceed the 0.70 suggested, indicating that the reliability of the constructs has been presented. Convergent validity indicates the extent to which the assessments under each construct measure the same attribute. The validity test result of all indicator variables in this questionnaire shows that loading factors are higher than 0.40, except for the observed variable FC4, meaning this indicator variable needs to be eliminated. All items have a loading above the suggested threshold of 0.708 (Hair Jr et al., 2016). Then, we examine the convergent validity at the construct level using the average variance extracted (AVE). AVE in each construct was above the 0.5 threshold, as Hair *et al.* (2019a) suggested. The result of the validity test is shown in Table 3.2.

The discriminant validity test represents the extent to which a proposed construct is empirically dissimilar from other constructs in the given model. It is measured using the Fornell and Larcker (1981) criterion that compares the square root of the AVE of each construct with the correlations of the latent variables (Hair Jr *et al.*, 2016) and the Heterotrait–Monotrait (HTMT) ratio of the correlations (Henseler *et al.*, 2015). The result of discriminant validity shows that the square roots of all AVE were much more significant than correlations among constructs (Table 3.3), and the HTMT result successfully meets the threshold of maximum a maximum of 0.9, thereby satisfying discriminant validity. Additionally, the proposed model's Standardised Root Mean Squared Residual (SRMR) was reported to be 0.045 (less than 0.08), further evidence of the appropriateness of the composite factor model proposed fits the collected data (Henseler *et al.*, 2014; Hair Jr *et al.*, 2016). The result of the discriminant validity test is available in Table 3.3 and Table 3.4.

Table 3.2: The result of Reliability and Convergence Validity

FACTORS	ITEMS	LOADINGS	CA	CR	AVE
Performance expectation	PE1	0.876	0.842	0.905	0.76
	PE2	0.887			
	PE3	0.853			
Effort Expectancy	EE1	0.888	0.933	0.952	0.833
	EE2	0.928			
	EE3	0.93			
	EE4	0.905			
Social Influence	SI1	0.938	0.922	0.951	0.866
	SI2	0.95			
	SI3	0.903			
Facilitating Condition	FC1	0.87	0.876	0.924	0.801
	FC2	0.914			
	FC3	0.901			
Perceived Risk	PR1	0.884	0.9	0.957	0.881
	PR2	0.924			
	PR3	0.927			
Force Majeure	FM1	0.922	0.813	0.915	0.843
	FM2	0.914			
Law Enforcement	LE1	0.887	0.794	0.905	0.827
	LE2	0.932			
Behavioural Intention	BI1	0.931	0.932	0.957	0.881
	BI2	0.937			
	BI3	0.947			

Note: CA, Cronbach's alpha; CR, composite reliability; AVE, average variance extracted

3.4.3 Structural model assessment

PLS-SEM is different from CB-SEM; it estimates the parameters to maximise the explained variance of the endogenous constructs. Hence, according to Hair Jr *et al.* (2021), examining the structural model is primarily based on heuristic criteria influenced by the model's predictive capabilities rather than testing goodness-of-fit. In this study, we employed a bootstrapping procedure with 5,000 resamples for the significance testing, and the sign of the parameters was consistent. The statistical test results show that the value of $R_a^2dj.$, coefficient of determination adjusted, is 0.640. It indicates that the variance of exogenous latent variables can explain the variance of the Behavioural Intention in using QRIS by 64.0%. The value of Q^2, predictive

Table 3.3: Discriminant Validity, Fornell and Larcker (1981) Criterion

Factors	BI	EE	FC	FM	LE	PR	PE	SI
BI	**0.938**							
EE	0.632	**0.913**						
FC	0.614	0.729	**0.895**					
FM	0.661	0.593	0.527	**0.918**				
LE	0.656	0.509	0.498	0.589	**0.91**			
PR	-0.285	-0.274	-0.241	-0.266	-0.212	**0.912**		
PE	0.632	0.634	0.536	0.613	0.569	-0.222	**0.872**	
SI	0.628	0.519	0.461	0.547	0.581	-0.178	0.623	**0.93**

Table 3.4: Validity testing, Heterotrait-Monotrait Ratio (HTMT) Criterion

	BI	EE	FC	FM	LE	PR	PE	SI
BI								
EE	0.677							
FC	0.679	0.805						
FM	0.758	0.68	0.624					
LE	0.753	0.58	0.588	0.723				
PR	0.305	0.293	0.265	0.305	0.236			
PE	0.713	0.715	0.623	0.74	0.682	0.253		
SI	0.678	0.559	0.511	0.632	0.674	0.193	0.706	

relevance, is 0.561, which suggests that the exogenous constructs have considerable predictive relevance in explaining the appointed endogenous variable, namely Behavioural Intention. The effect sizes (f^2), the relative impact of an omitted exogenous variable from the model on the endogenous variable, were reported as a part of the structural model assessment. Hair *et al.* (2019a) pointed out that the effect size examination should follow Cohen (2013) guidelines; the values of 0.02 refer to small, and the values of 0.15 and 0.35 refer to moderate and high f^2 effect sizes, respectively. This guiding principle also applies in examining the relative impact of predictive relevance or the q^2 effect size.

The results of the structural model in Table 3.5 show that all hypotheses are supported. The hypothesis testing result indicates that performance expectation $(\beta = 0.096; p < 0.05; f^2 = 0.012, q^2 = 0.008)$ and effort expectation $(\beta = 0.096; p < 0.05; f^2 = 0.009, q^2 = 0.008)$ were shown to have a significant positive influence on behavioural intention to use QRIS, how-

Table 3.5: Structural Model Hypothesis Testing

HYPOTHESIS	RELATIONSHIP	PATH COEFF	$t - value$	DECISION	f^2	q^2	95% CI LL	95% CI UL
H1	Performance Expectation ->Behavioural Intention	0.096	2.401*	Supported	0.012	0.008	0.019	0.175
H2	Effort Expectancy ->Behavioural Intention	0.096	2.081*	Supported	0.009	0.008	0.004	0.186
H3	Social Influence ->Behavioural Intention	0.185	3.556**	Supported	0.049	0.035	0.088	0.289
H4	Facilitating Condition ->Behavioural Intention	0.173	4.217**	Supported	0.037	0.026	0.092	0.254
H5	Perceived Risk ->Behavioural Intention	-0.06	2.614**	Supported	0.009	0.005	-0.108	-0.016
H6	Force Majeure ->Behavioural Intention	0.203	4.363**	Supported	0.057	0.04	0.113	0.295
H7	Law Enforcement ->Behavioural Intention	0.227	4.465**	Supported	0.074	0.053	0.126	0.325

***Significant at p-value <0.01, *significant at p-value <0.05*

ever with no significant effect size; thereby, supporting H1 and H2. Social influence was found to significantly affect the intention to use QRIS with a positive sign with small effect size ($\beta = 0.185; p < 0.01; f^2 = 0.049, q^2 = 0.035$) followed by facilitating condition ($\beta = .173; p < 0.01; f^2 = 0.037, q^2 = 0.026$); hence, supporting H3 and H4. The behavioural intention of adopting QRIS during the COVID-19 pandemic is most significantly influenced by perceived central bank's policy or law enforcement (LE) with a positive sign ($\beta = 0.227; p < 0.001; f^2 = 0.074, q^2 = 0.053$), followed by perceived COVID-19 pandemic or force majeure (FM) ($\beta = 0.203; p < 0.01; f^2 = 0.057, q^2 = 0.040$). Thus, hypotheses H6 and H7 are validated, respectively. Moreover, perceived risk was found to gain a significant negative influence on intention to use QRIS ($\beta = -0.060; p < 0.01; f^2 = 0.009, q^2 = 0.005$), although it has no effect size, which supports H5. Accordingly, it shows that the predictors of the UTAUT (Venkatesh *et al.*, 2003) used in our proposed model are still reliable in predicting the behavioural intention toward new technology adoption, particularly for the use of QRIS in Indonesia.

3.5 Discussion

The results of our study indicate that the COVID-19 pandemic (FM) significantly affected customers' intentions to use QRIS. These findings corroborate those of Strielkowski (2020), Horgan *et al.* (2020), and Sutarsa *et al.* (2020), who pointed out that COVID-19 has significantly helped accelerate the transformation of people's behaviour in adopting new technology, such as the use of e-health platform, digital revolution in academia and higher education, and digital payment instruments usage. Notably, the contactless characteristic of the QRIS payment is favourable for a user in retaining social distancing and protecting personal safety during the COVID-19 pandemic.

The outcomes of this study reveal that the perceived central bank's policy (LE) of introducing a new payment platform called QRIS in the country has greatly influenced people's intent to use it, followed by the COVID-19 pandemic (FM) factor. The result corroborates Janssen *et al.* (2018) and Carter and Bélanger (2005), who asserts that the perceived trustworthiness and credibility of the government is a crucial factor that determines the behaviour and intention to use the new service promoted by the government as well as the expectation of benefit related to the new technology, as mentioned by Aji *et al.* (2020). While being a significant determinant, the perceived risk (PR) component does not become a concern of participants when adopting QRIS in this study; it has no effect size. These findings may be attributable to the transparent and rigorous process of licencing for QRIS member approval with the dual-stage licensing process, which involves a dual-stage licencing process including the central bank and standard agency. This approach not only reduces the potential risks but subsequently helps establish and maintain the credibility of the central bank policy.

Performance expectation (PE) was found to influence the intention to use QRIS significantly; however, it has no effect size. This outcome may be attributed to the unique characteristic of QRIS as a national QR code standard that facilitates the interoperability of payment services that were previously fragmented. QRIS provides a new platform that mediates and settles transactions between consumers and merchants with different payment service providers in real-time verification, with no funds to be held. Additionally, the number of recorded complaints is negligible until this study is complete (Mediakonsumen, 2020).

This finding holds for the effort expectation (EE) as well. Although EE was determined to be a statistically significant variable, it has no effect size. This result is consistent with the findings of Riza (2021) and Kadim and Sunardi (2023); however, there is a discrepancy in the observed effect sizes. The observed discrepancy in the effect size may be attributed to the inclusion of additional variables in the UTAUT model to account for and distinguish the impact of COVID-19 and the central bank's policy. This factor was not considered in the analysis conducted by Kadim and Sunardi (2023), although QRIS was the same object being observed. QRIS has a unique feature as a payment channel; it does not need an application to be installed or an initial cost for infrastructure installation, such as an EDC machine or EFTPOS terminal. It is automatically added to the existing mobile payment application and only needs one step (touch) to pay the transaction, followed by verification and authorisation. Hence, QRIS is effortless and far from complicated in terms of ease of use.

Another evidence of our study is social influence (SI) significantly affects the intention to use QRIS. This result is in accordance with Morosan and DeFranco (2016), which exhibits a direct effect of social influence or subjective norm on the intention to use near field communication mobile payments (NFC-MP), as well as Lee (2009) and Rahi *et al.* (2018) for internet banking. This finding was also confirmed in the earlier study of mobile commerce by Shaw and Sergueeva (2019)) and the study on digital wallets by Widodo *et al.* (2019).

According to the result of our empirical study, facilitating condition (FC) was found to influence the intention to use QRIS significantly, which was corroborated by Venkatesh *et al.* (2003) and other studies, for example, Shaw and Sergueeva (2019) and Widodo *et al.* (2019), albeit with a relatively small effect size. These findings provide regulators and payment industry participants valuable feedback on how to increase the new technology product acceptance rate.

In addition, our findings indicate that the predictors of the UTAUT (Venkatesh *et al.*, 2003) included in our proposed model are still accurate in predicting the behavioural intention toward new technology adoption, specifically for the use of QRIS in Indonesia. Even with the newly added constructs, the significance of all UTAUT latent variables supports this result, although the effect size may vary. The unique characteristic of QRIS compared to other payment instruments typically explored in prior studies and the institution's credibility factor that introduced the new technology may account for these unconventional findings in this study employing the UTAUT model.

3.5.1 Theoretical contribution

Our study successfully distinguished the effect of government intervention (LE), the COVID-19 pandemic (LE), and common risks associated with technology adoption (PR), which is absent in the previous study of technology adoption in the context of the COVID-19 pandemic. This study reveals, with some extension, that UTAUT was sufficiently demonstrated as a reliable method for assessing people's intention to adopt new technology, even in the complicated context of pandemics and government policies, particularly for payment instruments in Indonesia. Another improvement is the alteration of the patterns of effect between variables within the model, which is shown by the additional latent variables, namely FM and LE, that outperformed the conventional determinants of UTAUT. As a result, this study contributes to the improvement of technology acceptance theory in many aspects, with a special emphasis on enhancing the UTAUT model.

3.5.2 Practical implication

Our empirical study demonstrates that the effect of the central bank policy (LE) on people's intention to adopt QRIS is greater than that of the pandemic (FM) and other UTAUT variables; therefore, we advocate that this measurement approach can be used as a complementary tool to assess the influence of the central bank's policies on individual behaviour.

As noted by Coglianese (2012), examining the audience's behaviour following policy implementation is essential for measuring the success of a regulatory institution, as people's behavioural change substantially influences the final objective of the public institution. It also corresponds with Kowalkiewicz and Dootson (2019) assertion that understanding people's behaviour has become increasingly crucial for public organisations in the digital age. Moreover, in response to the findings that central bank policy, pandemic, and facilitating conditions are the top three most influential variables affecting users' adoption of QRIS, it is suggested that increasing public awareness of the benefits of the new technology through public campaigns and cultivating a supportive environment, as suggested by Verplanken and Wood (2006), may improve the policy's success rate.

3.5.3 Limitations and future research

There are several limitations that need to be acknowledged. Firstly, the QR standard is defined specifically for Indonesia, which may differ in other countries. Therefore, future studies that want to replicate this model for a similar technology product and services in other countries should consider its specifications. Secondly, though it has a good size, the sample cannot represent all provinces and ensure demographic classification due to time and budget constraints. Accordingly, expanding the sample sizes, especially for merchant participants and the geographical location, is suggested for a better generalisation of the study and to investigate the effect of demographic characteristics on behaviour intention to use QRIS. Finally, the data collection method was a cross-sectional study restricted to Indonesia during the COVID-19 outbreak; therefore, examining the evolution of user behaviour over time is inconceivable. Furthermore, the results may not be generalised to different countries with various conditions, primarily due to the diverse impact of the COVID-19 pandemic. Further research with the extension of UTAUT or a more comprehensive model to accommodate other possible key determinants of new technology acceptance using other new technology products may be an exciting topic to explore.

3.6 Conclusion

This study examines the effect of Bank Indonesia's policy on people's behavioural intention to adopt new technology during the COVID-19 pandemic by incorporating new variables into the UTAUT model (Venkatesh *et al.*, 2003). We added new latent variables, namely law enforcement (LE), force majeure (FM), and perceived risks (PR), to capture the effect of central bank policy and to distinguish its effect from the covid-19 pandemic on people's behaviour in adopting new payment platform namely QRIS; and also separate the risk of the pandemic from the typical risk associated with the adoption of new technologies.

This study concludes that the central bank's policies have a considerable impact on people's intention to use a new payment platform, and the measure of the policy effect can be separated from the effect of the COVID-19 pandemic (FM). We also successfully isolate the effect of pandemic risk from common risks (PR) associated with the use of new technologies and other factors influencing the adoption of new technologies. This study found that the predictors of the UTAUT (Venkatesh *et al.*, 2003) used in our proposed model are still reliable to predict the behavioural intention toward new technology adoption even with the addition of new variables to capture the effect of government policy and unprecedented events like a pandemic. Finally, this research contributes significantly to the literature on technology acceptance and aids policy-makers in assessing the significance of their policy and optimising public acceptability of new technology products or services, especially in the setting of an unprecedented scenario such as the COVID-19 pandemic.

Chapter 4

The Adoption of New Payment Instrument, Government Intervention and Pandemic: A Study of Consumer and Merchant Behaviour in Using QRIS in Indonesia

Chapter Abstract

This article builds on our earlier study by examining the effectiveness of central bank policy in influencing intention to use a new payment platform during the COVID-19 pandemic using the Unified Theory of Acceptance and Use of Technology (UTAUT). This study employs our proposed three additional components that capture central bank policy and pandemic risk while distinguishing common risks associated with new technologies in the extended UTAUT or UTATUT2 (Venkatesh *et al.*, 2012) to evaluate the consistency of the new variables. In addition, demographic characteristics - specifically, age, gender, education, experience, user status, and geography are explored as moderating factors on the influence of these constructs on behavioural intention to adopt new technology. Our analysis used self-administered online survey data acquired with a one-month extension of our initial survey, utilising purposive sampling of 617 respondents who used QRIS during the pandemic. Our extended presented model confirms

our prior study's findings that force majeure (FM) and perceived government interference or law enforcement (LE) have a substantial direct and indirect effect on behaviour intention to use QRIS during the COVID-19 epidemic time. However, the habit was revealed to be the most influential factor influencing intention to use QRIS, outperforming all other UTAUT2 variables. These findings contribute to the advancement of the theory about technology adoption and government intervention, as well as to practical and regulatory advancements in the payment system business.

4.1 Introduction

The study of individual behaviour in adopting and using new technology is a mature research area in the literature on information systems and management. These studies attempt to comprehend how people embrace and utilise new technologies, with the first technology acceptance model (TAM) proposed by Fishbein and Ajzen (1977). Taherdoost (2018) advocate that one of the most prominent theories of information technology acceptance with vigorous empirical validation is the Unified Theory of Acceptance and Use of Technology (UTAUT), which was introduced by Venkatesh *et al.* (2003). The UTAUT provides an apparatus to examine the likelihood of success of new technology by evaluating the level of user acceptance. It is developed from its prominent origins of theories describing user acceptance in information technologies, namely the theory of reasoned action, the technology acceptance model, innovation diffusion theory, the motivational model, the theory of planned behaviour, the model of PC Utilisation, and the social cognitive theory.

In the context of a more specific technology, namely payment systems, numerous research studies have analysed the factors that influence people's intentions to use new payment instruments with varying results. For example, Akinyemi *et al.* (2013) and Liébana-Cabanillas *et al.* (2020) highlighted that the perceived usefulness of mobile payment and its simplicity has always been the driving element in the payments sector, specifically mobile banking and digital wallet. Aydin and Burnaz (2016) discovered that social influence has a low impact on intention to use mobile wallet while personal innovativeness had no direct effect on attitudes toward mobile wallet usage, which was previously believed to be a major driver. According to Sun *et al.*

(2012), religious affiliation influences consumer behaviour. The adoption intention of mobile payment seems to be driven by perceived usefulness among casual Muslims, whereas dedicated Muslims are impacted by perceived self-expression and subjective norms. According to payment Featherman and Pavlou (2003), perceived risks are a crucial determinant of behavioural intention to utilise mobile payment, particularly security or privacy risk and financial risk (Yang *et al.*, 2015). It is empirically demonstrated to have a negative effect on the intention to utilise internet banking and other payment instruments(Marafon *et al.*, 2018).

According to Rowan *et al.* (2021), the usage of fintech products and services, such as digital payments and remittances, increased significantly during the COVID-19 pandemic and is often higher in countries with more stringent COVID-19 containment measures. Many researchers have explored people's intention to adopt new technologies during the Covid-19 pandemic, such as mobile payment and digital banking, and for example, see Hoang and Le (2020) and Riza (2021). Government policy may also affect people's behaviour in adopting new technologies. For example, Sleiman *et al.* (2021) discovered that government support, such as government monitoring, substantially affects the intention to use a payment platform; while a policy proposed by an untrustworthy and illegitimate entity, which includes an institution of the state, is more likely to be rejected by its intended audience, for example, see Collins (2015) and Carter and Bélanger (2005)(2005).

In the context of Indonesia, Bank Indonesia introduced a policy in late 2019 that introduced a national standard for rapid response codes for payment transactions, allowing contactless transactions and interoperability across electronic money and mobile banking providers. As a result, distinguishing the impact of central bank policy and pandemics on people's use of non-cash payment instruments has become challenging. In light of the fact that the COVID-19 pandemic outbreak occurred in close proximity to the QRIS implementation by the central bank, our first study primarily examined the significance of Bank Indonesia's policy in influencing people's behaviour intentions toward the adoption of QRIS using the basic UTAUT model in the context of the pandemic. With our analysis, we were able to distinguish between the impact of central bank intervention (LE), the COVID-19 pandemic (FM), and common risks associated with technology adoption (PR), which was absent in the prior study on technology adoption in the setting of the COVID-19 pandemic. The findings show that people's perceptions of central bank policies and pandemic risk have the greatest impact on their willingness to use the new payment platforms.

Ragin (2006) iterates that the purpose of social research is to make sense of empirical instances using the researcher's theoretical beliefs about social processes, and researchers rely on replication to increase their confidence in the validity of their findings. Therefore, ensuring the level of consistency of a model is crucial to avoid misinterpretation and policy bias; for example, see Drost (2011) and Veroniki *et al.* (2021). In this context, based on our prior research, we expand our work with the primary objective of validating our suggested new predictors in separating the impact of government intervention and pandemic in influencing people's behaviour intentions using the Extended Unified Theory of Acceptance and Use of Technology (Venkatesh *et al.*, 2012). In addition, understanding the impact of demographic characteristics on new technology adoption behaviour might help policymakers segment their policies so that end users or merchants could better accept them. It would also be interesting to investigate the likelihood of a moderating role from the new proposed variable, namely law enforcement, force majeure, and perceived risk, in influencing people's willingness to accept new payment instruments.

A significant theoretical and managerial contribution is envisaged from this research project. First, this analysis verifies the significance of the newly suggested variables, law enforcement (LE) and force majeure (FM), which are able to distinguish the influence of government intervention and the COVID-19 pandemic in a more complicated model. Second, our analysis contributes to the expanding body of knowledge on new technology adoption, namely UTAUT2, in the context of government intervention and pandemics by examining the interaction route of each model variable. Third, we support this method as a tool to help central banks optimise their policies and increase the level of policy acceptance among the general public. Lastly, to our knowledge, no previous study has analysed the influence of government policy and the COVID-19 outbreak on people's behavioural intention to use new technology, especially a new payment technology that is proposed by a government.

4.2 Theoretical foundation and research framework

This section presents an overview of our previous work that modified the basic UTAUT in the context of government intervention and the COVID-19 pandemic. Then, we discuss the new constructs of UTAUT2 incorporated in the model to validate our previous work.

4.2.1 Previous work

Our previous work extends the original UTAUT model to account for the impact of the COVID-19 pandemic and the central bank policy on the behavioural intention to adopt new technology, specifically QRIS. We also include variable perceived risk (PR) to distinguish risks associated with the COVID-19 pandemic from common risks related to accepting new technology. Thus, the conventional UTAUT constructs, namely performance expectancy, effort expectancy, social influence, and facilitating condition, were combined with new latent variables, which are perceived risks (PR), force majeure (FM), and law enforcement (LE). Therefore, the hypotheses tested in the previous study were:

Hypothesis 1 (H1): Performance expectancy positively affects behavioural intention (BI) in using QRIS.

Hypothesis 2 (H2): Effort expectancy (EE) positively affects behavioural intention (BI) in using QRIS.

Hypothesis 3 (H3): Social influence (SI) positively affects behavioural intention (BI) in using QRIS

Hypothesis 4 (H4): There is a positive relationship between the facilitating condition (FC) and the behavioural intention (BI) in using QRIS.

Hypothesis 8 (H8): Perceived risk (PR) negatively influences behavioural intentions to use QRIS.

Hypothesis 9 (H9): There is a positive relationship between force majeure (FM) and behavioural intention (BI) in using QRIS.

Hypothesis 11 (H11): There is a positive relationship between law enforcement (LE) and behavioural intention (BI) in using QRIS.

The findings of this study show that the central bank's policy (LE) and the COVID-19 pandemic (FM) have a significant effect in determining people's intention to use new technology, with LE being the most significant predictor. Acceptance rates for the new payment platform may unquestionably be increased by the public's positive perceptions of central bank credibility and the benefits of complying with new policies, which is consistent with Carter and Bélanger (2005) and Aji et al. (2020). Despite being a significant element, the perceived risk (PR) has little effect size. This may be due to the belief that the risk has been mitigated by the central bank's rigorous licencing and supervisory procedure of the new platform.

Unexpectedly, two important UTAUT variables, namely performance expectation (PE) and effort expectancy (EE), were shown to be significant but with negligible effect size, which were usually considered the most critical variables that influenced new technology use. Our possible response was that it was due to the unique characteristics of QRIS compared to other payment instruments that have been studied extensively in prior research and the inclusion of new variables in the model. The result of our previous study is illustrated in Figure 4.1 below.

