THE IMPACT OF FINANCIAL TECHNOLOGY AND SELF-DECLARED RELIGIOSITY ON LOAN RISK, AND HOW FINTECH IMPACT PAYMENT SYSTEMS: EVIDENCE FROM MOBILE MONEY IN AFRICA

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Abstract

Fintech can disrupt the delivery of traditional financial services but can equally improve banking for the poor and has the potential to provide new solutions to old problems. Further, signalling theory provides a firm ground to understand how signals can be used by lenders to screen for quality borrowers, reduce uncertainty and facilitate lending. Particularly to informationally opaque borrowers in developing countries. My thesis proposes a model to screen loan applicants based on clients' adoption of financial technology. Using machine learning algorithms, my results show that, adopters of Fintech are associated with lower default likelihood. I find asymmetric relationship between new and repeat borrowers who adopt Fintech and loan spread. However, clients with bank account only are more likely to default compared to those who adopt Fintech and have bank account. This suggest that Fintech can unlock opportunities for adopters to improve their credit score by linking their Fintech account to their respective bank accounts.

Further, over the past decade, payments using Fintech has become critical to the financial systems in most countries in Sub-Saharan Africa. In the third chapter of my thesis, I empirically investigate the impact of the use of financial technology on the payments systems in Africa, financial inclusion and signiorage. Using the VAR-VEC model, my results show that Fintech provides financial inclusion. A variance decomposition analysis show that majority of the forecast error variance is due to own shock. Further, my results show a long-run causal relation between mobile money and payment system transaction, and the use of currency. This confirm that Fintech, can transfer informal cash to the formal banking system and lead to a significant reduction in the social burden of signiorage.

The final chapter of my thesis investigate the impact of borrowers' self-declared religiosity and religious connectedness on loan risk. Using a credit scoring algorithm, I find a significant reduction in default probabilities when borrowers signal as trustable to lenders via their voluntary self-declared religiosity. Further, I find that, all things being equal, borrowers who voluntarily self-declare their religiosity to signal their credit risk are likely to be charged higher interest rate. However, those who self-declare their religious connectedness are associated with the likelihood of receiving lower interest rate, and female borrowers who signal their credit by self-declaring their religiosity are associated with lower default likelihood.

CHAPTER 1. INTRODUCTION

1.1 Background

Financial technology, Fintech, however measured, has increased rapidly in developing economies since the past two decades, and growing exponentially every year (African Development Bank, 2013). Fintech, such as mobile money, continue to be on the ascendancy, and their impact on economic growth has been the focus of studies in recent times. According to the Global System for Mobile Communications Association (2020), there are over 1.2billion mobile money account users in Sub-Saharan Africa. Over USD3billion worth of transactions are performed each day using mobile money and the total monetary value of transactions stood at USD453billion in 2019. Additionally, Fintech has become a channel for distributing credit. For example, socially responsible investors use Kivazip.org to grant loans directly to entrepreneurs using mobile money. Further, Fintech is used for making payments, and receiving remittances, and continue to gain grounds. This can potentially be the default channel for transacting business in developing economies.

However, accessing financial services is particularly challenging for the many residents in developing countries. This is partly due to the fact that a significant proportion of informal sectors characterises the economies of these countries. The African Development bank's 2013 report on financial inclusion show varying but significant proportion of people residing in most African countries do not have access to financial products. For example, in Mozambique, more than seventy-five percent do not have access to financial products, compared to over sixty percent in Zambia, thirty percent in Uganda, thirty-five percent in Kenya, and forty-five percent in Botswana as of 2009. Despite efforts, Socio-economic indicators such as health, unemployment, poverty, illiteracy continue to dominate in the developing world, and the World Bank's 2017 Global Findex show that there is significant gender gap in accessing financial products in Africa.

My thesis addresses three main issues. First, in second chapter 2, I investigate whether Fintech, that is mobile money, can signal borrower credit quality, and if so, what is the impact on loan risk and spread. As the main contribution of this part of my thesis, I offer a model in consumer credit scoring where the borrowers' adoption and usage of Fintech, that is mobile money, prior to the loan contract can become an effective signal of borrower credit risk. Grounded on the signalling theory, I examine the impact of Fintech on loan performance in individual liability credit contracts. Further, I argue that the unobservable characteristics of the borrower and the severity of the borrowers' moral hazard is captured by the borrowers' adoption and usage of financial technology, Mobile Money.

The main argument and contribution in the second chapter of my thesis is that simple financial technological solutions using mobile enabled devices can help in the struggle to solve issues as complex as information asymmetry in the loans market. Hence, I propose an innovation in the loan screening process that capture the unobservable in underwriting loans and the associated risk of lending to many residents in developing countries. Further, my study will aid bank lending decisions and help many residents who do not have bank account but need access to finance. To the best of my knowledge, however, I have not seen this correlated with the nature of the decisions taken by lenders to grant credit or otherwise. Neither have I seen Fintech adoption used as a signal of borrower credit risk in individual liability loan contracts, both in the developed and developing world.

Second, in chapter 3 of my thesis, I examine the use of Fintech as an alternative payment instrument for the many residents in the developing world who are unbanked. As the main contribution of the second part of my thesis, I offer a different model for examining whether Fintech can provide for financial inclusion, substitute traditional payment system and the use of currency. Specifically, I contend that a cointegration relationship between mobile money, payment transactions and Cash indicates that Fintech provides for financial inclusion. Additionally, a cointegration relationship between Fintech and debit, credit, charge card and the use of cash indicates that Fintech can substitute traditional payment system. Further, I empirically investigate the impact of Fintech on payment system stability and financial sector deepening.

In chapter 4, I examine the impact of religion on financial contracts. Religion and religiosity have been shown in prior studies to play a significant role in a person's way of life and in business decision making. In this chapter of my thesis, I investigate whether borrowers' voluntary self-declared religiosity and religious connectedness to the lender at the loan application stage can impact on the performance of individual liability loan contracts and cost of debt. I contend that by voluntarily declaring their religion and religiosity, individual borrowers are signalling to the lender to be good credit risk. Hence, this will in turn positively impact on their loan performance. In summary, my thesis shows how financial technology adoption, can foster financial inclusion and signal borrower credit risk to improve lending to the many in developing countries who are informationally opaqued and lack access to finance. Additionally, my thesis provides new evidence of how religiosity, that is, voluntary self-declared religiosity impact financial contracts.

1.2 Significance of the study

Several studies link financial innovation to financial inclusion in developing market economies. However, there is a striking paucity of empirical studies on the connection between financial technology, Fintech, and the information gap in the lender-borrower relationship. I empirically explore the consumer loans market, with an emphasis on how financial technology influences the information asymmetry in the lender-borrower relationship, and the impact on default probabilities. Further, I aim to predict default based on the information available at the time credit was granted, and so include financial technology variable as a signal of borrower opacity and credit risk in individual liability credit contract. Particularly, in developing countries.

In financial markets, particularly in developing counters, where the problem of informational asymmetry is severe because of the presence of large informal sectors in these economies, borrowers typically know their financial position better than lenders. As a result, clients possess "hidden" information about their own financial circumstances for which they seek financing from a lending institution. Further, the lender cannot expect the borrowers to be entirely forthright about their individual financial circumstances, especially, in a society where there are numerous cultural nuances about borrowing. However, knowing the true financial circumstances and features of borrowers will be helpful to the lending institution for credit decisions.

Knowing the true characteristics of borrowers can benefit lending institutions, however, getting information about individual features from a third party can be costly, if not impossible, due to the lack of formal systems in developing markets that capture this information. In an industry which is becoming increasingly aware of the need to be sensitive to borrowers' needs, consumer lending should be given due consideration. It is quite surprising however, that this seems to be an under–researched area, particularly in developing open market economies. This is partly because, information about borrower and loan-specific characteristics are scarce due to their proprietary nature, as well as confidentiality issues associated with such data. I model the loan default rate of borrowers in a given loan cycle as a function of the clients' adoption and usage of Fintech, plus borrower and loan specific characteristics. Additionally, I include the branch of the lending institution where the loans were originated and disbursed.

Further, prior studies have provided theoretical frameworks to show that in a perfect competitive market impeded by asymmetric information, lenders can benefit from economies of scale when they obtain information about borrowers. My thesis is a contribution to the theory and empirics of technology adoption and asymmetric information growth in the credit market. Particularly in developing market economies. Extant studies have focused mainly on the financial technology and growth nexus, however, the overall effects of Fintech on asymmetric information in the lender-borrower relationship and its impact on default frequencies in developing world is to the best of my knowledge yet to be examined, theoretically and empirically. This study fills this gap in theory and literature.

My thesis is particularly important because most extant studies in the area of information asymmetry is from developed economies, hence, less is known about the potential for financial technology (Fintech) to mitigate the information gap between lenders and borrowers in developing countries, where most of the world's population resides and where the economic benefits of lending to household to smooth consumption is much needed. I assert that financial technology confronts the borrower opacity problem faced by lending institutions. By combining personal with financial data about borrowers and using statistical methods, I predict the future credit performance of customers to facilitate loan pricing and risk management. Furthermore, my thesis contributes to the literature by showing that women are equally or less risky when manging their finances using Fintech, and hence recommend increasing women's financial inclusion to bridge their access to credit through enabling financial inclusion policy and regulation.

Additionally, extant studies show that a person's religion or religiosity play a significant role in shaping their attitude, behaviours and decision making in both social and economic matters. Further, prior studies in the area of religion and financial contracts have mainly focused on how religion influence corporate and sovereign debt performance and credit terms using the geographical location of the parties as proxy for religion. Studies that have sought to investigated religion on individuals' loan performance have also at best used country-wide level survey data to infer individual borrowers' religion and religiosity. While this can serve as substitute in the absence of borrower-specific religious information that relates specifically to a loan contract, the results can be weak, obscure, or spurious when generalised to a consumer loan setting.

Unlike many prior studies in this area that have investigated the relationship between religion and loan performance that rely on country level and general population survey data to infer an individual borrowers' religious belief and religiosity to generalise. I argue that a country's level of religiosity which is used as proxy to measure individual citizens’ religiosity and by extension that of borrowers in many prior studies, can be an over-simplification. This is because a country’s level of religiosity is an amalgamation of different religions, and although one religion may dominate, this doesn’t necessarily mean that borrowers are members of the dominant religion or indeed any religion. Hence, this can lead to spurious result and weakness in the generalisation of outcome. I leverage on my unique dataset covering borrower and loan-specific characteristic to investigate the influence of borrowers’ self-declared religiosity and religious connectedness on loan performance in an individual liability credit contract.

However, there are a number of challenges that inhibits empirically examining the various consequences of individual borrowers' self-declared religiosity, and religious affiliation on loan performance for individual liability contracts. As a result, distinguishing among the various explanations underlying the effect of religiosity on loan performance is difficult. First, it requires information that identifies the individual borrowers’ own declaration of belonging to a specific religious belief. This information is in some jurisdictions, such as the US, barred. That is, the lender is legally prohibited from soliciting the information and or prevented from using the data to inform lending decisions due to discriminatory practices. However, this is not the case in all countries.

Also, prior studies, for example the work of Guiso et al., (2009) focused on high level aggregation at the country level, while others have in some cases relied exclusively on survey data collected on the religion or race of specific segment of the population and has at most been set up to segregate and discriminate against specific group rather than to reflect the religious beliefs of the entire market. Furthermore, this can confound any improvement in empirical outcomes from the different individual religious group interactions with statistical based discriminatory analysis. Especially when the excluded religious group are significantly prevalent within the entire population.

Also, even when dyadic data covering the individuals' religiosity are available, most studies have investigated the interaction between religiosity and loan performance at the country level or at most on corporate and sovereign debt than the consumer loans market. I fill this gap in literature, and I provide the first, to the best of my knowledge, empirical evidence of the interaction between individual borrowers' voluntary self-declared religiosity as signal of good credit risk. Furthermore, I examine how this impact on loan performance in a consumer loan setting using individual liability credit contracts in Sub-Saharan Africa where religion and religiosity play a pivotal role in the life of residents and in society.

Additionally, the digital revolution in developing countries, particularly in Africa is reshaping how residents in these economies make payments for financial transactions. However, despite the strong public interest in mobile money wallet and mobile payment eco-systems in developing countries, particularly in Kenya, there is only a small body of empirical academic research that policymakers can draw on to analyse the impact of this alternative payment instrument on the financial sector deepening, financial inclusion, and the stability in Kenya's payment ecosystem. This is all the more surprising given the significant increase in the usage of mobile money wallet and mobile payments in the last decade in developing countries, particularly in Sub-Saharan Africa. My thesis provides an empirical analysis of the use of mobile money on the payment system, financial inclusion, and the social cost of signiorage in developing countries.

1.3 Study Objectives

Globally, there is a growing interest in the increasing role the mobile enabled technologies can play in the lives of the many residents in the developing world. In the second chapter of my thesis, I am interested in exploring the how Fintech, that is, mobile money, can signal borrower credit risk to reduce loan risk, increase lending and reduce cost of providing credit to the poor. First, I investigate the signalling function of Fintech, and how this impact on borrowers' loan performance. Second, I examine whether borrowers' adoption of Fintech to be transparent to the lender and as signal of credit risk can lead to a reduction in borrowing cost. Third, I investigate the impact of the interaction between Fintech and gender on loan performance, and finally, whether borrowers' adoption of Fintech can substitute bank account ownership in reducing lending risk for the many residents in developing countries who do have access to formal bank account.

My thesis primarily seeks to achieve three key objectives. First, I contribute to our understanding of Fintech, that is mobile money wallet. Specifically, whether Fintech can be a signalling tool that reduce the information asymmetry problem faced by lending institutions when providing credit to borrowers who are severely informationally opaque. Second, my thesis contributes to the important role that Fintech, that is, mobile money wallets can play in fostering financial inclusion and ensuring financial sector deepening, and payment system stability. Finally, my thesis adds to our understanding and contribute to the extant literature by studying the effects of borrowers' self-declared religious beliefs and religious connectedness at the loan application stage on loan performance. That is, my study complements the body of research that examines the influence of religion, religiosity on corporate and individual decision-making process in financial contracts.

My thesis is divided into the following three sections with specific objectives:

In Chapter 2 the specific objectives are, to:

1. Estimate the probability of default for borrowers who adopt Fintech to signal their credit risk and evaluate the effect of the signal on loan performance.
2. Estimate the impact on cost of debt for borrowers' who adopt Fintech to signal their credit risk and evaluate effect on the loan performance.
3. Estimate the probability of default for female borrowers who adopt Fintech and evaluate the impact on the loan performance.
4. Estimate the probability of default and the impact on cost of debt for borrowers who continue to adopt Fintech as signal of their credit after repayment of first and in repeat loans.

5. Estimate the probability of default for repeat female borrowers who continue to adopt Fintech to signal their credit risk after repayment of first and in repeat loans.

In chapter 3 of my thesis, the specific objectives are:

1. Estimate the short and long-run impact of Fintech on payment system transactions and evaluate its impact on financial sector deepening and financial inclusion.
2. Estimate the forecast error decomposition variance and impulse response functions for Fintech and payment system transaction and evaluate its impact on the stability and efficiency of the payment systems.

In chapter 4,

1. Estimate the probability of default and impact on cost of debt for borrowers who self-declared their religion and religiosity prior to the loan contract and evaluate its impact on loan performance.
3. Estimate the probability of default for female borrowers who self-declared their religion and religiosity to the lender prior to the loan contract and evaluate its impact on loan performance.
4. Estimate and evaluate the impact of borrowers who self-declared their religious connectedness on the probability of default, and on cost of debt.
5. Estimate the impact of females who self-declared their religious connectedness on the probability of default, and on the cost of debt.

1.4 The structure of the study

To this end, in the second chapter of my thesis I examine various theoretical and empirical study in the area of information asymmetry, loan default, and the adoption and usage of financial technology. In addition, I provide the data used in this section of my thesis. Also, I describe the loan process and provide justification for the selected variables before presenting and evaluating the descriptive statistics of my dataset. Furthermore, I discuss the hypotheses, the empirical model, research method and my empirical results. Additionally, I present and discuss my robustness test results. Finally, I conclude by discussing the impact, and limitations relating to my work in this chapter and make recommendations for future research.

I introduce and provide background to the third chapter of my thesis, that is, I investigate the impact of Fintech on financial inclusion, traditional payment systems, financial sector deepening and payment system stability. This includes theoretical and prior empirical studies in the area of technology adoption and payment systems. In addition, I provide the empirical data that used in this section of my thesis before presenting and discussing the descriptive statistics of my dataset. In addition, I discuss the hypotheses that I test in the second chapter of my thesis, the empirical strategy, research method and my results. Further, I provide robustness test results, and discuss the impact of my work in this chapter and any limitations. Finally, I conclude and make recommendations for future studies.

The penultimate chapter, which is chapter 4 of my thesis, I investigate the influence of borrowers' self-declared religiosity and religious connectedness and its impact on loan performance and cost of debt. In this chapter, I examine prior studies on religion. Additionally, I review extant studies on the relation between religion, economic development, and loan performance. Further, I re-state the research objectives and discuss the hypotheses that I aim to test. I provide a descriptive statistic for the additional unique variable, that is, an analysis of the borrowers self-declared religiosity and religious connectedness. Furthermore, I present and discuss my empirical results and robustness test. I conclude on the fourth chapter of my where I outline the impact of this section of my study, conclusion, and any limitations before making some recommendations for future work.

CHAPTER 2. FINANCIAL TECHNOLOGY AND LOAN RISK

CAN FINTECH ADOPTION SIGNAL LOAN RISK? EVIDENCE FROM MOBILE MONEY IN GHANA

2.1 Literature Review

Fintech via mobile enabled devices can be thought of as a tool for solving an important problem in finance, information asymmetry. However, the performance of some of these finance technologies and their in-built risk identification features are yet to be empirically examined as a tool to address the problem of information gap between lenders and borrowers in credit markets in developing economies. Further, extant studies have investigated the impact of financial innovations on economic growth in developing countries. However, no studies to the best of my knowledge, has empirically analysed the growing trend of financial technology usage in developing market economies as a tool to address the problem of information asymmetry and the risk associated with lending. I depart from previous studies by investigating the use of fintech as a mechanism to address the severe asymmetric information problem in developing countries. In this section, I review the relevant theories and empirical literatures on the risk associated with lending and loan performance.

2.1.1 Information Asymmetry and Default Rate

In market equilibrium, demand equals supply; hence if prices work, credit rationing should not exist, but it does exist (Stiglitz and Weiss, 1981). Further, Stiglitz and Weiss (1981) contend that in credit rationing, even though some loan applicants are willing to pay a high interest, they may not receive credit, and Dehejia et al., (2012) in a related study contends that financially excluded people seek access to credit despite having to pay high interest rate, and this phenomenon is severe during periods of economic downturns. Even though asymmetric information problem affects all institutions in diverse shapes and forms, this is particularly severe for lending institutions because of the nature of their business, especially when they create assets by granting loans to borrowers (Flannery et al., 2004; Morgan, 2002; Iannotta, 2006). Diamond, (1991) show that these assets are illiquid in nature and are significantly affected by sensitive information.

Lending institutions often act on information that is less than complete and far from perfect, and as a result, they are often faced with at least some degree of risk or uncertainty in their lending decisions. However, risk is not the only factor lenders are sensitive to in the context of credit granted, the perceived benefit also provides lenders with an incentive for granting loans. Combining the perceived risk and perceived benefit leads to a *valence framework*[1] which in the context of the loan market assumes that lenders perceive risk as having both positive and negative attributes, and accordingly, lenders make decisions to maximize the net *valence* resulting from the negative and positive attributes of the decisions they make to grant loans or otherwise.

Theory and empirical evidence provide three main rationales to explain why borrowers may default on their loan obligations to a lender. First, poor self-management of a borrower's finances resulting from *hyperbolic* discounting leads to the irrational choice to immediately spend as shown in the work of Liabson et al., (2003). Second, the hypothesis that examine the borrowers' 'ability to pay' argue that a borrower will default on the loan contract when there is an unexpected shock such as health problems, bereavement, loss of employment, et cetera. Third, the empirical work of Kau et. al., (1994), the authors investigated default frequencies in the US mortgage market using analytical techniques for modeling default probabilities based on the 'strategic default hypotheses', and they find that when the value of an asset (mortgage) is less than the value of the outstanding loan used in acquiring the asset, then in the absence of transaction cost and reputational risk, the borrower will default.

The problem of information asymmetry has become a burden for many finance providers globally. As a result, this problem has become a cornerstone in finance research, and the work of Leland and Pyle (1977), Grossman and Hart (1981) and Myers and Majluf (1984) provide evidence to show, that the information gap between borrowers and lenders can have a significant impact on the financing and investment decision of the firm. In the Leland and Pyle (1977) study, the authors

[1] See Peter and Tarpey (1975). A comparative analysis of three consumer decision strategies. Journal of Consumer Research, 2 (1), pp. 29-37

consider what information or signal is conveyed to the financial market by entrepreneurs when these business owners vary their equity stake in the project that they seek finance for and assume that the entrepreneurs' level of equity in the project signal to the market the project's riskiness, and the subsequent pricing of the project in the market by investors.

Further, according to Leland and Pyle (1977), the greater the amount of equity that borrowers invest in a project that they seek finance for, the higher the quality associated to the project, and hence, attracts higher market valuation. In Myers and Majluf (1984), the authors contend that when managers decide to issue new shares to finance a positive net present value project in the presence of information gap between shareholders and the firm's managers, the issuance of these new equity send a signal to investors about the quality of the firm and this signal in turn lead to a decline in the equity price of the firm.

Borrowers' signal via their equity investment in a project as contended by Leland and Pyle (1977); and Myers and Majluf (1984) provides support to my thesis. In my thesis, and in the context of consumer financing where there is no internal or external collateral as security for loans, and in the presence of severe information asymmetry, borrowers can signal their risk characteristics to the market via their investment in financial innovation such as mobile banking and mobile money wallet to undertake both regular and one-off financial transactions. This investment by clients, that is fintech, can help the informationally opaque borrowers to reduce their opacity to the lending institution.

In a study that examined the presence of moral hazard and adverse selection in the US mortgage and automobile industry, Edelberg (2004) find significant evidence to show that borrowers' behaviour may be influenced by the loan terms. Related is the work of Karlan and Zinman (2009) that investigated the presence of moral hazard and adverse selection in the consumer credit card market in South Africa and find relatively significant evidence of moral hazard. The lending business, process and behaviour involves taking risk, because there is information gap between the lender and the borrower. Further, the lending process involves high risks because the borrower is not always willing or capable of paying the loan on time and in line with the agreed repayment schedule. Hence, for lender, selecting credible borrowers to reduce investment risk is critical to chieve the desired lending objective.

To a large extent, the perceived gap in the borrower-lender relationship influences the behaviour trend of both parties and as shown in the trust model of Kim et al. (2008) using online trading platform, the author find that risk, profit, and trust are critical factors that when deciding trading trends. In a related work using the online lending 'Prosper', Greiner and Wang (2010) show that lending behaviours are significantly influenced by reputation, and that reputation reduces uncertainties in the creditor-debtor relationship. The theoretical work of Jaffee and Russell (1976), Stiglitz and Weiss (1981) further show, that the problem of information asymmetry in the lender-borrower relationship hinders the efficient allocation of credit, thereby leading to credit rationing.

This phenomenon, either lead to an adjustment in the credit spread (Stiglitz and Weiss, 1981; or the loan size (King, 1986). In Stiglitz and Weiss (1981, 1983) theory of information asymmetry in credit markets, they find that an increase in default probabilities depresses the equilibrium quantity of loans available, especially in markets where credit reference bureau information on credit applicants is thin or not in existence; and where there is sever financial sector under-development. Ordover and Weiss (1981) in a related theoretical work, finds that, the presence of asymmetric information in the lender-borrower relationship does not permit a wholesale restriction on the terms of credit contract by state actors in the credit market.

Besters (1985) also showed in a theoretical framework, that by endogenously adding collateral at no extra cost to the borrower, the problem of information asymmetry can be addressed by lenders. Pagano and Jappelli (1993) contend that, where the problem of adverse selection is high, with associated increase in the level of information sharing across lenders, the number of loans disbursed by lenders increase to the detriment of borrowers considered 'safe', and as a result, these potentially 'safe' borrowers are eliminated from the market because of potential competition from new entrants as described in the used car analogy of

Akerlof (1970). However, these potentially safe credit applicants may precisely be what lenders require to be profitable.

Akerlof (1970) studied the used car market and show that, buyers considered used cars as 'lemons' because sellers are unable to communicate the quality of used cars to buyers, and hence, sellers withdraw from the market because they are unable to charge prices that reflect the true quality of the car, and this leads to market failure. However, Heal (1976), criticised the work of Akerlof, and contended that, sellers would wean from taking advantage of the buyers' lack of information when the first three conditions[2] as contended by Akerlof are met. This is because sellers will be keen to protect their reputation in the long run.

In a related work, Spence (1973) contend that by using 'signal' to communicate to buyers on the quality of used cars, the adverse selection problem in Akerlof (1970) can be mitigated. Further, Grossman (1981) provided evidence to show that, 'Warranties' can be used as a 'signal' to buyers on the quality of used cars in the adverse selection problem contended by Akerlof. Bond (1982) and Genesove (1993) in an indirect and direct test of the used car market, finds thin evidence in support of adverse selection. Whereas the former compared the frequency of used and new truck service history and found thin evidence of adverse selection in old used cars only, both find weak evidence of the adverse selection theory as contended by Akerlof, 1970.

In Spence (1973) framework that used education as a signal of worker productivity, Spence showed that through the signalling framework, a prediction can be made about the quality of workers using the workers' level of education. This finding led to further research using the signalling framework. For example, Ross (1977) in capital structure; and John and Williams (1985) on dividends. Basically, Spence (1973) contends that signalling act as a mechanism to reduce asymmetric information problem, adverse selection. In a study that investigated how imperfect information and uncertainty can lead to credit rationing in loan

[2] Akerlof contends that first, at the time of sale, the seller side of the market is more informed about the quality of the good than the buyer side; second, both the seller and buyer in the market value quality; and third, price is determined via negotiation not by the (more) informed party.

markets, Jaffee and Russel (1976) contend that, information gap in the lender-borrower relationship can lead to credit rationing, and this is because lenders lack access to total information about borrowers, and differentiating hidden action (leading to moral hazard) and hidden information (leading to adverse selection) is difficult, if not impossible, for lenders to identify in the loan underwriting process (Chiappori and Salanie, 2000).

Nevertheless, the theoretical framework of Stiglitz and Weiss (1981); and Godlewski and Weill (2011) show, that when lenders charge borrowers high loan spread, it induces a positive correlation between default probabilities and adverse selection. This is because credit applicants with high default probabilities will be inclined to accept high loan spread charged by the lender (Agarwal et al., 2010). In a study that examined applicants for car loans and a follow-up on their repayment trends, Adams et al. (2009) distinguished between moral hazard and adverse selection, and the authors find that moral hazard and adverse selection account for about sixteen (16) percent and eight (8) percent of auto loan default rate.

Further, the influential work of Ausubel (1991) that empirically examined the stickiness of the cost of fund and credit card interest rate, finds that interest rates are sticky because of the problem of adverse selection. As a result, consumer credit card holders have difficulty changing their credit card providers for alternatives with better interest rate. In a study that analysed pre-approved credit card solicitation, Agarwal et al. (2010) provided evidence to show that lenders sort by borrower information that is both observable and unobservable-suggesting the presence of adverse selection in credit lending. Lewis (2011) empirically examined adverse selection in the auction of goods on an online platform and find that when sellers are able to 'partially contract' on their gods when they reveal private information to potential buyers.

The theoretical work of Greenbaum et al., (1989); Rajan (1992) and Sharpe (1990) corroborated with these findings and show a positive relation between credit spread and the maturity period in the lender-borrower relationship. However, in a related work, Boot and Thakor (1994) show, that credit spread decreases as the lender-borrower relationship matures. Related is the study by Andrianova et al., (2015) that incorporate moral hazard and adverse selection in a theoretical framework. Andrianova et al., (2015) document that loan default rate among African banks is significantly affected by the level of institutional quality. Demetriades and Fielding (2012) also finds that, increasing default rate in developing countries in Africa account for the high liquidity held by lenders in these economies.

Prudent approach to lending is for lenders to gather both financial and non-financial information about borrowers to determine their credit worthiness prior to granting the loan. For repeat clients, prior relationship(s) with the lender is a significant factor that lenders rely on to decide whether to grant additional loans, price loans and determine any relevant conditions that may be relevant. Elyasiani and Goldberg (2004) in an empirical study show, that asymmetric information is less pronounced for repeat borrowers compared to first time borrowers, and this is because of prior relationship that the lender may have built with repeat borrowers during the borrowers' first spell with the lender. Allen (1983) show that creditors' refuse to grant future loans to repeat borrowers because of their past experience with loan default.

The related work of Demetriades and Fielding (2012) show, that asymmetric information is sever in developing countries in Africa, where low development in the banking sector exists, and lenders hold excessive liquidity. However, Honohan and Beck (2007) in a World Bank report on Africa, show that the low financial development in Africa is compensated by excessive liquidity held largely in foreign denominated assets and savings by African banks. This abundance of liquidity held by lending institutions in Africa, suggest that African banks do not necessarily lack available funds to meet the credit demand, instead, what African banks lack, is quality credit applicants to lend these excessive funds to enable these banks to generate profit (Andrianova et al., 2015).

Honohan and Beck (2007) further report that households and firms in developing market economies in Africa complain of lack of access to finance, whereas professional lending institutions narrate their challenge of finding credit worthy borrowers to lend their excessive liquid funds to. In a related study that focused on the Economic and Monetary Community of Central Africa (CEMAC) and the West African Economic and Monetary Union (UEMOA), Andrianova et al., (2011) find that asymmetric information account for the low financial sector development in developing market economies in Africa. Further, Andrianova et al., (2014) investigated what inhibit bank lending in Africa using dynamic panel model across selected African banks and find that default and weak regulations are the dominant factors.

In contrast to the findings of Honohan and Beck (2007), Demetriades and Fielding (2011) find that lack of good credit risk borrowers in these markets is not the rationale for the under-developed financial services sector in developing market economies in Africa, however, the lack of developed systems such as credit reference institutions that professional lenders can capably rely on to screen and monitor household and firms when they seek credit is a significant impediment that drives financial under-development in these economies in Africa. Related is the work of Gries, Kraft and Meierrieks (2009) that investigated the linkages between Financial Deepening, Trade Openness and Economic Development in 16 Sub-Saharan countries and find weak evidence to support the financial sector led growth hypothesis.

In an empirical study that sought to differentiate the impact of moral hazard and adverse selection on default rate based on advance offers to borrowers with diverse interest rate in South Africa, Karlan and Zinman (2009) find significant positive relation between moral hazard and default rate; whereas, adverse selection showed weak relation with default- suggesting that the presence of asymmetric information problem in the borrower-lender relationship account for 13% to 20% in default rate in countries where lenders offer credit to borrowers considered high credit risk. Petersen and Rajan (2002); Baas and Schrooten (2006); and Berger and Udell (2006) document that the problem of information asymmetry influence and determine the banking structure, and lending methodology used by finance providers.

Furthermore, in developing markets in Africa, because the information required by lenders to undertake comprehensive risk assessment of potential borrowers are in some cases not available or opaque (Hainz, 2003), lenders rely heavily on strict collateral requirement as security to address the problem prior to loan disbursement (Menkhoff et al., 2006). Boot (2000) in a related study that investigated the link between bank relationship with borrowers and the information gap in the lender-borrower relationship finds, that bank relationship with borrowers over time solve the problem of information asymmetry, adverse selection, and moral hazard. However, Gelbard and Leite (1999) studied 38 countries in Sub-Sahara Africa to measure financial development across six (6) indices and find that access to financial products in African economies is limited, coupled with high interest rate, low credit recovery rate and leading to high non-performing loans.

2.1.2 Information Asymmetry and Collateral

The path-breaking work of Stiglitz and Weiss (1981) and by the subsequent contribution of Wette (1983), provided an important theoretical model to show that credit rationing, and adverse selection are the result of asymmetric information in lending when the borrower has private information that is unknown to the lender about the quality of the project that the borrower is seeking to finance with debt. In the private information framework. Theories of asymmetric information and the use of collateral in the borrower-lender relationship shows that collateral mitigate the problem of information gap, i.e., ex-ante adverse selection and ex post moral hazard in lending relationships (Bester, 1985, and Besanko and Thakor, 1987).

Additionally, Bester (1987, 1994) provided further evidence to show that collateral reveal the true state of borrowers' project once the loan has been disbursed, and that the fear of losing assets pledged as collateral to the lending institution induces borrowers to repay loans. The empirical findings regarding the use of collateral as a conduit to mitigate the problem of information asymmetry has been mixed. A strand of empirical studies such as the works of Berger and Udell (1995), Harhoff and Korting (1998), Chakraborty and Hu (2006) that sought to test theories on the use of collateral and information asymmetry finds negative association between the use of collateral as security for loans and private information held by borrower.

Machaer and Weber (1998), Elsas and Krahnen (2000), Ono and Uesegi (2005) on the contrary find positive association. Whereas the works of Degryse and van Cayseele (2000), Jiminez, Salas, and Saurina (2006), Menkhoff, Neuberger, and Suwanaporn (2006), and Voordeckers and Steijvers (2006) all finds mixed evidence. In the empirical work of Berger et al. (2011a, 2011b) that sought to understand the link between the use of collateral as security for small business loans, finds that collateral serves a conduit via which credit rationing can be reduced. In the related work of Coco (2000), the author sought to understand the increasing use of collateral in loan contract in credit markets characterised by different levels of asymmetric information and find that the use of collateral can mitigate asymmetric information under some conditions to ensure the delivery of optimal lending.

In a related empirical study that sought to understand the role of collateral in mitigating the information asymmetry problem among small and medium size enterprises and how lenders enforce collateralised contracts in emerging markets, Menkhoff et al., (2011) finds that collateral reduces loan losses to lenders, however, the use of collateral significantly increases moral hazard. Additionally, Menkhoff et al., (2011) also find that guarantees were substitute for collateral and has become a common feature in professional lending institutions. Also, the work of Hart and Moore (1995) show collateral allows the lender to issue large loans and therefore subdue the time consistency problem.

Another strand of theoretical and empirical studies shows that although collateral reduces default by aligning the borrowers' interest to that of the lender, the use collateral is costly, and this is because both the lender and borrower incur further cost such as legal and monitoring cost (Chan and Kanatas, 1985), as well as collateral collection and marketing cost in the event of a bankruptcy (Barro, 1976). Sharing information facilitates and enables professional lenders to obtain information about previous repayment performance and current debt exposure of credit applicants, therefore, the mechanism for information sharing among lenders is important for reducing the information gap in the lender-borrower relationship (Pagano and Jappelli, 1993).

In accord to the observed risk hypothesis, Jimenez et al. (2006) contend that collateral requirements in credit agreements are less restrictive in economies where there is mechanism for information sharing among lenders. The empirical work of Brown et al. (2009) and Pagano and Jappelli (1993) provide evidence to show that information sharing among lenders reduces loan spread and adverse selection, particularly in developing countries in Africa where the problem of adverse selection is severe. However, due to the informationally opaqueness of borrowers and weak collateral enforcement environment in developing economies, particularly in Africa, theory suggests that the use of collateral as security for loans is higher in these markets (Bae and Goyal 2009, Behr et al. 2011, Hainz, 2003, Menkhoff et al., 2006).

2.1.3 Information Asymmetry and Agency Theory

Information asymmetry in the borrower-lender relationship can also be viewed in the context of principal-agent problem. Financial economists have for decades been developing theories that relied on the unrealistic assumption that market information is complete, and that all relevant and necessary market information is uniformly available to all market participants. Under such assumption of perfect market, the efficient and optimal allocation of resources can be achieved with little effort. However, the development of game theory as economic science has provided a different and profound dimension in the evaluation and analysis of complex economic phenomenon in the marketplace that is characterised by information gap between two market participants.

In the work of Jensen and Meckling (1976, p. 308), they contend that an agency relationship is '*a contract under which one or more persons (principals) engages another person (the agent) to perform some service on their behalf which involves delegating some decision-making authority to the agent*'. In this context, the actions of the agent who is the borrower is unobservable to the principal, the lender, and as a result this leads to the moral hazard problem (Hölmstrom, 1979). Furthermore, given that the principal is unable to ascertain the 'true' character of the agent, the principal bears the cost of the information gap, and this is reflected in the interest rate charged by lenders. Additionally, the threat of ex-post sanctions in the form of higher interest rate on future loans or the refusal by the principal to grant future credit creates ex ante incentives for the agent to serve the interest of the principal by repaying the loan in line with the credit contract.

To better understand the nature of uncertainty and to mitigate its potential harmful role in lending, particularly in developing economies in Africa, I refer to the principal-agent perspective, which aims to explain contractual agreement between two self-interested parties with dissimilar goals in the presence of information gap between both parties. Originally built on the agency theory, the principal-agent perspective, has been extended by scholars and information economists such as the works of Akerlof (1970); Rothschild and Stiglitz (1976); and Spence (1973) to include markets dominated by imperfect information. Garen (1994) investigated how well the principal-agent model can explain variations in CEO incentive pay and salaries and find that principal-agent approach play a critical role in determining executive renumeration.

Further, the work of Milgrom and Roberts (1992) extended the principal-agency theory in socio-economic environment where bounded rationality and information asymmetry exist. In the empirical work of Bergen et al. 1992; Mishra et al. 1998; Singh and Sirdeshmukh 2000, they viewed and applied the principal-agent theory in a buyer-seller relationship, where sellers are agents and buyers as principal. In their empirical works, Akerlof (1970); Arrow (1985); Jensen and Meckling (1976) contend, that information asymmetry arises in the buyer-seller relationship where buyers delegate the responsibility of delivering purchased good to sellers, because sellers as agents typically have more information about the products characteristics, and own practices.

The principal-agent perspective is a useful theoretical lens for understanding and mitigating information asymmetry, adverse selection, and moral hazard in the lender-borrower relationship, particularly in developing economies in Africa for several reasons. First, the concepts of hidden information and hidden action help us to identify the sources of information gap in the lender-borrower relationship. Second, the principal-agent perspective provides specific ways to reduce information gap, through its logic of signals and incentives, which can be extended to mitigate the problem of information asymmetry in the lender-borrower relationships. Adverse selection and moral hazard problems represent concerns for lenders, who cannot distinguish between borrowers who will default and those who will repay. In this study, I contend that adverse selection problems can be resolved by signals via financial innovations such as mobile money wallet and mobile payments transactions designed to reveal the borrowers' private information about their inherent characteristics.

Finally, from an information technology and system standpoint, the principal agent perspective maintains that the perceived risk in the lender-borrower relationship is determined by specific information problems (i.e., hidden information and hidden action), that could be potentially mitigated with the ubiquitous use of financial innovation and information systems, and as contended in the work of Eisenhardt (1989, p. 70) suggesting that the "next steps for agency theory research are straightforward: Researchers should focus on information systems, outcome uncertainty, and risk". Hidden information in the lender-borrower relationship in this study refers to pre-contractual misrepresentation of the borrowers' true attribute and hidden action refers to the borrower's post contractual shirking, contract default, and fraud, thereby reducing the promised payment of the credit amount and interest.

2.1.4 Signalling theory and Information asymmetry

Borrowers control the information that they provide lenders and can exaggerate or overstate the quality of the information provided. Thus, making high-risk borrowers to be almost indistinguishable from low-risk borrowers. Uncertainty associated with lending to informationally opaque borrowers leads to two information asymmetry problems - adverse selection (the distortion of information that results in pre-contractual misrepresentation of the borrower's true characteristics) and moral hazard (arising post contractually when borrowers do not fulfil their promises to repay the loan or engage in activities that benefit them at the lender's expense) as shown in the work of Pavlou, Liang and Xue (2007) in an online buyer and seller relationship.

In the seminal work of Spence (1973) that focused on US labour market, the study shows that job applicants were likely to engage in activities such as showing-off their rigorous educational attainments to prospective employers as a signal to distinguish them from other job applicants, and to enhance their employability. Spence (2002) further show that signalling theory fundamentally provide further insight to understand and to reduce the problem of information between two parties. In a related study, Connelly et al. (2011) corroborated this finding by showing that signalling theory helps to explain the behaviour of two parties when there is an information gap and both parties have access to different information.

Typically, and in lender-borrower relationship, the borrower, must choose whether and how to communicate (or signal) information about their credit worthiness to the lender, and the lending institution, must choose how to interpret the signal received. The use of signalling theory has dominated finance literature in recent years and the central principle as contended by Spence (2002), is to reduce the information gap between two parties. Spence (2002) further contend that the central tenet of the singling theory consists of the analysis of diverse signal types and the circumstance in which these signals are used. Signals convey information about borrower characteristics and lenders examine them to evaluate the credibility of a borrower's quality.

Related is the work of Wells, Valacich and Hess (2011) that show that signalling theory explains the relationship between signals and qualities and provides evidence to explain why some signals are considered reliable than others, and that the cost of sending misleading signal is prohibitively high relative to the benefit. In the context of a borrower-lender relationship, both good and bad quality borrowers have the chance to signal or not signal their true quality to the lender. When high-quality borrowers signal, they receive Payoff 'j', and when they do not signal, they receive Payoff 'k'. In contrast, low-quality borrowers receive Payoff 'm' when they signal and Payoff 'n' when they do not signal. From this, signalling represents a viable strategy for high-quality borrowers when 'j' is greater than 'k' and when 'n' is great then '*m*'. in these circumstance, high-quality borrowers are motivated to signal and low-quality borrowers on the contrary are not, resulting in what Connelly et al. (2011) describe as a 'separating equilibrium'.