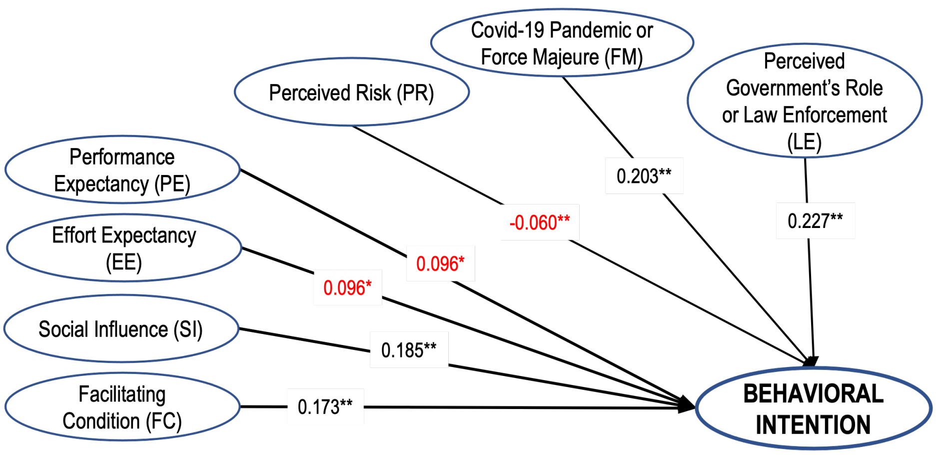


Figure 4.1: Previous study result based on the basic UTAUT (Venkantesh et al., 2003)
source: Author

Further examination in a more comprehensive model can help determine the generalisability of the proposed variables in determining the influence of government intervention (LE) and pandemics or any unexpected crisis (FM) on the new technology adoption behaviour.

4.2.2 Incorporating new constructs in the extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

Considering that our main objective was to verify our proposed constructs in the earlier research on UTAUT, we insert the additional constructs into the UTAUT2 model of Venkatesh et al. (2012) in order to evaluate its consistency in differentiating the influence of government intervention and pandemics on people's intention to use a new payment instrument. One of the reasons we utilise UTAUT2 to examine our proposed model is that UTAUT2 provides a better exposition than other technological acceptance theories; for example, see Rondan-Cataluña *et al.* (2015). Thus, we extended our previous model with UTAUT2 of Venkatesh *et al.* (2012) with more latent variables, namely hedonic motivation, perceived value and habit, and socio-demographic factors. This expansion of the UTAUT2-new technology adoption model is also suggested by Venkatesh *et al.* (2016), notably at the higher level of contextual elements, such as environment and institution attribution.

Hedonic motivation (HM)

Hedonic motivation (HM), which might denote perceived enjoyment, is defined as the extent to which users believe that using a particular technology is entertaining or giving them pleasure (Venkatesh *et al.*, 2012). Tamilmani *et al.* (2019) found that 58% of UTAUT2 empirical studies had included hedonic motivation in their model. It is revealed that HM significantly influences the intention to use such technology, despite his advice not to use the HM construct to study utilitarian purposes technology. Morosan and DeFranco (2016) explicate that the HM construct is the most significant variable influencing the use intention of Mobile Payment, which confirms his previous finding for hotel reservation websites (Morosan and Jeong, 2008) and smart-phone base technology usage (Oluwajana *et al.*, 2019; Shaw and Sergueeva, 2019). Hedonic motivation has also been proven to significantly affect the intention to use internet banking (Alalwan *et al.*, 2015). Accordingly, this indicates that when individuals perceive using such technology as entertaining and enjoyable, the likelihood of adopting the appointed technology will increase. Therefore, the following hypothesis is proposed:

Hypothesis 5 (H5): There is a positive relationship between hedonic motivation (HM) and the intentions to use QRIS.

Price value (PV) or Perceived value

Venkatesh *et al.* (2012) define price value (PV) as the cognitive trade-off of users between the perceived added benefits of the technology and the monetary cost of using them, following Dodds *et al.* (1991). The price value variable is also described as a perceived value in other studies (Shaw and Sergueeva, 2019; Liébana-Cabanillas *et al.*, 2020). The price value is empirically documented to be a critical predictor that affects the behavioural intention to use technology. According to the study of farmer behaviour in using peer-to-peer landing by Septiani *et al.* (2020), price value is a pivotal factor influencing the behavioural intention to use technology, as well as in the study of telebanking customers in Jordania Alalwan *et al.* (2016). Despite the contradictory result in the study of mobile payment in Indonesia (Widodo *et al.*, 2019), many authors see PV as an essential determinant of technology adoption; for example, Liébana-Cabanillas *et al.* (2020) found that price value was the most significant variable influencing the intention to use Apple Pay. This finding follows Shaw and Sergueeva (2019), in the case of mobile commerce usage in Canada, who pointed out that users are motivated by the value of a product and will continue to adopt it as long as it has good value. When the benefits of using new technology are perceived to be higher than its monetary cost, the willingness to accept such technology will tend to increase. Therefore, the following hypotheses were formed:
Hypothesis 6 (H6): Price value (PV) positively influences behavioural intentions to use QRIS.

Habit (Hb)

Venkatesh *et al.* (2012) define habit (Hb) as self-reported beliefs regarding the extent to which individuals tend to perform responses automatically based on a repetition process, following Limayem *et al.* (2007). A study conducted by Morosan and DeFranco (2016) demonstrates that habit has a positive effect on the use intention of mobile payment. This finding follows other researchers who point out that habit is a critical factor in influencing behavioural intention to use a peer-to-peer lending platform (Septiani *et al.*, 2020), public transportation (Chen and Chao, 2011), and health information system technology (Alsharo *et al.*, 2020). According to Widodo *et al.* (2019), habit is found to significantly determine the intention to use a digital wallet in Indonesia as the most influential factor. This finding follows Riza (2021) and Raza *et al.* (2018), who points out that customers' habit is the most substantial variable in predicting the intention to use mobile banking for an Islamic bank customer. Therefore, the hypothesis is proposed as follows:

Hypothesis 7 (H7): There is a positive relationship between habit (Hb) and behavioural intention (BI) in using QRIS.

Habit as moderating variables

Considering our aim to evaluate the role of the COVID-19 pandemic and government intervention on people's intention to use new technology proposed by the central bank, there is evidence of a relationship between individual habits and unprecedented events such as natural disasters or crises. Sheth (2020) pointed out that consumer habits had shifted drastically due to the COVID-19 pandemic and its containment measures. Unprecedented condition, such as natural disaster, causes significant psychological impact, including changing their previous habits (Shultz *et al.*, 2013; Liu, 2020). Hence, we also proposed a hypothesis as follows:

Hypothesis 10 (H10): There is a positive relationship between perceived force majeure (FM) and habit (Hb).

Walters and Simons (2020) state that effortful control was positively associated with habits and measures of self-automaticity. According to Verplanken and Wood (2006), policy interventions may alter an established habit, and its success rate is higher in a tailored-disrupted environment. However, a policy proposed by untrustworthy, incompetent and illegitimate institutions is likely to be rejected and fail to persuade the intended audience (Collins, 2015). The perception of the government's intervention toward the issuance of QRIS that reflects credibility and beneficial policy is represented in the construct of law enforcement (LE) in our previous study. As a result of the mediating role of habit, we proposed an additional hypothesis as follows:

Hypothesis 12 (H12): There is a positive relationship between law enforcement (LE) and habit.

Following this, we postulate that habit (Hb) mediates the relationship between force majeure (FM), law enforcement (LE) and behavioural intention (BI) in using QRIS.

Hypothesis 13 (H13): Habit (Hb) mediates the relationship between force majeure and behavioural intention in using QRIS

Hypothesis 14 (H14): Habit (Hb) mediates the relationship between law enforcement and behavioural intention in using QRIS

According to Venkatesh *et al.* (2003) and Venkatesh *et al.* (2012), demographic factors, namely age, gender, and experience, played a significant role as mediators of the exogenous variables in influencing behaviour intention to use new technology; it was confirmed by Teo *et al.* (2012) with other demographical factors which are education and household income. Chauhan *et al.* (2016) also iterate that occupation and marital status significantly affect the intention to use mobile banking; however, the location is not a relevant variable (Martinho *et al.*, 2017). Following this, we propose hypothesises that demographic factors, namely age, gender, education, experience, location, and user status, will moderate the effect of exogenous variables on behavioural intention in using QRIS. Based on the preceding discussion, Figure 4.2 depicts the proposed conceptual model with hypotheses.

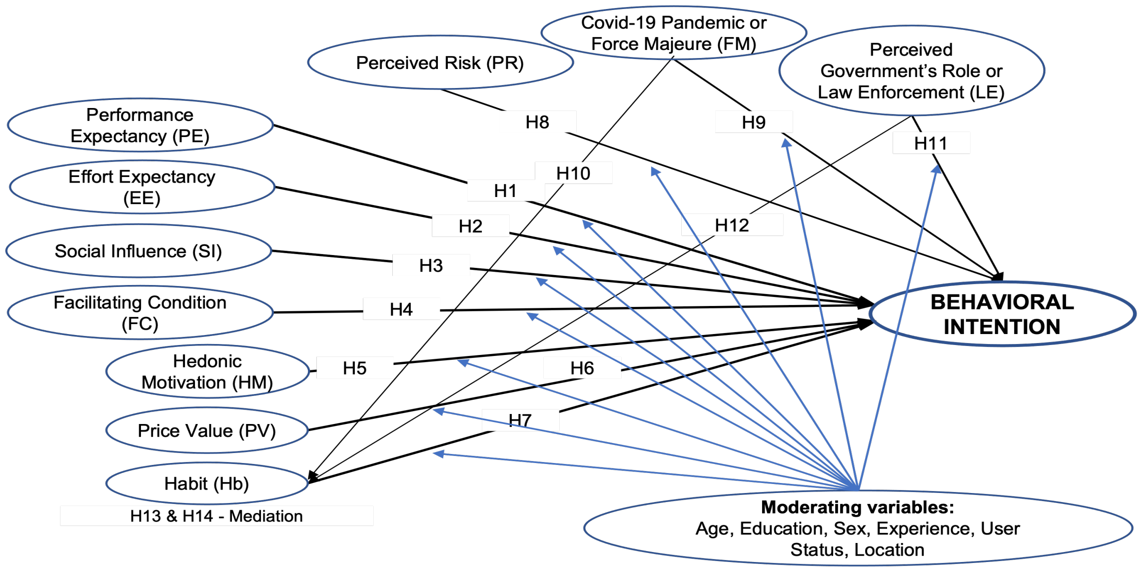


Figure 4.2: Research model
Source: Author, adapted from Venkatesh et al. (2012)

4.3 Research method

4.3.1 Data collection and item measurement

This study uses an online survey with self-administered questionnaires to collect data and applies a confirmatory methodology to test the proposed conceptual model and validate the research hypotheses. The study uses a non-probability sampling method, namely a purposive sampling technique, with a population of Indonesian QRIS users. The questionnaire consisted of questions about the demographic data of respondents and questions that represent indicators of latent variables built from previous hypotheses based on Venkatesh et al. (2012) with the additional constructs to determine government intervention and the Covid-19 pandemic on a five-point Likert scale. The detail of variable operationalisation can be seen in Appendix C.1. The research model and the relationship among variables were tested using the Partial least squares approach to the structural equation model (PLS-SEM) method using Smart PLS.

4.3.2 Evaluation of measurement model assessment

Hair Jr et al. (2016) emphasise the first stage in evaluating PLS-SEM results is testing measurement model reliability, convergence, and discriminant validity. The reliability test examines the consistency level of research measurements or the likelihood that the study results are similar to the assumption of a constant environment and a replicate measurement; for example, see Taherdoost (2016) and Hair et al. (2019). The model reliability will be tested by Cronbach's alpha and composite reliability with a minimum threshold value of 0.7, following Kline (2015). Convergent validity, which represents the extent to which the assessments under each construct actually measure the same attribute (Hair et al., 2019), will be evaluated by the size of the outer loadings in the constructs (indicator reliability) with a minimum threshold of 0.708, and convergent validity at the construct level using the average variance extracted (AVE) with a minimum threshold of 0.5%. As Henseler et al. (2015) indicated, the Fornell-Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio will be used to assess the discriminant validity of a proposed construct, which represents the extent to which a proposed construct differs empirically from other constructs in the given model.

4.3.3 Structural model assessment

Recall that PLS-SEM estimates coefficients that maximise the R Square values and minimise the error terms of the endogenous constructs Hair Jr *et al.* (2016); It maximises the endogenous latent variable's explained variance by estimating partial model relationships among their associated indicators rather than only explaining the correlation between manifest variables (Sarstedt et al., 2016). As a result, instead of focusing on the model's fit, the structural model is examined using heuristic criteria that are influenced by the model's predictive powers (Hair Jr et al., 2016). This research employed a bootstrapping procedure with 5,000 resamples for significance testing and examined the relationship between variables.

4.4 Results

4.4.1 Respondent's demographic profile

The participants in this study are 617 users of QRIS, consisting of 577 consumers and 40 merchants located in 31 provinces in Indonesia. The data were collected using an online Qualtric survey from February to April 2021, consisting of 262 males (42.46%) and 355 females (57.54%). The participants' average age is between 26 to 35 years old, with the majority educational level being a bachelor's degree (382 or 61.91%). Most respondents have marital status as married (354 or 57.37%), followed by those who are single-unmarried (252 or 40.84%), and only 11 respondents (1.78%) have divorced and widowed status. Respondents primarily dwell in provincial capital cities (226 or 36.63%), followed by district areas and Jakarta and adjacent areas (33.55% and 29.82%, respectively). The majority of respondents (507 or 82.17%) reported having an internet connection on their premises, while only 110 (17.83%) did not. Only 40 (6.48%) of the overall sample are merchants, whereas 577 (94.76%) are customers. Most of the respondents (310 or 50.24%) had used QRIS for more than a year. The respondent demographic profile of this study can be seen in Table 4.1.

Table 4.1: Respondent's Demographic Profile

VARIABLE	DESCRIPTION	N	(%)
Gender	Male	262	42.46%
	Female	355	57.54%
Age	18 – 25	183	29.66%
	26 – 35	185	29.98%
	36 – 45	157	25.45%
	46 – 55	86	13.94%
	>55	6	0.97%

Continued on next page

Table 4.1: – continued from previous page

VARIABLE	DESCRIPTION	N	(%)
Educational Level	Junior High school/Primary Edu	4	0.65%
	High school/equivalent	120	19.45%
	Diploma	42	6.81%
	S1	382	61.91%
	S2/S3	69	11.18%
Marital status	single (unmarried)	252	40.84%
	married	354	57.37%
	divorced	9	1.46%
	widowed	2	0.32%
Location	Jakarta capital city and surrounding (Jabodetabek)	184	29.82%
	Province Capital City	226	36.63%
	Outside province cap.city	207	33.55%
Internet access	Available	507	82.17%
	Not available	110	17.83%
Duration of Use QRIS	< 3 Months	92	14.91%
	3 – 6 Months	96	15.56%
	6 Months – 1 Year	119	19.29%
	>1 Years	310	50.24%
Position of QRIS User	Consumer	577	93.52%
	Merchant	40	6.48%

Source: Data processing.

4.4.2 Result of measurement model examination

As mentioned in section 3.2, the reliability of the construct was tested by Cronbach's alpha and composite reliability. Our result found that all Cronbach's alpha and composite reliability values of the constructs exceed 0.70, as suggested by Kline (2015), as evidence of the reliability of the constructs. The convergent validity is measured at the indicator and construct levels of the model. The result of the indicator reliability test shows that all indicators of latent variables in this questionnaire had loading factors higher than 0.40, indicating the existence of indicator reliability, except for the observed variable FC4, then will be removed from the model examination as suggested by Acock *et al.* (2013). We discovered that the average variance extracted (AVE) for each construct was above the 0.5 thresholds proposed by Hair *et al.* (2019b), indicating the convergent validity of each construct. Therefore, we suggest that the reliability and validity of the constructs and indicators used in this study comply with all the suggested thresholds. Table 4.2 shows detail of Cronbach's alpha and composite reliability, outer loadings and average variance extracted (AVE).

Table 4.2: The Result of Reliability and Convergence Validity

FACTORS	ITEM	LOADINGS	AVE	CA	CR
Performance expectation	PE1	0.868	0.841	0.904	0.759
	PE2	0.888			
	PE3	0.857			
Effort Expectancy	EE1	0.869	0.921	0.944	0.808
	EE2	0.901			
	EE3	0.918			
	EE4	0.907			
Social Influence	SI1	0.936	0.923	0.952	0.868
	SI2	0.955			
	SI3	0.903			
Facilitating Condition	FC1	0.853	0.861	0.916	0.783
	FC2	0.902			
	FC3	0.900			
Hedonic Motivation	HM1	0.926	0.910	0.944	0.848

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Table 4.2: – continued from previous page

FACTORS	ITEM	LOADINGS	AVE	CA	CR
	HM2	0.939			
	HM3	0.897			
Price Value	PV1	0.925	0.890	0.932	0.821
	PV2	0.937			
	PV3	0.854			
Habit	Hb1	0.888	0.888	0.931	0.818
	Hb2	0.911			
	Hb3	0.913			
Perceived Risk	PR1	0.883	0.895	0.934	0.825
	PR2	0.914			
	PR3	0.927			
Force Majeure	FM1	0.926	0.829	0.921	0.854
	FM2	0.922			
Law Enforcement	LE1	0.882	0.779	0.899	0.817
	LE2	0.925			
Behavioural Intention	BI1	0.925	0.926	0.953	0.872
	BI2	0.933			
	BI3	0.943			

Note: CA, Cronbach's alpha; CR, composite reliability; AVE, average variance extracted.

The discriminant validity test is examined by two measures, namely the Fornell-Larcker criterion that compares the square root of the AVE of each construct with the correlations of the latent variables and the Heterotrait–Monotrait (HTMT) ratio of the correlations Hair Jr *et al.* (2016). It shows that all constructs in the model satisfied discriminant validity, as evidenced by the square roots of all AVE were much higher than correlations among constructs, as shown in Table 4.3, and the HTMT successfully met the threshold of 0.9. In addition, the Standardised Root Mean Residual (SRMR) of the proposed model was reported to be 0.043, providing additional evidence that the proposed composite factor model fits the obtained data well (Henseler et al., 2014).

Table 4.3: Discriminant Validity, Fornell and Larcker (1981) Criterion

VARIABLE	BI	EE	FC	FM	HB	HM	LE	PR	PE	PV	SI
BI	**0.934**										
EE	0.641	**0.899**									
FC	0.617	0.754	**0.885**								
FM	0.663	0.632	0.549	**0.924**							
Hb	0.766	0.583	0.520	0.585	**0.904**						
HM	0.704	0.750	0.673	0.664	0.698	**0.921**					
LE	0.672	0.532	0.515	0.610	0.602	0.625	**0.904**				
PR	-0.300	-0.291	-0.258	-0.291	-0.216	-0.276	-0.230	**0.908**			
PE	0.628	0.670	0.577	0.634	0.614	0.702	0.564	-0.245	**0.871**		
PV	0.511	0.492	0.472	0.460	0.536	0.563	0.449	-0.226	0.453	**0.906**	
SI	0.633	0.560	0.492	0.581	0.680	0.647	0.594	-0.209	0.649	0.476	**0.931**

Note: the squared root of AVE is shown on the diagonal; correlations of the constructs are below the diagonals.

Table 4.4: Validity testing, Heterotrait-Monotrait Ratio (HTMT) Criterion

VARIABLE	BI	EE	FC	FM	HB	HM	LE	PR	PE	PV	SI
BI											
EE	0.694										
FC	0.691	0.845									
FM	0.757	0.723	0.648								
Hb	0.844	0.644	0.592	0.682							
HM	0.767	0.818	0.757	0.765	0.776						
LE	0.783	0.617	0.619	0.749	0.718	0.730					
PR	0.325	0.316	0.288	0.334	0.240	0.304	0.261				
PE	0.711	0.762	0.678	0.759	0.710	0.802	0.684	0.281			
PV	0.562	0.541	0.537	0.533	0.603	0.625	0.536	0.253	0.522		
SI	0.685	0.607	0.550	0.665	0.751	0.706	0.697	0.227	0.736	0.524	

4.4.3 Structural model assessment

In this study, we tested for statistical significance using a bootstrapping method with 5,000 resamples, and the result indicated that the parameter's sign did not change. The statistical test results show that the value of $R^2adj.$, coefficient of determination adjusted, is 0.705 for BI and 0.432 for Hb, which indicates that the variance of exogenous latent variables can explain the variance of the Behavioural Intention in using QRIS by 70.5%; while its exogenous variables influence habit by 43.2%. The value of Q^2, predictive relevance, is 0.618 for BI and 0.352 for Hb, which suggests that the exogenous constructs have considerable predictive relevance in explaining the appointed endogenous variable, namely behavioural intention (BI) and habit (Hb). As part of the structural model evaluation, the effect sizes (f^2) that refer to the relative impact of an omitted exogenous variable on the endogenous variable were reported. Following the standards of (Cohen, 2013), the values 0.02, 0.15, and 0.35 represent small, moderate, and large f^2 effect sizes, respectively. This metric is also applied for analysing the relative effect of predictive relevance or the Q^2 effect size.

The results of hypothesis testing show that facilitating conditions were shown to have a significant positive influence on behavioural intention to use QRIS ($\beta = 0.138; p < 0.01; f^2 = 0.027, Q^2 = 0.016$) while perceived risk has a negative influence with no effect size ($\beta = -0.061; p < 0.01; f^2 = 0.013, Q^2 = 0.008$), thereby supporting H4 and H8. However, not all hypotheses are supported. The behavioural intention of adopting QRIS during the COVID-19 pandemic is most significantly influenced by Habit with a positive sign ($\beta = 0.406; p < 0.01; f^2 = 0.227, Q^2 = 0.145$), followed by Law Enforcement (ß = 0.184; p < 0.01; f2 = 0.059, q2 = 0.034), Force Majeure ($\beta = 1.42; p < 0.01; f^2 = 0.031, Q^2 = 0.018$). Thus, Hypotheses H7, H9, and H11 are validated, respectively. Moreover, Force Majeure ($\beta = 0.346; p < 0.01; f^2 = 0.134, Q^2 = 0.093$) and Law Enforcement ($\beta = 0.391; p < 0.01; f^2 = 0.171, Q^2 = 0.119$) was seen to gain a significant positive influence on Habit, which was in support H10 and H112. Following this, the mediating effect of Habit in the relationship between Force Majeure and Perceived Government Role with Behavioural Intention was assessed by finding the indirect effect. The bootstrapping procedure (with 5,000 resamples) presents the individual indirect effect of Habit in mediating Force Majeure and Behavioural Intention with significant value, and the confidence intervals did not contain a value of zero ($\beta = 0.140; p < 0.01$). The mediation effect of Habit in mediating Perceived Government Role and Behavioural Intention was also found to be positively significant ($\beta = 0.159; p < 0.01$); hence, H13 and H14 were supported.

The study exhibits that demographic factor is found to mediate facilitating condition (FC) in affecting behavioural intention of adopting QRIS during the pandemic, namely Age ($\beta = -0.099; p < 0.01$), Gender ($\beta = -0.098; p < 0.01$), Education ($\beta = -0.097; p < 0.01$), Experience ($\beta = -0.098; p < 0.01$), and Location ($\beta = -0.098; p < 0.01$); while this effect is not occurred for user status or in other latent variables, as shown in Appendix C.2. In the tested model, however, the results show that performance expectation, effort expectancy, social influence, hedonic motivation, and price value have no significant impact on the behavioural intention of adopting QRIS during the COVID-19 pandemic; therefore, H1, H2, and H3, H5 and H6 were rejected. The result of Structural Model Hypothesis Testing is shown in Table 4.5.

Table 4.5: Structural Model Hypothesis Testing

HYPOTHESIS	RELATIONSHIP	PATH COEFF	t-VALUE	DECISION	$f2$	$Q2$	95%CI LL	95%CI UL
H1	Performance Expectation -> Behavioural Intention	0.018	0.476	Not Supported	-0.001	-0.003	-0.058	0.095
H2	Effort Expectancy -> Behavioural Intention	0.033	0.761	Not Supported	0.003	0.000	-0.053	0.116
H3	Social Influence -> Behavioural Intention	0.020	0.474	Not Supported	-0.001	0.000	-0.066	0.109
H4	Facilitating Condition -> Behavioural Intention	0.138	3.692**	Supported	0.027	0.016	0.066	0.211
H5	Hedonic Motivation -> Behavioural Intention	0.049	0.867	Not Supported	0.003	0.000	-0.060	0.156
H6	Price Value -> Behavioural Intention	0.005	0.176	Not Supported	-0.001	0.000	-0.055	0.064
H7	Habit -> Behavioural Intention	0.406	8.490**	Supported	0.227	0.145	0.312	0.499
H8	Perceived Risk -> Behavioural Intention	-0.061	2.712**	Supported	0.013	0.008	-0.106	-0.018
H9	Force Majeure -> Behavioural Intention	0.142	3.107**	Supported	0.031	0.018	0.053	0.231
H10	Force Majeure -> Habit	0.346	8.199**	Supported	0.134	0.093	0.261	0.429
H11	Law Enforcement -> Behavioural Intention	0.184	4.242**	Supported	0.059	0.034	0.100	0.269
H12	Law Enforcement -> Habit	0.391	9.131**	Supported	0.171	0.119	0.306	0.476
H13	Force Majeure -> Habit -> Behavioural Intention	0.140	6.012**	Supported			0.098	0.187
H14	Law Enforcement -> Habit -> Behavioural Intention	0.159	6.105**	Supported			0.110	0.211

*Note(s): **Significant at p-value < 0.01, *significant at p-value < 0.05.*

4.5 Discussion

Our current study that modifies UTAUT2 to include new latent variables, namely law enforcement (LE), force majeure (FM), and perceived risk (PR), successfully verifies our previous study in the basic UTAT model with the conclusion that government intervention and the COVID-19 pandemic significantly influence the behaviour of individuals to use the new payment platform, namely QRIS. The intention to adopt QRIS was directly influenced by perception regarding the Covid-19 pandemic (FM), which corroborates previous studies; for example, see Zhao and Bacao (2021) and Sukendro *et al.* (2020) for an e-learning platform, and Aji *et al.* (2020), for e-wallet. This study found that perceptions of government intervention (LE) in initiating and promoting new payment instruments had a positive and direct effect on public intentions to adopt QRIS, corroborating the findings of Duan *et al.* (2020), who found that government intervention significantly affects the likelihood of new product adoption behaviour by the audience. The effect of FM and LE on the intention to use QRIS also occurs indirectly through habit. It was also discovered that perceived risk (PR) has a substantial negative impact on the intention to use QRIS but has no effect size, which corroborates our previous study. Comparing QRIS to other digital payment instruments such as mobile banking, e-wallet, and card payment may explain the near-zero effect size of perceived risks seen in our study. According to King (2020), the central bank prudentially regulates QRIS and enables all types of retail payment services. As a result, the risk perception may decrease, and the central bank's credibility may be strengthened. As expected, the research findings show that habit (Hb) plays the most significant role in shaping behaviour intention to use QRIS, which is consistent with previous studies. For example, Widodo *et al.* (2019) revealed that habit is the primary predictor of user acceptance of digital wallets in Indonesia, whereas Riza (2021) and Raza *et al.* (2018) confirmed the essential significance of habit in the adoption of mobile banking by users of Islamic banks. However, behavioural intention is not only primarily influenced by habit but also by FM and LE to a substantial degree. Thus, habit mediates the effects of LE and FM on the intention to use QRIS. This finding corroborates the study of Yuan *et al.* (2021) on green products and Griffith and O'Connell (2010) on food consumption, in addition to Collins (2015), who asserted that government initiative could influence an individual's behaviour if a legitimate and credible institution conducts the intervention. Consequently, taking into account the recommendation of Verplanken and Wood (2006) in order to increase the public's acceptance of the new payment platform, the central bank could optimise its role by fostering a supportive environment and increasing public awareness through public campaigns that can influence consumer habits, thereby increasing the likelihood that consumers will intend to adopt the new payment technology. Another piece of evidence shows that the unprecedented condition, namely the Covid 19 pandemic, had shifted consumers' habits of settling their transactions and eventually naturally persuaded them to use QRIS. These findings corroborate Liu (2020) in the study of natural disaster impact in China, and Sheth (2020), who explains that existing habits have been modified by the ubiquity of digital technology products and services, especially during the pandemic. Unexpectedly, our research found that five out of seven determinants of UTAUT2 do not significantly impact the behavioural intention to use QRIS during the pandemic, namely performance expectation, effort expectancy, social influence, hedonic motivation, and price value. There are several plausible explanations for these findings. First, the addition of the new constructs in the model may have affected the significance of the original latent variables of UTAUT2 and their path. Specifically, the two factors of the Covid-19 pandemic and government intervention have predominately affected the intention to adopt QRIS during this unprecedented period, therefore outperforming other factors of UTAUT2 that were previously applicable under normal conditions. Another possibility may have come from the QRIS's distinct characteristics compared to other new technologies that have been examined in the previous studies, such as digital payment; hence, our study results differently. The performance expectation of QRIS features was not a concern of participants in this study, possibly because QRIS has been proven to successfully mediate and settle transactions between consumers and merchants with a low percentage of recorded complaints relative to other payment instruments, for example, see Mediakonsumen (2020). The result also applies to effort expectations (EE). QRIS does not require a sophisticated application (or new hardware); it is automatically added to the existing mobile payment software and only needs one step (touch) to pay, validate, and authorise a transaction.

As a result, effort expectations do not become a concern of users. Regarding detail of QRIS's ease of use, see DOKU (2022). The QRIS feature that facilitates all payment providers and treats other digital payment instruments as non-competitive products may also explain the insignificance of the hedonic motive (HM) in our model. In addition, according to Tamilmani *et al.* (2019), hedonic motivation is not a relevant factor in explaining technology products for utilitarian purposes with no enjoyment objective, following Widodo *et al.* (2019) for the study of digital wallet adoption. With its role as a payment channel that facilitates all providers with the lowest transaction costs in a more convenient contactless feature, QRIS outperforms other conventional payment methods, such as mobile banking, debit cards, credit cards, and cash payments, in terms of price value. This advantage may be the reason why in our study, the intention to adopt QRIS is not affected by price value (PV) and has resulted in an adverse outcome of Liébana-Cabanillas *et al.* (2020), but following Widodo *et al.* (2019). In addition to this, according to central bank policy, the consumer does not need to pay any fees to settle their transaction using QRIS, and micro-business merchants and social institutions were excluded from merchant discount rate obligation during the pandemic (maximum 0.7% for big merchants). Therefore, neither the consumer nor small-scale retailers are financially affected by the use of QRIS. In addition, we discovered that demographic variables do not significantly moderate the effect of exogenous variables on the intention to use QRIS. However, the influence of facilitating condition (FC) on behaviour is mediated by age, gender, education, experience, and location, but not by user status (consumers or merchants).

4.6 Contribution

This present study aims to verify our proposed exogenous latent variables in distinguishing the role of government intervention and pandemics on individuals' behaviour to adopt new technology among consumer and merchant users in Indonesia, using a more complex model UTAUT2; hence, several theoretical implications emerge from this study.

4.6.1 Theoretical contribution

Our study modifies the UTAUT2 model in three essential aspects. First, the empirical results successfully differentiate the pandemic risk (FM) and common risk (PR) related to new technology embedded in the UTAUT2 model. We found that FM significantly influences, directly and indirectly, the intention to use QRIS. Second, our empirical findings demonstrate that government intervention (LE) significantly impacts an individual's intention to use QRIS, which is captured in the extended UTAUT2 model. Our result corroborates Mandari *et al.* (2017) and Duan *et al.* (2020) and is consistent with our earlier research. Our third improvement is the alteration of the path for the habit that mediates other exogenous latent variables, which corroborates Verplanken and Wood (2006) and Sutarsa *et al.* (2020). This study demonstrates that habit did, in fact, mediate the effect of the pandemic and government intervention on behavioural intention, suggesting that both variables disrupted the payment system environment and significantly influenced the modification of people's habits, which altered their intention to utilise QRIS. As a result, our theoretical contribution is the modified adoption model that is able to capture and differentiate the effect of government intervention, pandemic risks, and typical risks associated with new technology adoption for individual users and merchants using the basic UTAUT and extended UTAUT2 model.

4.6.2 Implication for practice

According to the results of this study, habit, force majeure, and perceived government's role are the most influential factors determining the adoption of QRIS in Indonesia, with their direct and indirect relationship. Therefore, we suggest that the central bank could increase QRIS acceptance by optimising these three factors, i.e. expanding public campaigns to promote QRIS as a new contactless payment instrument in collaboration with government publicity programmes to increase public awareness of COVID-19 protocols. Promoting QRIS to avoid the possibility of infection by COVID-19, which can be spread using conventional instruments, such as cash or cards. Further initiatives should include promoting a credible policy that can provide a supportive environment for contactless payment instruments or an inconvenient environment for traditional payment, as suggested by Verplanken and Wood (2006); subsequently, these initiatives will encourage people to use QRIS contactless payment. However, the effectiveness of the policy depends on the government's credibility and the proposed technology's benefit. As Verplanken and Wood (2006) argued, a central bank needs to preserve its credibility and the public's trust to implement monetary policy effectively. Strengthening the facilitating conditions, such as expanding QRIS's coverage area outside of major cities and adding more merchants to boost the network effect, are also factors to consider. It includes collaborative initiatives with mobile networks and digital payment service providers to increase coverage throughout the archipelago. Expanding QRIS's coverage area and providing a conducive environment for secure contactless payments will attract more users.

4.7 Conclusion

In conclusion, the findings of this study corroborate those of our previous studies using the UTAUT model to distinguish the effects of government intervention and the pandemic on the intention to use a new payment platform, QRIS. Government intervention (LE) and the COVID-19 pandemic (FM) were confirmed to significantly influence people's behaviour toward using QRIS, directly and indirectly, mediated by habit (Hb). With the addition of the new variables, our research found that five out of seven determinants of UTAUT2 do not have a notable impact on the behavioural intention to use QRIS during the pandemic, namely performance expectation, effort expectancy, social influence, hedonic motivation, and price value. Our empirical result also concludes that the facilitating condition (FC) directly influences the intention to use QRIS; however, its impact was mediated by demographic factors such as age, gender, education, experience, and location, except for user status. Hence, our study brought several theoretical and practical implications.

Despite the significant result of this study, there are several limitations that need to be considered. First, Indonesia's definition of QR standard may differ from other countries; thus, future studies that aim to replicate this model should consider its specification. Second, for a greater generalisation of the study, expanding the sample sizes, especially for merchant participants, is suggested; and studying user behaviour over time is impossible due to the data collection approach being a cross-sectional study. Finally, it is suggested that future study explores payment system data using more contemporary methods, such as a machine learning approach that can analyse both structured and unstructured data, to investigate user behaviour and policy-related issues in greater depth.

Chapter 5

Forecasting Inflation Using Payment System Data: An Interpretable Machine Learning Approach

Chapter Abstract

This paper evaluates the performance of prominent machine learning (ML) algorithms in predicting Indonesia's inflation rate using the payment system, capital market, and macroeconomic data. We compare the forecasting performance of each machine learning model, namely penalised regression, ensemble learning, and super vector regression, to that of the univariate time series ARIMA and SARIMA models. We examine various out-of-bag sample periods in each ML model to determine the appropriate data-splitting ratios for the regression case study. This study indicates that all ML models produced lower RMSEs and reduced average forecast errors by 45.16 per cent relative to the ARIMA benchmark; with the Extreme Gradient Boosting model outperforming other ML models and the benchmark, as evidenced by the RMSE, MAE, and Diebold-Mariano tests. Using the Shapley value, we discovered that numerous payment system variables were highly predictive of inflation. We explore the ML forecast using local Shapley decomposition and show the relationship between the explanatory variables and inflation for interpretation. The interpretation of the ML forecast highlights some significant findings and offers insightful recommendations, enhancing previous economic research that uses a more established econometric method. Our findings advocate ML models as supplementary tools for the central bank to predict inflation and support monetary policy.

5.1 Introduction

Understanding the economy's current situation is essential for policymakers to make sound decisions. The conventional forecasting technique is reliable under normal circumstances; however, macroeconomic forecasting during times of crisis and extraordinary circumstances such as the COVID-19 pandemic has been empirically proven to be challenging; for example, see Gadea Rivas and Perez-Quiros (2015). Prior to the COVID-19 pandemic crisis, the global economy was already fragile, uncertain, complex, and ambiguous; see, for instance, Juhro and Syarifuddin (2017). Thus, forecasting economic indicators using traditional linear regression approaches may become tenuous due to their limited ability to identify complex variables with abundant data and information. In order for policymakers to be able closely to monitor economic conditions, alternative tools for macroeconomic forecasting are required.

As a result of the increasing complexity of the economic structure, central banks have begun to consider alternatives to the time-series regression models traditionally employed for forecasting key macroeconomic variables, such as Artificial Intelligence (AI) and Machine Learning (ML) approaches, see Doerr *et al.* (2021). ML has many advantages despite some concerns regarding causal inference and interpretation of its results, as well as determining which factors should be considered when making a specific policy recommendation; for instance, see Lazer *et al.* (2014). Its adaptability allows them to uncover complex hidden structures that were not explicitly stated and accommodate massive data sets with many regressors without overfitting Mullainathan and Spiess (2017). Additionally, Athey (2019) suggests that researchers may conduct more sophisticated empirical and multidisciplinary research by being familiar with these approaches.

This paper aims to estimate Indonesian inflation rates, the main concern for central banks, using machine learning models that utilise various payment system data, capital market variables, and macroeconomic data. According to Aprigliano *et al.* (2019), payment systems are characterised by high-frequency data that record economic transactions between economic participants; hence, they can be employed as an alternative data source for macroeconomic forecasting. In addition, it would be beneficial to make the ML prediction result more interpretable.

As a result, the current study contributes to the body of knowledge in various ways. First, this study contributes to a growing body of literature that successfully compares machine learning models to conventional econometric techniques in economic forecasting, incorporating a novel approach to the interpretability of ML forecasts. Second, our study compares the performance of ML models on different data splitting ratios for regression, a topic that is rarely adequately covered. Lastly, to the best of our knowledge, this is the first study to use machine learning techniques to forecast inflation in the Indonesian economy using payment system data and compare the ML model's forecast performance on various data splitting ratios for a regression case study.

The Indonesian economy has effectively maintained low inflation in recent years, notably since the central bank implemented inflation targeting. However, it appears to be critical to providing the most accurate inflation rate forecast for emerging economies, particularly in exceptional circumstances such as during economic crises or pandemics. Furthermore, making ML prediction more accessible and understandable would be advantageous and provide more meaningful insight into policy recommendations. The remainder of the essay is organised as follows. The second section discusses previous studies. The dataset utilised in this study is explained in Section 5.3. The methodology is outlined in Section 5.4. In Section 5.5, the empirical results of all observed ML models were discussed. Section 5.6 presents an overview of the findings of the study. The appendices of this study provide additional information regarding payment system data and empirical results.

5.2 Related literature

5.2.1 Machine learning and economic forecasting

Machine learning (ML) is commonly used for prediction, processing vast amounts of data by clustering and grouping, and providing a classification with an advanced algorithm in a "black box" for automation purposes. Nevertheless, ML functionality, particularly supervised ML, has rapidly advanced into the field of interpretation and causal inference and has been effectively implemented in practice (Athey, 2015, 2019).

Many studies have examined various machine learning methodologies to forecast macroeconomic variables such as economic growth, and the number of studies in the literature is rising. Yoon (2021) uses ensemble learning approaches such as Gradient Boosting and the Random Forest algorithm to predict GDP growth in Japan, whereas Milačić *et al.* (2017) and Lepetyuk *et al.* (2020) employ neural networks and deep learning methods using the US dataset. Several researchers have also compared various machine learning methods to forecast macroeconomic variables; for example, see Richardson *et al.* (2021) and Tamara *et al.* (2020). Their result suggests that many machine learning methods outperformed the traditional econometric approach. Numerous research in banking and finance domains have also found that the use of machine learning models for forecasting considerably increases the accuracy of their results. Heaton *et al.* (2017), for instance, uses deep learning hierarchical decision models to solve financial forecasting and stock index classification problems, whereas Patel *et al.* (2015) uses a two-stage fusion approach for stock market index prediction.

In addition to employing financial and economic data for economic forecasting, alternative data, such as that from payment systems, have been utilised in quantitative research to forecast macroeconomic indicators, especially in developed countries. In Canada, for instance, Galbraith and Tkacz (2018) showed that payment-system data, particularly debit card and check transactions, can improve GDP forecasting. This finding is supported by Chapman and Desai (2020), who also include the Covid-19 pandemic in their models. In support of these findings, Barnett *et al.* (2016), has criticised the theory that suggests simple sum monetary indicators, i.e., ignoring credit cards from money supply measurement, is incompatible with the economic theory that develops the models that use the data. Inconsistency between data generation and modelling methodology caused an unstable demand and supply for money, resulting in poor measures and severe long-term costs to the profession and economies Barnett *et al.* (2021).

Several researchers have used machine learning to help optimise central bank policy. Chakraborty and Joseph (2017), for example, offered a number of machine learning models for central bank usage and policy context, whereas Zulen *et al.* (2018) employed text analysis to determine stakeholders' expectations to predict the central bank's policy rate. Various machine learning algorithms have also been applied to forecast inflation rate and suggested to optimise central bank policy; for example, see Medeiros *et al.* (2021) and Rodríguez-Vargas (2020). Furthermore, Lu (2020) examines financial market risk indicators that can promote monetary policy effectiveness through macro-control monetary policy adoption using a neural network algorithm. In recent years, interpretable machine learning has gained popularity by extending the focus of machine learning from optimising forecast accuracy (or minimising forecast error) to the interpretability of forecasting results; for example, see Lundberg and Lee (2017) and Molnar (2020). The interpretability approaches are not limited to measuring the importance of input variables for model prediction; for example, see Buckmann *et al.* (2021) but are also attempting to reveal the causal inference approach of machine learning models in macroeconomic forecasting.

In the context of Indonesia, there is a limited study that employs machine learning methods to examine macroeconomics, particularly inflation. Some authors have used the long short-term memory (LSTM) method to forecast the inflation rate in Indonesia; for example, see Zahara and Ilmiddaviq (2000) and Savitri *et al.* (2021). These papers are similar to mostly machine learning studies in regression that emphasise maximising prediction accuracy. However, there are no causal inferences of the observed variables in the model, and it is unclear how the ML prediction result can be useful for policy analysis or improving forecasting accuracy relative to the more established econometric model. In addition, there is evidence that simple univariate forecasting algorithms are difficult to outperform and frequently more accurate than the more complicated multivariate model; for example, see Banerjee *et al.* (2005) and Ang *et al.* (2007), especially for short-term period forecasting Chayama and Hirata (2016).

Many previous studies examining the performance of machine learning models to predict macroeconomic indicators used univariate econometric models such as AR(Auto-Regressive) or ARIMA (Auto-Regressive-Integrated-Moving-Average) models as a benchmark; for example, see Richardson *et al.* (2021) and Özgür and Akkoç (2021). Therefore, in this study, we use the ARIMA as the benchmark model to examine the performance of various machine learning models. In addition, the absence of studies on inflation using non-traditional explanatory variables in developing countries, particularly Indonesia, encourages us to examine non-traditional data for inflation forecasting, such as payment systems data and a few data from the capital market.

5.2.2 Literature related to explanatory variables

Theoretically, the advancement of payment instruments has a reversal effect on inflation by reducing the demand for money for transactions in the economy; for example, see McCallum and Goodfriend (1989) and Dias (2001). This conclusion is supported by Csonto *et al.* (2019), who revealed that the digitalisation of the economy has a negative impact on inflation in the short term. Lubis *et al.* (2019) and Adil *et al.* (2020), for example, found that technological advancement in the payment system negatively impacts the demand for money as the intermediary target of monetary policy in controlling inflation.

The majority of economic literature discusses the negative effect of inflation on the capital market; for example, Feldstein (1983) pointed out that a higher rate of inflation can cause a substantial reduction in the ratio of share prices to tax earnings. Albulescu *et al.* (2017) corroborates the findings and also notes that its effect significantly occurs when monetary policy is countercyclical, as mentioned by Zhang (2021). Juhro and Njindan Iyke (2020) found that stock market capitalisation was a negative and significant predictor of inflation, which corroborates Wahyudi *et al.* (2017) in their study on South Asia countries, except for Thailand, which showed a positive impact. While Hashmi *et al.* (2021) discovered that inflation in Indonesia had a negative effect on stock market returns in the short term but a positive effect in the long term.

The exchange rate, in theory, can affect inflation directly through imported consumer goods and indirectly through imported intermediate goods. The exchange rate's effect on inflation is the highest and most immediate for import prices and decreases along the pricing chain; however, the extent and speed of exchange rate pass-through appear to vary between product categories, see Ortega and Osbat (2020). Nevertheless, fluctuations in exchange rates and inflation may also result from monetary policy (Gortz *et al.*, 2020). According to Warjiyo (2013), in a small open economy like Indonesia, exchange rate movements may not necessarily represent its fundamental value, and depreciation of the rupiah had no significant pass-through effects on tradeable core inflation.

According to Mæhle (2020) and Agung and Juhro (2020), the interest rate has a negative effect on inflation in the monetary policy framework by impacting several channels and intermediary targets. In the case of Indonesia, Utama *et al.* (2017) corroborated that policy rates negatively and significantly affect the provincial inflation rate; and the effect of policy rate on inflation is not immediate and displays distributed lags; which following Kusuma (2013) and Warjiyo and Juhro (2022). Cochrane (2016), however, criticises this idea using a simple modern economic model of monetary policy like the new Keynesian model and demonstrates a more complex model and shows that when the Fed raises nominal interest rates, inflation will smoothly grow in the short and long run. Considering inflation's positive response to interest rate increases, he advises that central banks should take the issue seriously. Following this, Lukmanova and Rabitsch (2020) highlighted that a temporary nominal interest rate shock causes inflation and economic activity to fall, whereas a persistent inflation target increase causes the nominal interest rate, inflation, and economic activity to rise. In his study of Indonesia, Lie (2019) stated that an immediate reduction in Bank Indonesia's inflation target may led to a decrease in average inflation and nominal interest rates, and vice versa. One argument is that policymakers may have reduced the monetary policy variable to anticipate future inflation; as a result, prices rise, albeit lower than they would have if the policy rate had not been raised. Consequently, the causal interpretation of inflation and interest rate is may differ with respect to the role of inflation expectation, expected rate, channel utilised, and level uncertainty.

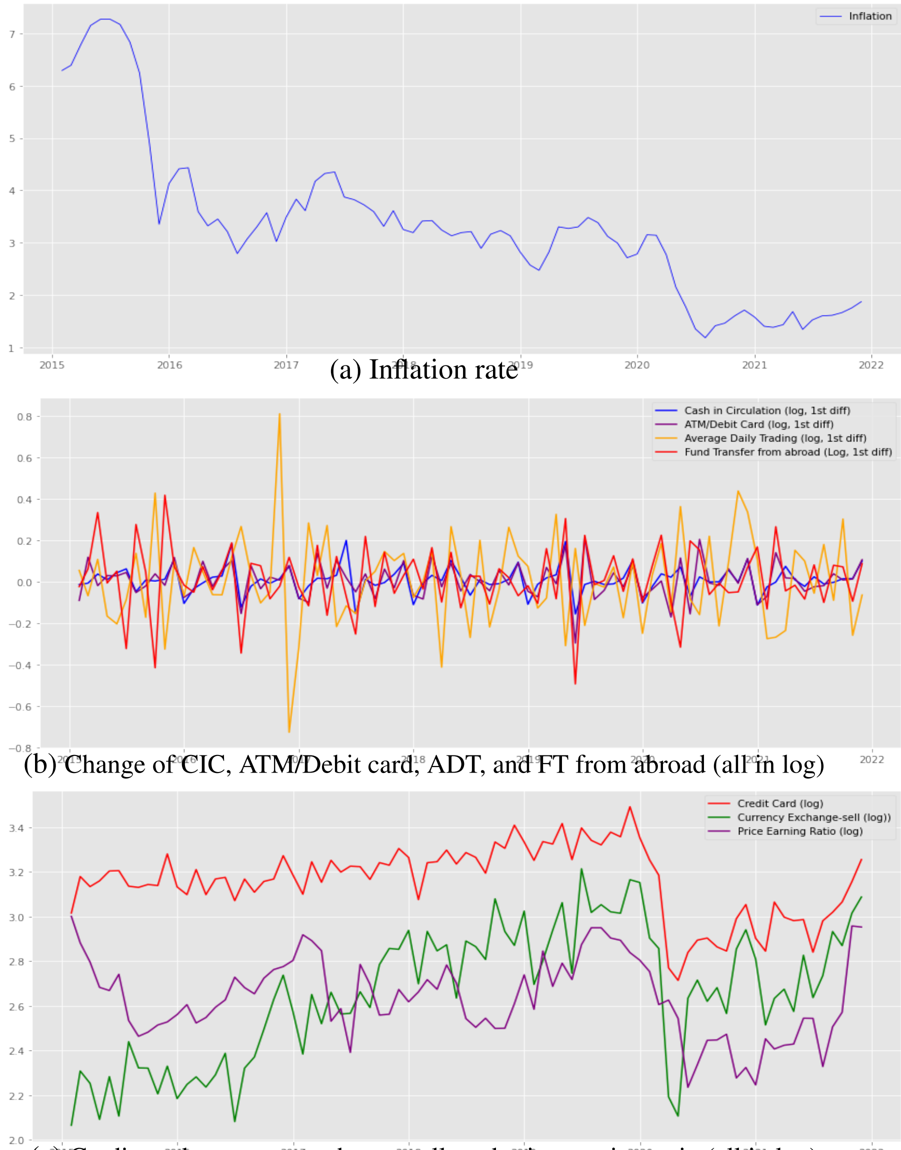
5.3 Dataset

A payment system, according to Indonesia (2004), is a legal framework composed of institutions and procedures for the transfer of funds in order to fulfil liabilities emerging from economic activities. On the basis of transaction size, the Indonesian payment system is classified into two categories: high-value payment systems and retail payment systems. Bank Indonesia's

BI-RTGS (Real-Time Gross Settlement) system was the only one that handled high-value payments. The commercial clearing system and Bank Indonesia worked together to handle smaller payments. Bank Indonesia uses SKNBI (the National Clearing System) to handle the retail transaction of credit and debit transfers as well as paper-based payment instruments like checks and *bilyet giro (BG)*. The commercial clearing system handles transactions involving card-based payment instruments (ATM/debit cards and credit cards), electronic money, electronic wallets, and non-bank money transfers among its members. Appendix Figure D.1 shows the payment system in Indonesia.