In such cases, lenders can accurately distinguish between high and low credit risk borrowers. However, in contrast, when both types of borrowers or applicants benefit from signaling, this leads to what Connelly et al. (2011) further describe as 'a pooling equilibrium', and in this case, lenders are unable to differentiate between the two categories of borrowers. In a related study using signalling theory, Zhang and Wiersema (2009) shows how unobservable quality of firms are signalled to prospective investors by CEOs of corporate institutions via the use of observable quality of the firms such as the year-end financial accounts. In a general and basic illustration of the signalling theory, Kirmani and Rao (2000) differentiate between two categories of firms, high-quality, and low-quality entities, and contend further that each entity may know their true quality, however, outsiders such as creditors, investors and customers may not, leading to information asymmetry.

Stiglitz (2000) contend that though it is well-known that information available to the market is imperfect, practitioners and economist assume that the impact of the imperfection is insignificant, and this is because such imperfection impact on the market work in the same way as the impact of perfect information. Stiglitz (2000) identified two main types of information, where asymmetry is particularly important. First, the quality of information, and second, the intention of the signaller. In the latter case, the receiver is concerned with the intention or behaviour of the signaller as shown in the empirical work of Elitzur and Gavious (2003). In the former, the information gap is important when a party is not fully aware of the characteristics of the other party (Stiglitz, 2000).

In previous studies, borrowers' 'quality' has been the distinguishing feature in most signalling theories and models. However, the meaning of this feature is open to diverse interpretations. For this thesis, 'quality' refers to information on unobservable characteristics of the borrowers or loan applicants that will affect the lenders' decision to grant credit or otherwise. Signals convey information about borrower characteristics and lenders examine them to evaluate the credibility and validity of a borrowers' qualities. Financial innovation services such as mobile banking, mobile money and mobile payments in recent years has facilitated the transfer of funds and payments using short messaging services (SMS). The impact of these financial innovation services on the livelihood of residents in developing economies, particularly in Africa have captured the attention of several researchers, partly because these financial innovations using mobile enabled devices have been shown to have the potential to revolutionize economies where financial infrastructure is lacking.

In an empirical study using survey data that solicited responses from both M-PESA users and non-users in Kenya to estimate the impact of M-PESA on the type of transactions that users undertake, William, Ray and Suri (2013) find that more than 40 percent of M-PESA users in the survey transfer payments to family and friends for support on a regular basis. Fifty-three percent (53%) of non-M-PESA users in survey use mobile transfers and mobile payment to support family and friends on a regular basis. In a related study that sought to disentangles hidden information from hidden action among borrowers in the high-risk consumer lending market in South Africa, Karlan and Zinman (2009) find evidence of significant moral hazard problem relative to adverse selection on undisclosed information and its overall impact on default.

The transactional data from the ubiquitous use of financial innovation via mobile enabled devices such as mobile phone leave footprints that provide dual signals. First, these transactional data reveal the borrowers' historical purchases, donations, business and non-business expenditures, formal and informal income to facilitate comprehensive risk analysis and loan underwriting by the lender; and second, the transactional data can signal to lenders about the borrower quality to mitigate the problem of information asymmetry, adverse selection, and moral hazard. Financial economist and researchers have also emphasised on borrowers' and lenders' social network that impacts loan repayment behaviours. The emergence of online borrowing platforms has not only provided lenders with borrowers' personal information but also provided social networks for lenders to assess borrowers' reputation and the impact of reputation on loan repayments.

For example, the works of Lin et al. (2013) and Björkegren and Grissen (2015) find that borrowers' social network information can enhance the success rate of lending, significantly reduce information asymmetry in trade, loan repayment and loan default frequency. In a study that examined social and intellectual capital in a lender-borrower relationship in microfinancing, Nahapiet and Ghoshal (1998) find that lenders' transaction cost and risk decline for borrowers' who have high social and intellectual capital within networks. This is because, borrowers found to be reputable in the society or network have higher probability of adhering to the credit terms than counterparts with low reputation and lenders benefit from informational economies of scale.

Financial innovation, mobile banking, mobile money wallet and mobile payments facilitates the identification of borrower features that lender do not observe, such as the frequency and value of transfers from the borrowers' formal and informal income that is used as payments to informal money lenders, and also to support family and friends. These transactions may significantly affect the available disposable income that form the basis for calculating the loan amount disbursed and the repayment affordability of the borrower. Regular and irregular payments to family and friends may provide signal of a likely moral hazard problem that is not captured in the credit reference bureau information. Such an explanation would be consistent with the existence of private information about borrowers that explain the information gap in the lender-borrower relationship.

The introduction of credit reference bureaux in the financial services industry became a feature in developing market economies in the last few decades with the objective to reduce the information gap in the borrower-lender relationship (Lin, Ma, Malatesta and Xuan, 2011). Extant theoretical models that sought to understand link between information sharing and asymmetric information such as the work of Pagano and Jappelli (1993), presented a model with adverse selection and sought to empirically examine the impact of information sharing on the credit market and loan default frequencies. Pagano and Jappelli (1993) find, that exchange of information among professional lending institutions reduces interest rates charged by lenders, loan loss frequencies and improves the quality of borrowers in the banks' loan portfolio and incentivise loan repayment because borrowers' loan performance are shared among multiple lenders.

Related is the work of Padilla and Pagano (1997) that point out that the punitive effect of credit bureaus arises only from the exchange of negative information about the borrowers' historical loan performance. This is because, according to Padilla and Pagano (1997), the sharing of such negative historical credit performance impact negatively on borrowers' reputation in the society they live, hence, borrowers exert more effort in their loan repayment. However, in a related theoretical model, Pagano and Jappelli (1999) find contradictory evidence, that the sharing of borrowers' historical information does not have any relation with loan default frequencies and credit spread charged by professional lenders.

In a developing market economy such as Ghana, where some form of formal third-party institution exists to provide information about loan applicants' and their credit history, the problem of moral hazard can distort the information lenders receives from third party credit reference bureau. Hence, most of the information lenders receive from these third-party credit reference agencies are thin, and at best, this thin information file only helps lenders to fulfil their legal 'Know Your Customer' (KYC) obligation. In a study that focused on information sharing in developing countries, credit information bureaux were found to act as information agents that facilitate increase in transparency of credit markets, however, in many developing market economies, credit information bureaux are still immature, and borrower information sharing among lending institutions remains thin (Luoto, McIntosh and Wydick, 2007). Further, Luoto, McIntosh and Wydick (2007, p. 315) find, that developing market economies, particularly "*Africa remains the region of the world with the least developed credit information systems*".

Related is the work of Jappelli and Pagano (2002) that investigated the link between information sharing, lending and default frequencies using a cross-country approach, and find that lending increases significantly among professional lenders in countries where credit information is shared among lenders relative to a country's gross domestic product (GDP). Furthermore, Jappelli and Pagano (2002) provided empirical evidence to show that loan default frequencies and credit risk is less severe in economies where information sharing exists. However, the work of Jappelli and Pagano (2002) is based on survey data and the authors' measurement of default loan loss provision is open for distortion based on the accounting rules that may be different for each country in the survey as rightly identified in their paper. Accordingly, my thesis complements the existing literature by directly investigating how Fintech can reveal borrowers' private information that are not held by information sharing bureaus but can impact significantly on loan performance.

Financial innovation technology via the use of mobile phone networks and mobile money has become a channel for distributing loans for consumer durables, such as pay-as-you-go energy solutions[3]. These channels for distributing credit have enable forms of credit different from the traditional lending institutions such as banks and micro financial institutions. However, all these channels of credit distribution face a fundamental problem: information asymmetry, i.e., adverse selection and moral hazard. How can the lending institution assess whether a potential borrower will repay or default once the loan is granted? The problem is severe in developing economies, where residents have no formal credit score, and

[3] Customers receive the device from the creditor and payments are done on an instalment basis using mobile money account transfer.

few interact with the formal financial systems and institutions (Demirguc-Kunt, et. al., 2014).

There is a striking paucity of empirical studies on the link between financial innovation and information asymmetry in developing markets, particularly in Africa. I empirically explore the consumer loan market, with an emphasis on how financial innovation influences the asymmetric information problem in the lender-borrower relationship, and it impact on default probabilities in developing economies in Africa. Further, I aim to predict default based on the information available at the time credit was granted, and so include the Fintech variable as a measure of borrower opacity. In this section of my thesis, I contend that pre-contractual problems, adverse selection and post-contractual problems, moral hazard can be addressed using Fintech. Furthermore, I posit that the ubiquitous use of Fintech, that is mobile money, in developing countries can provide low-cost, and easy-to-authenticate signal that communicates otherwise unobservable characteristics of borrowers to lenders.

Additionally, I contend that low-risk borrowers have access to and use of financial innovation technology services such as mobile money wallet and are willing to share transactional information via their usage of Fintech to lenders to facilitate comprehensive loan underwriting and loan pricing. As a result, the transactional information acquired by lenders from the applicants' usage of Fintech become an efficacious signal to the lender. Lenders can gain from making decisions based on information obtained from these signals generated from the borrowers' usage of mobile wallets. On the contrary, high-risk borrowers would not or do not use Fintech, and or are unwilling to share transactional information about their income and expenditures accumulated via their usage of financial innovation technologies.

To mitigate information asymmetry problem in the borrower-lender relationship in developing economies, my thesis builds upon the principal-agent and signalling perspective to propose a model that mitigate the information gap. Using the signal and transactional data gathered from the borrowers' acquisition of Fintech can facilitate the acquisition of private information about borrowers that fill the information gap. This also can overcome the agency problems of hidden information and hidden action through the use of Fintech as a signalling channel. I empirically test my proposed model with a sample of 12,071 consumer loan data from a major consumer lending intuition in Ghana. The findings of this study have several important implications for understanding the impact of financial innovation technology services such as mobile banking, mobile money, and mobile payments on asymmetric information, particularly in developing economies in Africa.

2.1.5 Credit scoring

In 1936, Fisher attempted to differentiate between two groups of population, and to achieve this, he introduced discriminant analysis in statistics. In a study to differentiate the origins of skulls and two variations of iris, Fisher (1936) used discriminant analysis technique to measure the plant size and the origins of skull to achieve this objective. Thereafter, numerous studies have used discriminant analysis. In the context of credit markets, for example, the work of Durant (1941) used discriminant analysis to differentiate and predict 'bad' loans from 'good' loans in a study for the National Bureau of Economic Research in the United States.

However, in a critique of the use of statistical methods, Capon (1982) contend that by using statistical method, the reasons for actual default were not considered when assessing future credit applicants. The use of credit scoring technique took shape in the 1960's when lending via credit card had reached a peak and a faster process to decide whether to grant credit or otherwise became necessary. This led to the automation of the decision process and a credit scoring technique was developed to undertake this function, which later became a tool used for extending other forms of credit to different categories of customers, in particular to small and medium enterprises.

In the empirical work of Myers and Forgy (1963) that compared the performance of numerous discriminant and multiple regression analyses to determine their credit quality of loan applicants, the authors document that discriminant analysis techniques with equal weight were as predictive as multiple regression analysis. The authors further document that, by varying the discriminant analysis technique, higher scores can be obtained at lower score level that better separate groups and reduces the cost of potentially credit worthy clients. Related is the work of Beaver (1967) who initiated a bankruptcy prediction model to determine the likelihood of a firm becoming bankrupt using financial indicators.

These two distinct streams of works were followed by Altman (1980) who provided a description of the lending process as an integrated system and suggested procedures for assessing and analysing commercial loans. The literature on credit scoring has mostly focused on commercial loans than on retail loans, and this is largely because the data required for building corporate loans scoring system has been more readily available compared to retail loans. Furthermore, some of the various borrower-specific characteristics required to build consumer credit are some jurisdictions prohibited by law, and sensitively protected by organisations to ensure their competitive advantage over competitors in the loans market.

Further, corporate credit scoring models use financial information such as balance sheet and other financial statements information and is different from retail credit scoring systems that uses a portfolio approach given that the loan size for retail loans are relatively smaller compared to corporate loans. Some lenders continue to underwrite loans using applicants' personal and socio-economic characteristics and subjective methods, whereas others use a more 'objective' methodology such as credit scoring models[4]. Credit scoring as a lending methodology convert the subjective assessments of the credit applicants' creditworthiness into an `objective' measurement through a `scientific' process using statistical analysis. The statistical analysis generates a score that captures the risk profile of prospective borrowers and the probability that the loan will be repaid or otherwise.

Credit scoring model is fundamentally a quantitative set of methods used by lenders to help in the lending decision, and to determine whether the credit applicants should be granted credit or otherwise. The rationale for scoring credit applicants is to differentiate between "good" and "bad" borrowers, and to provide lenders with information on the likelihood of the credit applicants' ability to repay loan. The main advantages of credit scoring models over the traditional five C's

[4] Credit scoring sum these borrower characteristics using statistics to arrive at a score, and this core signal to the lenders whether the credit applicant is likely to repay debt or default.

method is that it has the ability to provide faster decision to the lender concerning the potential credit worthiness of loan applicants, consistency in decision outcomes, ease in monitoring, cost efficient and can incorporate macro-economic factors and changes in credit policy (Rosenberg and Gleit, 1994; Thomas et al., 2002 and 2005). Following Altman (1968) seminal paper on credit score modeling, several variants of credit scoring models have emerged, both in literature[5] and in practice.

Further, the Basel accord directions, specifically in the area of credit risk and capital management, has also influenced the methods and approach taken by financial institutions globally to assess and manage credit risk and capital allocation. Linear and quadratic discriminant analysis, multivariate regression, linear and logistic regression, and Markov chain models are some of the classical methodologies used by lenders to credit score loan applicants (Baesens et al., 2003a, Baesens et al., 2003b, Thomas, 1998, West, 2000). The works of Chi and Hsu, 2012; Wang et al., 2011; Huang et al., 2007; Ince and Aktan, 2009; Martens et al., 2010; Ong, Huang, Tzeng, 2005 and Baesens et al (2003) document, that the application of artificial intelligent methods such as evolutionary computing, artificial neural networks, decision trees and support vector machines are able to successfully evaluate credit risk.

However, logistic regression and linear discriminant analysis are the two main statistical credit scoring methods used by practitioners to score credit applicants. Logit regression process enables the modeling of probability for discrete outcome given an input variable. Further, It is a useful analytical technique for classification problems, where the outcome variable is categorical as shown in the works of Baesens et al., (2003b), Desai et al., (1996), Lee and Chen (2005), Lee et al., (2002), Thomas (2000), and West (2000), Similar to other supervised machine learning, logistic regression learn a functions from the features of the sample dataset to the targets variable to predict probabilities.

[5] See the works of Laitinen (1999) on the prediction of credit risk ratings, Byström, Worasinchai, and Chongsithipol (2005), Philosophov and Philosophov (2002).

The application of these different methods in credit scoring facilitates and enables financial institutions to convert their 'subjective' assessments of potential borrowers' ability to repay loans into an 'objective' outcome. Marron (2007) in a related study document, that credit scoring provides lenders with an assessment of the credit applicants' ability to repay loans, safeguards the lenders capital, and the threat of any capital deterioration associated with loan losses. The use of statistical modelling, and the application of probabilistic models in consumer lending in developing markets has emerged. In developing economies in Africa, the empirical works of Viganó (1993) for Burkina Faso and in Asia the work of Schreiner (2004) exists in the literature and are considered the 'best' in these markets for micro-financial institutions. However, these studies used limited sample of between 31 to 100 disbursed loans, hence making it difficult to generalise.

Credit scoring models using customer behaviour enables professional lending institutions to make decisions about who to lend to and on what terms. However, in a related, Finlay (2009) criticised the modeling of consumer lending decisions taken by lenders as a 'set of classification problem' and contends that this approach leads to a misrepresentation of the main objectives of professional lenders. Furthermore, Finlay (2009) contends that the exact rationale for professional lending institutions to grant credit can best be described in terms of some unremitting financial measurement such as income, profit generated from the lending portfolio and the state of non-performing loans. The challenge in Finlay (2009) argument is that the classification model enables professional lender to select customers with higher probability of repaying loans and thereby contributing to the key objectives of lending institutions-which is an increase in interest income and profitability.

Additionally, the transfer of credit scoring methodology from developed economies to developing market economies appear to have been unsuccessful due to lack of systems to capture borrower related financial activities needed to build a reliable risk scoring models that reflect the risk profile of credit applicants. Consumer scoring models are successful in developed economies because majority of consumers work in the formal sector and information about their household income can be easily checked and traced to their employer. However, the reverse is the case for developing economies, where the informal sectors form a significant part of these economies but is excluded in risk scoring models. The related empirical work of Hart (1999) finds that the informal economy becomes the entire economy in circumstances where the state has collapsed.

Further, consumer credits scoring in developed economies are successful because majority of the population have bank accounts, and lenders can access the customers' financial information to make credit decisions. However, in developing economies, transactions are mostly cash-based, and this is because the proportion of residents in developing countries with bank accounts is relatively small (Porteous, 2006). As a result, lenders have difficulty in making meaningful credit decisions. Additionally, the formal and informal nature of most developing economies mean that the consumers' total household income can be a mix of income generated from both the formal and informal sectors of the same economy.

Additionally, consumer credit scoring models developed in western economies and transferred to developing economies do not factor in these two streams of income when calculating the credit applicants' loan affordability. Hence, without addressing these fundamental weaknesses in western developed consumer scoring models, the application of these models transferred from developed economies to developing market economies become questionable. Extant theoretical research summarized above shows that exchange of borrower information across lenders provides an incentive that can act as a discipline mechanism for borrowers to honour loan repayment obligation and increase credit availability in the marketplace. However, to the best of my knowledge, no empirical investigation exists on how lenders can address asymmetric information problem in developing countries where credit scoring information do not exist using financial innovation technology. Where such system exists, information held is thin and at best, only helps lenders to fulfil their *Know-Your-Customer* obligations imposed by law.

My thesis fills this gap by providing a model to address the problem of information asymmetry in the lender-borrower relationship, particularly in developing countries where the problem is severe. I use customer level data, information on individual loan contracts and borrowers' usage of financial innovation to document the link between financial innovation and information asymmetry and its impact on default probabilities in developing economies. Further, logistic regression models have been used in several prior studies in consumer scoring models. However, a key element that differentiates this study from previous ones is that it is the first to incorporate the borrowers' usage of financial innovation technologies such as mobile banking, mobile money wallet, and mobile payments as a measure of asymmetric information in the borrower-lender relationship, particularly in developing market economies.

Consumer credit risk scoring models, unlike investment banking product such as credit swaps, options, et cetera, that are traded on regulated exchanges globally, has attracted less attention, though these models have been developed since the 1950s and appears to be seemingly robust and work under different economic conditions prior to the most recent financial crises when financial institutions globally began to re-evaluate their risk models (Malik and Thomas, 2010). Bagherpour (2017) in a study conducted to empirically examine mortgage default rate in the US using large sample dataset with quarterly intervals between 2001 to 2016 and machine learning models such as Random Forest, K-Nearest Neighbors (KNN), Factorization Machines, and Support-Vector Machines finds that Factorization Machines predicted an area-under-the-curve (AUC) values of eighty-eight (88) and ninety-one (91) percent which were the highest in comparison to the other predictor models.

Further, Bagherpour (2017) contends that machine learning models are better able to identify and provide predictor strength of the features under consideration, and terms of performance, the traditional logistic model is outperformed by non-parametric models. Related is the work of Xiaojun et. al. (2018), the authors employed their novel machine learning to predict borrowers default frequencies. Xiaojun et. al. (2018) contend that their choice of algorithms (LightGBM and

XGBoost) significantly reduces the overfitting problem that characterises credit scoring and machine learning models, and further finds that LightGBM show a better performance (approximate accuracy of 80%, and error rate of 20% respectively), and that their model is grounded in theory and supported by several empirical studies in literature.

Kvamme, et. al. (2018) in their novel convolutional neural networks approach using time series data related to customer transactions in current accounts, savings accounts, and credit cards to predict mortgage default in Norway, the authors obtained a receiver operating curve- area under the curve (ROC-AUC) of 0.918 and 0.926 for networks and networks in combination with a random forest algorithm respectively using deep learning classification techniques. However, the sample data used for their study excluded borrower-specific features which has been shown to impact loan performance and default frequencies (Bonne, 2000, Schwarz, 2008). Related is the work of Koutanaei, et al. (2015) that used a hybrid credit scoring model to test four feature selection algorithms and ensemble learning classifiers and finds that Principal Component Analysis (PCA) outperformed others in feature selection.

Further, Koutanaei, et al. (2015) document that artificial neural network adaptive boosting (ANN-AdaBoost) outperformed other classifiers such as genetic algorithm (GA), information gain ratio, and relief attribute evaluation function when considering their classification accuracy. However, in a related study that compared standard parametric method such as logistic regression that use binary classification of good or bad borrowers’, and non-parametric methods that includes random forests (RF), k-nearest neighbours (KNN) and bagged k-nearest neighbours (bKNN) to estimate default frequencies among borrowers, Kruppa, et al. (2013) adopted machine learning methods in their study and finds that on their test data, random forest algorithm has the highest area-under-the-curve (AUC). Though their finding show that random forest regression outperforms standard logistic regression, it only does so for loans with short maturities.