We identify the variables in the payments system as well as the macroeconomics and capital market data that are available for analysis and aggregated to monthly data from January 2015 to December 2021, as depicted in Figure 5.1. Figure 5.1a displays graphs of the inflation rate over time. The dependent variable is inflation, defined as the percentage change in the consumer price index per month (year on year). The base year of price indices base year is 2012. In addition, we incorporated macroeconomic factors and capital market statistics, as depicted in figures 5.1b and 5.1c. The variables used in our dataset are listed and described in detail in Appendix Table D.2. All data were collected from Bank Indonesia (Indonesian Financial Statistics, Indonesian Payment Systems, and Financial Market Infrastructure Statistics) and the Indonesian Bureau of Statistics.

For the purposes of this study, we are interested in the relationship between payment system statistics and inflation. We observe a number of payment system variables that appear to have a close relationship with the inflation rate, including the retail payment instruments that tracked transactions between individuals and small business entities, as well as the wholesale payment instruments that could represent the entire economic activity. In addition, capital markets and other aggregates of macroeconomics that may have relations with the inflation rate are also observed.



(a) Inflation rate

(b) Change of CIC, ATM/Debit card, ADT, and FT from abroad (all in log)

(c) Credit card, currency exchange-sell, and price earning ratio (all in log)

Figure 5.1: Time series of some selected variables

5.4 Methodology

In this section, we provide a brief description of the various ML and benchmark models we considered for forecasting inflation; however, for greater detail, please refer to the original literature. In classic econometrics, particularly linear regression, one of the conventional objectives was to infer a causal relationship between regressors and target variables; however, high correlations between features can result in multicollinearity issues, resulting in interpretive bias (Brooks, 2003). Machine learning techniques, on the other hand, emphasise prediction, see Shmueli (2010); therefore, they emphasise enhancing predictive accuracy in classification problems involving structured and unstructured data while minimising forecast error in regression problems (James *et al.*, 2013).

In this research, we apply some of the acknowledged machine learning models, including the ridge, lasso regression, and elastic net, all of which are well-known for their use of regularisation techniques that make use of shrinkage estimators to lower the prediction variance by reducing the parameter estimates in the standard OLS model. This method may truncate model complexity when many variables are added to the model; see Smeekes and Wijler (2018). Other machine learning techniques that are less susceptible to multicollinearities, such as ensemble learning and support vector machines, as described in Sandri and Zuccolotto (2008) and Dormann *et al.* (2013), will also be employed in this study. All the observed machine learning models are supervised models, where the dataset is labelled and defined to train the algorithm in making a prediction.

5.4.1 Benchmark and machine learning models

Benchmark models and SARIMA

The ARIMA model is used as a benchmark in this work to evaluate the forecasting performance of the observed ML methods. The regular ARIMA model incorporates the autoregressive and moving average terms. A complete ARIMA (p,d,q) model can be written as follows:

$$y_t = c + \sum_{i=1}^{p} \phi y_{t-i} + \sum_{j=1}^{q} \theta \varepsilon_{t-j} + e_t \tag{5.1}$$

where y_t is the differenced and stationary series of relevant variables (inflation), ϕ and θ are the autoregressive and moving average coefficients, ε_t is the error term, and e_t is the white noise error term. The order of differencing required to achieve stationarity is represented by d, the order of the autoregressive part is represented by p, and the degree of the moving average section is represented by q. These parameters are determined by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) and comparing them with the information criteria of the models. The seasonal ARIMA model (SARIMA) was developed by incorporating seasonal factors into the ARIMA model described above. SARIMA models are written as:

$$ARIMA(p,d,q)(P,D,Q)m \tag{5.2}$$

where $(P,D,Q)m$ denotes the seasonal component of the model, and m is the number of seasons or number of observations per year. The seasonal component of the model is quite similar to the non-seasonal component (p,d,q), but it is involved in seasonal period back-shifts.

Ordinary least square (OLS)

The main objective of an estimation technique is to fit the target variable's prediction function in equation (5.3), using potential regressors to determine the target variable's forecasted values that can be written as follows:

$$y = f(X) + e_t \tag{5.3}$$

where y represents the explanatory variable, f is a fixed but unknown function of regressors $X1, X2, ..., Xn$, and e is a random error term. Basically, ordinary least squares (OLS) estimation seeks to minimise the least square errors in the form:

$$\beta_x = argmin\beta x \sum_i = 1^n (y_1 - \beta_0 - \sum_j = 1^p \beta_j x_{ij})^2 \tag{5.4}$$

However, under penalty function constraints, shrinkage estimators in shrinkage models (such as the ridge, lasso, and elastic net) reduce the least square errors to the absolute minimum.

Ridge Regression

Ridge regression is a form of linear regression where the coefficients are estimated using a ridge estimator instead of ordinary least squares (OLS). This estimator is widely used to address the problem of multicollinearity and when dealing with a large number of input variables, see Hastie (2020). In addition to least squares, ridge regression is a method for estimating the coefficients of multiple-regression that is similar to least squares but uses a penalty in the form of $L2$ regularisation, where the penalty is on the squared magnitude of the coefficients, to minimise the coefficient of each of the regressor (Hastie *et al.*, 2009). More formally, the ridge regression estimates the coefficients by minimising the following equation:

$$\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda\sum_{j=1}^{p}\beta_j^2 = RSS + \lambda\sum_{j=1}^{p}\beta_j^2 \tag{5.5}$$

where λ is a tuning parameter that controls the relative importance of the shrinkage penalty. It enables features with a relatively insignificant contribution to the target variable to approach zero coefficient value. In the particular case of λ equal to zero, the penalty term has no effect, and ridge regression will produce the least squares estimates. However, as λ grows, the impact of the shrinkage penalty grows, and the ridge regression coefficient estimates will approach zero, reducing the magnitude of the estimated coefficients but will not result in the exclusion of any of the variables. While least squares generate only one set of coefficient estimates, ridge regression will produce a different set of coefficient estimates, β_λ^R, for each value of λ.

Lasso Regression

Lasso regression is a shrinkage-based alternative to ridge regression that overcomes the difficulty of omitting irrelevant features from the regression equation; using $L1$ regularisation to create more parsimonious models by imposing a penalty with a value equal to the absolute value of the coefficients' magnitude (Hastie *et al.*, 2009). Thus, lasso regression can be employed for feature selection; models developed using lasso regression are often far easier to comprehend than those generated using ridge regression (James *et al.*, 2013). The lasso regression solves the minimisation problem of the specified equation as follows:

$$\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + (\lambda \sum_{j=1}^{p}|\beta_j| = RSS + \lambda \sum_{j=1}^{p}|\beta_j| \tag{5.6}$$

The lasso regression has a similar formulation to ridge regression, except that the β_j^2 term of penalty in the ridge has been replaced with $|\beta_j|$. The $L1$ penalty function has the effect of compelling some of the estimated coefficients to be precisely equal to zero; thus, the lasso narrows the coefficient estimates towards zero during the regularisation process. For further explanation, see Tibshirani (1996).

Elastic net (ENT)

The Elastic net regression is a hybrid of lasso and ridge regression methods that overcomes the shortcomings of lasso and ridge algorithms when dealing with highly correlated data. The combination of $L1$ and $L2$ penalty functions allows for learning the sparse selection but, at the same time, stabilises regularisation paths and removes limitations on the number of selected variables. The elastic net algorithm has the following form:

$$\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda(\alpha \sum_{j=1}^{p}|\beta_j| + (1-\alpha)\sum_{j=1}^{p}\beta_j^2) \tag{5.7}$$

Combining a lasso and ridge algorithm in conjunction, the relative importance of the two penalties, $L1$ and $L2$, is set by a tuning parameter, α. If α, is equal to zero, then it becomes a ridge estimator. Alternatively, if α is equal to one, the estimator changes into the lasso estimator. Another type of proposed machine learning method is ensemble learning, which attempts to construct predictive models by combining the strength of a cumulation of simple base models (Hastie *et al.*, 2009), namely random forest and extreme gradient boosting.

Random Forest (RF)

Random forest, introduced by Breiman (2001), is a decision tree–based ensemble learning method built using a forest of many regression trees that reduces the variance error of a model's result. It is a non-parametric method; thus, it approaches the multicollinearity problem slightly differently than parametric approaches such as OLS or lasso regression. It uses a bagging (bootstrap aggregation) approach, i.e., by introducing randomness from a subset of the training dataset where each tree is independently built, and then the output of trees is averaged to produce predictions, see (Müller and Guido, 2016). According to Hastie *et al.* (2009), the random forest regression approach is performed as follows:

Step 1. Begin by performing the following for $b = 1$ to B:

1. From the training dataset, create a bootstrapped sample set, Z of size N.

2. Develop a random forest tree, T_b, using the bootstrapped data by recursively repeating the following procedure for each terminal node of the tree, until the minimum node size, n_{min}, is reached.

   - Randomly select m variables from p variables.
   - Choose the optimal variables/split-points from the m.
   - Divide the node into two child nodes

Step 2. Output the ensemble of trees $\{T_b\}_1^B$.

To make a prediction at a new point x:

$$\hat{f}_{rf}^{B}(x) = \frac{1}{B} \sum_{b=1}^{B} T_b(x) \tag{5.8}$$

The final output, $\hat{f}_{rf}^{B}(x)$, is calculated by averaging the outputs of all the trees.

By averaging over numerous trees, volatility is reduced, and predictive performance is stabilised. Because each tree generated during the bagging process is identically distributed $(i.d.)$, therefore the expectation of an average of B such trees is similar to the expectation of the individual (bootstrap) trees, thereby lowering variance and improving forecast performance (Hastie *et al.*, 2009).

Extreme Gradient Boosting (XGB)

XGB is a boosting ensemble learning developed by Chen and Guestrin (2016), which is a scalable tree-boosting system. The XGB model integrates several weak learner trees to develop a strong learner through additive learning, includes regularisation to prevent over fitting and improves the training process. It was improved based on a gradient-boosting algorithm, see Friedman (2001). For a given data set with n observations and m features $D = (x_i, y_i)(|D| = n, x_i = R^m, y_i \epsilon R)$, a tree ensemble model uses K additive function, which has a prediction function as follows:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \epsilon F \tag{5.9}$$

where $F = f(x) = w_q(x)(q : R^m - > T, w \epsilon R^T)$ is the space of regression trees (also known as CART, see (Hastie *et al.*, 2009). Here, q denotes the structure of each tree that corresponds to an observation's leaf index. The number of leaves on the tree is denoted by T. Each f_k is associated with an independent tree structure q and leaf weights w. Unlike decision trees, each regression tree has a continuous score associated with each leaf; we use ω_i to denote the score associated with the $i - th$ leaf. The XGB also applied a regularisation learning objective to help minimise overfitting with the given below:

$$L^{(t)} = \sum_{i=1}^{n} l(\hat{y}_i, y_i) + \omega(f_t) \tag{5.10}$$

where l denotes the loss function, n denotes the number of observations, and ω is the regularisation term expressed by:

$$\Omega(f) = \gamma T + 1/2\lambda||\omega||^2 \tag{5.11}$$

where ω is the score vector in the corresponding leaves, λ is the regularisation parameter, and γ is the mini loss. Then, we will add ft in the tree ensemble model in equations (5.10) and

(5.11) to minimise the following objective function:

$$L^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + Omega(f_t) \tag{5.12}$$

where $\hat{y}_i^{(t-1)}$ be the prediction of the $i-th$ instance at the $t-th$ iteration. Then, using the second-order approximation of the f_t that was greedily added in equation 5.12, we obtained the simplified objective function at step t.

$$L^{(t)} = \sum_{i=1}^{n} l(g_i f_t(x_i) + 1/2 f_t^2(x_i)) + Omega(f_t) \tag{5.13}$$

Support vector regression (SVR)

One of the popular supervised machine learning algorithms is the support vector machine (SVM), first proposed by Cortes and Vapnik (1995), which can be used for both classification and regression problems. It uses a distinct objective function compared to the least-squares or the shrinkage methods such as ridge and lasso regression and the elastic net. Hamel (2011) iterates that the SVM algorithm tries to find a line/hyperplane (in multidimensional space) that predicts or separates a data set into different classes, for example, two different groups, by using a small subset of training data points (called support vectors).

Suppose we are given a training data set consisting of n data points $\{(x_1, y_1), \cdots, (x_n, y_n)\}$ $\subset X$ x $\mathbb{R}$, where X represents the space of the input patterns (e.g. $X = \mathbb{R}_d$), with the input data x_i and d is the total number of data patterns, and output $y_i \in \mathbb{R}_d$. The basic SVR objective is to construct a function $f(x)$ that has a maximum ε deviation from the dependent variable, y_i, while being as flat as feasible for all the training data, see Smola and Schölkopf (2004). Therefore, we are unconcerned with errors as long as they are less than ε, but we will not tolerate deviations greater than this threshold. In the case of a linear function, given a regression training set, the specified equation is as follows:

$$f(x) = (w, x) + b \tag{5.14}$$

where w is the weight vector or coefficient, x is the input vector, and b is the bias. Flat, in the case of equation (5.14) means a small value of w. The b is then estimated by minimising the regularised function as a convex optimisation problem:

$$min\frac{1}{2}\left\|w\right\|^{2} \tag{5.15}$$

Subject to:

$$y_i - (w.x_i) - b \leq \varepsilon_i \tag{5.16a}$$

$$(w.x_i) + b - y_i \leq \varepsilon_i \tag{5.16b}$$

To solve the optimisation problem and obtain the estimation of w and b, equation (5.15) is then transformed into equation (5.17) with the introduction of slack variables, ξ_i and $\xi_i^{'}$, so that the objective function of support vector regression is written as folllows:

$$min\frac{1}{2}\left\|w\right\|^{2} + C\sum_{(i=1)}^{l}(\xi_i + \xi_i^{'}) \tag{5.17}$$

Subject to the constraints

$$y_i - (w.x_i) - b <= \xi_i + \varepsilon_i \tag{5.18}$$

$$(w.x_i) + b - y_i <= \xi_i^{'} + \varepsilon_i \tag{5.19}$$

$$0 \leq \xi_i, \xi_i^{'}, \tag{5.20}$$

$$For\ i = 1, 2, \cdots, l\ hold\ with\ f(x) = (w, x) + b \tag{5.21}$$

The constant penalty C modulates the trade-off between margin maximisation and the minimisation of the slack variables. In a supervised-learning setting of super vector regression, the training and test data are assumed to be independent and identically distributed (iid), derived from the same fixed but unknown probability distribution function (Awad and Khanna, 2015). This model can also be extended to non-linear regression by using the kernel trick.

5.4.2 Model estimation and hyperparameter optimisation

The empirical analysis begins with partitioning the dataset into test and training datasets for both the regressor and the target variable. The rule of thumb for the data splitting ratio commonly used in the classification case study is 70:30; for example, see Nguyen *et al.* (2021) and Vrigazova (2021). To the best of our knowledge, there appears to be no benchmark or guidelines in data splitting ratio for regression study case of machine learning models. Due to the small size of the dataset (84 observation period), we used the first 68 observations as a training set, while the remaining 16 data were used to evaluate the out-of-sample predicting accuracy (80:20). The testing data set will be extended to various ranges from 6 months, nine months, 12 months and a maximum period of 24 months (70:30), as commonly used by several central banks for inflation prediction, to determine the most effective data-splitting ratio with the lowest forecast error.

We employed a fivefold cross-validation technique to avoid overfitting; the testing subset that was set aside during the training process was then used to examine the model's generalisability (out-of-sample forecasting). We employ Python 3 with various libraries such as NumPy, Pandas, Sklearn, Matplotlib, and Statsmodels to perform analysis and predictions (the detail of the libraries is shown in Appendix Table D.3). The model is then estimated using data from the training set in this arrangement. To choose the ideal hyperparameters, it is necessary first to identify the parameters that reduce forecast error in the training data set to the lowest possible level. Once the hyperparameter tuning is complete, we will use the test set to evaluate the out-of-sample predictive accuracy of the fitted model.

Practically, while optimising hyperparameters with the training set, a validation procedure was carried out using cross-validation, and the training set was partitioned into training and validation sets (Figure 5.2). Cross-validation separates the data into five randomly generated partitions. One partition is reserved as a validation set. On the remaining four partitions, the model is fitted. Then, we specify the hyperparameters that we wish to optimise and the respective ranges to examine. We employ a search algorithm to find the optimal values for the hyperparameters, which minimises the forecast errors of the partitioned data set withheld. Each partition is then used as a validation set; the process is repeated until each partition has been processed. GridSearch is used to cross-validate hyperparameters in order to determine the best hyperparameters. See Feurer and Hutter (2019) and Yang and Shami (2020) for more detail. Based on the parameters suggested by GridSearch, we then try to find the best hyperparameter with the lower MSE and RMSE.

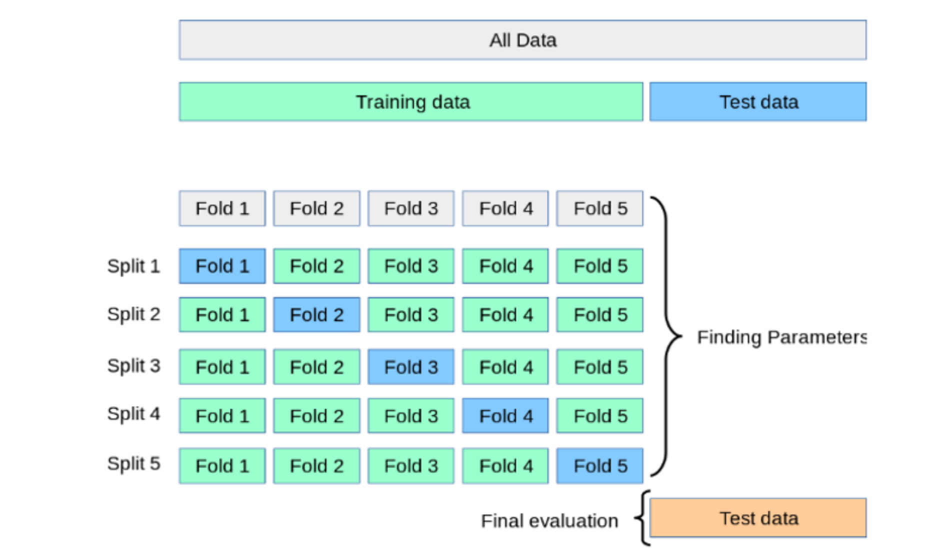


Figure 5.2: The procedure of Cross-Validation and finding model parameters
Source: Pedregosa et al. (2011)

This procedure is carried out without involving the test set. After optimising the hyperparameters, the test set is used to evaluate the model's out-of-sample forecasting ability. To avoid overfitting the model to the training data set, we restrict our search for hyperparameter values to a range of values based on prior research. This procedure enables the fitted models to analyse the unobserved test dataset. Table 5.1 summarises the hyperparameters optimised for each model, the range of values explored, and the proposed optimal values. When no value is supplied for a parameter, we use the default value of the Python Machine Learning algorithm.

5.4.3 Forecast evaluation methodology

After applying the obtained machine learning models to the test dataset, all proposed models are evaluated by comparing their forecast accuracy to the ARIMA regression model as a benchmark using various parameters such as RMSE (root mean square error) and MAE (mean absolute errors). MAE is the sum of the absolute values of prediction error or the difference between expected and actual values. According to Das and Cakmak (2018), it offers us an indication of the magnitude of the mistake, but we cannot tell whether the model is overpredicted or underpredicted. MAE is a measure strongly preferred and frequently used by both practitioners

Table 5.1: Hyperparameter range and value

Model	Hyperparameter	Range	Optimised value
Ridge	Lambda	0.001 to 0.9	0.001
Lasso	Lambda	0.001 to 0.9	0.001
Elastic net	Lambda	0.001 to 0.9	0.001
	Alpha	0.05 to 0.95	0.05
Random Forest	Max Depth	2 to 50	9
	Max Features	2 to 20	4
	n_estimator	10 to 1000	131
XGB	learning_rate	0.005 to 0.5	0.08
	n_estimators	10 to 1000	500
	max_depth	2, 4, 6, 8, 10	10
	Subsample	0.1 to 0.9	0.4
	Colsample_bytree	0.1 to 0.9	0.7
SVM	C	0.1 to 50	50
	Epsilon	0.0005 to 1	0.065
	Kernel function	Linear/Polynomial/RBF	Linear

Source: Author computation.

and academics to assess the forecast accuracy of machine learning models. MAE is calculated by using the following formula.

$$MAE = \sum_{(t=1)}^{n} \left[\frac{(y_t - \hat{y}_t)}{y_t} \right] \tag{5.22}$$

where y_t is the observed value, $\hat{y}_t$ is the forecast value of inflation, and n is the total number of observations. We also measure the forecast accuracy of each model by calculating the root of the mean squared error (RMSE), the average sum of squared errors. The lower the RMSE score, the better the model. It is formulated as follows:

$$RMSE = \sqrt{\frac{\sum_{(t=1)}^{n} (y_t - \hat{y}_t)^2}{n}} \tag{5.23}$$

where y_t and $\hat{y}_t$ are the actual and forecast values of inflation, respectively, and n is the total number of forecasts. Additionally, the Diebold-Mariano statistic test (Diebold and Mariano, 2002) is used to see if each of the ML model forecasts differs considerably from the benchmark model. By confirming the existence of the null hypothesis, the DM test determines the statistical significance by comparing the averages of the two loss functions (we choose MSE), thereby indicating that both models provide the same level of forecast accuracy.

5.4.4 Feature importance

In this study, we examine the feature importance of the proposed machine learning models using Shapley values, as suggested by Lundberg *et al.* (2020). Shapley feature importance is a model-agnostic which means that it can be applied to any machine learning model without regard to its specific characteristics. Shapley values are a measure of marginal contributions from a given feature on a particular model. This method originated from cooperative game theory that was introduced by Lundberg and Lee (2017) for the interpretation of machine learning prediction. It provides a general solution to the problem of attributing a reward obtained in a cooperative game to the individual players based on their contribution to the game, which is called SHAP (SHapley Additive exPlanations). Shapley values ϕ measure feature importances based on the relative contribution of a feature i, weighted and summed across all possible feature value combinations and is formally defined via a value function v given by:

$$\phi_{i(v)} = \sum S \subseteq F \setminus (i) \frac{|S|!(|F|-|S|-1)!}{|F|!} \left[f_{(S \cup i)}\ x_{(S \cup i)} - f_S(x_S)\right] \tag{5.24}$$

where S is a subset of the features used in the model and F is the complete set of all features, $f_{(S \cup i)}$ is a trained model that includes a given feature present, and f_S is a trained model that does not include the appointed feature. Then, we compare predictions from the two models on the current input $f_{(S \cup i)}\ x_{(S \cup i)} - f_S(x_S)$, where x_S represents the values of the input features in the set S. Following the computation of the preceding differences for all feasible subsets $S \subseteq F \setminus (i)$, the Shapley values are calculated and applied as feature importances that are averagely weighted over all conceivable differences. SHAP values are used to describe the change in model prediction when a feature is included in the model. Given a model $f(z)$, SHAP explains how features combine additively to shift the model's conditional expectation

$E[f(z)|z = x]$ away from the base value $E[f(z)]$. Then we average all these differences and result in:

$$\phi_i(x) = \frac{1}{M} \sum_{m=1}^{M} \phi_i^m \tag{5.25}$$

Obtaining aggregate Shapley values requires the technique to be performed repeatedly for each feature, where M refers to the number of iterations; for a more detailed explanation, see Molnar (2020). Although the aggregate analysis shows which variables are important, it does not explain how the model learned its functional form. Following Buckmann and Joseph (2022), a local Shapley decomposition will be carried out to investigate the importance of local factors in an individual prediction for each feature, based on previously fitted data in accordance with Lundberg *et al.* (2019), who was also suggested that the tree-based model has greater accuracy than other ML models such as the neural network.

5.5 Empirical Results

5.5.1 Model forecast performance

This section presents the result of the inflation forecast obtained by various machine learning algorithms compared to a time series model based on payment system data from January 2015 to December 2021 with a training-testing data split ratio of 80:20. The results found that all ML models generate forecasts with lower root mean square errors (RMSE) than the ARIMA benchmark. Indicated by the lowest RMSE and MAE values and DM test statistics, the XGB model outperforms univariate regression and other machine learning models that are able to minimise average forecast errors by 53.22 per cent relative to the benchmark.

Table 5.2: Performance metrics comparison of ML models and DM test related to the comparison with benchmark ARIMA model, 2020m9 – 2021m12

MODEL	PERFORMANCE METRICS			STATISTIC TEST	
	MAE	RMSE	RMSE Reduction (%)	DM TEST (Rel. to ARIMA)	$p-value$ (Rel. to ARIMA)
1. ARIMA (BM)	0.63	0.67			
2. SARIMA	0.503	0.527	21.31	3.988	0.001
3. OLS	0.35	0.406	39.39	3.508	0.003
4. Ridge	0.346	0.402	40.01	3.472	0.003
5. Lasso	0.298	0.34	49.3	4.695	0.000
6. Elastic net	0.317	0.364	45.62	4.216	0.001
7. Random Forest	0.351	0.417	37.76	4.462	0.000
8. XGB	0.264	0.313	53.22	4.875	0.000
9. SVR	0.315	0.368	45.07	4.442	0.000

Source: Author computation.

The Diebold and Mariano (1995) test statistics and the p-values of the DM test statistics, which are shown in the fifth and sixth columns of Table 5.2, are employed to evaluate the significance of forecast accuracy for each model relative to the ARIMA model, which serves as the benchmark. The results of the DM test indicate that the null hypothesis can be rejected, indicating that there are statistically significant differences between the forecasts produced by the ML models and the ARIMA benchmark. The results of the MAE and RMSE indicate that the ML methods significantly improve the accuracy of inflation rate prediction of the ARIMA benchmark by 45.16%. Figure 5.3 depicts the actual inflation rate and out-of-sample prediction derived from each machine-learning model from September 2020 to December 2021. As can be observed, the majority of machine learning models appropriately predict inflation volatility, with the XGB model exhibiting the best performance, followed by the lasso regression.

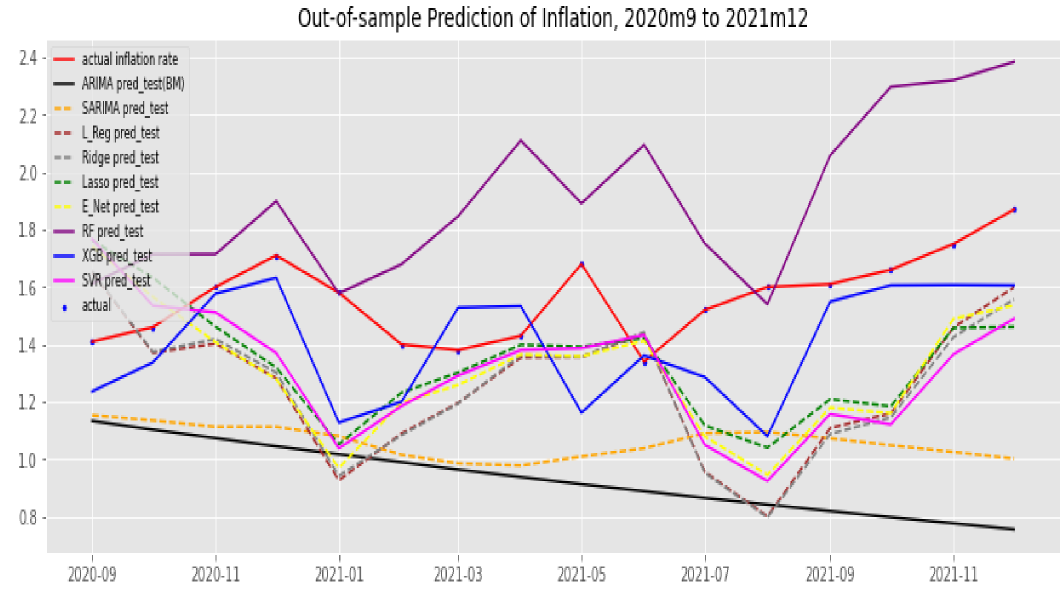


Figure 5.3: Out-of-sample prediction of the inflation rate of Indonesia of all ML models, 2020m9 to 2021m12

Source: Author

The ensemble learning model, notably XGB regression, produces exceptional outcomes in the out-of-sample prediction, while random forest does not perform well. Comparing the prediction outcomes for the entire sample period (training and testing datasets) of all ML models, we discovered that XGB regression models had the lowest RMSE and MAE. In addition to achieving the lowest forecast errors, the XGB was also able to precisely estimate the inflation rate in the case of an inflation decline in 2016 and throughout the Covid-19 pandemic period at the beginning of 2020 (see Figure 5.4). Moreover, the penalised regression model, lasso regression, predicts the inflation rate for the following sixteen months more accurately than more complicated ML models like Random Forest and SVR. This finding supports the argument of Gosiewska *et al.* (2021)that a simple ML model can achieve better performance than a complex ML model, which is favourable for interpretability and policy recommendation.

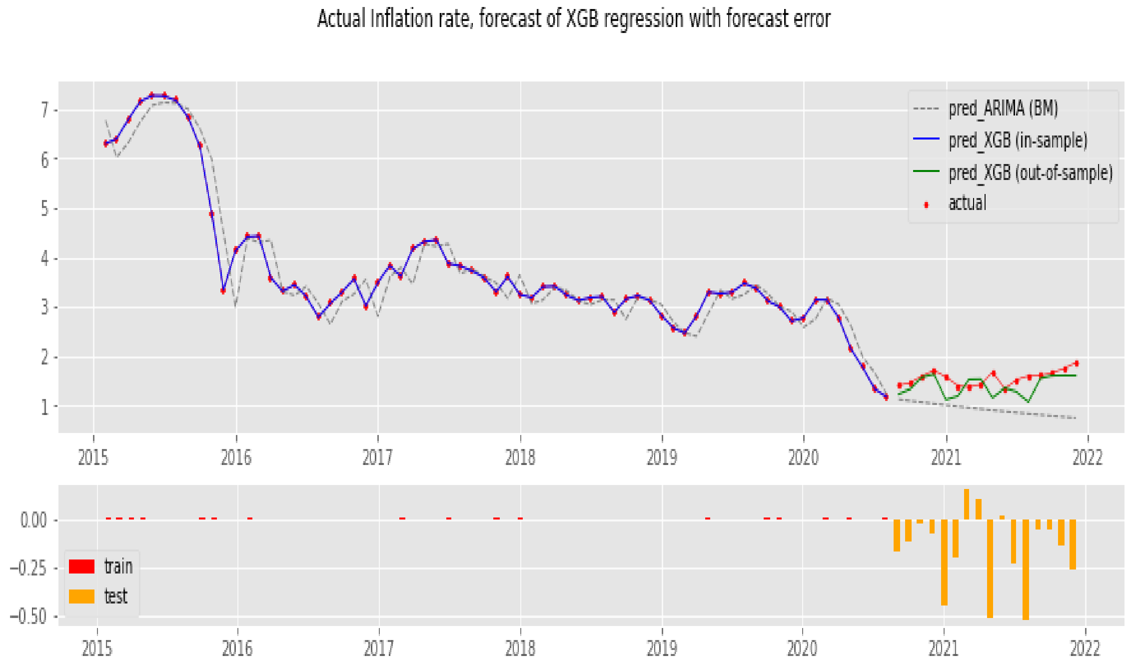


Figure 5.4: The inflation rate of Indonesia (log) for the period from 2015Q1 to 2021Q6 and forecast of XGB regression with forecast error

Source: Author

Our study finds that the XGB regression outperforms other machine learning and standard univariate econometric models, corroborating previous empirical studies. For example, Yoon (2021), and Richardson *et al.* (2021) forecast GDP using a macroeconomic dataset, and Lundberg *et al.* (2019) predict mortality risk and risk of kidney diseases with interpretation. The XGB prediction seems overfitting in the training dataset; however, it performs well in the out-of-sample prediction and a suggested ML model for forecast interpretation due to its lower bias (Lundberg *et al.*, 2020).

5.5.2 Impact of training and testing data split ratio on forecast accuracy

The observed ML models were also fitted to various training-to-testing data split ratios to evaluate their forecasting performance across different time periods. Figure 5.5 shows the root mean square error (RMSE) of inflation rate prediction from the time series econometric models and observed machine learning models with various data split ratios.

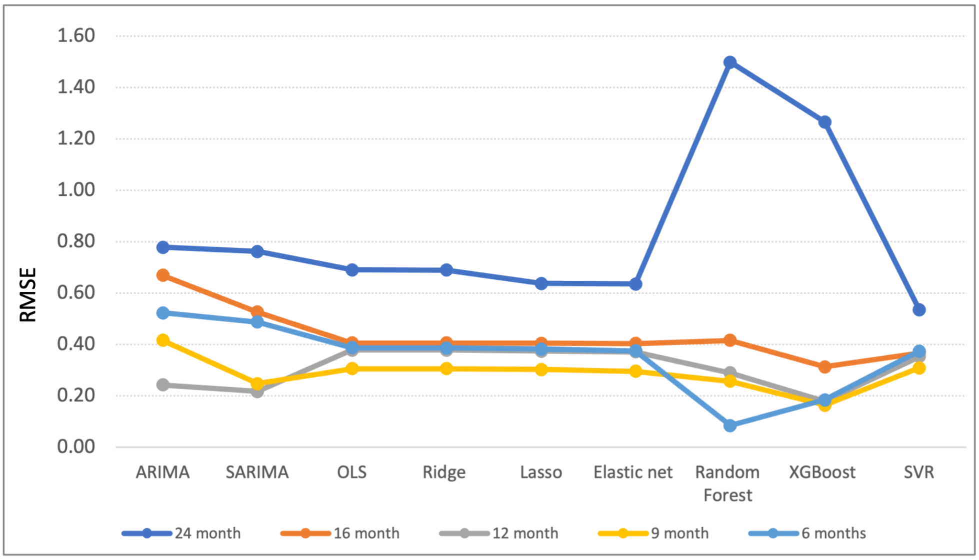


Figure 5.5: RMSE of the examined models for various out-of-sample prediction periods (24, 16, 12, 9, and 6 months)

Source: Author

The y-axis of Figure 5.5 depicts the various models examined in this study, whereas the x-axis indicates the root mean square error (RMSE) for inflation rate forecasts. In this research, we examine the accuracy of forecasts made by several ML models using 24, 16, 12, 9, and 6-month testing periods with diverse data splitting ratios. In general, the RMSE of the model's predictions falls as the testing data period decreases and the training data set increases. Nevertheless, the accuracy of each algorithm may vary depending on the size of the training and test sets. Despite the remarkable and consistent prediction performance of ensemble learning, Random Forest and XGB regression experience a rapid increase in forecasting error over the longer-term period (24 months).

Although most machine learning models can produce MAEs and RMSEs that are less than those of the ARIMA model in various out-of-sample periods, the prediction performance of univariate time series regression, ARIMA and SARIMA, on 12-month test data was found to be superior to that of all ML models with the exception of XGB. The results support the assertion made by Banerjee *et al.* (2005), who discovered that more complicated multivariate models did not easily defeat a simple univariate time series model.

5.5.3 Interpreting machine learning results

This study also presents the interpretation of the ML model's result, particularly ML with the highest prediction performance, the XGB, using the SHAP value to explain feature importance and causal inference. Our finding follows Lundberg *et al.* (2020), who advocate the use of the gradient-boosted tree model for ML's result interpretation due to its high accuracy and low bias, both local and global explanation using SHAP value.

Feature importance

Based on the XGB model's result, as suggested by Lundberg *et al.* (2019), we apply the TreeExplainer to compute the Shapley value to determine the contribution of each explanatory variable on the model output for each individual data from the training dataset. We then measure the global contribution from each feature on the model output that ranked according to the mean value of all Shapley values across the sample data, which is called feature importance. Figure 5.6 shows the impacting features on the inflation model output using SHAP values.

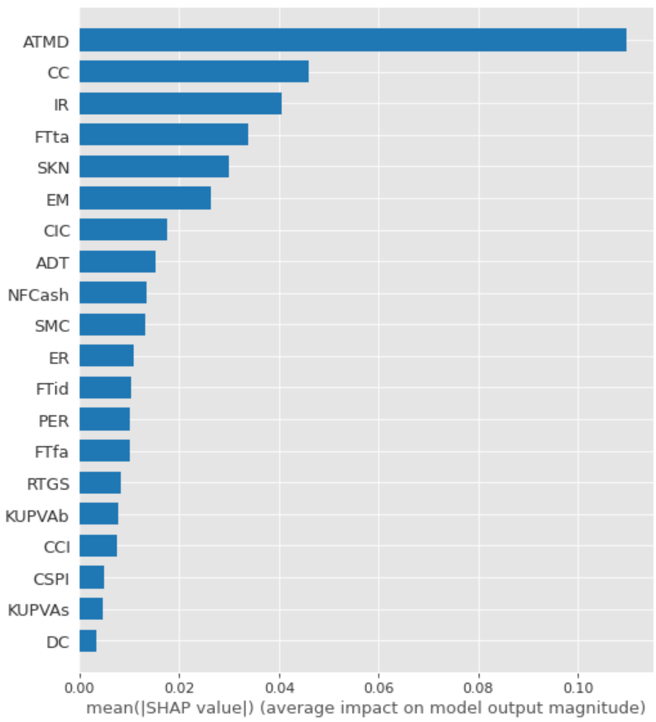


Figure 5.6: Feature Importance of Inflation dataset on XGB Prediction
Source: Author

Figure 5.6 depicts the ranking feature contribution to the model prediction using global SHAP values derived from the XGB model. The y-axis displays all the analysed features, while the x-axis displays the average magnitude of the SHAP values that illustrate the change in model output when we remove such a variable. The feature importance analysis reveals that ATM and debit cards (ATMD), credit cards (CC), and interest rates (IR) are the top three predictors that have significant contributions in predicting the inflation rate represented by the overall SHAP value in the XGB model. The study discovered that several indicators typically employed for inflation forecasting, particularly in the inflation targeting framework, or for macroeconomic forecastings, such as the exchange rate, the return of the capital market, and the composite price index, were found to be less significant than expected.

Feature importance explanation

Figure 5.7 shows the worldwide SHAP values in a summary plot for the XGB prediction model based on inflation rate data. In the summary plot, a high value for individual data of a feature corresponds to a red dot, while a blue dot represents a low value. The x-axis displays the SHAP value of individual data in each feature's prediction across the observation periods, which measures the extent to which the removal of a feature affects the change in prediction. It should be noted that the interpretation of summary plots for classification and regression ML models may have some common ground but may also differ at some point.

In the case of a classification ML model that classified the observed variable in a binary number, 0 does not have cancer, 1 for positive for cancer, and the result can be clearly interpreted, for example, as an increase of feature X1 will increase the risk of a person being diagnosed with cancer, whereas the feature X2 will have a negative effect on the probability that some individuals having cancer (for further explanation, see Lundberg *et al.* (2019). By observing the concentration of red dots with the positive Shapley value of feature credit card (CC) in Figure 9, we can conclude that a rise in the use of CC may lead to an increase in the inflation rate. In contrast, the cluster of blue dots in the positive Shapley value for the interest rate (IR) feature suggests that an increase in the IR may result in a decline in the inflation rate.

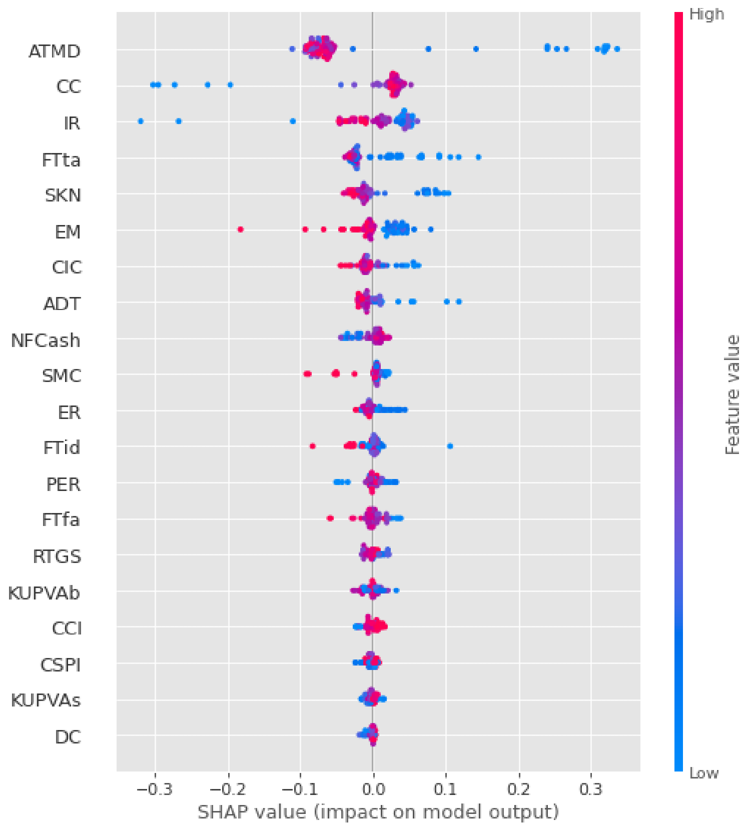


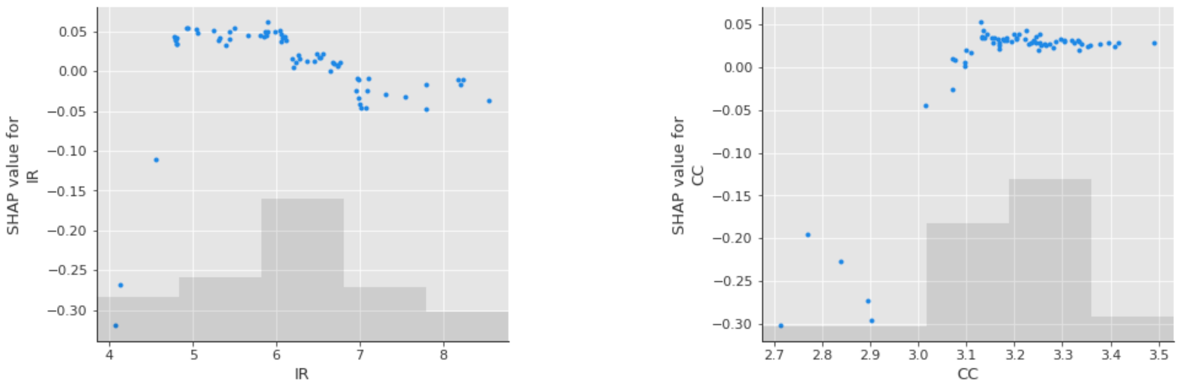
Figure 5.7: Summary plot of SHAP value of Inflation dataset based on XGB Prediction
Source: Author

However, is it reasonable to conclude that an increase in the usage of ATMD for transactions will lead to an increase in inflation? According to economic theory and most empirical studies, the increase in money or other forms of money resulted in a rise in the inflation rate, see Fender (2012) and Warjiyo and Juhro (2022). Consequently, time periods must be considered when interpreting the results of the ML regression model, as will be detailed in the following subchapter. In addition, since the XGB method is a nonparametric ML model, unlike linear models, the relative importance of each feature in determining the observed variable might shift as the model learns from the data.

Local Shapley Interpretation

1) Dependence Plot

After we examine the importance of each feature and determine how each feature affects the aggregate model performance using global SHAP values, we then explore the level of importance of each explanatory variable across different observation points of the dataset using the local Shapley values. We use dependence plots to comprehend the relationship between the value of each explanatory variable and the model's predicted outcomes, which are represented by the SHAP values of each observed point, as shown in Figure 5.8.

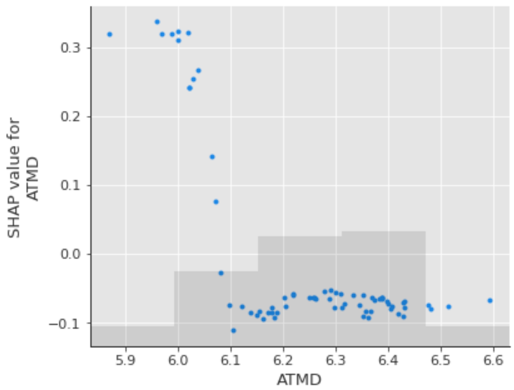


(a) Dependece Plot of Interest Rate (IR)

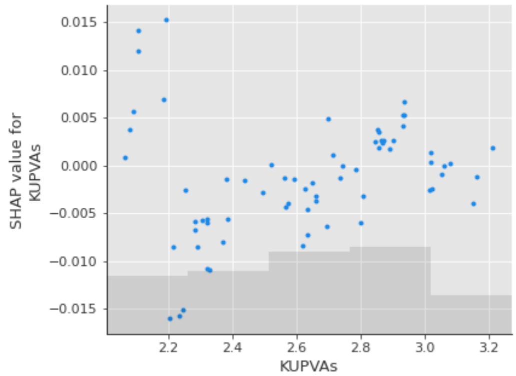
(b) Dependece Plot of Credit Card (CC)

Figure 5.8: Dependence plot of SHAP value of Interest rate (IR) and credit card usage (CC)

The outcome of the dependence plot depicted in Figure 5.8 can be interpreted as follows: SHAP values above the y-axis = 0 (positive) indicate a predicted increase in inflation, whereas SHAP values below the y-axis = 0 (negative) indicate a decrease in the prediction of inflation. As shown in Figure 5.8a, the dependence plot of interest rate demonstrates a negative slope, from positive to negative SHAP values, with a few outliers; therefore, an increase in interest rate led to a fall in the inflation rate. The point at which the distribution of SHAP values crosses the y-axis = 0 represents the threshold at which the model's prediction changes from an increase to a drop in the inflation rate, with the change occurring at an interest rate of approximately 6.6%. In contrast, Figure 5.8b shows that the credit card has a positive slope, and the majority of the dots have a positive value, indicating a positive relationship with the inflation rate; an increase in credit card transactions leads to an increase in inflation. This outcome is consistent with previous empirical research.



(a) Dependece Plot of ATM and Debit Card (ATMD)



(b) Dependece Plot of currency exchange-sale transactions (KUPVAs)

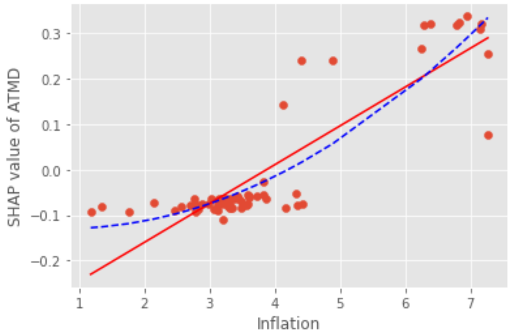
Figure 5.9: Dependence plot of SHAP value of ATM and Debit Card (ATMD) and currency exchange-sale transactions (KUPVAs)

Attempting to interpret the relationship between each predictor and the observed variable using a dependence plot can be challenging due to the limited amount of data included and the ambiguous pattern of the scatter plot. For instance, in the case of ATMD shown in Figure 5.9a, the SHAP values are predominantly negative throughout the periods, indicating a negative association with the inflation rate. The ATM or debit card provides access to a customer's savings account and the ability to make purchases; hence, it can be considered a type of money. Therefore, an increase in ATMD may influence the rise in money demand and, consequently, inflation (Pramono *et al.*, 2006). However, some researchers use debit cards (and other card payments) as a proxy for payment instrument innovation that may replace cash and make transactions more effective; hence, it negatively influences money demand which subsequently negatively impacts inflation. For instance, see Lippi and Secchi (2009) and Lubis *et al.* (2019).

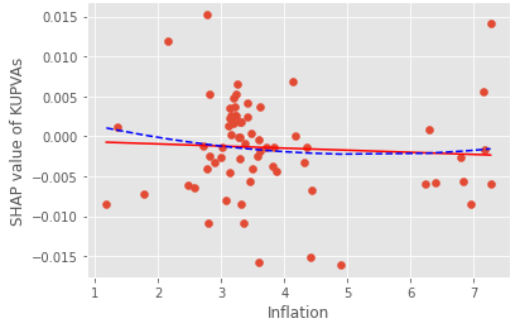
The dependent plot of currency exchange-sale transactions (KUPVAs), as represented in Figure 5.9b, reveals that the plot of SHAP values is randomly dispersed, presenting an ambiguous pattern. Taking into account the inconclusive result of the dependence plot of ATMD and KPUVAs, we construct a functional form of each feature's SHAP values and the observed value, following Buckmann and Joseph (2022), for an in-depth analysis.

2) Feature Functional Form

As indicated in the beeswarm plot in Figure 5.7, the functional form is built using local Shapley decompositions acquired by the XGB model. The functional form maps the local Shapley values of each feature individually to their observed values and visualises their relationship. Local Shapley decompositions were plotted using the best-fitting polynomials of the first and second degrees.