Additionally, in a study using nonlinear nonparametric estimating models of consumer credit risk and a combination of credit bureaus and transactional data from a commercial lender in the US, Khandani, et al. (2010) propose an amalgamation of features and contend that their model significantly improves the predictive strength using features in the latter dataset. However, Khashman (2011) constructed a novel approach to predict consumer credit risk using an emotional neural network that considers the emotional attributes such as the anxiety and confidence and compares the findings with the standard neural network model during the learning process. In the study, Khashman (2011) sought to simulate the decisions making process of human experts in credit risk evaluations and finds that in terms of accuracy with minimum error, speed and simplicity in credit decisions, emotional neural network model outperformed the conventional neural networks.

In the empirical work of Harris (2013) undertaken in Barbados, a developing market economy, the author used support vector machine (SVM) algorithm on two class definitions of default (loans overdue up to 90days, and over 90days overdue loans) and document that the classification model used for the dataset with broader (over 90days) definition of default class resulted in significantly higher accuracy in predicting loan defaulters reliably compared to credit underwriting using human judgement. This suggest that credit scoring using machine learning leads to a significant accuracy in assessing the credit risk of borrowers compared to using the tradition five 'C's' in loan underwriting.

Beque and Lessmann (2017) constructed a somewhat feed-forward neural network framework called Extreme Learning Machine (ELM) and compares its performance with other predictive methods such as artificial neural networks (ANN), decision trees (DT), support vector machines (SVM) and regularized logistic regression (R-LR). The authors contends that the Extreme Learning Machine (ELM) approach combines prediction performance with computational efficiency, suggesting that the Extreme Learning Machine (ELM) can be a reliable alternative to other consumer credit risk scoring models. However, as shown in the empirical work of Wu and Miao (2015), the number of nodes in the hidden layer in the meta-parameters in Extreme Learning Machine (ELM) are usually selected by trial-and-error. Furthermore, Lahiri and Ghanta (2009) find that the activation function of the hidden layer neurons in the meta-parameters in Extreme Learning Machine (ELM) often is dependent on the input data.

When evaluating the performance of a credit scoring model, there are many methods used to achieve this objective. Several extant studies on credit scoring models are built on samples of historical client data and with the dual objectives to generalise the outcome and to mitigate the problem of over-fitting (Huang et. al, 2004). To achieve these dual objectives, Huang et al., (2004) developed a machine learning models to predict credit ratings using US and Taiwan datasets and finds that improving the performance of the evaluation-metric during model development phase is critical in an attempt to overcome the over-fitting problem and to enable better generalisation of findings. The work of Wang et al., (2005) employed a version of the support vector machine (SVM) learning called fuzzy support vector machine to empirically evaluate the performance of different machine learning models used to examine the credit risk of consumer loans, and their findings show that the fuzzy support vector machine achieve a better generalisation and concur with the finding of Huang et. al, (2004).

Accuracy is one metric used to measure a credit scoring model accurately when a cross-validation dataset is used to classify loan applicants. However, in an empirical study Harris (2013) contends that predictive accuracy should be used when the dataset has a normal distribution. Harris (2013) further proposes the use of precision and recall, a measure of how the classifier model is able to correctly classify positive predictions and a measure of what the actual proportion of the dataset were positive and predicted to be positive respectively. However, the empirical work of Hand and Henley (1997) finds that recall and precision does not mitigate the potential cost of misclassification associated with using credit scoring models.

The ability of a credit scoring model to minimise the disproportional cost associated with misclassifying clients who may be able to repay their loans but were denied loans (Type II error), and clients who may default but were granted credit (Type I error) is another approached use in literature to evaluate the performance of a classification model (West, 2000). However, in the empirical work of Lee and Chen (2005) that evaluated the performance of credit scoring using two-stage hybrid modeling techniques with artificial neural networks (ANN) and multivariate adaptive regression splines (MARS), the authors document that forecasting the misclassification cost is difficult.

Furthermore, the empirical work of Provost, Fawcett, and Kohavi (1998) show that Classification accuracy is not an appropriate evaluation criterion for all classification tasks. For the above reason and for my thesis, I evaluate and compare different methods with respect to their estimates of class probabilities. Additionally, I use the Receiver Operating Characteristic-Area under the curve (ROC-AUC), which is another model evaluation technique widely used in literature and in practice (Swets, 1988). The ROC curve is a two-dimensional measure of a classifier's performance where the proportion of actual negatives predicted as negative, and the proportion of actual positives predicted as positive are graphically plotted on the Y and X axis respectively. I only considered tasks of binary classification, which facilitates the use of logistic regression and allows me to compute the area under the ROC curve, described above, which I rely on heavily in my analysis.

2.1.6 Financial technology (Fintech)

Market interaction is commonly characterised by asymmetric information. In his seminal work, Arkelof (1970) show that private information can lead to market malfunctioning. In theory, the main prominent models of information asymmetries in credit markets, describes how uneven information in the borrower-lender relationship impact on loan quantity and performance. This uneven information may relate to the lending institutions' ability to assess the borrowers' credit risk, ex-ante, and or the lenders' ability to ensure that borrowers use the loan for the purpose for which it was granted, ex post. Further, depending on the level of uneven information, the quantity of loanable funds and the return for investors may increase or decrease (De Meza and Webb, 1987; Stiglitz and Weiss, 1981).

For many banks operating in developing countries, it is of critical importance to have an accurate means of assessing the credit worthiness of individuals in a population. The credit risk status may not be the sole determinant of bank lending, but it provides a useful indication of the underlying risk profile and quality of loan applicants. Pragmatically, a better understanding of individuals' credit risk status can inform lending decisions and loan pricing with significant benefits for banks, households, developing agencies and will help businesses meet the needs of their target population. However, identifying individuals with good credit risk status is notoriously difficult, particularly in developing countries where the residents are severely informationally opaque.

Providing support to lending institutions to manage credit risk is a critical function of financial system. Additionally, understanding the product and services provided by lenders to household is equally important to enable borrowers to manage the risk inherent in these financial products. For example, understanding the risk embedded in a credit contract helps households to take exposure that matches their risk tolerance. Further, aligning the individual household's risk preferences with that of the lending institutions helps lenders to provide innovative products that add value and to manage credit risk effectively. However, imperfections within financial markets can affect the delivery of these innovative financial products. This could in turn limit the households' ability to access financial innovation technologies such as mobile banking and mobile money wallets that could equally provide lenders with a mechanism to mitigate this market imperfection resulting from asymmetric information.

In a competitive loan market hindered by asymmetric information, lenders can benefit from having private information about borrowers to enhance loan performance. Hence, if financial innovation enhances borrower financial and non-financial information for quality loan underwriting, then borrowers who adopt financial innovation to reduce their opaqueness will be associated with low credit risk and this will in turn reduce asymmetric information via reduced default probabilities. A lending institution that is better informed on the credit risk of borrowers can screen out risky borrowers, ex-ante, and hence reduce the cost of default to the lender, ex post, and interest rate to borrowers.

The recent financial crisis of 2007-2008 exposed weaknesses in traditional financial institutions. Further, the emergence of rapidly growing advancement in technology has facilitated the ease with which customers can view their financial information, and this has been the main drivers of the rise in financial innovation technology (Anikina et al., 2016). For my thesis, it is important to define what I mean by financial innovation technology. Financial innovation technology (Fintech) is a term used to commonly describe firms that offer financial services using modern technology in the financial services sector. These firms have become noticeable feature in the past decade and has been claimed to improve the efficiency of financial systems and service delivery (Vlasov, 2017; and Vovchenko et al., 2017).

Further, financial technology innovation, Fintech, such as mobile money wallets are gaining traction in many developing market economies as alternative to formal bank account, and a convenient means to undertake financial transactions. As a result, several studies have examined the impact of consumer adoption of mobile phone technology on the socio-economic well-being of users (World Bank, 2021:2022; Demirgüç-Kunt et al., 2017). With the growing and everyday use of cell phone enabled smart technologies, the use of mobile phone as a channel to deliver financial services is on the ascendency and has become necessary. Financial innovation technology (Fintech), which is an amalgamation of finance and information communication technology (ICT), has emerged in response to this trend (Dahlberg et al., 2015).

The penetration of mobile phone usage and financial innovation technology platforms such as mobile banking, mobile payments and mobile money wallet has been on the ascendancy in developing countries (Global System for Mobile Communications Association, 2019). This has been possible due to the high mobile phone penetration in these economies, coupled with the fact that there are more people with mobile money accounts compared to traditional bank account (Porteous, 2006). In many developing countries, the widespread use of mobile phone network as a new channel for interpersonal transfers of funds has emerged and is on the ascendancy. Further, this has removed the geographic limitation in risk sharing relationships.

World Bank report in 2012 estimate that about '*three quarters of the planet's population now has access to a mobile phone*', and finance technology applications such as Mobile Money via mobile phones has the potential to be a significant tool with which lenders can use to reduce the problem of information asymmetry. DeYoung et al., (2004) examined among others, the impact of technological changes on bank viability and document that technological changes has intensified competition in the banking sector, and at the same time provided an opportunity for financial institution to exploit technology for potential growth to increase profit. Additionally, Financial institutions and mobile payments service providers generate income from mobile payment transactions fees and from transactions on float.

According to the Global System for Mobile Communications Association (2020), mobile operator income is expected to reach $48.7bn by 2025 from $44.3bn in 2019. Hence for mobile payments service providers, the development of mobile enabled form of payment system offers the potential to offer new services to increase customer base, lower cost of payment transactions and increase revenue. Financial intermediation theory asserts that the introduction of professional financial intermediaries such an banks and other forms of financial intermediation is critical to reduce the cost of transaction between market participants (Gurley and Shaw 1960); and the low cost associated with mobile lending, mobile money and mobile payments has achieved this objective (Medoff, 2002). Additionally, the work of Bold et al, (2012); Jenkins, (2008), Porteous, (2006); and Ehrbeck et al., (2012) all document a positive relationship between financial inclusion for the many residents in developing countries excluded from the mainstream banking system, and financial innovation adoption.

In developing countries, recent example of financial innovation technology is mobile banking services that enables user to receive funds into their mobile money wallet accounts and to make basic payments via the clients mobile enabled devices such as mobile phone without the need to have a formal bank account. Some of the main services that financial innovation technology services such as mobile banking and mobile money account owners receive from providers includes making peer-to-peer payments, transfer of funds, mobile balance recharge, remittances, mini bank statements, receive alert for upcoming payments, shopping, balance enquiries, and PIN changes. Using mobile banking permits customers to access these financial services on-the-go without the need to visit the bank.

Mobile money account, a product of the convergence of technology and financial services has facilitated the over 3 billion residents in developing market economies to undertake financial transactions via mobile money payments and remittances (Aker et al. 2020, Jenkins, 2008; World Bank, 2021:2022). Mobile money account ownership operated via standard mobile phone has been a promising alternative to the lack of access to mainstream banking services for the many residents in developing countries (Jenkins, 2008). According to the 2021 World Bank's global findex survey, adult population with bank account ownership increased between 2011 to 2021 by fifty percent (50%) to reach seventy-six percent (76%), and between 2017 to 2021 the average rate of account ownership in developing economies increased by eight percentage points, from sixty-three percent (63%) to seventy-one percent (71%).

To own a mobile money account, one is required to possess a mobile telephone that can take a registered sim card from the mobile money and telecom provider. Once the registered sim card has been obtained, the user can then deposit funds via the mobile money providers' agents, which are usually located in shops. The cash is then electronically deposited in the customer's mobile money account. Mobile money account holders can transfer money via SMS to other people even on different networks and make withdrawals at their network's agents anywhere in the country. Users of mobile money are charged a fee depending on the amount sent and withdrawn from the agents.

The main financial innovation technologies (mobile banking, mobile payments, and mobile money wallet) used in developing markets allows users and account holders to perform three main broad things: (1) Store funds in the form e-wallet that that is accessible via mobile enabled technology such as mobile phones, (2) use the e-wallet to undertake for everyday payment transactions, and (3) allow users and account holders to transfer funds between two mobile money accounts (Janatan and Camilo, 2008). Furthermore, the work of Lee et al. (2007) document, that financial innovation such as mobile financial services platform using mobile phone device has made it possible for financial service providers to extend financial services to new customers that hitherto could not be reached.

Users of mobile money store funds on their mobile enabled devices, commonly known as *mobile money wallet*. This enables mobile money account holders to undertake domestic payments and transfers funds from Person-to Person, for example, payment for an informal purchase of a used item between two individuals: or for official payment to the self-employed tailor. Also, mobile money facilitates payment from Business-to-Person such as payment of employee salaries via the employee's mobile money account; or payments from Person-to-Business for the purchase of goods and services (International Telecommunication Union, 2013). This development in financial innovation technology platforms has enabled large datasets and information about potential credit applicants' available to be generated and manipulated in ways that were previously impossible. For example, in the empirical work of Björkegren and Grissen (2018) that used mobile telephone call data, they document that patterns in individuals' call behaviour using mobile phone can predict the credit risk of borrowers.

Additionally, the empirical works of Blumenstock et al., (2015); Gonzalez et al., (2008); Onnela et al., (2007); Palla et al., (2007); and Soto et al., (2011) document that individuals' mobile phone usage generate rich records on credit applicants and provide insight into the individuals' socioeconomic lifestyle, such as mobility, social connections, and consumption. Furthermore, in developing countries, there is the widespread usage of mobile phone with over 850million mobile phone connections and 300million users of mobile internet (Global System for Mobile Communications Association, 2020). Further, mobile phone and mobile enabled devices has become one of the main sensors of human behaviours, and financial innovation technology such as banking and mobile money wallets via mobile phones open the door to be used as proxies to study the problem of information asymmetry in the borrower-lender relationship.

M-Pesa is an example of financial innovation technology system which permits adopters and users to receive electronic currency in exchange for cash. This electronic currency can be stored on mobile phones or sent to other users of this financial innovative technology via mobile communication devices since it was launched in Kenya in 2007 by Safricom, a mobile telecommunication network operator. Thereafter, the adoption and use of mobile money account has increased rapidly in developing countries, and according to the Global System for Mobile Communications Association (2020) there are 1.2 billion registered mobile money account users, 44.1billion transactions valued at $767billion across 310 services in 96 countries globally. Developing countries account for a significant proportion of the global activity. For example, in Sub-Saharan Africa, 157 live services are delivered using mobile money account, has 548million registered account with transaction volume and value of 27.4billion and USD490billion respectively (Global System for Mobile Communications Association, 2020.

Similar to credit and debit card payments in developed countries, mobile money payments and transfers services are method that enable individuals to pay for goods and services via their mobile money account using standard mobile phone and has the benefit of providing convenience to users via wireless infrastructure that enables it usage anywhere and at any time (Iman, 2018). Furthermore, mobile money payments is a non-cash medium for undertaking financial transactions that offer benefits is similar to credit and debit cards used in developed economies. In developed countries, for example in the United States, the work of Anguelov et al., (2004) find that the percentage of households who use debit cards increased significantly to reach 50% in 2001 from 20% in 1995 and achieved the highest growth rate (an increase of 41.8%) among the diverse forms of retail payments that included cash, cheques, and credit card between the period from 1995 to 2000.

In a related study that sought to evaluate and shed light on the use of checks and other noncash payment instruments in the United States of America using survey data, Gerdes and Walton (2002) find that in 2000, debit cards accounted for 11.6% of all retail transactions. Related is the work of Weiner (1999) that contends that debit card, which has become widely available, provide direct transactional properties of automatic teller machine (ATM) cards, and offers the convenience at the point-of-sale for consumers, similar to credit cards. mobile money bundles the many desirable properties of different payment tools, and like debit card and cheques, consumers can use their mobile money wallet for direct transactions from existing funds in their mobile wallet. Compared to checks, mobile money wallet has additional desired benefits. This benefit includes providing mobile money wallet users the convenience of carrying money on mobile phone rather than plastic cards, cheque books, and permits real-time transactions at the point of sale.

Extant studies have identified numerous factors associated with the use of debit cards as an instrument to undertake financial transactions. In the US, Kennickell and Kwast (1997) used the 1995 survey of consumer finances to understand who and what drives users to adopt electronic banking services. The authors find that there is an inverse association between adoption and age, and a positive association with financial assets and education. The authors also find no significant association between income and the adoption debit card. Carow and Staten (1999) applied survey data administered to 6,451 credit card holders who use their card to purchase gasoline in the US to investigate consumer's preference for debit, credit card and cash.

In the work of Carow and Staten (1999), the authors find among others that debit card users were more educated, younger, and that the likelihood of consumers using debit card is dependent on the number and type of credit card available and held by individuals. Related is the work of King and King (2005) that used survey of consumer finance data collected in the United States of America's in 1998 and find that negative sentiments about credit card is positively associated with debit card usage and are negatively related to household' assets. As a payment instrument for retail transactions, mobile money competes with debit and credit cards.

Particularly, a comparison of mobile money and debit cards is interesting because of their close similarities and distinctive differences. Both enable account holders to carry an amount of "virtual" money. Further, similar to debit account holders with overdraft limit, mobile money operators offer short-term credit line that allows consumers with active mobile money wallet account to use these as a financing mechanism. Inactive mobile account users are restricted by the amount of money available in their mobile money account just as with debit card. Also, similar to debit, there is a daily limit that most providers impose on mobile money wallet withdrawal.

In a related study in the United States of America using survey data to understand consumers' usage of electronic banking services and products, Mantel (2000) proposed the theory of Obstacles, Incentives, and Opportunities. The author contends that obstacles are the factors that limit the consumers' ability to access payment channels, for example, access to a debit card may require consumers to have sufficient cash-inflow to open and use a formal bank account. Hence, those consumers without adequate cash-inflow are unable to access and use debit cards to undertake financial transactions. The author contends that Incentives offers are the mechanisms used by providers to encourage the adoption of a specific payment instruments, and opportunities are the innovative methods for using the identified payment mechanism in diverse circumstances.

Further, the work of Prelec and Loewenstein (1998) in the area of double-entry mental accounting theory. The authors contend that the mental burden associated with paying later after purchases when consumers use credit card diminishes the net utility that comes with the purchase, and hence, encouraged the use of debit card because of the benefit associated with prepayment purchases. Unlike developed economies in Europe and America that continue to use consumer credit scoring as a tool to assess borrowers' credit risk in retail credit markets, consumers in developing countries are typically much more informationally opaque and majority do not operate a formal bank account that yields credible financial information to facilitate credit risk assessment.

To address the informational opacity problem, banks use a number of different lending methodologies, and one of such methods is the use of collateral (Thakor and Udell, 1991; Beaudry and Poitevin, 1995; Schmidt-Mohr, 1997). In the case of the lender, I use in my thesis, loans are considered secured when a written assurance, not a guarantee, is received from the borrowers' employer that as long as the borrower remains an employee of the employer, monthly repayments would be deducted from earnings and made payable to the lender. Loans are then disbursed using the lending institutions' mobile money wallet account and paid into similar account held by borrowers.

Jack and Suri (2014) investigated the effect of mobile money on consumption using 3,000 randomly selected households across Kenya. The authors find that, limited access to mobile money account network reduced food and non-food purchases of household by seven percent and ten percent respectively across users and nonusers of mobile money account. Related is a study by Riley (2018) that examined the use of fintech and household consumption in Tanzania, a country that low rainfall impact on disposable income. The author compared households with and without mobile money wallet account and find, that mobile money users are able to smooth and maintain household consumption because it improves risk sharing among residents. The author also finds that more than a third of the respondent received remittances using mobile money compared to just two percent that used bank account, with each person having at least one mobile phone.

Blumenstock et al., (2010) studied the use of mobile phone across gender groups and economic status of individuals. The authors used individuals mobile phone calls duration metrics, and other socioeconomic indicators for mobile phone penetration in Rwanda and finds a correlation between household expenditures and mobile phone calls made to and from international networks and local districts calls. Blumenstock et al., (2015) used mobile phone metadata as inputs to individual phone subscriber wealth in their model to predict income and wealth throughout Rwanda. Blumenstock (2018) used the "digital footprints" of individuals in a survey data collected in Rwanda and Afghanistan to infer on the socioeconomic characteristics of mobile phone users in these two countries.

In the related work of Jack and Suri (2016), the authors investigated the impact of mobile money wallet account and household consumption in Kenya. The authors find that in developing economies where bank branches are scarce for individuals to open a bank account, coupled with low availability of fixed telephone lines, and where mobile phone ownership and usage is prevalent, the use of mobile money wallet account has substituted bank account ownership. This is because mobile money account owners are able to deposit funds into their mobile wallet linked to a mobile phone that can be transferred to other users and at the same time be converted back into physical cash.

In developed economies, Turner et al., (2008) surveyed 184 young adults in the United Kingdom and find among others that personality and individual attributes of mobile phone users such as age and gender were *differentially associated with some aspects of phone-related behaviours*. Eagle et al. (2010) used landline and mobile phone call records in the United Kingdom to quantify the correlation between social network diversity and individuals' economic wellbeing. The findings of the authors revealed a strong correlation between individuals' relationships with their diverse social networks and economic development of communities. The authors conclude that an individual who frequently receive and make calls from social connections that are outside of the person's immediate community is associated with being part of higher socio-economic class.