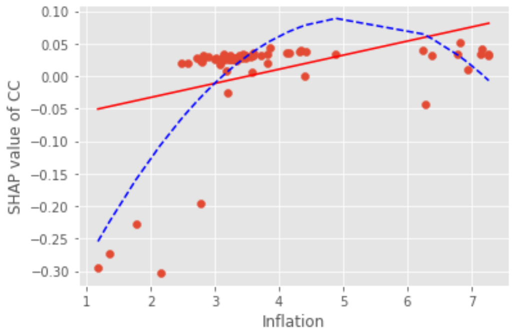
(a) Functional Form of ATM and Debit Card (ATMD)



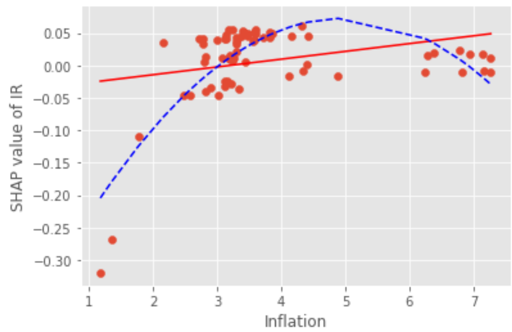
(b) Functional Form of of currency exchange-sale transactions (KUPVAs),

Figure 5.10: Functional Form of ATMD and SMC

For instance, Figure Figure 5.10, demonstrates the functional structure of ATMD and KUPVAs in the inflation prediction model. The data indicate that ATMD has a positive slope, indicating that an increase in the use of ATM and Debit cards leads to a rise in the inflation rate. This result is consistent with economic theory and prior economic research: for example, see Fender (2012) and McLeay *et al.* (2014). The functional form of ATMD and inflation rate provides a better explanation, supplementing the dependence plot as previously shown in Figure 5.9a. In contrast, the slope for currency exchange-sale transactions (KUPVAs) is flat, as illustrated in Figure 5.10b, indicating that its influence on inflation is negligible. The results align with the global SHAP value outcome presented in Figure 5.7, which suggests that KUPVA is the second least significant component inside the model.



(a) Functional Form of Credit Card



(b) Functional Form of of Interest Rate

Figure 5.11: Functional Form of Interest Rate and Stock Market Capitalisation

Figure 5.11 depicts other examples, including credit cards and interest rates. The functional form of credit cards (CC) suggests that rising credit card use is associated with rising inflation, which corroborates Geanakoplos and Dubey (2010). Figure 5.11b depicts the interest rate functional form, which suggests that increases in the interest rate lead to increases in inflation. This finding, however, contradicts the conventional literature on monetary policy and most empirical studies, which hold that an increase in the interest rate due to a contractionary central bank policy decreases inflation and economic activity in the short run, with a lagged effect, for example, see Agung and Juhro (2020) and Mæhle (2020).

Because the result of the dependent plot and the functional form for interest rate were contradictory, and the result of the functional form is ambiguous and contradicts the economic theory and previous research, further examination is needed, particularly in the technical aspect. Following Buckmann and Joseph (2022), we then remove the outliers or extreme input values to resolve the issue. Figure 5.12 shows the functional form of the interest rate after extreme values have been removed. The evidence suggests that interest rate has a negative impact on the inflation rate. Accordingly, we conclude that the functional form graph strengthens the dependence plot when explaining the outcome of ML prediction, especially when trying to comprehend the relationship between each feature or predictor and the observed variable.

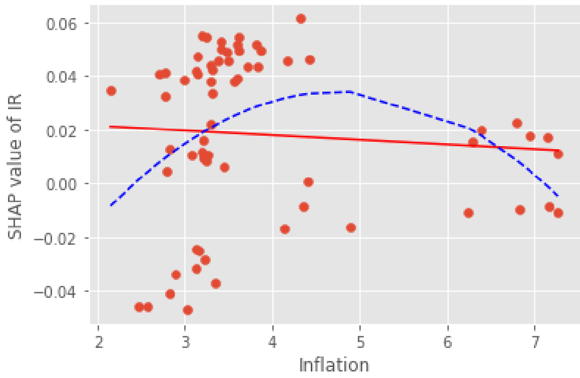


Figure 5.12: Functional form of Inflation (after outliers' removal)

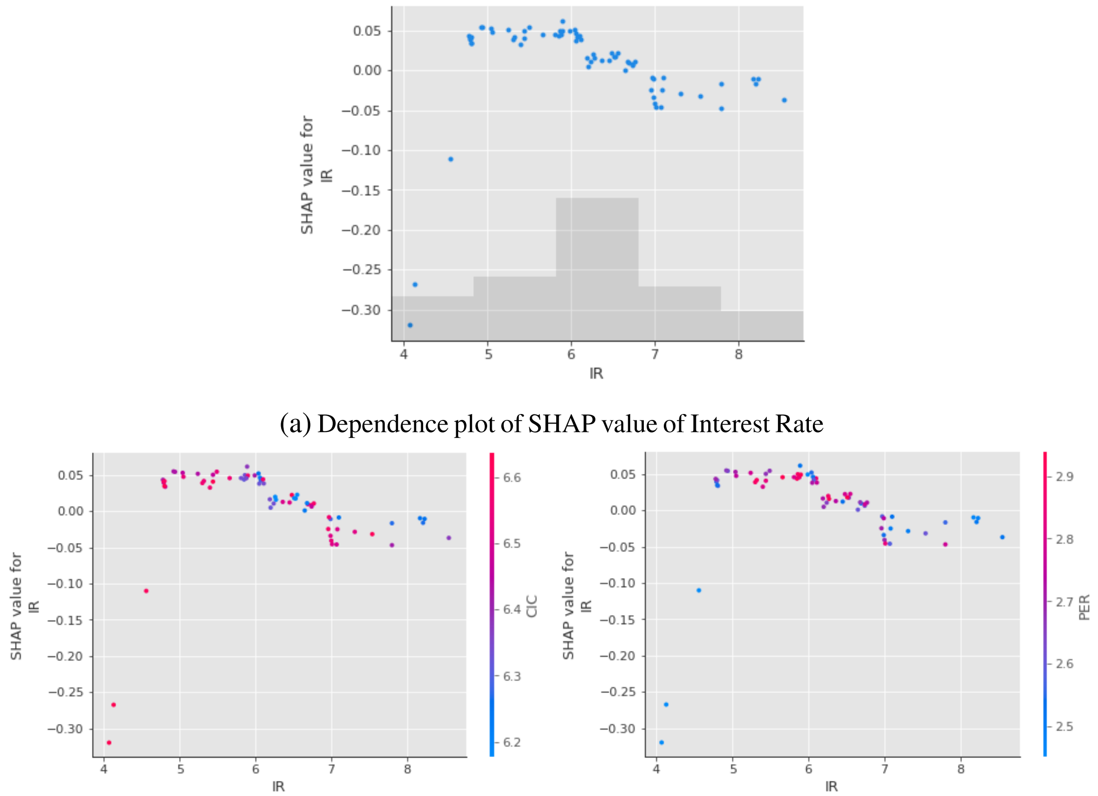
3) Interaction between features

We extend the use of dependence plots to capture not only the relationship between the SHAP value of each feature and the model's predicted outcomes but also the interaction between features during the observed period. As an illustration, we compare the dependence plots of interest rates with and without interactions with the price-earning ratio (PER) and the currency demand (CIC) in the XGB model equation as shown in Figure 5.13. Figure 5.13a depicts an interest rate dependence plot graph, with interest rate values shown on the x-axis and SHAP values (or model influence) indicated on the y-axis. Figures 5.13b and 5.13c illustrate the interaction of interest rates on currency demand (CIC) and the price-earnings ratio (PER), respectively, based on each feature's attribution to the model's forecast.

In the interaction dependence plot, each data point represents individual data in distinct periods of observations, coloured differently based on connected parameters, which are currency demand (CIC) and price earning ratio (PER), at the high and low values.

Figure 5.13b reveals that most data points with a notably low-interest rate correspond to higher currency demand (red dot); these data points have positive SHAP values. As the interest rate increases, SHAP values of IR decrease, and this relationship continues linearly as more data points with negative SHAP values. We discovered that the density of CICs with low values (blue dot) increases when the interest rate is high, despite the occurrence of a few CICs with high values. This finding corroborates the quantity theory of money and previous study, for example, Beyer *et al.* (2017) and Lubis *et al.* (2019).

In the case of the price-earning ratio (PER), most data points with low-interest rates correspond to a higher stock market earning ratio (red dot) with positive SHAP values, and vice versa. PER tends to decrease as the interest rate increases and SHAP values reduce. As demonstrated in Figure 5.13c, the



(a) Dependence plot of SHAP value of Interest Rate

(b) Interaction plot of IR and CIC

(c) Interaction plot of IR and PER

Figure 5.13: Dependence plot of Interest rate and interaction plot with other variables

negative relationship between IR and PER continues linearly to a more data point of low PERs (blue dot) gathered as SHAP values become negative, which corroborates Ehrmann and Fratzscher (2004) and Zhao and Bacao (2021).

Further discussion

The forecast error minimisation is the primary objective of ML models; this study discovered that the ML models successfully reduced the forecast error on average by 45.16% compared to ARIMA, a univariate time series model, with the ensemble models, especially the XGB model, performing the best. However, the performance of ensemble learning is not much superior to that of other ML models when used to make longer-term predictions (24 months). Therefore, while employing a regression ML model for prediction, it is crucial to consider the prediction period and data splitting ratios.

Using global SHAP values, this study exhibits that seven of the top ten most influential predictors are payment system variables; therefore, it is reasonable to conclude that payment system indicators are critical measures for inflation forecasting. Our findings are partially consistent with those of earlier studies that used data from payment systems for macroeconomic forecasting. For instance, a study by Aprigliano *et al.* (2019) demonstrated that payment system transaction data track economic activity and improve macroeconomic forecastings such as GDP, consumption, and investment. It was also confirmed by Chapman and Desai (2020) for forecasting macroeconomic indicators using payment system data during the Covid-19 pandemic period. However, its performance may vary slightly depending on the nowcasting scenario. Further examination using local SHAP value decomposition and dependence plot, we explain how each explanatory variable affects the inflation rate, as indicated by its contribution to the model prediction in the XGB model. We then use the functional form plot to emphasise the dependence plot's result in highlighting the relationship between each predictor and inflation.

Based on the dependence plot and functional form plot, we found that ATMD and credit card transactions positively impact the inflation rate, whereas interest rate has a negative impact on inflation. These results align with those of earlier empirical research mentioned above. To give a more accurate interpretation, we recommend removing some outliers data, with the result seen in Figure 5.12, and increasing the quantity of data input into the model. As seen in Figure 5.7, the Global SHAP value reveals that some variables are of low significance to the model. For instance, the currency exchange-sale transaction (KUPVAs) has a flat slope, as illustrated in Figure 5.10b. Similarly, the delivery channel transaction (DC) also demonstrates a flat slope, as depicted in Figure D.7b in the Appendix.

As seen in Figure 5.7, the Global SHAP value examination result reveals that some variables are of low significance to the model, for example, the currency exchange–sale transaction (KUPVAs) and delivery channel transaction (DC). These variables are then further examined using a dependence plot and functional form graph, showing scattered patterns and a flat slope, respectively, as shown in Appendix Figure D.4 and D.7. Another example is the exchange rate (ER); we found that an increase in the exchange rate leads to an increase in the inflation rate, as shown in the Appendix D.6 (Figure (b)), which corroborates with previous economic studies; for example, see Isnowati *et al.* (2020) and Amhimmid *et al.* (2021).

We explore how interest rates interact with other predictors based on their attribution to the model prediction of the XGB model using an interaction dependence plot. For example, an interest rate (IR) increase is associated with a low level of cash usage (CIC) and a decrease in capital market indicators such as stock market capitalisation (SMC), as depicted in the Appendix Figure D.9, which follows the previous study. Further explanation of the relationship between the interest rate and other variables in the XGB model is presented in the interaction-dependent plot graph shown in Appendix Figure D.8.

In addition to extreme input values exclusion, the independence assumption of explanatory variables is another technical aspect of machine learning interpretation that should be considered. Violating this assumption may lead to biased coefficient values, erroneous predictions, and distorted Shapley values, as suggested by Aas *et al.* (2021). The above discussion of how to interpret ML results sheds light on ML's data-driven nature and its ability to comprehend complex structures in economy-related issues. As a result, we believe that exploring machine learning models in the economics field would broaden the tools accessible to academics and policymakers for handling more complicated issues and comprehending more complex data, both structured and unstructured, in today's digital and borderless world.

We are in favour of using machine learning as an alternative method for economic forecasting, but we believe that in order for the ML used to be technically consistent and appropriately interpreted, especially for applied economics and policy implication analysis, the results must be made interpretable by adhering to guiding principles in forecasting such as the independent assumption of variables and the robustness check. The ML results should also be compared with econometric results and discussed with previous empirical studies.

5.6 Conclusion

This paper examines several prominent machine learning algorithms for estimating Indonesia's inflation rate from 2015 to 2021, utilising various payment systems, capital markets, and macroeconomic data. Overall, our findings indicate that all machine learning (ML) models produce forecasts with lower RMSEs than the ARIMA benchmark and can reduce average forecast errors by 45.16 % compared to the ARIMA benchmark. The RMSE, MAE, and Diebold-Mariano tests demonstrate that the XGB has the best forecasting performance. Generally, the accuracy of each algorithm varies with the size of the data split, and the forecast error of the model's predictions decreases as the ratio of testing data to training data decreases; however, Random Forest and XGB regression experience a worsening forecast error in the more extended period of data (24 months).

The feature importance analysis employing global and local SHAP values yielded several interesting results. First, ML forecast results can be appropriately interpreted using several tools, such as feature importance, dependence plots, and functional forms, which complement one another to provide a more accurate causal inference. The expansion of local Shapley decomposition could also shed light on the relationship between the explanatory variables within the ML model. However, caution is required in the interpretation, which must adhere to forecasting principles and be compared to existing economic theory and empirical study. Second, seven of the ten most influential predictors are payment system variables, indicating that payment system indicators are essential for inflation forecasting.

Finally, this study contributes to the growth of interdisciplinary research in applied economics and machine learning, which can deliver more relevant knowledge to the practice field than discipline-specific research alone. Our findings advocate the adoption of machine learning algorithms as complementary tools to assist the central bank in anticipating future conditions and comprehending its primary objective of maintaining price stability. Based on the empirical findings, this work encourages and supports further research in applying machine learning models to determine the causal relationship between economic variables, including incorporating more contemporary features, both structured and unstructured data.

Chapter 6

Conclusion

6.1 Conclusion and Policy Implication

Numerous nations have widely viewed the Inflation Targeting Framework (ITF) as the "state-of-the-art formula" for monetary policy. This recognition stems from empirical evidence indicating the presence of instability in the relationship between nominal income and money demand. This can be attributed to the rapid advancement of financial and payment system instruments, which presents a significant challenge for central banks in their efforts to manage the money base effectively. The increasing pace of innovation in payment systems, which has led to changes in people's behaviour, has raised concerns about the ability of central bank policies to manage public expectations and the overall economy effectively. In recent times, there has been a notable surge in technological advancements, specifically in the field of machine learning (ML). This advancement has led to its widespread adoption in various sectors, including the financial industry and other areas of the economy. Consequently, there is a growing interest and potential benefits in investigating the feasibility of employing machine learning techniques for macroeconomic prediction and analysis.

This thesis is focused on the area of study interest. This study focuses on analysing payment system-related subjects in Indonesia through the utilisation of several methodologies, including time series analysis and quantitative survey. In addition, we employ machine learning models to analyse payment system data, focusing on the central bank's advantage. Exploring the impact of payment systems on macroeconomics, how regulators and socioeconomic factors may influence people's behaviour in adopting new payment instruments, and how a contemporary approach and payment system statistics may be useful for optimizing economic forecasting are essential topics for central banks and policymakers who seek to improve the effectiveness of payment systems and monetary policy. The outcomes of our examination enabled us to address our primary research questions.

The conclusions drawn from the second chapter suggest that the money demand function in Indonesia is stable, with a suggested structural break in 2011Q2 related to the central bank's new policy regarding a new minimum reserve requirement for commercial banks. The results of the cointegration test and error correction models indicate a causal relationship between money demand, both narrow money demand and currency demand, and its traditional determinants (income and interest rate), as well as the technological advancement of the payment instrument. In order to maintain future monetary policy effectiveness, the study suggests that the central bank should have a comprehensive understanding of how technological advances in the payment system affect money demand and how previous central bank actions may have triggered a structural break in the economy.

The results of Chapter Three reveal that we successfully distinguished the effect of central bank intervention (LE) and the COVID-19 pandemic (FM) and the common risks associated with technology adoption (PR), which was absent from the prior study of technology adoption in the context of the pandemic. We introduced new latent variables to represent central bank policies, the pandemic, and the common risks associated with the adoption of new technologies. It is found that perceived central bank policy (LE) and pandemic risk (FM) were the most influential factors influencing the adoption of QRIS, which will be verified by the results of chapter four in a more complicated model. This research makes a substantial contribution to the literature on technology acceptance and assists policymakers in evaluating the significance of their policy and optimising public acceptability of a newly governmental technology product or service, particularly in the context of an unprecedented situation such as the COVID-19 pandemic.

In Chapter 4, I applied these new variables to the extended Unified Theory of Acceptance and Use of Technology (UTAUT 2) to test the consistency of the new additional variables with additional data gathered from the survey. Our study confirms our prior study's findings that pandemic (FM) and perceived government interference or law enforcement (LE) substantially affect behaviour intention to use QRIS, direct and indirect. Our research findings further indicate that the facilitating condition (FC) directly affects the intention to use QRIS; however, its influence was mediated by demographic variables such as age, gender, education, experience, and location, with the exception of user status. In addition, the habit was revealed to be the most influential factor influencing intention to use QRIS, outperforming all other conventional UTAUT2 variables. These findings contribute to the advancement of the theory of UTAUT2 and government intervention, as well as to business practice and regulatory advancements in the payment system industry.

Finally, the analysis of Chapter Five revealed that all ML models had lower RMSEs than the ARIMA benchmark and could reduce average forecast errors by 45.16 percentage points compared to the benchmark. We found that the accuracy of each technique varies depending on the amount of the data split based on evaluations of forecast error among selected ML models under various data splitting scenarios. The RMSE of the model's predictions reduces as the ratio of testing data to training data falls, although Random Forest and XGB regression experience a worsening forecasting error for the more extended period of data (24 months). Following Lundberg *et al.* (2019, 2020), we successfully interpret the results of ML forecasting using the SHAP value and examine them in light of economic theory and prior empirical research. Numerous payment system data and capital market indicators were found to be strongly predictive of inflation. Our findings suggest that monetary policy could benefit from a greater comprehension of people's policy responses and the use of ML models as an alternative forecasting tool.

Collectively, the empirical findings presented in this thesis suggest a number of policy implications. First, the conclusions of Chapter 2 indicate the long-term relationship between real money demand, real consumption, the policy rate, and payment instrument innovation. The suggested break corresponds to the central bank's release of a new policy to limit the influx of capital and neutralise its effect on domestic liquidity, as explained by Warjiyo (2017). This result implicitly addresses concerns regarding the possibility of a central bank policy weakening due to technological advancements in the payment system; for example, Tule and Oduh (2017) and Wiafe *et al.* (2022). Hence, to ensure the continued effectiveness of future monetary policy, the research proposes that the central bank should have a thorough comprehension of the impact of technological advancements in the payment system on the demand for money, as well as the potential structural shifts in the economy that may have been instigated by prior actions taken by the central bank.

Second, our findings in Chapters 3 and 4 confirmed that even in the presence of the COVID-19 pandemic, the central bank's policies (LE) significantly influence individuals' intentions to adopt a new payment platform. Our study was able to distinguish between the policy effect and the pandemic effect, as well as the effect of pandemic risk (FM) from common risks (PR) associated with the use of new technologies. These findings were confirmed in the basic UTAUT model (Venkatesh *et al.*, 2003) and the extended UTAUT model (Venkatesh *et al.*, 2012), with demographic variables serving as moderators. This research not only contributes significantly to the literature on technology acceptance but also provides an alternative measurement approach that can be used as a complementary tool to assess the impact of central bank policies on individual behaviour, as proposed by Coglianese (2012) and Kowalkiewicz and Dootson (2019). Because habit, force majeure, and perceived central bank's role are the most influential factors determining the adoption of QRIS in Indonesia, directly and indirectly, we suggest that the central bank could increase QRIS acceptance by optimising these three factors, i.e., by expanding public campaigns to promote QRIS as a new contactless payment instrument in collaboration with government publicity programmes to raise public awareness of pandemic protocols.

Lastly, our findings in Chapter 5 indicate that all machine learning (ML) models produce forecasts with lower RMSEs than the ARIMA benchmark, with the interpretation of the ML prediction result, which is rarely discussed in the previous ML study. Considering the result of the study that shows the advantages of ML for inflation prediction and the significance of the payment system, our study supports the need to incorporate machine learning algorithms as supplementary tools to aid the central bank in forecasting future conditions and comprehending its primary objective of maintaining price stability. Additionally, the use of payment system data may provide greater opportunities for optimising the prediction of inflation.

This thesis proposes that additional research is required to determine the causal relationship between payment system data and economic indicators using a variety of machine learning algorithms. It is recommended that the comparison of these ML models with econometric models employing a more sophisticated econometric approach, such as VAR/VECM or ARDL, expands the existing empirical findings and encourages additional research in this field. Furthermore, the inclusion of a broader range of non-traditional factors, such as data with a higher frequency encompassing both structured and unstructured data, could potentially lead to favourable results in the research.

In sum, this thesis has examined the economics of the payment system in Indonesia. It addresses numerous pertinent research problems related to macroeconomics, policy effect analysis, and the performance of contemporary ML forecasting tools, which employed various techniques and yielded intriguing results. With the rapid development of payment system technology, however, rigorous scientific research will be essential for the adequate evaluation of policy recommendations adopted to ensure, on the one hand, an increase in economic efficiency and monetary policy effectiveness and, on the other hand, the security and convenience of the public.

6.2 Limitations

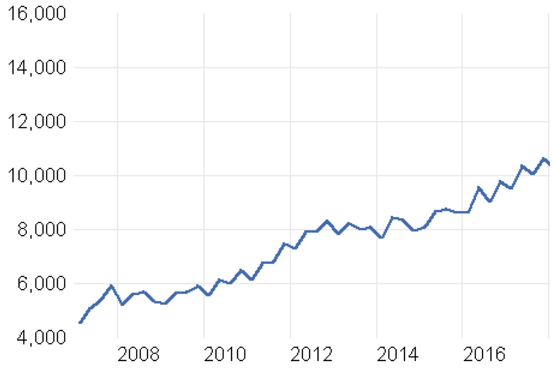
The major limitation of this thesis is the limited data on payment systems available for further analysis. For example, the data for electronic money has only been available since the year 2007, which is still aggregated of both card and digital e-money. The data of e-money is also only limited to the banking industry and e-money issued by fintech companies that voluntarily report to the central bank. However, the e-money data gathered represents the big player of e-money in the economy. Additionally, in our study, we did not consider cryptocurrency that might affect the money demand equation as examined by previous scholars in other countries because cryptocurrency is not legally regulated as a payment instrument in Indonesia. Future research may consider that the number of structural breaks could also be extended into more than one break to accommodate other possible policies or events that may cause structural breaks in the money demand equation.

There are some limitations that necessitate acknowledgement for chapters three and four. First, it is important to note that the QR standard, known as QRIS, is specially designed and implemented for the context of Indonesia. It is crucial to acknowledge that this standard may vary in its application and specifications in other countries. Hence, future research endeavours aiming to replicate this model for similar technology products and services in different countries had to take into account its specifications. Furthermore, despite its adequate size, the sample is limited in its ability to accurately represent all provinces and achieve comprehensive demographic classification, mostly due to constraints related to time and funding. It is recommended that the study be improved by increasing the sample sizes, particularly for merchant participants and across different geographical locations. This will enhance the generalizability of the findings and allow for a more comprehensive examination of the impact of demographic variables on the intention to use QRIS. The data collection approach employed in this study was a cross-sectional design, which was limited to the context of Indonesia during the COVID-19 outbreak. Consequently, it is not feasible to investigate the changes in user behaviour over time.

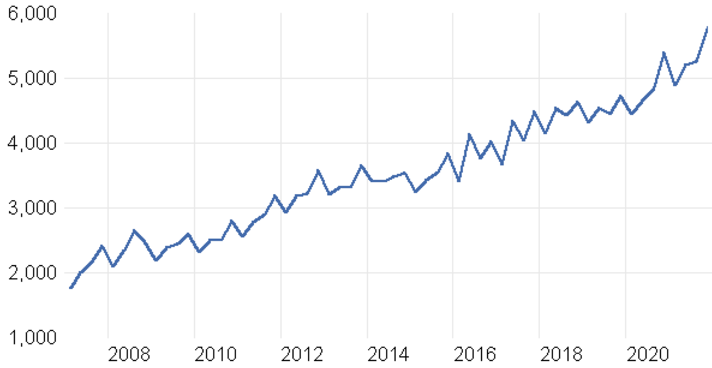
Although the local Shapley decomposition has the potential to offer valuable insights into the relationships between explanatory variables within a machine learning model, it is crucial to approach data interpretation with caution. It is important to ensure that such interpretation adheres to established forecasting principles and is rigorously compared to existing economic theory and empirical research. Furthermore, the objective of Chapter 5 was to investigate the potential of utilising payment system variables and financial market variables as predictors of inflation. This approach was chosen due to the comprehensive nature of payment system statistics, encompassing various economic activities such as consumption, saving, business transactions, and government expenditure. Additionally, the analysis was supplemented by capital market statistics that related to investment activities. Hence, the methodology employed in Chapter 5 can be characterised as a departure from economic theory, as it primarily relies on a data-driven approach inherent to machine learning models. The primary objective of this approach is to optimise predictive accuracy by minimising forecast error rather than delving into the exploration and interpretation of the relevant estimates for each determinant variable. We do acknowledge that the existing literature on forecasting inflation considers several macroeconomic variables, including the unemployment rate, industrial production, and real consumption, which are considered significant predictors of inflation. Hence, the aforementioned matter will be the focal point of investigation in forthcoming research, utilising a comprehensive econometric model as a standard for comparison. The further analysis will integrate macroeconomic indicators recommended by economic theory, more variables from payment systems data and the inclusion of unstructured data sources.

Appendix A

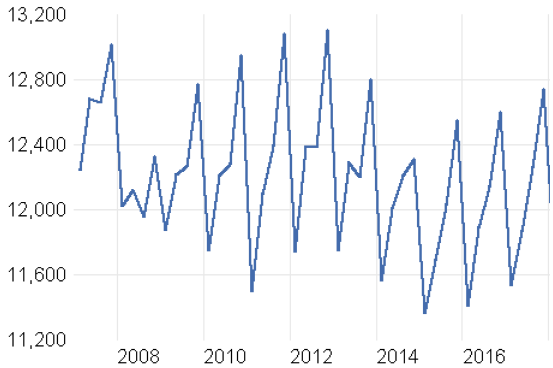
The data of Chapter 2



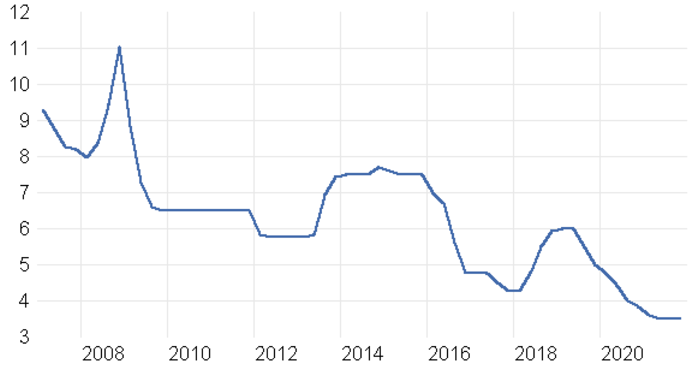
(a) Real Money Demand (RM1)



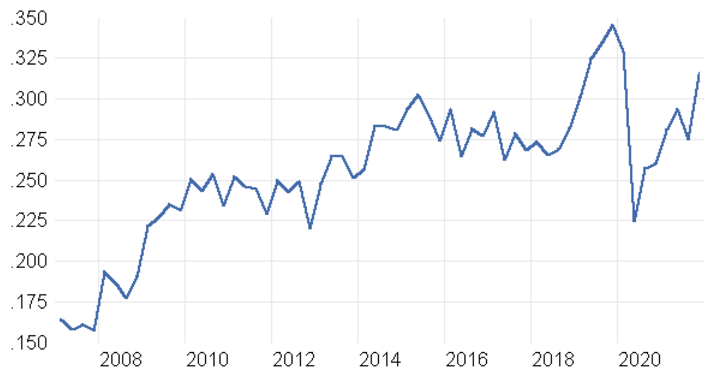
(b) Real Currency Demand (RCOB)



(c) Real Consumption (RCONS)



(d) Interest Rate



(e) Payment System Innovation

Figure A.1: Statistics of Payment System

Table A.1: Review of Previous Studies

No	Author	Data frequency	Dependent Variable(s)	Explanatory Variable(s)	Methodology used	Findings
1	Anglingkusumo (2005)	Quarterly data, 1981 to 2002	Real money balance (M1)	CPI, nominal deposit rate, household consumption.	Johansen Cointegration Test, and VECM	Co-integrating relationship of money balance (M1) determinants that is also interpreted as a constant velocity.
2	Pramono et al. (2006)	Monthly and quarterly data, 1999 - 2005	M1, Cash in Circulation (CUR)	Private Consumption, interest rate, Financial innovation (card payment (CP), credit card, ATM, CIC/CP, Consumption/CUR	Johansen Cointegration Test, vector error correction model (VECM)	Non-cash payment instrument negatively influence money demand (M1 and cash outside bank), thus Non-cash payment instrument may replace the role of cash payment for economic transaction.
3	Arintoko (2011)	monthly data, 2007 to 2017	money balance (M1)	Real GDP, policy rate and deposit rate, currency ratio and e-money.	Vector Error Correction Model (VECM)	Co-integrating relationship of money balance (M1) found with income, interest rates, currency ratio and e-money.
4	Zams (2018)	Monthly data, 2003M1 to 2016M6	Money demand (M1, M2), and the real divisia money (DM1 and DM2)	Real GDP, Deposit Rate, Exchange Rate, 3-Months Treasury Bills, CPI.	Johansen test, the G-H test and autoregressive distributed lag (ARDL)	Confirm the cointegration relationship between money demand (M1, M2), and the real divisia money (DM1 and DM2) and their determinants.

Continued on next page

Table A.1: – continued from previous page

No	Author	Data frequency	Dependent variable(s)	Explanatory variable(s)	Methodology used	Findings
						Real money demand in Indonesia is stable over the sample period.
5	Lubis et al. (2019)	Monthly data, 2005 to June 2017	Currency demand	Credit card (CC), GDP, Inflation, deposit rate, CC/Population, card payment infrastructure	Generalized method of moments (GMM) and VECM	Cointegrating relationship among variables of currency demand.
6	Mahatir et al.	Monthly data, 2009M1 to 2019M12	Money Supply	E-money, Interst Rate, Inflation	Johansen Cointegration Test, and VECM	Co-integrating relationship exist among variables of M1
7	Leong et al. (2021)	Quarterly data, 1996Q1 to 2019Q4.	Real M2 and divisia money	Real GDP, interbank rate (IR) and nominal exchange rate (ER).	ARDL and CUSUM/ CUSUMSQ test	Demand for money was stable in Indonesia.
8	Dekle and Pradhan (1997)	1974 to 1995	Narrow money demand (M1) and broad monet (M2)	Interest rate, ER	Johansen Cointegration Test,	Indonesia, Thailand, and Singapore have an unstable narrow money demand. The estimated real broad money equations are unstable for the ASEAN-4, except for Malaysia. The inclusion of dummy variables of financial liberalization policy on 1983 and 1988 does not help in achieving stability in Indonesia.

Continued on next page

Table A.1: – continued from previous page

No	Author	Data frequency	Dependent variable(s)	Explanatory Variable(s)	Methodology used	Findings
9	Doguwa (2014)	Quarterly data, 1991Q1 to 2013Q4.	Real broad money (M2)	real interest rate, income (GDP), Bureau de Change exchange rates, and ER premium.	the G-H test and CUSUM/ CUSUMSQ test	A stable demand function exists in Nigeria during pre- and post-global financial crisis period.
10	Dunne and Kasekende (2018)	1980–2013	Real M1	inflation rate, real GDP, nominal exchange rate, financial innovation (M2/M1).	panel data methods: Dynamic Fixed Effects (DFE), Mean Group (MG(Baumgartner and Homburg) , Pooled Mean Group (PMG)	Financial innovation has significantly negative impact on the demand for money in both the long run and the short run.
11	Mlambo and Msosa (2020)	Quarterly data, 1995 to 2014.	Money demand	Inflation, interest rates and GDP, and financial technology (Mobile Subscriptions and ATM).	GMM	A stable demand function exists in Nigeria during pre- and post-global financial crisis period.
12	Adil et al. (2020)	Quarterly data, 1996Q2 to 2016Q3.	Narrow Money demand (M1) and broad monet (M3)	GDP, interest rate, exchange rate, stock price, and financial innovation (a deterministic time-trend, and dummy variable).	ARDL and CUSUM/ CUSUMSQ test	A stable long-run relationship exists among money demand determinants in India. Financial innovation and institutional changes are important for money demand stability improvement.

Table A.2: Lag Length Selection Criteria for Specification 1 (Real Narrow Money Demand)

LAG	LOGL	LR	FPE	AIC	SC	HQ
0	275.901	NA	4.41e-10	-10.192	-9.586	-9.961
1	312.892	62.379	1.95e-10	-11.015	-9.803*	-10.552
2	337.074	36.983	1.45e-10	-11.336	-9.518	-10.641
3	367.425	41.658	8.72e-11	-11.899	-9.475	-10.973
4	387.317	24.183	8.19e-11	-12.052	-9.021	-10.894
5	409.431	23.415	7.44e-11	-12.291	-8.655	-10.902
6	450.301	36.863*	3.50e-11*	-13.267	-9.024	-11.646*
7	469.347	14.192	4.34e-11	-13.386	-8.538	-11.533
8	486.581	10.137	6.87e-11	-13.435*	-7.98	-11.350

Source: Author computation.

Table A.3: Lag Length Selection Criteria for Specification 2 (Real Currency Demand)

LAG	LOGL	LR	FPE	AIC	SC	HQ
0	289.473	NA	2.59e-10	-10.724	-10.118*	-10.493
1	316.801	46.082	1.68e-10	-11.168	-9.957	-10.706
2	333.253	25.162	1.69e-10	-11.186	-9.368	-10.492
3	373.142	54.749	6.97e-11	-12.123	-9.699	-11.197
4	390.806	21.475	7.14e-11	-12.189	-9.158	-11.031
5	401.940	11.789	9.99e-11	-11.998	-8.361	-10.608
6	444.104	38.031*	4.47e-11*	-13.024	-8.781	-11.403*
7	465.745	16.125	5.00e-11	-13.245	-8.396	-11.392
8	485.481	11.609	7.17e-11	-13.391*	-7.937	-11.307

Source: Author computation.

Table A.4: Results Using Alternative Measures for Payment System Innovation and Additional of the Control Variable

INDEPENDENT VARIABLES	MONEY AGGREGATES					
	LRM1			LRCOB		
C	6.451*** (10.655)	7.332*** (8.673)	7.067*** (7.891)	5.372*** (6.267)	4.018*** (3.395)	3.158** (2.611)
LRCONS	0.429*** (3.724)	0.323** (2.447)	0.365*** (2.716)	0.447*** (2.737)	0.608*** (3.291)	0.678*** (3.734)
IR	-0.014** (-2.472)	-0.011* (-1.748)	-0.010 (-1.574)	-0.001 (-0.080)	-0.009 (-1.076)	-0.013 (-1.413)
PSINV		-0.404* (-1.8434)			-0.521* (-1.698)	
ATM/COB	-0.520 (-1.210)		-0.146 (-0.249)	-0.132 (-0.216)		-1.476* (-1.859)
CPI		-0.004 (-1.212)	-0.005 (-0.934)		0.010* (1.926)	0.017** (2.485)
trend	0.020*** (14.395)	0.024*** (6.139)	0.025*** (4.513)	0.019*** (9.843)	0.009 (1.621)	0.001 (0.180)
Dum11Q2	0.109*** (5.163)	0.104*** (5.468)	0.103*** (4.663)	0.118*** (3.961)	0.119*** (4.461)	0.140*** (4.690)

Appendix B

The questions of indicators and latent variables of Chapter 3

Table B.1: Questions of indicators and latent variables using UTAUT and new variables

FACTORS	INDICATORS
Performance Expectancy	1. I find QRIS (QR code Indonesian Standard) useful in my daily life.
	2. Using QRIS (QR code Indonesian Standard) helps me accomplish things more quickly.
	3. Using QRIS (QR code Indonesian Standard) increases my productivity.
Effort Expectancy	1. Learning how to use QRIS (QR code Indonesian Standard) is easy for me.
	2. My interaction with QRIS (QR code Indonesian Standard) is clear and understandable.
	3. I find QRIS (QR code Indonesian Standard) easy to use.
	4. It easy for me to become skilful at using QRIS (QR code Indonesian Standard).
Social Influence	1. People who influence my behaviour think that I should use QRIS (QR code Indonesian Standard).
	2. People who are important to me think that I should use QRIS (QR code Indonesian Standard).
	3. People whose opinions that I value prefer that I use QRIS (QR code Indonesian Standard).
Facilitating Conditions	1. I have the resources necessary to use QRIS (QR code Indonesian Standard).
	2. I have the knowledge necessary to use QRIS (QR code Indonesian Standard).
	3. QRIS (QR code Indonesian Standard) is compatible with other technologies I use.
	4. I can get help from others when I have difficulties using QRIS (QR code Indonesian Standard).
Perceived Risk	1. I am worried that my personal information can be stolen in the transaction using QRIS (QR code Indonesian Standard).
	2. I think using QRIS (QR code Indonesian Standard) can cause me to lose money, or my transaction might be altered by someone else.
	3. Overall, I believe that the overall risks of QRIS (QR code Indonesian Standard) are high.
Force Majeure	1. I think using QRIS (QR code Indonesian Standard) is safer (in this pandemic period).
	2. I think using QRIS (QR code Indonesian Standard) is necessary to avoid jeopardy.
Law Enforcement	1. I was suggested by the authority to use QRIS (QR code Indonesian Standard) for the particular transaction.
	2. I think the authority's suggestion to use QRIS (QR code Indonesian Standard) was beneficial to me.
Behavioural Intention	1. I intend to continue using electronic money in the future.
	2. I will always try to use QRIS (QR code Indonesian Standard) in my daily life.
	3. I plan to continue to use QRIS (QR code Indonesian Standard) frequently.

Appendix C

The questions of indicators and latent variables and results of Chapter 4

Table C.1: Questions of indicators and latent variables using UTAUT2

FACTORS		INDICATORS
A Performance Expectancy	1.	I find QRIS (QR code Indonesian Standard) useful in my daily life.
	2.	Using QRIS (QR code Indonesian Standard) helps me accomplish things more quickly.
	3.	Using QRIS (QR code Indonesian Standard) increases my productivity.
B Effort Expectancy	1.	Learning how to use QRIS (QR code Indonesian Standard) is easy for me.
	2.	My interaction with QRIS (QR code Indonesian Standard) is clear and understandable.
	3.	I find QRIS (QR code Indonesian Standard) easy to use.
	4.	It easy for me to become skilful at using QRIS (QR code Indonesian Standard).
C Social Influence	1.	People who influence my behaviour think that I should use QRIS (QR code Indonesian Standard).
	2.	People who are important to me think that I should use QRIS (QR code Indonesian Standard).
	3.	People whose opinions that I value prefer that I use QRIS (QR code Indonesian Standard).
D Facilitating Conditions	1.	I have the resources necessary to use QRIS (QR code Indonesian Standard).
	2.	I have the knowledge necessary to use QRIS (QR code Indonesian Standard).
	3.	QRIS (QR code Indonesian Standard) is compatible with other technologies I use.
	4.	I can get help from others when I have difficulties using QRIS (QR code Indonesian Standard).
E Hedonic Motivation	1.	UsingQRIS (Quick Response Indonesian Standard) is fun.
	2.	Using QRIS (Quick Response Indonesian Standard) is enjoyable.
	3.	Using QRIS (Quick Response Indonesian Standard) is very entertaining.
F Price Value	1.	QRIS (Quick Response Indonesian Standard) is reasonably priced
	2.	QRIS (Quick Response Indonesian Standard) is a good value for the money.
	3.	At the current price QRIS (Quick Response Indonesian Standard) value provides a good value.
G Habit	1.	The use of QRIS (Quick Response Indonesian Standard) has become a habit for me.
	2.	I am addicted to using QRIS (Quick Response Indonesian Standard).
	3.	I must use QRIS (Quick Response Indonesian Standard).
H Perceived Risk	1.	I am worried that my personal information can be stolen in the transaction using QRIS (QR code Indonesian Standard).
	2.	I think using QRIS (QR code Indonesian Standard) can cause me to lose money, or my transaction might be altered by someone else.
	3.	Overall, I believe that the overall risks of QRIS (QR code Indonesian Standard) are high.
Force Majeure	1.	I think using QRIS (QR code Indonesian Standard) is safer (in this pandemic period).
	2.	I think using QRIS (QR code Indonesian Standard) is necessary to avoid jeopardy.
I Law Enforcement	1.	I was suggested by the authority to use QRIS (QR code Indonesian Standard) for the particular transaction.
	2.	I think the authority's suggestion to use QRIS (QR code Indonesian Standard) was beneficial to me.
J Behavioural Intention	1.	I intend to continue using electronic money in the future.
	2.	I will always try to use QRIS (QR code Indonesian Standard) in my daily life.
	3.	I plan to continue to use QRIS (QR code Indonesian Standard) frequently.

Table C.2: Results of structural modelling analysis with moderating varables

FACTORS	PATH COEFFICIENT	T-VALUE	P-VALUE	DECISION
*Age * FC -> Behavioural Intention*	-0.099	3.29	0.001	Supported
*Age * FM -> Behavioural Intention*	0.049	1.132	0.258	Not Supported
*Age * Habit -> Behavioural Intention*	0.049	1.181	0.238	Not Supported
*Age * LE -> Behavioural Intention*	0.05	1.149	0.25	Not Supported
*Sex * FC -> Behavioural Intention*	-0.098	3.34	0.001	Supported
*Sex * FM -> Behavioural Intention*	0.047	1.126	0.26	Not Supported
*Sex * Habit -> Behavioural Intention*	0.05	1.204	0.229	Not Supported
*Sex * LE -> Behavioural Intention*	0.05	1.153	0.249	Not Supported
*Edu * FC -> Behavioural Intention*	-0.097	3.328	0.001	Supported
*Edu * FM -> Behavioural Intention*	0.048	1.136	0.256	Not Supported
*Edu * Habit -> Behavioural Intention*	0.05	1.193	0.233	Not Supported
*Edu * LE -> Behavioural Intention*	0.049	1.138	0.255	Not Supported
*When * FC -> Behavioural Intention*	-0.098	3.352	0.001	Supported
*When * FM -> Behavioural Intention*	0.049	1.131	0.258	Not Supported
*When * Habit -> Behavioural Intention*	0.05	1.193	0.233	Not Supported
*When * LE -> Behavioural Intention*	0.049	1.133	0.257	Not Supported
*Location * FC -> Behavioural Intention*	-0.098	3.223	0.001	Supported
*Location * FM -> Behavioural Intention*	0.049	1.133	0.257	Not Supported
*Location * Habit -> Behavioural Intention*	0.049	1.174	0.240	Not Supported
*Location * LE -> Behavioural Intention*	0.05	1.145	0.252	Not Supported
*User Stat * FC -> Behavioural Intention*	-0.010	0.742	0.458	Not Supported
*User Stat * FM -> Behavioural Intention*	-0.018	0.079	0.937	Not Supported
*User Stat * Habit -> Behavioural Intention*	-0.041	1.019	0.308	Not Supported
*User Stat * LE -> Behavioural Intention*	0.029	0.356	0.722	Not Supported

Source: Author computation.

Appendix D

The data of Chapter 5

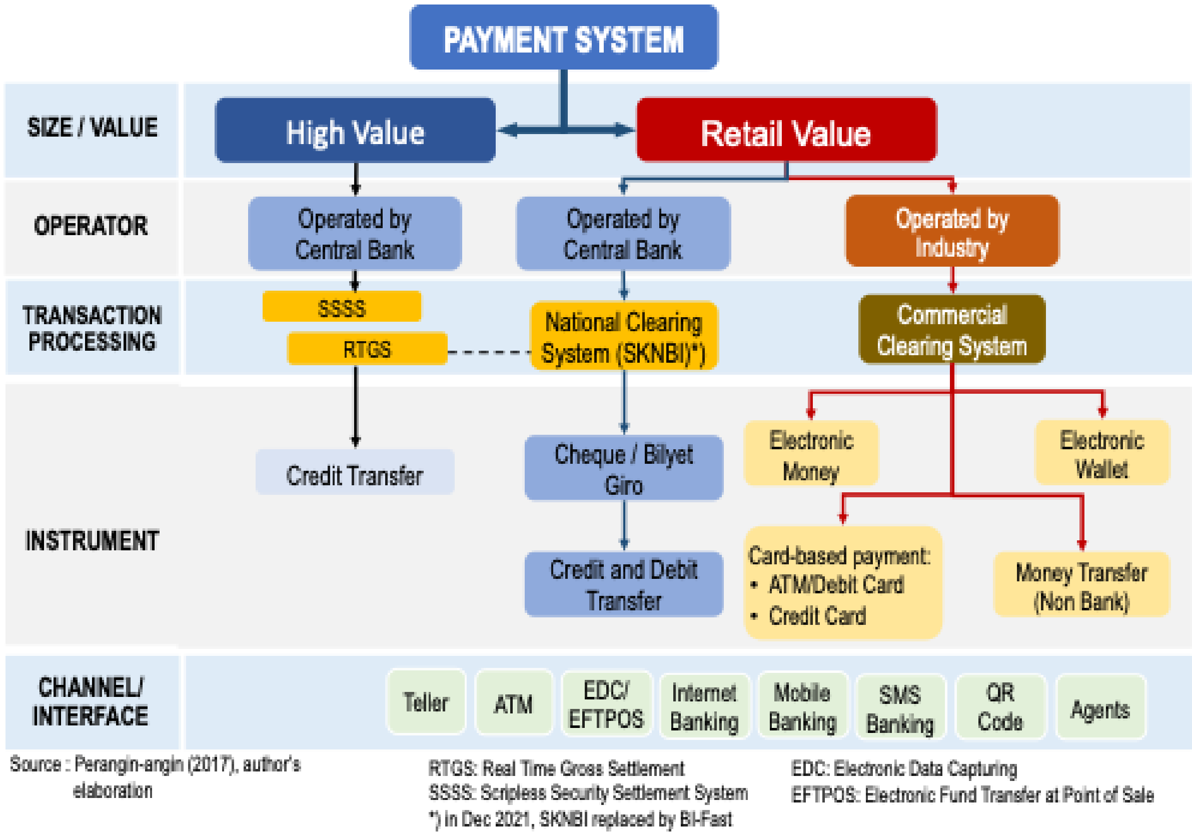


Figure D.1: The payment system in Indonesia

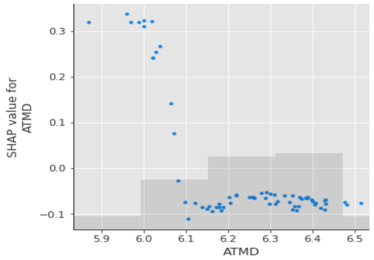
Table D.1: Descriptive Statistics

Variable	Mean	Std Deviation	Min	Max	No. Obs.
EM	7611.99	9246.98	212.10	35100.10	96
ATMD	522.53	100.43	318.46	730.94	96
CC	23.49	3.56	15.09	32.83	96
CIC	645.31	129.41	442.48	959.81	96
NF_Cash	5.62	45.16	-122.19	150.66	96
DC	1930.80	817.92	879.76	4383.59	84
RTGS	5951.68	1090.37	3730.29	9307.35	96
SKN	316.76	64.32	217.62	511.24	96
FTta	3254.23	5828.07	69.97	46989.26	96
FTfa	4717.35	1600.36	590.81	8085.51	96
FTid	7027.35	9001.76	128.75	39177.01	96
KUPVAb	14.13	4.93	7.58	33.98	96
KUPVAs	13.99	4.53	7.57	24.87	96
ER	13679.86	910.44	11404.00	16367.00	96
JIBOR	5.92	1.41	3.55	8.55	96
CSPI	5557.17	644.35	4223.91	6605.63	96
SMC	6150642.46	989160.53	4374682.33	8255623.54	96
ADT	8416.30	3052.87	4389.63	20513.34	96
PER	14.73	2.84	9.35	21.87	96
CCI	112.87	13.52	77.31	128.17	96
IF	3.76	1.87	1.18	8.43	96

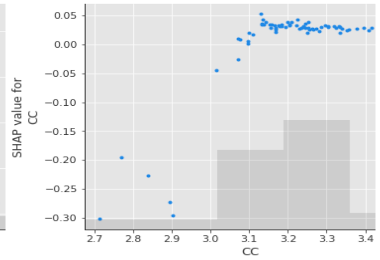
Table D.2: Important indicators of payments system and other variables used in this study