In a related study that sought to understand the impact of demographic and social factors on mobile phone usage in developing countries, Frias-Martinez et al., (2010) used the behavioural, social and mobility information obtained from mobile phone call records, and finds that behavioural and social variables, including the number of incoming and outgoing calls, plus the social network of the callers revealed a statistically significant variances in male and female mobile phone users. Additionally, the empirical work of Sundsøy et al., (2016) that achieved a model accuracy of 70.40%, the authors employed a machine learning algorithm to examine standard mobile phone network logs to predict 18 categories of individuals' profession, financial, social and mobility patterns, and individuals' employment status in a developing country in South Asia.

Related to my thesis is the work of Khandani et al., (2010), the authors used US consumers' transactional data and credit bureaux information to predict default rates in a consumer credit model. In their empirical work Khandani et al., (2010) analysed transactional data from several individual accounts that included but not limited to the use of Automated Teller Machine (ATM) usage, Online Bill Payment, Credit Card activities, Check issuances, Debit Card payments, Account Fees, varied Deposits and Withdrawals, et cetera. Mobile money account statement provides similar transactional information that is comparable to formal bank account statement as shown in appendix 2. Mobile money facilitates transactions from different sectors of the economy that includes bulk disbursements, international remittances, merchant payments, retail, and bill payments such as utilities, healthcare, education, agriculture, and transportation. This is in addition to accessing credit, insurance, and savings products to manage future shocks.

The work of Blumenstock et al., (2018) examined default enrolment into account ownership and savings in Afghanistan. The authors randomly assigned workers to different varieties of savings account that are linked to wages and find that workers who received their pay through direct payments into a mobile money wallet and bank account are associated with higher savings than workers who were paid cash in hand. The work of Breza et al., (2020) collaborate this finding. In a field experiment work in Bangladesh that examined the impact of account ownership and the individuals' ability to manage household financial shocks, Breza et al., (2020) show that workers who receive wages directly into mobile money wallet account or bank account are associated with lower report of instances where they were unable to mitigate unforeseen shock due to lack of financial resources.

In the area of digital credit, the works of Björkegren (2010) suggested that individuals' mobile phone call record and patterns can be used to predict repayment and proposed that it could be used as alternative to generate credit scores. Mobile money account has been shown to help low-income households to save and can be used as a channel to deliver credit products to households by electronically transferring loans to borrowers' mobile money account. However, the problem of repayment arises. A problem that is exacerbated in developing countries because income and expenditure data about borrowers are often unreliable and incomplete to facilitate credit risk assessment of clients before loans are disbursed to help lenders to mitigate losses that may arise due default.

For many lenders operating in developing countries, it is of critical importance to have an accurate means of assessing the credit risk status of individuals in a population. Björkegren and Grissen (2019) used machine learning algorithms on clients' mobile phone call metadata in South America to predict loan repayment performance of borrowers. Further, in recent times, the pervasive use of mobile money account via cell phones, large datasets with millions of interactions are generated, stored in real time and in some cases anonymized by mobile network and internet service providers in developing economies. This has facilitated several studies to understand the impact of mobile telephony on the economic, social and well-being of users.

In my thesis, I extend the use of mobile money account in developing countries into a new application domain, that is, to mitigate asymmetric information problem in the consumer loans market. Unlike the work of Björkegren and Darrell Grissen (2010; 2019), I use the borrowers' adoption and usage of financial innovation technology to empirically predict the likelihood of loan repayments and to examine the impact of fintech on the cost of borrowing to consumers. I propose a cardinal measure of consumer credit risk that combines traditional credit factors such as debt-to-income ratio captured as ‘affordability’ in my dataset with consumer mobile money account ownership and usage, which greatly enhances the predictive power of my model.

In developing economies financial access to low-income residents have increased rapidly against the backdrop of mammoth disparity in consumer experience and complexity (Agarwal et al., 2018; Anagol et al., 2017; Badarinza et al., 2019). Furthermore, in the last decade there has been an unprecedented growth in access to consumer financial products, with an estimated 1.2 billion adults gaining access to a bank or mobile money account globally (World Bank, 2021). Suri (2011) in an empirical study that investigated the adoption of technology among two groups of farmers in Kenya, find that only farmers with higher gross returns adopt and use innovative technology compared to their counterparts with low gross returns given the high cost associated with technology adoption.

Further, Callen et al. (2019) empirically examined the impact of savings when households are connected to mobile money account and find that using financial innovative technology as a tool for collecting savings deposit from Sri Lankan households significantly increased savings. The authors also find that this protects individuals from financial shocks. As new financial innovation technologies (Fintech) are introduced at scale and used on daily basis to address societal and economic related challenges in developing market economies, an important question at the heart of this debate is to what extent risks to lenders who offer credits to consumers in developing countries using innovative technologies can be mitigated. I posit that financial innovation enables lenders to receive more precise signals of the borrowers' creditworthiness.

Empirically studying this question has been challenging for several reason. First, one has to find borrowers who have adopted and are actively using financial innovative technologies such as mobile money account. Second, even when one has identified individuals who are actively using mobile money accounts, these users should have received a credit facility from a lender and must have been actively using mobile money account during the loan tenor. Third, accessing borrower and loan-specific data that is associated with the borrowers’ usage of mobile money wallet account is mammoth task in developing countries because this information is considered proprietary data, governed by data protection laws and lenders perceive this information as an asset that give them competitive advantage.

2.1.7 Consumer adoption of mobile money wallet

The digital revolution in developing countries is reshaping how residents in these economies make payments for financial transactions. According to the Global System for Mobile telecommunication Association (2021), the use of mobile payment instruments is on the ascendancy, and mobile money operators, usually mobile telecommunication firms, issue mobile money wallets and keep the electronic account on the subscriber identity module card (SIM) in the mobile phone for users. Mobile payments comprise of all non-cash and non-paper payments instruments such as debit or credit cards, direct transfer and all forms of money transactions using electronic channels (Singh, 1999).

The financial services sector is one of the lead industries to adopt the use of digitally mobile and internet technologies in the consumer banking and commerce space (Laukkanen, 2005), and in recent times has been known to share similar features as a high technology driven sector (Pousttchi and Schurig, 2004). The Bank for International Settlements' Committee on Payment and Settlement Systems defined mobile wallet as "a reloadable multipurpose prepaid card which may be used for small retail or other payments instead of coins" (CPSS, 2003, p. 22). Mobile money wallets and mobile payments are different from cash cards or credit cards that are facilitated by a professional financial intermediary. Financial transactions undertaken using mobile money wallet and mobile payments are done using mobile enabled devices and are transacted off-line at lower cost (Cronin et al., 2000).

Further, in an exploratory study that explored how mobile financial service can be used to create value for consumers, Laukkanen and Laurone (2005) provided evidence using in-depth qualitative interviewing method to document that financial innovation technologies such as mobile banking has changed the way retail banking business are conducted by significantly reducing cost, and increased customers' experience by providing convenience in the services that clients receive. Additionally, in a study that analysed the use of multiple channels as distribution strategy in the delivery of financial services, Coelho and Easingwood (2003) used sales and costs, control and flexibility as performance indicators to empirically establish the relationship between the various distribution channels for banking services, and documents that innovative technologies such as mobile banking is becoming the default channel to provide financial services and is replacing traditional models of banking in a competitive landscape.

Studies on financial innovation technologies in developed and developing economies have broadly focused on two main themes. The first strand has focused on rationale for the adoption and use of financial innovation technologies such as mobile banking and mobile money wallets. The second strand focused on the impact of the adoption of financial innovation technologies and the utility derived from these innovative technologies by adopters. On the adoption front, theoretical models have been developed to understand the rationale for individuals accepting to use financial innovation technologies. The main theories in consumer adoption studies have chiefly used theoretical models on technology acceptance, such as the theory of reasoned action (TRA) by Fishbein (1963), innovation diffusion theory (IDT) by Rogers (1983), Technology Acceptance Model (TAM) proposed by Davis (1989)[6] and its succeeding variants, such as the unified theory of acceptance and use of technology (UTAUT)[7] (Venkatesh et al., 2003).

6 Davis (1989) proposed that dimensions of technology acceptance significantly impact behavioural intention to use a new technology.

7 The longitudinal nature of this study in a survey using 215 respondents from four distinct organizations, the Unified Theory of Acceptance and Use of Technology (UTAUT) model captures the essential elements of the other different models previously proposed.

However, the bedrock upon which these succeeding variants of consumer adoption studies and theories were developed is the works of Fishbein (1963) and Ajzen and Schifter (1985). In Fishbein (1963) proposed theory of reasoned action (TRA), the author contends that a person's attitude towards innovation is grounded on the individuals' assessment and belief with respect to the specific innovation that the person intends to adopt. According to Fishbein, in the individuals' journey to adopt any proposed innovation, behaviours emerge as a result of several psychological variables interacting in the adoption process, and that the person's social behaviour is under the control of some external factors. According to Ajzen and Fishbein (1975) and, Ajzen and Fishbein (1980), the theory of reasoned action (TRA) generally explains most human behaviour and is dependent on what the individual belief to be important in predicting his/her behaviour.

According to Rogers and Williams (1983) innovation diffusion theory (IDT), the adoption of innovation is a process that reduces uncertainty, and this is achieved when the individual gathers and analyse relevant information about the technology to a point of belief. This belief subsequently leads to a rejection or acceptance. In a follow-up study, Rogers (1995) proposed five crucial beliefs that affect individuals' adoption and usage of innovation. First, Rogers contend that the innovation must have relative advantage and defined this as "the degree to which an innovation is perceived as being better than the idea it supersedes" (p. 212). Analysing the benefit derived from the innovation relative to the cost incurred in acquiring and using the innovative technology, and deriving a positive utility is crucial to its adoption according to Rogers. Rogers' relative advantage accords with the earlier work undertaken by Davis et al., (1989) in their technology acceptance model (TAM), that innovation must be useful to be adopted.

Second, innovation must be compatible, which Rogers contends to be "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and the needs of potential" (p. 224). Basically, Rogers contend that for innovation to be adopted, it must align with the individuals' cultural values and beliefs, and the social norms of the adopters' environment. The ease of use, of the innovation, i.e., complexity is the third factor that according to Rogers, influence the adoption of innovative technologies. Rogers defined this as "the degree to which an innovation is perceived as relatively difficult to understand and use" (p. 242). This reflects the physical or mental effort required to use the proposed innovation. Trialability and observability is the fourth and fifth factors. Rogers contends that trialability allows adopters to test the innovation to ascertain its meaningfulness. Observability allows other potential adopters to visibly see the benefits of the innovation and is defined by Rogers as "the degree to which the results of an innovation are visible to others" (p. 244).

However, the omission of trust in the Technology Acceptance Model (TAM), coupled with the assumption that no barriers exist to prevent customers from using innovative technologies, hampers clients' adoption and use of innovative technology. In a study that examined limited trust in developing market economies, Humphrey, and Schmitz (1998) show that economic transactions involve risk and trust is vital to manage the risk. This is particularly true in the case of mobile banking and mobile money wallet transactions, where financial service providers, mobile money operators (usually mobile telecom operators) and customers are physically separated. Hence, exigencies are difficult to predict and integrate into terms and conditions of the services provided to customers. Additionally, in a related work that incorporated trust in the Technology Acceptance Theory (TAM) to study experience online users, Gefen et al., (2003) document that trust is crucial to customers in deciding to adopt or not to adopt innovative technologies.

Mobile payment and Mobile Money wallet are channels for receiving funds and making payment using mobile enabled technology devices such as smart mobile phones and can take the form of Customer-to-Merchant transactions; employer-employee payroll payments, and/or Person-to-Person transactions (International Telecommunication Union, 2013). Most of these theories are constructed based on behavioural concept than contextual. However, mobile money wallets and mobile payment in developing countries are technology driven and encompasses the users' acceptance of these new forms of payment, and the risk associated to the everyday usage of cash in financial transactions-thereby making mobile money wallet and mobile payments more behaviourally driven.

Contextual factors are important to understand the mobile payment dynamics in developing countries. For example, in Africa, high financial sensitivity influences the adoption of mobile payments, whereas in Asia, cost of mobile payment transactions, internet access, incidence of fraud and the regulatory environment are some of the contextual factors influencing the adoption of mobile payments (Barker et al., 2008; and Curtis and Payne, 2008). In an empirical study that examined the theoretical frameworks on the adoption and usage of technology to understand mobile payments acceptance features, and in the context of mobile-based financial services delivery, Rakhi and Srivastava (2014) document that adoption readiness and perceived risk are critical factors that determine the usage of mobile payment.

Mallat et al., (2004) and Veijalainen et al. (2006) in a related study contends, that the fast-paced adoption of mobile-enabled devices and their inherent capabilities to obtain financial services, plus the ease with which these devices can be carried anywhere and anytime are the main rationale for the adoption of mobile banking across various strata of populations, both in developing and developed markets economies. By so doing, mobile-enabled financial innovation technologies such as mobile banking can improve operational efficiencies such as reduction in operational cost (Laukkanen and Lauronen, 2005), and facilitates the provision of financial services needed by residents in remote areas where internet services are weak and no formal banking services exist (Cruz et al. 2010; Dasgupta et al. (2011).

Related is the empirical work of Yang (2009) who document that decrease in transaction fees and speed of undertaking financial transactions motivate the adoption of mobile banking technology among South Taiwanese using the Rasch measurement model of innovation adoption. In a related empirical study using survey data collected in Korea from respondents who had prior knowledge of mobile banking and mobile financial services, Suh et al. (2009) investigated the behavioural intentions of users of mobile banking and mobile financial services and document among others, that 'perceived usefulness' motivated customers adoptions of mobile banking and mobile financial services. Additionally, the authors finds that trust and ease of usage is critical in the adoption and use of these financial innovation technologies.

Laukkanen et al. (2007) in a survey of 1,525 respondents from a large commercial bank in Scandinavia, document that the value that adopters of financial innovation technology receive from adopting innovation, coupled with barriers to innovation usage were the most constraining factors to adopters using mobile banking. The authors further contend that barriers have traditionally inhibited mobile banking adoption, such as customers preference to interact with bank tellers were no longer an obstacle to mobile banking adoption. In an empirical study that evaluated the benefit of financial innovation technology such as mobile banking among clients of a major bank in Finland, Karjaluoto et al., (2002) document that mobile platforms offer a convenient and supplementary method for customers to manage their finances without handling cash.

In developing countries, particularly in Kenya, Mbogo (2010) studied the various drivers that contribute to the successful usage of mobile payments among small enterprises and concluded that among others that, accessibility, and cost of undertaking mobile payment transactions positively influence residents' intention and actual usage of mobile payment and related services in Kenya. In a related work, Kim et al., (2007) document that mobile internet service is a positive driver of mobile payment and related services. Mobile payment is defined as any form of payment that requires the use of mobile enabled device such as mobile phone, tablets, et cetera, and is capable of being connected to a mobile communication infrastructure to initiate, sanction, and confirm a personal or business transaction (Au and Kauffman, 2008).

In an exploratory study using and adaptation of the decomposed theory of planned behaviour (DTPB) in Malaysia, a developing country, Nor and Pearson (2008) incorporated trust to examine its impact on individuals' intention to adopt and use Internet banking. Nor and Pearson (2008) document that trust is crucial to customers' adoption and use of mobile internet banking. Related is the work of Kim et al., (2008) who developed a theoretical framework to describe the trust-based decision-making process of consumers using structural equation modeling technique, and they document that trust and perceived risk are crucial among internet consumers in their purchasing decisions.

The main motivation for the introduction of mobile money wallet and mobile payments in the 1990s was to provide users and other stakeholders such as merchants, with alternative forms of payment channel that facilitate the settlement of relatively small financial transactions at lower cost to both merchants and the users (Van der Heijden, 2002). The empirical work of Thakur and Srivastava (2014) show, that mobile payment adoption remained significantly high in developing countries in Africa (Kenya) and in Asia (Philippines). However, in some Asian countries, for example in India, where the economy was chiefly driven by cash transactions for small to large purchases, the adoption of mobile payment is relatively low (Thakur and Srivastava, 2014; and Chakravorti, 2017).

Similar studies undertaken in developing economies in Asia (Yao and Zhong, 2011; and Sripalawat et al., 2011) and South America (Cruz et al., 2010) all provide further evidence that monetary risk adversely affect user's intention, perception, benefit, and usage of mobile payment as a new form of payment towards a cashless economy. According to the Global System for Mobile Communications Association (2019), there are over *1billion* Mobile Money account users in Sub-Saharan Africa and rising, and the monetary value of Mobile Money transactions in Africa stood at over USD453billion in 2019 compared to more than $1 trillion in transactions in 2021.

Electronic forms of payments such as mobile banking, mobile money wallet and mobile payments are seen to provide some benefit to users. These benefits, ranges from ease of accessibility, convenience, fast transaction speed, and offers users control and privacy for conducting financial transactions (Birch and Young, 1997; Daniel, 1999; Ramsay and Smith, 1999). As a result, central banks have championed the usage, efficiency, reliability, and effectiveness of mobile payments, because mobile payments and transfers are seen as alternative to cash, and as a mechanism to reduce, if not to eliminate, the usage of cash, and to move to a cashless economy. Further, mobile payments are seen as a means to reducing the cost of financial transactions, particularly in developing economies where the cost of offering financial services to residents are prohibitively high (Rotman et al., 2010).

The theoretical work of Shapiro and Varian (1999) document, that one of the key characteristics of network enabled products such as mobile payment, is the perceived benefit that such payment systems bring to users. Kauffman and Wang (1999) provided further evidence to collaborate this finding, and document that, technology enabled mobile payments increase as benefit to users' increase. However, in a related empirical work, Dahlberg et. al., 2002 document that customers were unwilling to use mobile payments when the process for using this new form of payment is more procedural to complete, and the cost is greater than alternative conventional methods of payment.

The adoption of these financial innovation technologies provides financial institutions and mobile payments service providers such as mobile telecom operators an avenue to generate income from mobile payment transactions fees and from transactions on float. Hence, for these mobile payments service providers, the development of mobile technology enabled payment system offers the potential to lower cases of fraud and cost of payment transactions to facilitate the provision of new services to customers. Bold, et al, (2012) document that in Sub-Saharan Africa, the use of mobile enabled financial technology via mobile phones for mobile money wallet and mobile payment services is the chief driving force behind the progress made towards financial inclusion in recent times.

The work of Dias and McKee (2010) accord to this finding and document, that mobile phone users in developing countries who do not have formal bank accounts now use mobile money wallet for bill payment, payroll deposits, remittances, loan receipts and payments, airtime top-up, groceries, payment of transport fares and other financial services related transactions. In developed countries in Europe, Suoranta et al., (2005) studied consumers of financial services in Finland using quantitative survey to review technological advancement in mobile banking, and document that delivering financial services using innovative technologies is crucial for banks' survival in a competitive landscape, and using mobile banking is pivotal to achieving the dual objective of providing convenience to customers and achieving the desired business advantages that add value to the banks' profitability.

In developing economies, these forms of financial innovations are used primarily for Person-to-Person transactions and remittances. However, there is a growing trend in the usage of mobile payment as a medium to pay for good from merchants and for irregular and regular bill payments such as school fees, gas, electricity, and water (Information Technology Union, 2013). Mobile money and mobile payments have been found to facilitate payments and the drive to move the unbanked into the mainstream financial systems in developing countries, and this has led to an increase in government revenues needed for development and effective market participation (Jenkins, 2008). Ehrbeck et al., (2012) show, that in Sub Saharan Africa, the emerging partnership amongst financial institutions, mobile telecommunication and money operators is a striking indication of a positive move towards ensuring that the many residents of Sub-Saharan Africa who are unbanked move into mainstream financial systems.

My thesis is motivated by the signalling framework pioneered by Akerlof (1970) and Spence (1973), and in recent times the work of Jack, Ray and Suri (2013) and Björkegren and Grissen (2018). I contribute to this body of work, and I offer new empirical evidence on the importance of signalling in the loan markets, particularly in developing countries using Fintech. Thus, borrowers more prone to defaulting will avoid using Fintech such as mobile money wallet to signal or reveal private information to lenders. This makes Fintech a credible signal, particularly for borrowers who actively rely on the use of financial innovation technology for regular and irregular financial transactions.

Additionally, the use of Fintech such as mobile money as channel for distributing credit, making payments, and receiving remittances has and continue to gain grounds, and will potentially be the default channel of transacting business for many of the population who do not have access to bank account in developing countries. The findings in this section of my thesis also add to the work on adverse selection, specifically related to credit markets. Studies such as the works of Fama (1985), Granovetter (1985), Petersen and Rajan (1994), Uzzi (1999) and, Agarwal and Hauswald (2007) all show that professional financial intermediaries are repositories of both soft and hard borrower information and characteristics. This is because professional financial institutions benefit from the expertise and the economies of scale associated with acquiring borrowers' information.

In my thesis, I explore how mobile banking and mobile money wallets can be used within the context of the borrower-lender relationship. Although some studies exist, on how to use financial innovation such as mobile banking and mobile money wallets as a channel to offer and service formal credit from banks or micro financial institutions, these are not as widespread as it being used to store value and to undertake financial transactions (Ivatury & Mas, 2008). Further, the use of Fintech has to the best of my knowledge, not been used to examine the information gap in lender-borrower relationship in credit markets, and I fill this gap in theory and in literature.