No	Label	Short Description	Unit
1	RTGS	BI-RTGS transaction value comprises customer transactions, interbank money market, government, and monetary management transactions, among others.	Billions of Rp
2	SKNBI	National Clearing turnover is broken down by transaction type. It includes credit clearing (bulk and individual credit transfers), debit clearing (bulk and individual checks, bilyet giro, and others), and pre-fund and pre-fund usage (for credit and debit clearing).	Billions of Rp
3	ATMD	ATM and debit card transactions include cash withdrawals, purchases, and intra- and inter-bank transfers.	Billions of Rp
4	CC	Credit card transactions include withdrawals of cash and purchases.	Billions of Rp
5	EM	Electronic money transactions are classified into the following categories: purchasing, initialization and top-up, transfer between e-money, cash withdrawal, and redemption.	Billions of Rp
6	DC	The delivery channel refers to transactions that are completed over the phone, via SMS, mobile banking, or over the internet.	Billions of Rp
7	FT	Money transfer by nonbank includes: i) international outgoing fund transfers (FTta), ii) incoming fund transfers or transfers from abroad (FTfa), and iii) fund transfers within the Indonesian territory (FTid).	Billions of Rp
8	KUPVA	The value of currency exchange transactions comprises of: i) buy transactions (KUPVAb) and ii) sell transactions (KUPVAs).	Billions of Rp
9	CIC	Cash data include currency in circulation (CIC) and the difference between deposit and withdrawal transactions to the central bank (NFCash).	Billions of Rp
10	ER	Exchange rate (ER) of USD against Indonesian	Rupiah Rp
11	IR	One-month money market interest rate (IR), taken from Jakarta Interbank Offered Rate (JIBOR)	%
12	CSPI	Composite Stock Price Index, end period	point
13	SMC	Stock Market Capitalization	Billions of Rp
14	ADT	Average Daily Trading	Billions of Rp
15	PER	Price Earning Ratio (PER), average	times
16	CCI	Consumer Confidence Index	point

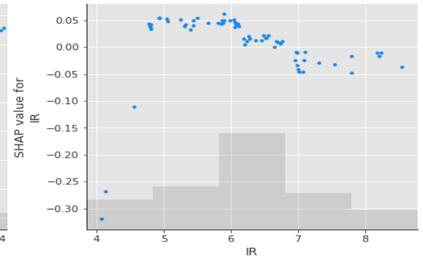
Dependence plot of the XGB result



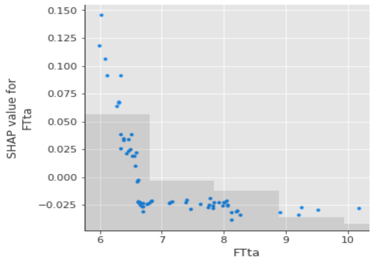
(a) ATM and Debit Card



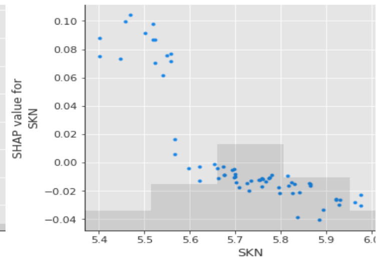
(b) Credit Card



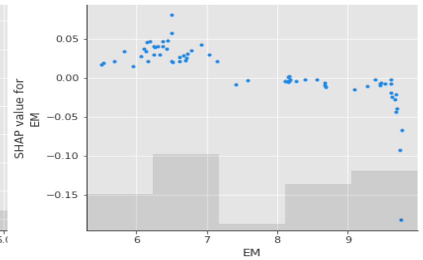
(c) Interest Rate



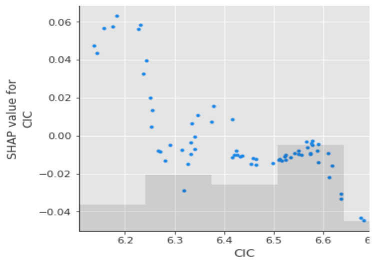
(d) Fund Transfer (to abroad)



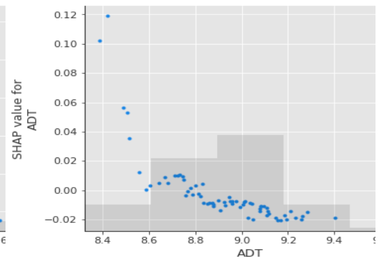
(e) National Clearing (SKN)



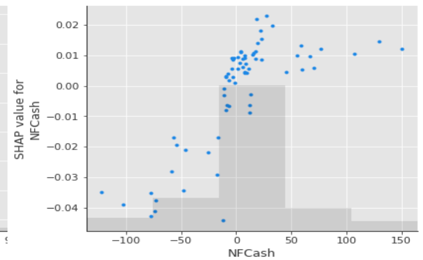
(f) Electronic money



(g) Cash in Circulation (CIC)



(h) Average Daily Trading (ADT)



(i) Net flow cash (NFCash)

Figure D.2: Dependence plot of all explanatory variables (1)

Dependence plot of the XGB result (2)

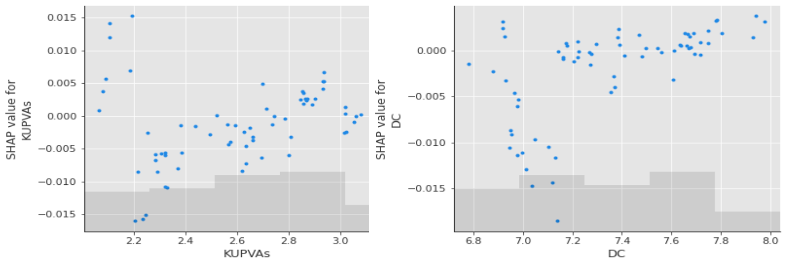
(a) Stock Market Capitalisation (b) Exchange Rate (ER) (c) Fund Transfer-local (FTid)

(d) Price Earning Ratio (PER) (e) Fund Transfer-from abroad (f) Real time gross setlement

(g) Currency exchange-buy (h) Consumer confidence index (i) Composite stock price index

Figure D.3: Dependence plot of all explanatory variables (2)

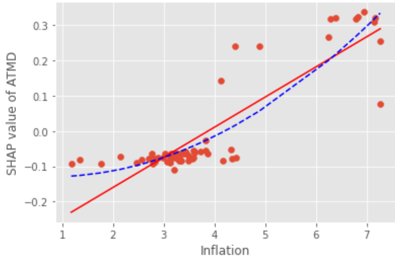
Dependence plot of the XGB result (3)



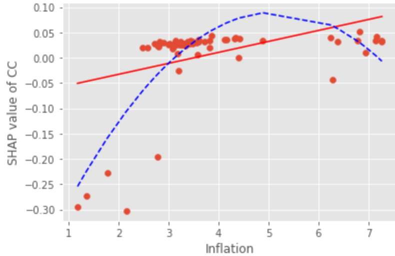
(a) Currency exchange - sell (b) Delivery channel (DC)

Figure D.4: Dependence plot of all explanatory variables (3)

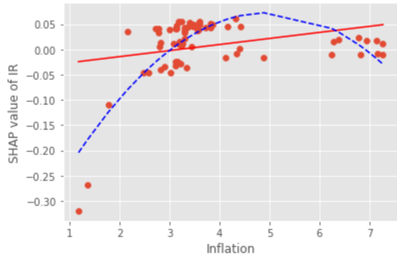
Functional form plot of the XGB result



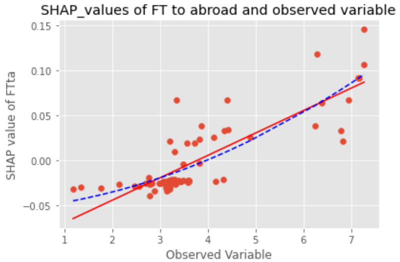
(a) ATM and Debit Card (ATMD)



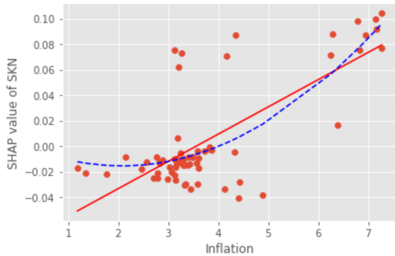
(b) Credit Card (CC)



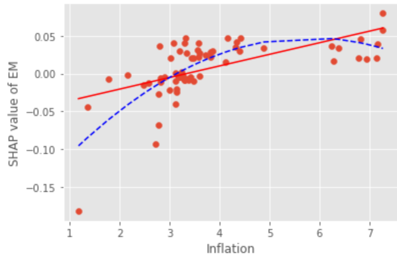
(c) Interest Rate (IR)



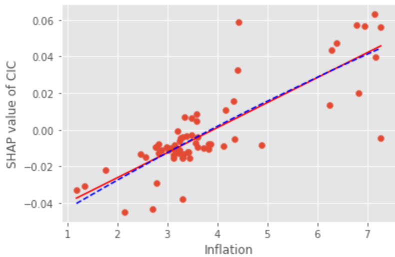
(d) Fund Transfer (to abroad)



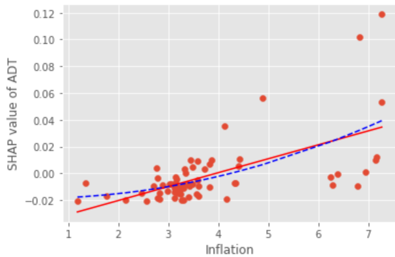
(e) National Clearing (SKN)



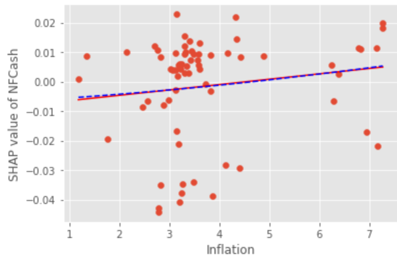
(f) Electronic money



(g) Cash in Circulation (CIC)



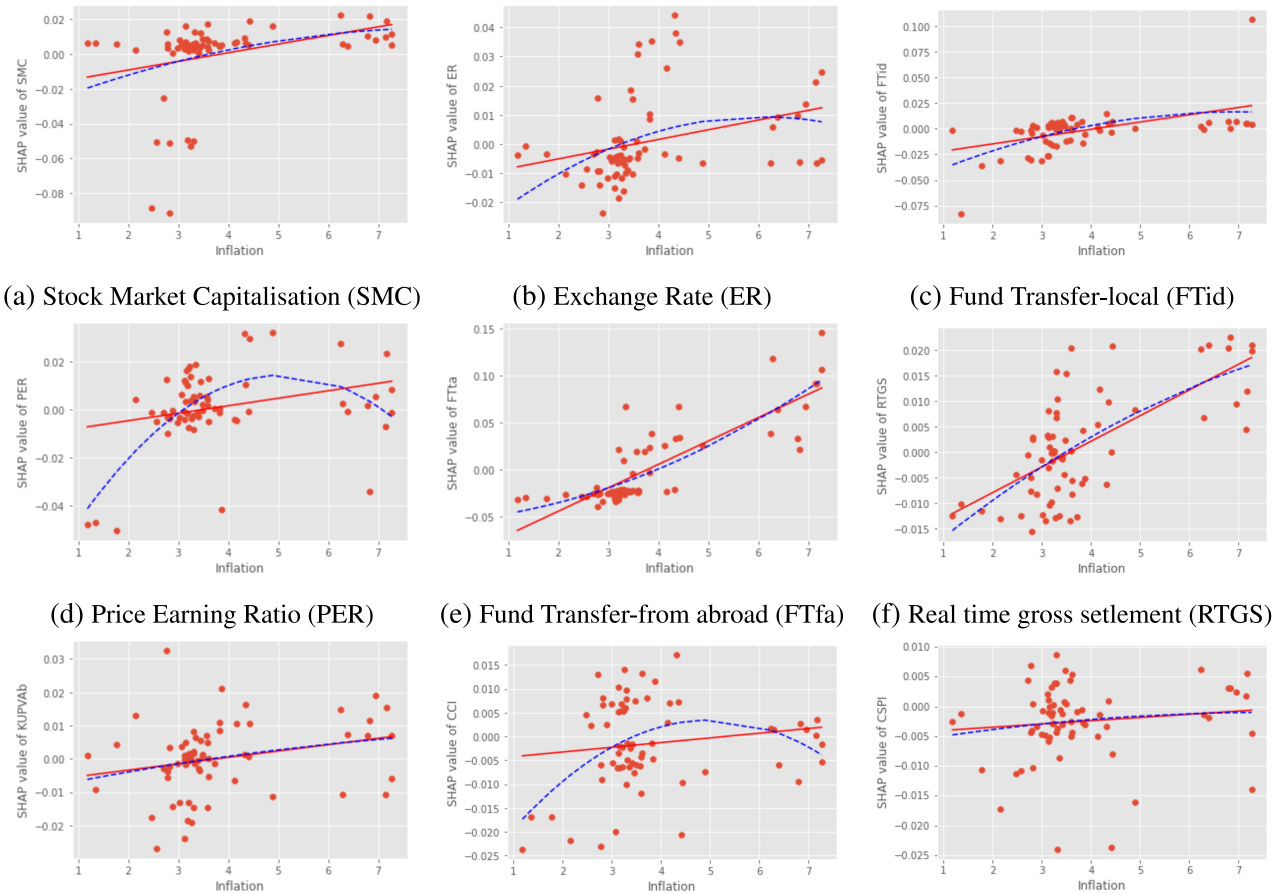
(h) Average Daily Trading (ADT)



(i) Net flow cash (NFCash)

Figure D.5: Functional Form plot of all explanatory variables (1)

Functional Form Plot of the XGB result (2)



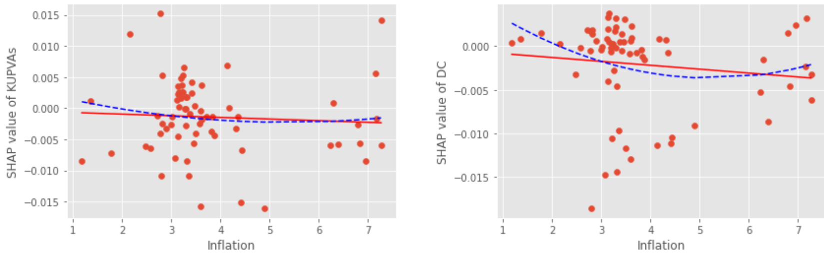
(a) Stock Market Capitalisation (SMC) (b) Exchange Rate (ER) (c) Fund Transfer-local (FTid)

(d) Price Earning Ratio (PER) (e) Fund Transfer-from abroad (FTfa) (f) Real time gross setlement (RTGS)

(g) Currency exchange -buy(KUPVAb) (h) Consumer confidence index (CCI) (i) Composite stock price index (CSPI)

Figure D.6: Functional form plot of all explanatory variables (2)

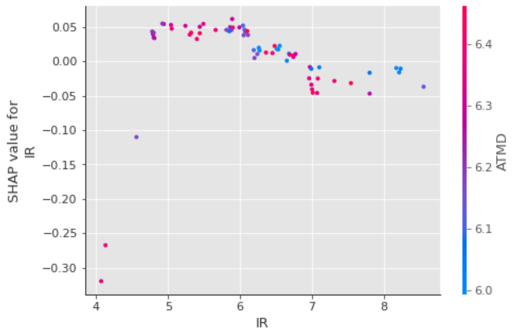
Functional form plot of the XGB result (3)



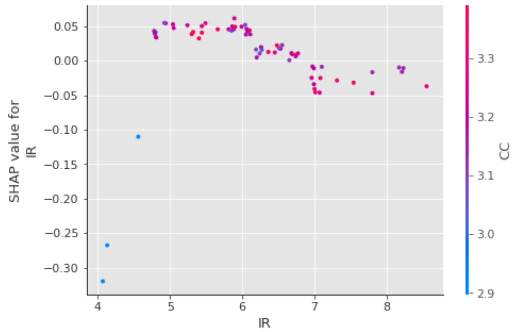
(a) Currency exchange - sell (KUPVAs)   (b) Delivery channel (DC)

Figure D.7: Functional form plot of all explanatory variables (3)

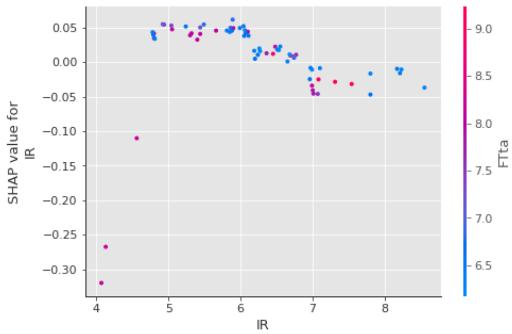
Interaction dependence plot of interest rate (IR) and other variables



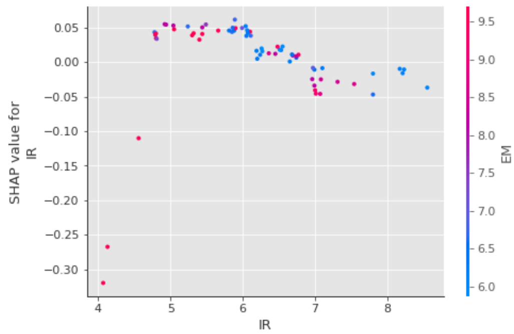
(a) IR and ATM/debit card (ATMD)



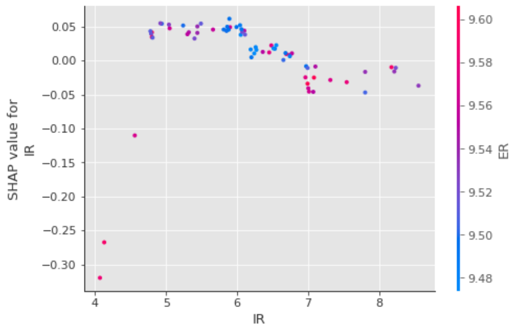
(b) IR and credit card (CC)



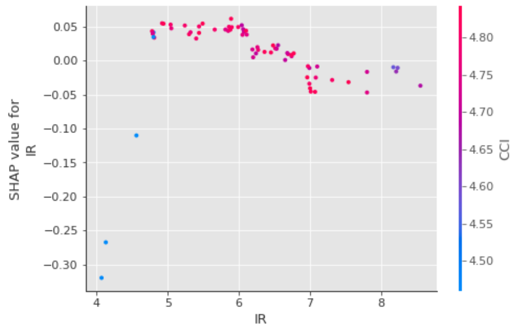
(c) IR and fund transfer-to abroad (FTta)



(d) IR and electronic money (EM)



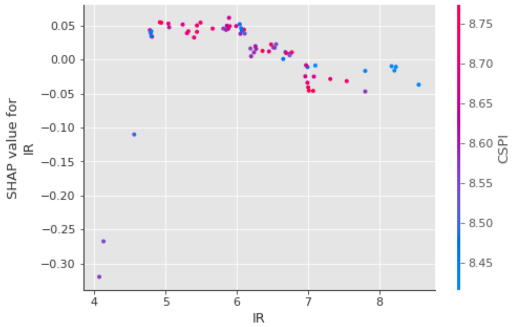
(e) IR and exchange rate (ER)



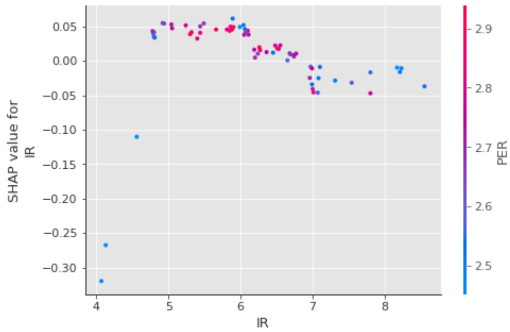
(f) IR and consumer confidence index (CCI)

Figure D.8: Interaction dependence plot of interest rate (IR) (1)

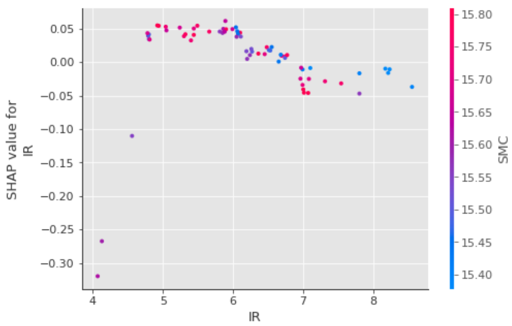
Interaction dependence plot of interest rate (IR) and other variables (2)



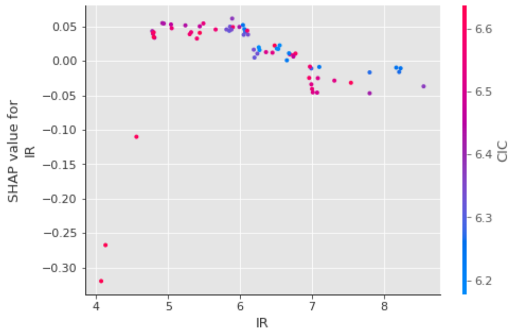
(a) IR and CSPI



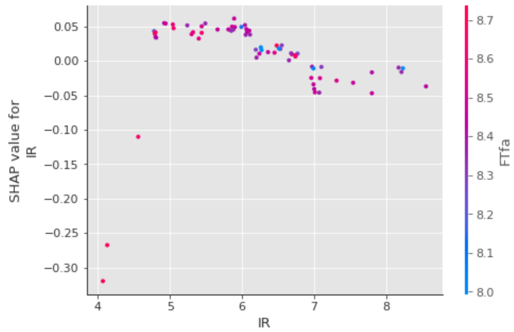
(b) IR and price earning ratio (PER)



(c) IR and stock market capitalisation(SMC)



(d) IR and currency demand (CIC)



(e) IR and fund transfer-from abroad(FTfa)

Figure D.9: Interaction dependence plot of interest rate (IR) (2)

Table D.3: List of Python Libraries Installed and Used in the Analysis

No	Name of Phyton Library	The use of Phyton library
1	import pandas as pd	Importing and building data processing library
2	import numpy as np	Importing and building linear algebra library
3	import seaborn as sns	Importing and building a visualisation library
4	import matplotlib.pyplot as plt	Importing and building a visualisation library
5	%matplotlib inline	Importing and building a visualisation library
6	from sklearn.metrics import mean_absolute_error, mean_squared_error	Importing and building measure model performance library
7	import math	Importing and building data processing using Math
8	from IPython.core.display import HTML	Importing and building a visualisation library
9	from matplotlib import pyplot as plt	Importing and building a visualisation library
10	from datetime import datetime	Importing and building a library for setting the date and time of the data
11	import statsmodels.formula.api as smf	Importing and building a library for time series analysis plot, ACF and PACF, and visualisation
12	import statsmodels.tsa.api as smt	
13	from statsmodels.tsa.seasonal import seasonal_decompose	Importing and building a library for decomposing data into trend and seasonal
14	from pylab import rcParams	Importing and building a visualisation library
15	from statsmodels.tsa.stattools import ADF	Importing and building a library to analyse statistics for stationarity
16	pip install pmdarima	installing a library to analyse using ARIMA (pmdarima)
17	from pmdarima import auto_arima	Importing and building a library to analyse using ARIMA
18	from statsmodels.tsa.arima.model import ARIMA	Importing and building a library to analyse using ARIMA
19	from statsmodels.tsa.statespace.sarimax import SARIMAX	Importing and building a library to analyse using SARIMA
20	from sklearn.metrics import mean_squared_error	Importing and building a library to measure model prediction performance
21	from statsmodels.tools.eval_measures import rmse, aic	Importing and building a library of model performance
22	from math import sqrt	Importing and building a library of model performance
23	from sklearn.model_selection import train_test_split	Importing and building a library to Split the dataset
24	from sklearn.preprocessing import StandardScaler	Importing and building a library to scale the data (StandardScaler)
25	from sklearn.preprocessing import MinMaxScaler	Importing and building a library to scale the data (MinMaxScaler)
26	from sklearn.linear_model import LinearRegression	Importing and building a library of Linear Regression
27	from sklearn.metrics import mean_absolute_error, mean_squared_error	Importing and building a library to measure model prediction performance
28	from sklearn.metrics import r2_score, median_absolute_error	Importing and building a library of model performance
29	from sklearn.preprocessing import scale	Importing and building library Ridge and Lasso
30	from sklearn.linear_model import ElasticNet	Importing and building a library of Elastic Net
31	from sklearn.model_selection import cross_val_score	Importing and building a library of data processing using Cross Validation
32	from sklearn.model_selection import GridSearchCV	Importing and building a library of data processing using Grid Search and Grid Search
33	from sklearn.ensemble import RandomForestRegressor	Importing and building the Random Forest Library
34	from xgboost import XGBRegressor	Importing and building a library of XGB
35	import xgboost as xgb	Importing and building a library of XGB
36	from sklearn import linear_model, svm	Importing and building the SVR library
37	from sklearn.svm import SVR	Importing and building the SVR library
38	!pip install shap	installing a Shap value library
39	import shap	Importing and building Shap value library

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