I add to this literature in three ways. First, I show that borrowers' usage of financial innovation technology can signal to lenders about the risk quality of borrowers. Second, borrowers' adoption and use of Fintech, such as mobile banking and mobile money wallets account generate significant financial and lifestyle information about borrowers that can be accessed by the lender for quality loan underwriting. Third, the evidence shows, that although soft information about the borrower may be lost due to decentralisation of the electronic market (Hauswald and Marquez, 2003), Fintech using mobile phones platforms can also facilitate the production and transmission of new sources of hard information relevant for loan underwriting and credit risk management.

Affirmative evidence would support the hypothesis of my study. That is, (i) lenders who are investors will rationally adapt to informational asymmetry by relying on signals of credit quality; and (ii) borrowers' adoption and usage of financial innovation technology such as mobile money wallet provide such signal to lenders. I test whether borrowers' adoption and usage of financial innovations is associated with lower ex post defaults in consumer financing, particularly in developing economies. In my thesis, I use borrowers' ownership and usage of Fintech such as mobile money wallet account ownership as proxy for private information to test the ex-ante and ex-post theories of asymmetric information, adverse selection, and moral hazard in the borrower-creditor relationship in a consumer loan setting.

2.1.8 Significance of mobile money in Africa

The digital revolution in developing countries is reshaping how residents in these economies make payments for financial transactions. Mobile Money wallet has become a channel for receiving funds and making payment using mobile enabled technology devices such as mobile (International Telecommunication Union, 2013). Globally, registered mobile money accounts grew by 12% to reach 1.75 billion in 2023, the number of registered agents grew by 22% in 2023 to reach 18.6 million, an increase that was driven chiefly by a significant increase in agents in Sub-Saharan Africa (Global System for Mobile telecommunication Association 2023 report). According to the Global System for Mobile telecommunication Association (2023), economies that have mobile money services had their total gross domestic product grow by almost 1.50% bigger because of the presence of mobile money, highlighting the importance of mobile money in developing countries. Particularly in Africa.

Of the total 85billion and USD1.4trillion mobile money transaction volume and value in 2023, 62billion were originated in Sub-Saharan Africa with a total transaction value of USD912billion (Global System for Mobile telecommunication Association 2023 report). Further, the report shows, that in 2023, more than a third of new registered and active mobile money accounts users globally were from West Africa. In a 2023 Global System for Mobile telecommunication Association survey, nearly half of all 'Global Adoption Survey respondents offer responsible credit', and 44% of the number of mobile money services providers offered options for adopters to save. Furthermore, the survey shows that several mobile money service providers have begun offering insurance and 23% of services in 2023 offered insurance to their clients. These highlights the important role that mobile money play in helping the poor to save and to insure against future financial shocks.

2.2 Empirical Data and Loan process

2.2.1 Data

In this section I briefly introduce the dataset used for this empirical study. Unlike the standard practice, I deviate by introducing the dataset before discussing the model and empirical strategy. The dataset used for the estimation in this thesis come from a major lending institution in Ghana, a developing market economy. This lender specialises in small to medium loans in the retail consumer lending space, and the same data have been used for the lender's own credit underwriting. My dataset contains various socio-demographic and loan characteristics collected by the lender for 12,820 individual clients who were granted loans during the period from 2016 to 2020. The observation period ends in December 2020. The total sample consists of 10,249 repaid loans and 2,571 that were in default.

All borrowers had no bad credit report prior to the loan approval and each record of the borrower contains more than 35 attributes (features) covering socio-economic data such as age, gender, disability, religion, ownership of a bank account and mobile money account, telephone number, date of birth, profession, job type, employment sector, et cetera. Additionally, loan characteristics that includes loan type, loan amount, interest rate, other loan related fees, monthly instalments, loan balances for defaulted borrowers, branch of the lending institution where the loans were processed and disbursed, loan status (default and non-default), date that each loan gained this status, et cetera were collected. However, many features were not informative for credit risk, for example, email address of the borrower, name of loan recovery officers, et cetera. Hence, I eliminate these features to avoid the problem of over-fitting caused by too many variables. A detailed description of the remaining variables used for my thesis is shown in Table 1.

All loans were disbursed in the various branches of the lending institution where clients applied for credit to finance consumer good, pay higher education fees, medical bill, electricity, et cetera. In this study the data collected is from the lending institution's database systems (ERP), and for security and fraud related reasons, all information on borrowers and loan characteristics are kept in different database systems. Hence, a unique identifier (loan identification and client number) was used to search the multiple database systems of the lending institution to gather the features needed for this study. The definition of default is in tandem with the Bank for International Settlement standard, that is, the borrower is in default if she or he is more than 90 days overdue.

Additionally, the definition of a non-default/default variable is derived based on the performance of the borrower. For all borrowers, I have features that I present in Table 1 along with the definitions of these variables and whether they are continuous or categorical. The first parts of the characteristics are socio-demographic variables, and they characterize the borrower at the initial loan application stage. Among others, there are categorised variables related to the client's employment situation. The lender calculates and records the relevant 'affordability' threshold based on the income, and the borrowers' affordability depends on the category of loan type that the borrower qualifies for, employer and their 'disposable' income. In addition to the 18 features, a new feature Identity Index was created to condensed information about the borrowers' identity and the identity documents presented by the borrower to the lending institution at the loan application stage.

The second part of the variables characterises the relationship between the borrower and the lender. The interest rate variable varies across borrowers and is dependent amongst others on the type of loan, borrowers' employer's risk profile. For example, a borrower who is employed with a state security service as a security personal may have an affordability that ranges between 40-50 percent of the 'disposable' income, and this determines the maximum loan amount that the borrower can access. The interest rate variable includes a fixed one (1) percent and eleven (11) percent loan insurance and processing fees respectively across all borrowers. The borrowers' region is designated by the branch of the lending institution's office where the loan was initiated and disbursed, and the borrowers' address.

Preparing the dataset for training is an important stage prior to building my model. First, I checked for any missing features. It must be noted that out of the total dataset of over 14,000, I use 12,820 for empirical evaluation in my thesis. The remaining data has missing values which has been eliminated for the purposes of having a complete dataset that has all the values relevant for my thesis. Of the 12,820 individual liability loan contracts, 749 relates to repeat clients and 12,071 for first time borrowers from the same lending institution. The final sample of 12,820 I use for my analysis is considered sufficient for my empirical analysis.

Before further analysis could be undertaken, it was necessary to convert these features into a "quantified" form for each item so that a direction from best to worst would exist for purposes of interpreting association and other statistical operations. These qualitative and some quantitative data were coded to create categorical features in which each dummy is set equal to 0 if the category variable is not present, otherwise 1 when present. For examples, the variable "Bank Account" is coded as a binary number 0 or 1, and the variable "Loan type" which has 8 different values is coded as integers from 1 to 8. Undertaking this pre-processing technique, enable all the selected features to be transformed into numerical or integer. Also, because socioeconomic characteristic does vary, these are added into the regression model directly. This approach is in accord with the empirical work of Thomas (2000).

Finally, the sample dataset I obtain and use for this thesis consists of information on only borrowers who were eventually granted loans by the lender and does not consist of information on rejected loan applicants. There were two main reasons that account for this approach. First, the lender does not collect data on refused loan applications, and second, the true creditworthiness of loan applicants whose loan application was declined by the lender is unknown to the lender. For this reason, a potential selection bias may occur in the estimated results. This is a common problem in the credit scoring literature, and I assume that other potential borrowers have similar characteristics as those in the dataset used in this thesis.

2.2.2 Loan process

All loans were granted in the offices of the financial institution, where loan applicants apply for credit or through what is commonly referred to as 'Outreach Loan Master'[8] to finance the purchase of consumer goods, pay rent or bills such as medical and to finance their education. The lending institution has two main types of loans, (1) Controller salary loan. This type of loan is for employees who receive their monthly salary via the controller and accountant general's department of the ministry of finance. (2) Employee salary loan. This type of loan is targeted at two main sub-groups of customers, i.e., employees of state institutions but is not paid through the Controller and an Accountant General's office, and employees of private sector corporate institutions.

The loan requirements include among others, a duly completed loan application form, payslips, completed direct debit form, employer mandate form, identity document such as driving licence, passport, staff identity card, national identity Card, et cetera. The maximum loan repayment period is eighty-four (84) months and the interest rate charged by the lending institution depends on the type of loan applied for, and ranges from a minimum of eighteen percent (18%) to a

[8] An employee of the lender who visits targeted potential clients interested in taking credit from the lender.

maximum of thirty-one percent (31%) per annum. Additionally, loan processing and loan insurance fees are paid by borrowers irrespective of the type of loan applied for and granted by the lending institution.

Once the loan applicants submit all the relevant documents to the lender, a data entry officer creates a customer profile in the lender's ERP system that captures all the customer details. For example, the customers' staff identity card is selected, and checks are undertaken to ascertain the accuracy of personal details, customer identification number, employment details, credit details, et cetera. The loan applicant is then assigned a credit analyst who is charged with the responsibility of underwriting the loan. The credit analyst undertakes a second verification exercise by checking the lending institution's ERP system to ascertain whether the loan application and customer information is captured accurately on the system.

Additionally, the client's personal details such as social security and national insurance number, date of birth, employment details, income, bank, and mobile money account details, next of kin, and credit history are checked by the credit analyst using third party organisations. Further, the credit analyst contacts each applicant with the contact numbers provided or any other contact numbers found on the applicants' credit reference details. The credit analyst checks the loan application details, credit reference information and proceeds to asks the loan applicant random questions to confirm certain details before proceeding to the next stage.

In the next stage, the credit analyst computes the loan applicants' affordability[9] by selecting the appropriate loan type. The credit analyst then proceeds to 'blocks' the applicants' calculated affordability with a request to the applicants' employers' payroll team via a salary mandate document. The signed employer mandate document provides assurance to the lender that the loan instalment will be deducted from the applicants' salary each month to be transferred to the lender. The loan affordability stage is a critical element of the loan process. When assessing the applicants' affordability, the credit analyst determines the

[9] The affordability calculation is a measure of the loan applicants' financial capacity to repay existing debts, new debts at present and into the future.

proportion of the customers' net income that is available for deductions toward the loan instalment.

The loan affordability also determines the maximum loan amount a loan applicant can access. For example, a qualified controller salary loan applicant with an affordability of GH¢390 will be entitled to a maximum of GH¢10,745.78 for a maximum loan period of 84months. Once the affordability of the loan applicant is established, the credit analyst then set up the loan in the lending institution's ERP systems. The set up includes the loan amount, loan term, and the loan type. Finally, the loan is disbursed to the loan applicant via the applicant's bank account or mobile money wallet account once the loan contract is signed.

2.2.3 Lending and Debt Recovery in Ghana

Ghana has 33 banks, 23 Savings and Loans Institutions, 11 finance houses, 134 Micro Financial Institutions, 147 rural and community banks and 2 credit bureaus. Further, in Ghana, the annual growth in outstanding credit extended by deposit taking banks increased from 12.60% in 2021 to 30.2% as at the end of December 2022, and represents a significant increase compared to 5.8 per cent growth as at end of December 2020 (BoG, 2020 and 2022). The Bank of Ghana annual report further show that as of December 2020, total outstanding credit using BoG inter-bank rate was USD8.29 billion compared to USD8.16 billion in 2019. Additionally, the total outstanding credit provided by banks declined by 14.7 per cent in 2019 compared to 4.2 per cent in 2020 in real terms.

In Ghana, the 2020 Borrowers, and Lenders Act (Act 1052) governs all lending activities in the country. Hence, lending decisions by banks cannot be overlooked as they are the principal providers of funding to government, corporate institutions, and individuals. This Act of parliament enabled the establishment of the *Collateral Registry* with the primary objective to register Security Interest and collaterals provided by borrowers to secure loans from any lending institution in the country. Further, when a security interest is registered with the *Collateral Registry*, the lender is not required to proceed to court to enforce the right of possession of the security when the borrower default on the loan contract. In the case of non-payment, the Registrar issues a certificate to certify the realization processes once the lender has served the defaulter with a 30-day demand notice.

The borrowers, and lenders Act (2020) in Ghana involves comprehending the intricate legal landscape, and observing the laws in the Act is essential, promising not just efficient loan recovery, but maintains fairness in the debt recovery process. This is crucial, fosters trust and upholds the ethical side of business operations in the country. In Ghana, the civil court system is designed to ensure that legal disputes between parties are resolved efficiently and equitably and offers several levels of scrutiny to preserve justice. Further the Credit Reporting Regulations 2020 mandates lending institution to report all credit contracts including defaulters to a credit reference bureau to enhance responsible lending and borrowing. This is crucial, fosters trust and upholds the ethical side of business operations in the country.

2.2.4 Justification of selected features

Default, which is the dependent variable chosen is dichotomous; and is assigned the value of 1 if loans were repaid and 0 if otherwise. The main objective of this thesis is to empirically evaluate the link between borrowers' usage of financial innovation on default frequencies, hence, the independent variables used for the study were selected based on that justification. By selecting seventy-five percent (75%) of clients who have repaid their loan, and twenty-five percent (25%) of borrowers who defaulted on their loan obligations this may give biased results. However, this has been necessary in order to obtain sufficient cases of the relevant variable used for the study.

The variables used for this study consists of and has been grouped under two main categories, i.e., individual borrowers' household characteristics (age, gender, religiosity, profession, employer, formal and informal sources of income, next of kin, gender of next of kin, bank, and mobile money wallet account ownership; and loan characteristics (loan amount in Ghana Cedi, loan instalments, tenure of loan, type of loan, affordability ratio, interest rate, repaid and defaulted borrowers). Further, I perform a Heckman's test to evaluate any sample selection bias, and I present my results in appendix (B) supplementary tables (76) and (77). My results show no evidence of sample selection bias.

2.2.5 Household and individual borrowers' features

Gender and age are borrower characteristic under the household used for developing a hypothesis in this study. Extant studies have shown that women are sensitive of the misfortune that come on them as a result of defaulting on their loan obligations, hence leading to high loan repayment frequencies among women, other studies have also shown the impact of loans on women are stronger compared to their male counterparts (Rahman- 1998; Pitt and Khandker 1998). It is against this background that it is hypothesized in this thesis, that loans granted to a female should have less default frequencies than their male counterparts.

Religiosity is also another borrower characteristic used for developing hypothesis in this thesis. As discussed in the preceding chapter (2.5), several empirical studies show that borrowers' loan status, that is, default or non-default, is significantly affected by the religiosity of borrowers. However, almost all prior studies have measured borrowers' religiosity based on the geography of the lending institution, and this may not necessarily reflect the religious belief of residents located in these geographical areas used in these prior studies. This thesis departs from these extant studies, and I measure borrowers' religiosity as declared by borrowers at the loan application stage before the lender disbursed the loan. It is against this background that it is hypothesized in my thesis, that borrowers' who are religious should have less default frequencies than their non-religious counterparts.

Clients are required to provide identification documents that confirm their identity to facilitate the loan underwriting process. Further, these identification documents ae used by the lending institution to undertake pre-processing checks which are required and in accord with the central bank's regulations for lenders to establish and authenticate the identity of their clients, i.e., Know-Your-Client (KYC). The lending institution used as a case study for this thesis accepts various forms of identity documents that include employee identity documents, passport, driving licence, national voter identity card. From the dataset obtained from the lending institution's database, it was observed that there was no uniformity in the identity documents presented to the lender by borrowers, i.e., borrowers could present various forms of accepted identity documents and are encouraged to provide identification document with their photo on them photo.

Additionally, lending institutions report the status of borrowers to a central depository at the central bank using the borrowers' identity documents presented when the loan was originated. However, without a uniform and generally accepted form of identity document across lending institutions, borrowers choose which form of accepted identity document to present as long as it has their photo on them. Some of the accepted form of identity documents disclosed by clients such as passport and driving license has the clients' full name, date of birth, photo, and identity number of the customer. Equally, some of the accepted identity documents, for example, the voter identity card has the name, photo, and age of the client but short of the day and month in which the client was born.

Further, employees' identity cards do not have the clients date of birth disclosed on them, hence the identification of defaulting clients using these forms of identity document is difficult and, in some cases, impossible to be tracked by any lender. Furthermore, in Sub-Saharan Africa, forty-five (45) percent of residents lack a form of identity documents (Global System for Mobile Communications Association, 2020). Where some forms of identity documentation exist, residents have multiple forms of national identity documents with no unique identifier. Hence, for example, an individual can hold multiple forms of identity documents with different identification numbers. It is against this background that it is hypothesized in this thesis, that borrowers' who present multiple identification documents to be verified by the lender are more likely to be traced and hence are less likely to default.

In the domain of Fintech, particularly mobile banking and mobile money wallets, previous studies have attempted to examine the link between demographic characteristics such as age, education level, gender, and income level to find specific market segment for mobile banking. In a study that examined bank customers in Finland using a survey of 1,300 respondents, Laukkanen and Pasanen (2008) document that users and non-users had varying socio-demographic features, with users between the age category of 25 to 34. Related is the work of Laforet and Li (2005) that examined demographic, attitudinal and behavioural characteristics of online and mobile banking users in six major cities in China using survey. The authors document that users of mobile banking were more educated, receive formal salary, and were predominantly males.

In a related study that explored consumers' existing financial services behaviour and attitudes towards telephone and Internet banking in the United Kingdom, Howcroft et al. (2002) document that older consumers place less value on convenience compared to younger consumers, in addition to the potential time savings associated Fintech in their everyday banking services. Further, Howcroft et al. (2002) find that telephone banking was a dominant factor in managing bank-customer relationship. These studies show that demographic features are important variables that influence the adoption or non-adoption of mobile banking.

2.2.6 Loan features

Every loan disbursed come with its own associated terms and conditions. The interest rates represent the cost of finance to the borrower, and the interest rate the lending institution charge borrowers varies and is dependent on the type of loan and the borrowers' employers' reputation. Economic and financial theory has shown that high cost of debt is positively associated with high default frequencies, all things being equal. It is against this background that it is hypothesized that borrowers with lower interest payment on their loans should have less default frequencies than their counterparts who are charged higher interest rate. The loan amount and tenor may have influence on the default frequencies. The loan tenor may have an inverse relationship with default frequencies, and this is because all things being equal, the greater the period of time given to the borrower to repay the loan, the more paying back the loan becomes difficult.

2.3 Descriptive Statistics and Analysis

I describe my data that I use to empirically investigate the impact of Fintech on loan performance and cost of debt. Differences among the features of default and non-default borrowers are examined under this theme. This includes socio-economic and loan-specific features. To examine these differences, comparisons are made between their means and frequencies. Further, I computed the unconditional default probabilities for the nine categorical variables that I use in the second chapter of my thesis, and I present the results in table (6). The objective is to examine how these features on their own impact on default likelihood, and to show the discriminatory ability of my categorical independent feature on default and non-default borrowers who adopted Fintech or otherwise.

I use two categories of datasets for my empirical analysis. The first cohorts of borrowers consist of a total sample size of 12,071 borrowers who were new clients to the lender and had received their first loan. The second cohorts consist of 749 borrowers who repaid their first debt and had received their second loan from the same lender. Both cohorts of borrowers constitute defaulted and non-defaulted borrowers who adopted or did not adopt Fintech prior to the loan application and credit contract. The second cohort of borrowers repeated their self-declaration of using Fintech and provided proof of their continuous usage of mobile money wallet account to the lender at the second loan application stage. This was done prior to the borrowers signing their respective credit contract, and the subsequent disbursement of the loan. In both cohorts, borrowers had completed their respective loan cycles and had either repaid their loans or were in default.

I present a description of the variables that I use for this section of my thesis in table (1) below. In total, I use seventeen (17) variables for the empirical analysis in the first part of my thesis. The variables I use consists of borrower-specific and loan-specific characteristics of clients. The borrower-specific characteristics I use are age, gender, profession, employment, income category, mobile phone account ownership, number of identification documents presented by each borrower to the lender, ownership of formal bank account, and or mobile money account. The second category of variables I use are loan-specific characteristic and they are:

loan amount, interest rate, loan tenor, loan affordability-to-income ratio for each borrower. Furthermore, I include economic variables, that is, annual gross domestic product (GDP) growth rate and annual inflation rate.

My first sample dataset, that is cohort I, consist of borrowers who were in receipt of their first loan from the lender and were in default or repaid their debt. Borrowers in cohort II received their second loan after successfully repaying their first loan. In both cohorts of borrowers, more than half (59.48%) and (63.55%) were female compared their male counterparts that constituted 40.52% and 36.45% as shown in tables (2) and (3). When analysed together with the unconditional probability of default in table (6), female borrowers are less likely, 13.73%, to default compared to their male counterparts, 30.89%. In both cohorts I and II of borrowers in my dataset, majority either have at least one (1) or no mobile phone account, 83.18% and 55.14%, compared to 16.82% and 44.86% of their counterparts who own two (2) mobile phone accounts.

The bank collects information on borrowers' ownership of financial innovation technology, that is, mobile money. The objective of collecting this additional information is to provide alternative channel via which clients can repay their monthly loan instalments. Furthermore, the bank does not use that information about the clients' adoption and usage of Fintech to improve the lending process to reduce default and to improve loan portfolio quality. I present an analysis of borrowers who adopted Fintech in tables (2), (3) and (6). Significant proportion, 7,238 of borrowers representing 59.96% of the total sample of 12,071 borrowers in the first cohort adopted Fintech, compared to 4,833 representing 40.04% who did not have Fintech, that is, mobile money wallet account.

When borrowers constituting cohort II were equally examined, 68.09% adopted Fintech, compared to 31.910% who had no mobile money wallet account. Majority, 52.20% of borrowers who adopted Fintech are between the ages thirty (30) to forty (40) years, and of this, 79.20% (2,922) had one (1) registered mobile phone account that is used to transact mobile money and mobile banking activities. I present in appendix (B) supplementary table (61) collinearity test using the variance inflation factor, and the results show no multicollinearity among my selected variables used in my empirical analysis. The loan maturity is essentially how long the loan is approved for. It ranges from 1 month to 360 months.

Majority of borrowers (60.01%) have loans with maturities beyond twelve (12) months. Loans are in Ghana Cedis (GH¢) which is the local currency. However, for ease of interpretation and comparison, I convert the loan amount into United States dollars (US$). Further, I categorized loans according to their amounts disbursed. Significant proportion of the loans disbursed by the lending institution were between US$280 and US$850. In terms of default, loan amount exceeding US$280 were more likely to default than any other category of loan amount. Further, loan amount less than US$850 were significantly less likely to default in the loan categories based on the odds ratio results, table (4).

The minimum and Maximum loan offered by the lender is US$142.41 and US$24,000 respectively, table (4). When the average loan amount received by both defaulters and non-defaulters were compared, the former received higher loan amount, approximately US$250 more than the later. However, non-defaulters were in receipt of the maximum, US$24,000, loan amount compared to their defaulting counterparts who received approximately US$11,300 less. This suggest that the lender reward good repayment behaviour. Similarly, borrowers who adopted Fintech received approximately US$4,200 more than their non-adopting counterparts. This suggest that borrowers who adopt Fintech are more likely to qualify for the maximum loan amount. However, non-adopters of Fintech received approximately US$94 more on average in terms of loan amount. Further, the average loan amount for females is lower, that is, US$170 less compared to their male counterparts.

Affordability and interest rate depicts the criterion used to assess the loan amount that the borrower is eligible for based on the borrowers' disposable income, and the interest rate is the cost of the loan respectively. Tables (2) and (3) show that across the two cohort, majority of the borrowers, 99.26% in first group and 99.86% in the second client group were granted loans based on more than 35% affordability but were more likely to default based on the odds ratio compared to their counterpart who were granted loans on the basis of 35% affordability. Regarding the interest rate charged by the lending institution, defaulters were charged lower, approximately 4.51% less than their non-defaulting counterparts in terms of the average cost of debt charged by the lender across the two categories. Similarly, borrowers who adopt Fintech were charged 1.60% higher compared to their non-adopting counterparts (Table 6). This may suggest a loan pricing anomaly.

Clients may have other sources of income apart from their main formal employment. This income is from informal work undertaken in the informal sector of the same economy. According to the sample dataset, larger proportion, 83.83% and 91.46% of borrowers are employed in the formal across the two cohorts. Respectively. Further, 96.33% of clients in the first cohort receive formal salaries compared to 95.333% in the second cohort for majority of both defaulting and non-defaulting clients have formal source of income. However, some clients have informal sources of income in addition to the income they receive from their main formal employment. 99.78% of defaulters and 99.72% of non-defaulters receive salary from formal employment compared to 0.22% and 0.28% of the same category of borrowers who were in receipt of both formal income and business income respectively.

Distinctively, default is more likely to occur across borrowers with additional sources of income aside their main formal employment according to the unconditional default probabilities in table (6). From the summary of the dataset in table (II), larger proportion of borrowers in across both cohorts of clients own more than one mobile phone account, and of this, majority were non-defaulters. Additionally, majority of borrowers, 59.96% in cohort (I) and 68.09% in cohort (II) used financial technology, that is mobile money wallet account, and of this, significant proportion were non-defaulters. This suggest that significant proportion of loan applicants were willing to signal their credit risk using Fintech.

Furthermore, majority of borrowers, 64.80% and 69.34%, in both default and non-default category respectively who declared ownership and use of mobile money wallet account are between the ages of thirty-one (31) and forty (40) years old. In analysing this with the unconditional default probabilities in table (6), default is less likely to occur for borrowers with two and three mobile phone accounts compared to clients who had one or four mobile phone accounts. Borrowers are required by the lending institution to provide evidence of their employment and sources of income for a minimum period of three to six months prior to their loan application.

The accepted evidence includes bank statements and or payslips. From table (2), majority, 80.17% and 92.32% of borrowers in the non-default categories in cohorts (I) declared ownership of bank account and mobile money account compared to 19.83% and 7.68% of their counterparts who defaulted. I find similar pattern for borrowers in cohort II. This suggest that non-defaulters are tech savvy and are able to operate a formal bank account and or Fintech account across both cohorts of borrowers compared to their defaulting counterparts. In analysing this with the unconditional default probabilities in table (6), borrowers with no bank account, and borrowers who did not adopt Fintech are more likely to default than their counterparts who have a formal bank account and or have adopted Fintech.

From tables (2) and (3), larger proportion of non-defaulters, 80.67% in cohort (I) (92.99%) cohort (II) are skilled and are engaged in a professional employment compared to 19.33% and 8.44% for borrowers in the default category. Furthermore, Majority, 96.33% and 91.46% of client are employed in the public sector, compared to 16.18% and 8.54% in first and second group of clients respectively. Of this, majority re non-defaulters. Additionally, 41.13% of borrowers are located in Accra compared to 39.45% and 19.42% located in the Kumasi and Takoradi in the first cohort, compared to 41.79%, 39.92% and 18.92% for in same branches in cohort (II). Accra is the capital city of the Ghana where many businesses and state institution are located. Kumasi and Takoradi are second and third largest city. Borrowers located outside the national capital city, Accra, have higher likelihood of default compared to their counterparts in the national capital city of Accra, tables (2) and (3).

I present an analysis of borrowers who adopted financial technology in table (5). Of the total number of non-defaulting borrowers, 6,682, who adopted Fintech, majority, 64.77%, are female compared to their male counterparts, 35.23%. This suggests that female borrowers are tech savvy and are able to use financial technology to manage their finances. Additionally, significant proportion, 52.35% of clients who adopted Fintech are between 30 to 40 years old. This is followed by 21.86% for clients in the 41 to 49 years old, and 7.84% for borrowers who are in the 20-29 years age range. Also, majority, 5,593 of the total clients representing 77.27% who adopted Fintech have at least one mobile phone account.

Table 1. Description of individual and loan characteristics in the sample

VARIABLES	DESCRIPTION
1. Age	Client age in years
2. Gender	Gender of the client
3. Income Category	Sources of income for client
4. Employer	Sector of the economy where client is employed
5. Profession	Knowledge and skill of clients
6. Loan Amount	Amount disbursed as loan to client
7. Loan Tenor	Time given to clients to repay loan with interest
8. Identity Info.	Borrower identification document(s) provided to lender
9. Affordability	Proportion of income that determine loan amount
10. Mobile Phone	Number of mobile phone and account held by client
11. Bank Account	Client ownership of formal bank account
12. Loan status	Client’s loan status
13. Fintech	Client ownership of active mobile money wallet account
14. Interest Rate	Percentage charged as cost of the loan to client
15. GDP growth	Annual Gross Domestic Product growth rate in Percentage
16. Inflation Growth Rate	Annual Inflation growth rate in Percentage
17. Region	Branch of the lender where loan originated and disbursed

Table 2. Descriptive statistics of categorical variables for borrowers - Cohort I

VARIABLES	TOTAL SAMPLE (12,071) PERCENTAGE	DEFAULT CLIENTS (2,497) PERCENTAGE	NON-DEFAULT CLIENT (9,574) PERCENTAGE
FINTECH			
Yes	59.96 (7,238)	7.68 (556)	92.32 (6,682)
No	40.04 (4,833)	40.16 (1,941)	59.84 (2,892)
GENDER			
Male	40.52 (4,891)	30.89 (1,511)	69.11 (3,380)
Female	59.48 (7,180)	13.73 (986)	86.27 (6,94)
INCOME CATEGORY			
Salary	96.33 (11,628)	20.68 (2,356)	79.74 (9,272)
Other	3.67 (443)	31.83 (141)	68.17 (302)
EMPLOYER			
Private	16.18 (1,953)	5.89 (115)	94.11 (1,838)
Public	83.82 (10.118)	23.54 (2,382)	76.46 (7,736)
PROFESSION			
Professional	90.96 (10,980)	19.33 (2,122)	80.67 (8,858)
Other	9.04 (1,091)	34.37 (375)	65.63 (716)
IDENTITY INFO.			
>1 Identity Info.	37.22 (4,493)	38.86 (1,746)	61.14 (2,747)
=1 Identity Info.	62.78 (7,578)	9.91 (751)	90.09 (6,827)
AFORDABILITY			
35% (1)	0.74 (89)	88.76 (79)	11.24 (10)
Other (0)	99.26 (11,982)	20.18 (2,418)	79.82 (9,564)
MOBILE PHONE			
2 Phones =1	16.82 (2,030)	13.40 (272)	86.60 (1,758)
Other = 0	83.18 (10.041)	22.16 (2,225)	77.84 (7,816)
BANK ACCOUNT			
Yes	96.12 (11,614)	19.83 (2,303)	80.17 (9,311)
No	3.79 (457)	42.45 (194)	57.55 (263)
BANK BRANCH			
Accra	41.13 (4,965)	20.79 (1,032)	79.21 (3,933)
Kumasi	39.45 (4,762)	17.35 (826)	82.65 (3,936)
Takoradi	19.42 (2,344)	27.26 (639)	72.74 (1,705)

Table 3. Descriptive statistics of categorical variables for borrowers - Cohort II

VARIABLES	TOTAL SAMPLE (749) PERCENTAGE	DEFAULT CLIENTS (74) PERCENTAGE	NON-DEFAULT CLIENT (675) PERCENTAGE
FINTECH			
Yes	68.09 (510)	5.29 (27)	94.71 (483)
No	31.91 (239)	19.67 (47)	80.33 (192)
GENDER			
Male	36.45 (273)	13.19 (36)	86.81 (237)
Female	63.55 (476)	92.02 (438)	7.98 (38)
INCOME CATEGORY			
Salary	95.33 (714)	9.52 (68)	90.48 (646)
Other	4.67 (35)	17.14 (6)	82.86 (29)
EMPLOYER			
Private	8.54 (64)	3.13 (2)	96.88 (62)
Public	91.46 (685)	10.51 (72)	89.49 (613)
PROFESSION			
Professional	94.93 (711)	8.44 (60)	91.56 (651)
Other	5.07 (38)	36.84 (14)	63.16 (24)
IDENTITY INFO.			
>1 Identity Info.	31.11 (233)	16.31 (38)	83.69 (195)
=1 Identity Info.	68.89 (516)	6.98 (36)	93.02 (480)
AFORDABILITY			
35% (1)	0.13 (1)	100 (1)	0.00 (0)
Other (0)	99.87 (748)	9.76 (73)	90.24 (675)
MOBILE PHONE			
2 Phones =1	44.86 (336)	9.23 (31)	90.77 (305)
Other = 0	55.14 (413)	10.41 (43)	89.59 (370)
BANK ACCOUNT			
Yes	97.06 (727)	9.77 (71)	90.23 (658)
No	2.94 (22)	13.64 (3)	86.36 (19)
BANK BRANCH			
Accra	41.79 (313)	10.86 (34)	89.14 (279)
Kumasi	79.84 (598)	4.85 (29)	95.15 (569)
Takoradi	18.29 (137)	3.51 (11)	96.49 (302)

Table 4. Descriptive statistics of continuous variables

Non-Defaulters (9,574)					Defaulters (2,497)			
Variables	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Age	20	68	39.97	8.943	22	67	40.89	9.282
Interest Rate	8.4100%	72.6600%	50.1937%	13.8760%	13.9500%	72.0000%	45.6794%	10.2056%
GDP	6.2001%	8.1289%	7.8420%	0.6864%	6.2001%	8.1289%	7.1600%	0.9431%
Loan Amount	142.4096	24209.6269	1036.8556	1136.6676	142.4096	12873.8251	1292.648818	1178.1743
Loan Tenor	1	96	28.54	20.217	1	96	34.73	20.891
No Fintech Clients (4,833)					**Fintech Clients (7238)**			
Variables	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Age	20	67	40.34	9.108	20	68	40.04	8.962
Interest Rate	15.13%	72.66%	48.30%	12.63%	8.41%	72.00%	49.90%	13.74%
Loan Amount	142.4096	19937.3398	1145.9413	4076.91	500.00	24209.6269	1052.2615	4006.12
Loan Tenor	3	96	31.63	20.825	1	96	28.61	20.21
Male Clients (4,891)					**Female (7,180)**			
Variables	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Age	20	68	39.9	9.089	22	67	40.33	8.971
Interest Rate	8.4100%	72.0000%	46.8399%	11.9942%	13.9500%	72.6600%	50.9084%	13.9243%
Loan Amount	142.4096	24209.6269	1191.3896	4471.8609	142.4096	16462.5463	1020.5451	3693.5706
Loan Tenor	1	96	30.6	20.731	2	96	29.28	20.345

Table 5. Analysis of Fintech adoption by age and gender

Age Categories	Non-default (Percentage)	Default (Percentage)	Number of mobile phone account ownership				Gender Categories	Non-default (Percentage)	Default (Percentage)
			1	2	3	4			
20-29	524 (7.84)	40 (7.19)	437	106	18	3	Female	4328 (94.23)	265 (5.77)
30-40	3498 (52.35)	280 (50.36)	2,992	629	138	19			
41-49	1461 (21.86)	131 (23.56)	1,203	309	71	9	Male	2354 (89.00)	291 (11)
50-68	1199 (17.94)	105 (18.88)	961	268	62	13			

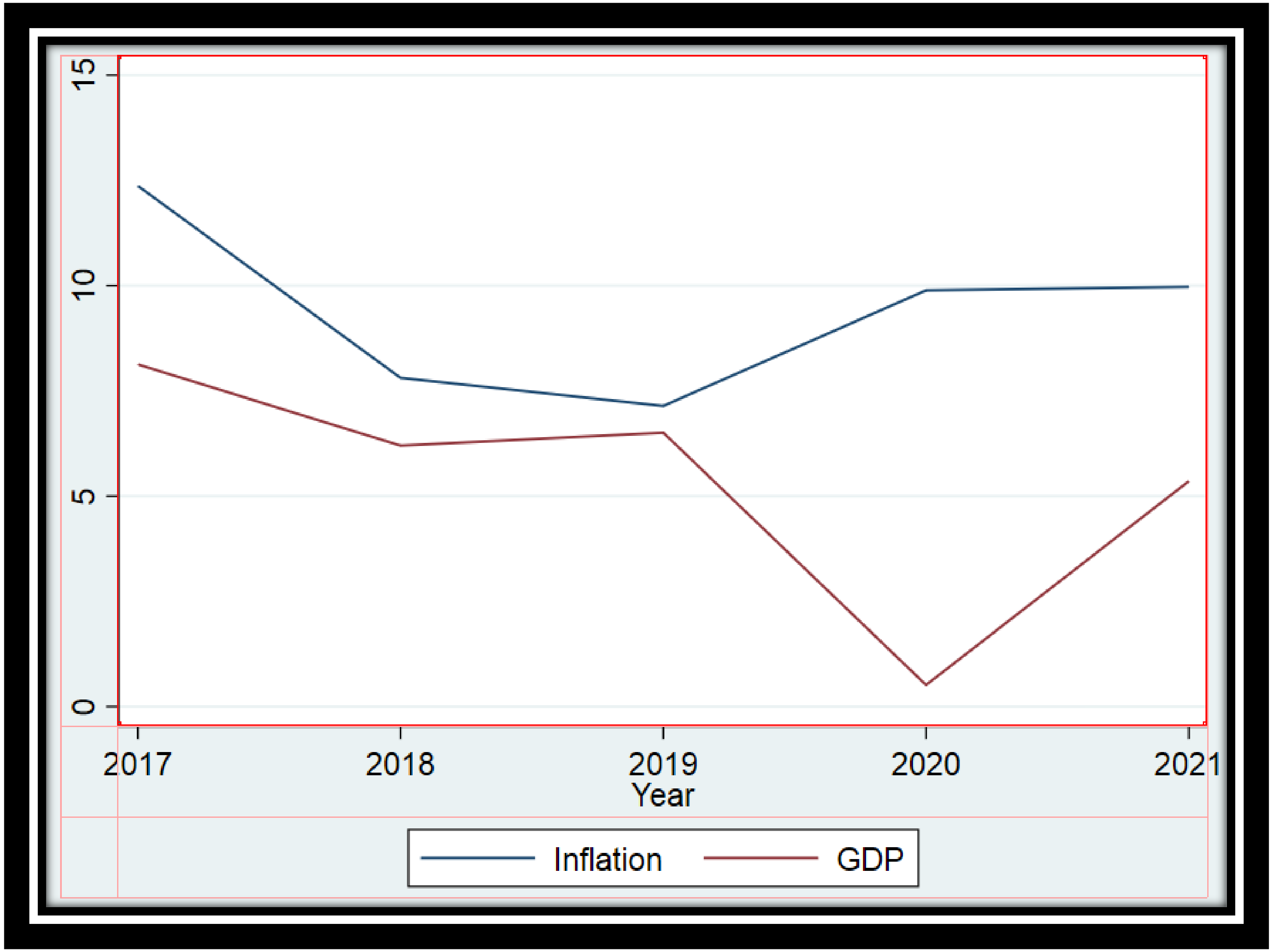

Figure 1. Graph of Annual Gross Domestic Product and Inflation

Table 6. Unconditional default probabilities

VARIABLES	PROBABILITY OF DEFAULT
1. FINTECH	
Yes	7.68%
No	40.16%
2. GENDER	
Male	30.89%
Female	13.73%
3. INCOME CATEGORY	
Salary	20.26%
Other	31.83%
4. EMPLOYER	
Public	5.89%
Private	23.54%
5. PROFESSION	
Professional	19.33%
Other	34.37%
6. IDENTITY INFO.	
>1 Identity Info.	38.86%
=1 Identity Info.	9.91%
7. LOAN AFORDABILITY	
35% (1)	88.76%
Other (0)	20.18%
8. MOBILE PHONE OWNERSHIP	
2 Phones =1	13.40%
Other = 0	22.16%
9. BANK ACCOUNT OWNERSHIP	
Yes	19.83%
No	42.45%

2.4 The Model

2.4.1 Signalling theory.

The idea behind the credit market signalling model I propose is that there are attributes of potential borrowers that the lender cannot observe, however, this unobservable attribute affects the borrowers' loan performance, that is, default or repay. This will in turn impact on the bank's interest income and capital due to non-performing loans. Further, Diamond and Rajan (1999), and Kishan and Opiela (2000) show that there is a positive relationship between loan growth and capital requirements and credit regulations. For simplicity, let us suppose that there are just two groups of borrowers. Group (A) is transparent to the lender regarding all financial information, that is, both formal and informal income and expenditures are declared at the loan underwriting stage. This is to aid the bank decision making, and this group of borrowers are assigned the value of 1 by the lender for being informationally transparent.

The second group of borrowers, group (B), are not informationally transparent regarding their income and expenditures because, for some reason this borrower group believe this information will have an adverse effect on their risk profile and are assigned a value of 2 for being informationally opaque. In this, the information values do not depend on the level of investment in the signal by the two groups. If there is no way for the lender to distinguish between these groups of borrowers, this will lead to a pooling equilibrium. Further, if both groups stay in the loan market, the average interest charged to the two borrower groups will be 2 - k, where k is the fraction of the population in borrower group (B) who exit the loans market, and everyone will get that charged interest rate.

If the informationally transparent group, through dissatisfaction or for any other reason exits the loans market, the average borrower-quality and interest income to the lender drop to 1; a phenomenon commonly referred in the loan and insurance market as adverse selection problem and as shown in the seminal work of Akerlof (1970). Now let us suppose also that there is something called financial innovation technology, Fintech, which I will denote by *F*, and can be acquired or invested in by both borrower groups. It is assumed to be visible and generate financial information about the borrowers' formal and informal income, expenditures and lifestyle that can be presented to the lender to aid the loan underwriting. Further, it is assumed that its acquisition costs differ for the two borrower groups, but that is not the focus of my thesis[10].

I posit that in this circumstance, low-risk borrowers will acquire and use Fintech. Further, it is assumed that these low-risk borrowers will be willing to share the transactional information generated from their usage of financial innovation technology to aid loan underwriting and pricing. As a result, the transactional information acquired from the borrowers' usage of financial innovation technology becomes an efficacious signal to the lender. Lenders can gain from making decisions based on information obtained from these signals generated from the borrowers' usage of mobile enabled financial innovation services such as mobile money wallets. On the other hand, borrowers who are more prone to default would be unwilling to signal their 'true' quality using Fintech. This is because financial innovation technologies such as mobile money wallet and mobile banking will reveal private information to lenders that were previously unobservable, and this will result in a separating equilibrium.

Furthermore, in this separating equilibrium framework, financial innovation technology becomes a credible signal of borrower risk, particularly for borrowers who have no formal bank account or have dormant bank account and actively rely on the use of mobile money for their regular and irregular financial transactions. Also, borrowers with active bank account who decides not to leave 'footprints' of specific transactions that will negatively impact on their risk profile and loan request may choose to transact using their mobile money wallet account as substitute. In such circumstances, lenders can accurately distinguish between high and low-quality borrowers in the loans market.

[10] See the work of Ndofor and Levitas (2004) for more emphasis on signalling cost.

Equilibrium in general, and specifically in the situation described above has two components. First, the returns and the costs of investing in financial innovation technology. That is, borrowers make rational investment choices with respect to financial innovation technology. Second, lenders have beliefs about the relation between the signal and the quality of borrowers. These beliefs are based on incoming information generated from the borrowers' usage of mobile enabled financial innovation technologies, such as mobile money wallets in the marketplace. In equilibrium, the beliefs must be consistent, that is, they must not be disconfirmed by the additional information generated via the borrowers' adoption and usage of Fintech, and the subsequent experience with respect to the loan performance, that is, default, or non-default.

Therefore, it could be said that the beliefs must be correct. But one should also notice that the lenders' beliefs determine the interest rate that may be offered to the two categories of borrowers. This interest rate in-turn determines the benefit to borrowers for investing in Fintech. Also, this determines the investment decisions that individual borrowers make with respect to financial innovation technology, and ultimately determines the quality of the actual relationship between borrower-quality and financial innovation that is observed by the lender in the marketplace. Further, in this theory, I posit that Fintech provide a signal that can be used to convert a pooling equilibrium outcome to a separating equilibrium, and in such circumstance, lenders are able to accurately distinguish between high and low-quality clients.

2.4.2 The proposed framework with Signaling, Selection, and Pooling

The model I postulate is of interest for two reasons. First, it illustrates a case in which there is only a separating component of the equilibrium, with no pooling component and, second, it shows that the critical measure for having a separating component in equilibrium is that there is a net benefit to both the borrower and the lender. This is because the signal issued by borrowers is positively correlated with an attribute associated with the borrowers' usage of Fintech, and contributes positively to the loan performance, default, or non-default. This benefit can result, as in preceding examples, from signaling costs that are negatively correlated with the valued attribute associated with financial innovation. In this simple example, the information generated from the transactional data gathered using Fintech is assumed to have been obtained at a fixed cost to the borrower and the benefit to the lender comes from subsequent discovery of the attribute ex-post lending.

The idea behind the model is that the value of borrowers to the lender is not directly observed, at least during the time of the loan application. The value which I denote as 'j' is distributed on the interval [jmin, jmax]. Further, let the distribution of 'j' in the borrower population be f(j). Individual borrowers have a choice, that is, they can apply for credit from a lender who do not distinguish among the two groups of borrowers and hence charge everyone the same interest rate, or they can apply for credit from a lender who distinguishes between the two borrower-groups based on the clients' adoption and actual usage of Fintech at a cost to the borrower, denoted by '*F*'. As a result of which the lender eventually learns the value of 'j' for individual borrowers and hence charge the relevant interest rate accordingly.

Further, in my framework, the loan markets in developing market economies are assumed to be competitive, and those individual borrowers who choose lenders that distinguishes between the two borrower-groups, the interest charged is $j - F$. If the borrower chooses a lender that do not require clients' adoption and usage of mobile money at a cost to the client and does not distinguish among the two classes of borrowers, then it is assumed that the interest rate charged is the average value of the individual borrowers who apply for credit from this lender. Additionally, let us suppose that the average value of borrowers in the pooling lender is $\acute{Y}$. If we consider the optimizing decisions of individual borrowers, it is clear that if:

$$j - F < \acute{Y}$$

then the borrower will prefer to choose a lender that separates the two groups of borrowers.

In contrast, when both groups of borrowers benefit from signaling, this leads to a pooling equilibrium and lenders are not able to distinguish between the two groups of borrowers[11]. However, in this model, there is no pooling equilibrium because as shown in the empirical work of Wells, Valacich and Hess (2011), the cost of sending misleading signal is prohibitively high relative to the benefit. Additionally, because borrowers and lenders have partially competing interests in this framework that I posit, borrowers have incentive to "cheat" deliberately by producing false signals so that lenders will select them as shown in the work of Johnstone and Grafen (1993).

However, this problem is mitigated when the borrower is required to provide evidence consistent with the underlying quality associated with the signal sent to the lender[12]. Finally, Fintech enables the unobservable attribute of borrowers at the time of the loan application stage to become observable attribute via the borrowers' adoption and usage of financial innovation technology to signal quality. This has two sources of value. First is the direct effect on the loan performance to the lender. Second, borrowers' can signal their 'true' credit quality via their declaration and usage of Fintech which the lender can either confirm that the borrowers is 'good' credit risk, and this can lead to lower interest rate.

This lower interest rate compensates borrowers for the cost of acquiring and using Fintech as a signaling tool, and to be informationally transparent to the lender. The lender's confirmation of the borrowers' signal to be 'true' or otherwise is purely dependent on the daily transactional footprint generated from the borrowers' usage of financial innovation technology, that is, mobile money wallet and payment account. As stated earlier, in my proposed signalling model, evaluating the cost of using financial innovation to the borrower is outside the scope of my thesis, and may be the subject of a follow up study in the future.

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[11]. See the work of Cadsby et, al., (1990) for further review of the separating and pooling equilibria.
[12]. Refer to the work of Zajac (2001), Davila, Foster, and Gupta (2003), Busenitz et al. (2005), Cohen and Dean (2005), Durcikova and Gray (2009) for more discussions on signaling cost and quality.

2.5 Empirical strategy

2.5.1 Logit regression model

The lag between theory and empirical applications of these theories probably has several explanations. Primarily, the scarcity of adequate data sets that offer a large sample of standardized contracts for which performances in credit contracts are recorded, particularly in developing countries may account for this phenomenon. I fill this gap in the consumer finance literature in developing economies. I use borrower and loan-specific characteristics, and financial innovation as a measure of information asymmetry and its impact on default in consumer lending. Further, I use bagged logit regression model. Logistic regression has been shown in several empirical studies to be the most promising algorithm in credit scoring models.

The purpose of this section of my thesis is to proof by providing a simple and general test of how FinTech can be used to address the severe asymmetric information problem in credit markets, particularly in developing market economies. My basic claim, following the work of Spence (1973; 2002), and Björkegren and Grissen (2018) is that the theoretical notion of asymmetric information infers, in statistics, a positive relationship between two conditional distributions. Also, the work of Malik and Thomas (2010) motivate my empirical strategy. Prior studies, such as the work of (Stiglitz and Weiss 1981; Ramakrishnan and Thakor 1984; Boyd and Prescott 1986) provide theoretical frameworks that show, that in a perfect competitive market impeded by asymmetric information, lenders can benefit from economies of scale when they obtain information about borrowers.

I contend that Fintech can provide lenders a mechanism that can be harnessed to the benefit of market participants. The null hypothesis in the empirical framework is that borrowers who adopt and use Fintech such as mobile money wallet and payment are ‘good’ credit risk. This is because, Fintech reveals *hidden* financial and lifestyle information about borrowers that would have otherwise not been available to the lender, at least at the loan application stage. The *hidden* information ranges from informal income, routine and other lifestyle expenditures that are mostly not captured in the borrowers' bank account statements presented to the lender but are critical in the loan underwriting and decision making. Furthermore, loan applicants and borrowers who do not have access to formal bank account prior to the loan application use mobile money account as a *pseudo* bank account that the lender can use to assess loan applicants financial and lifestyle information to aid the lending decision.

To empirically implement the framework outlined in the preceding section, I measure financial innovation based on borrowers' ownership and usage of mobile banking, mobile money wallet and mobile payment account, or otherwise. I refer to borrowers who do not own and use mobile banking, mobile money wallet and mobile payment account as "opaque" and contend that when loan applicants and borrowers are less transparent in their relationship with the lending institution, the information asymmetry problem for the lender become severe. Critical to my empirical strategy is the measure of opacity, and the primary measure I use to measure opacity is shaped by the existing research and the prevalent use of mobile financial technologies such as mobile banking, mobile money wallet and mobile payments in developing market economies.

Specifically, the strategy addresses the quality of the borrower, and how well the lender "knows" the borrower. The measure of information asymmetry I construct therefore attempts to capture how well the lender know the borrower absent any information provided by the borrower to the lender at the loan application stage to aid the loan underwriting. The primary focus of this paper is to empirically examine how financial innovation mitigate information asymmetry, and how this impact on default probabilities. I construct a measure of information asymmetry based on the availability of data on loan applicants who became borrowers, and who either have or do not have active mobile money account prior to the loan disbursement. Further, I categories borrowers into two main categories, default, and non-default, and I split each main category into two sub-categories. That is, default borrowers who had or did not own a mobile money account; and non-defaulters who had or didn’t have active mobile money account prior to the loan contract and disbursement.

The identifying assumption is that lenders are more dependent on the financial information about the borrowers generated via the borrowers’ Mobile Money accounts transactions, and the ability of Fintech to collect detailed additional financial and lifestyle information about the borrower for loan underwriting, pricing, and monitoring. Unlike audited financial account, the financial information gathered from the borrowers’ usage of Fintech is free from the accruals and estimates made in audited financial statements. Further, for borrowers who do not have access to formal bank account, Mobile Money account act as a pseudo bank account and hence captures the financial information necessary for quality loan underwriting. In my thesis, I introduce a new feature, that is, Fintech, and I empirically examine the impact of the new feature on asymmetric information holding all things constant.

First, I test the relation between each class of borrowers and each independent variables selected excluding the branches of the lending institution where the loans were originated and disbursed. The general specification I test:

$$\mathrm{Lstatus} = \alpha 1 + \mathrm{X}1\beta 1 + \mathrm{X}2\beta 2 + \mathrm{X}3\beta 3 + \cdots \mathrm{Xn}\beta\mathrm{n} + \varepsilon\mathrm{i} \qquad (1)$$

Note: Lstatus refer to default and non-default status of borrowers respectively.

Second, because my main hypothesis is that Fintech (mobile money wallet account and mobile banking) mitigates the problem of information asymmetry in the borrower-lender relationship and this in turn reduces the probability of loan default, I examine how variation in the opacity of the borrower affects default rate, and whether the effect is consistent with the information asymmetry hypotheses outlined above. Also, because it is generally known that the borrower's ex-ante probability of default is unobservable, the application of bagged Logit regression technique directly estimates the probability of default, and as a result, I am able to avoids this problem. This technique is also capable of handling both continuous and dummy variables.

Additionally, unlike simple standard linear regression that for example, if a feature 'H' takes on the values of 1……..k, the idea is to transform this class feature to 'k' numeric indicator features (k1,…,kH) to which the standard regression can be fitted. The feature kH, which is the indicator feature for class 'k', takes on the value of 1 whenever class 'k' is observable, otherwise 0. The standard regression technique to credit scoring is a linear discrimination approach that argue that the probability of default (Pd) is related to the scoring application features X1, X2,.., Xn by:

$$\mathrm{Pd} = \mathrm{Z0} + \mathrm{X1\beta1} + \mathrm{X2\beta2} + \mathrm{X3\beta3} + \cdots \mathrm{Xn\beta n} \qquad (2)$$

However, the above standard regression technique has some drawbacks. Usually, the predictions given by the right-hand side of the regression functions fit to the class indicator features are not confined to [0, 1] and can even become negative, i.e., $[-\infty \text{ to } + \infty]$, but the left-hand side of the above equation can only take the values 0 and 1. Further, as shown in the work of Hastie, Tibshirani, and Friedman (2001), where there are multiple classes, this technique suffer from 'masking problems', i.e., a third class is masked by the first two classes and hence, the third class become inseparable from the first two.

A better way to address the drawback is to make the left-hand side of Eqn. (3) a function of *pd* by using Logit regression that models the posterior class probabilities that can take a wider range of values [Pr (H = k | X = x)] for the 'K' classes accordingly. By using Logit regression technique, the log of the probability odds is matched by a linear combination of the featured variables, while at the same time ensuring they sum to one and remain in (0, 1). The probability of default is determined by the independent featured variables, and here it is assumed that this is linear and additive and of the form:

$$\mathrm{Log}\,(\mathrm{Pd}/\,(1\,-\,\mathrm{Pd})) = \alpha 0 + \Sigma\, \mathrm{X1\beta1} + \mathrm{X2\beta2} + \mathrm{X3\beta3} + \cdots \mathrm{Xn\beta n} + FinTechi\,\varphi\, + \varepsilon_i \qquad (3)$$

The left-hand-side variables are measures of the loan status, i.e., default or non-default. The key right-hand-side variable of interest is *FinTech* which measures the level of information asymmetry, and represents measures, described above, of the degree to which the lender must further investigate and monitor the borrower. The key coefficient of interest is φ, which is, how financial innovation reduces information asymmetry and how this in turn affects default probabilities. In equation (3), FinTech measures borrower opacity and borrowers who adopt and actively use FinTech are considered to be less informationally opaque compared to their non-adopting counterparts in the framework that I propose.

An "opaque" borrower is a borrower with thin publicly available credit bureau information but no mobile money account. A "transparent" borrower is a borrower with publicly available credit information and mobile money account. Because the dependent variable is binary, i.e., default or non-default, the binary Logit model is used to analyse the data and is represented as a dichotomous variable taking the value of 1 for default and zero for non-default. Using logit binary regression enables the classification model to simultaneously consider all the potential discriminatory variables. Additional benefit for using logistic regression model compared to other techniques that produce only classification is that the logit model produces explicit class probability estimates.

Further, the inclusion of a constant term in the specification model is often used as a test for specification error (Scott 2001). Further, Bech and Gyrd-Hansen (2005) show that in a related work that the inclusion of dummy variable soaks up the preference for the base comparator in the specification. Additionally, the choice of logistic regression for this study is motivated by the empirical findings of Ross (2000) as reported in Thomas (2000), Boyle et al (1992), Desai, Crook, and Overstreet (1996, 1997), Henley (1995), Srinivasan and Kim (1987), and Yobas, Crook, and Ross (2000). The setup distinguishes hidden information effects on default probabilities.

Additionally, the inclusion of financial innovation in the model improves the banks' knowledge of applicants' characteristics and permits more accurate prediction of default probabilities. Further, this allows lenders to target and price their loans better, mitigating adverse selection and moral hazard problem. Extant empirical literature hasn't contributed much to our knowledge of how the prevalent use of financial innovation technologies such mobile banking, mobile money wallet and mobile payments in developing market countries has impacted the loan markets and of its relevance to credit market performance. Specifically, how FinTech can be harnessed to mitigate the severe information gap between lenders and borrowers that continues to hinder many households from accessing credit, and the growth of many developing economies.

My proposed theoretical framework and predictions offer some guidance as to the impact of Fintech as a channel for assessing borrowers' credit risk. However, no such guidance exists in literature, on the use of Fintech as a tool to gauge the asymmetric information problem in the lender-borrower relationship. Particularly in developing market economies where the use of financial innovation technologies is prevalent, but the problem of information asymmetry is profound. In the model I present in my thesis, I contend that borrowers' adoption of Fintech can signal their 'true' credit risk. Further, Fintech can reveal 'hidden' private financial and lifestyle information about borrowers that are missing in credit bureau records but are significant to mitigating the information asymmetry problem in the lender-borrower relationship, and this in turn can reduce default rate.

Contrary to the findings of Padilla and Pagano (1997), in this model, the exchange of credit information about the quality of borrowers between lenders, either directly or via third-party institutions such as credit reference bureaus has no effect on interest rate because the lender has a pre-determined fixed interest rate for each borrower category, and only accepts applicants with no prior history of default as shown on the borrowers' thin credit report from the credit reference agency. Additionally, the inclusion of Fintech in my model improves the banks' knowledge of applicants' characteristics and permits more accurate prediction of default probability. Further, this allows lenders to target and price their loans better, easing adverse selection problems and reduces the problem of moral hazard.

2.5.2 Panel regression model

Further, I use a subsample of my dataset and panel regression algorithm to empirically examine how the continuous use of Fintech by borrowers in their repeated interaction with the lending institution impact on the second loan performance and cost of debt for the borrowers. I proceeded as follows to undertake my panel data analysis using the correlated random effect model. First, I run a fixed-effect model using my four time-demeaned regressors and I examined their effect on my dependent variable by splitting the error terms into two components u_i and εi as:

$$y_i = \alpha + x_{i1}\beta_1 + x_{i2}\beta_2 + x_{i3}\beta_3 + x_{i4}\beta_4 + u_i + \varepsilon_i \qquad (4)$$

Now, because these four covariates have repeated observation over time, I transform equation (4) to capture the time component as:

$$y_{it} = \alpha + x_{it}\beta + u_i + \varepsilon_{it} \qquad (5)$$

In equation (5), u_i represent the individual borrower-specific error term that is fixed over time. I then focus on two estimators, that is, the 'between' estimator that uses the mean of all observation for individual borrowers *i* as follows:

$$\overline{y}_i = \alpha + \overline{x}_i\beta + u_i + \overline{\varepsilon}_i \qquad (6)$$

The 'between' variation is considered inefficient when compared to the random effect. This is because it calculates the average of the dependent and independent regressors, and then uses the latter to determine the former. In this approach, it doesn't use much of the information in my dataset since it is built using only the means, and I am unable to estimate the effect of my regressors where their means are time invariant for individual borrowers. As a result, I examine the 'within' variation (fixed effect) estimator by subtracting equation (5) from (6) to get equation (7) below, and I present the result in appendix (B) table (76).

$$\left(y_{it} - \overline{y}_i\right) = (x_{it} - \overline{x}_i)\beta + (\varepsilon_{it} - \overline{\varepsilon}_i) \qquad (7)$$

The fixed-effect result in appendix (B) table (76) is the first level regression that examines the within-group variation for my time-varying regressors. appendix (B) table (77) is the second level regression that examines the variation across group. When the first level and second level regression are taken together, in the fixed-effect (within) model, only the covariate *Ln(GDP growth)* significantly explains the likelihood of default. Also, in the 'between' variation estimator, difference in covariates *Ln(LAmount)*, *Ln(tenor)* and *Ln(GDP growth)* significantly impact on individual borrowers' likelihood of default. A drawback of the fixed-effect model is that it cannot be used to examine the time-invariant nature of some of my regressors. This is because my time-invariant regressors will have a zero within variation since they do not vary over time and their mean will be the same as all the values.

Second, I perform the random-effect model to examine the effect of my time-varying regressors' coefficients on my dependent variable. Third, I compare the results of my fixed-effect and random-effect models using the Hausman test statistic. The Hausman static test whether the unique errors are correlated with the independent variables. The null hypothesis in the Hausman test is that the preferred model is Random-Effect. The result for my computed Hausman test is presented in appendix (B) supplementary table (73). The Hausman test result provides evidence that show significant differences in the coefficients, and as a result, the fixed-effect model is the appropriate strategy.

Fourth, to be cautions, I test the presence of random-effect by using the Breusch-Pagan Lagrange multiplier (LM). The Breusch-Pagan Lagrange multiplier (LM) test result in appendix (B) supplementary table (74) is insignificant and suggests that there is no random-effect hence the true model is the fixed-effect model. Finally, I check for any heteroscedasticity problem for my fixed-effect model. The null hypothesis is homoscedasticity, and I present the result of the heteroscedasticity test in appendix (B) supplementary table (75). The test result for the heteroscedasticity provides evidence to accept the null. That is, I accept the null hypothesis that it is homoscedastic and that there is no heteroscedasticity problem with my fixed effect model. The Hausman test in support the fixed-effect model, and the Breusch-Pagan Lagrange multiplier (LM) test reject the random-effect model.

However, given the drawback associated with the fixed-effect model, that is, the model's inability to estimate time-invariant variable, and since I am also interested in the within' effect of my time-invariant characteristics on my outcome variable, I expand on equation (5) above by including $\overline{x}_i$ to derive equation (8) below:

$$y_{it} = \alpha + \beta_1 x_{it} + \beta_2 \overline{x}_i + \beta_3 k_i + u_i^{residual} + \varepsilon_{it} \qquad (8)$$

In equation (8), k_i is the time-invariant individual borrower characteristics for which I do not need to include group means, and do not have to worry about interpreting the inclusion of $\overline{x}_i$. In this way, I can control for the unobserved heterogeneity that is associated with the time-varying regressors in the equation. Furthermore, the effect of any unobserved characteristics carried in the x_{it} is shifted into the effect of $\overline{x}_i$ and β_1 will approximate the coefficient in the fixed-effect model. Additionally, β_3 will also give me approximately, the OLS estimates for my time-invariant regressors (k_i) such as gender in my empirical dataset.

After adding the individual means (x-bar) for the time-varying variables to the model, I control for the correlation between the explanatory variables and the time-invariant component of the error term. That is the individual Fixed-Effect ui. As a result, my estimation of the beta is consistent. My approach is consistent with Mundlak's (1978) for a fixed-effect model where time-invariant dummy variables such as gender can be investigated. By this approach, I use the random-effect model to implicitly estimate the fixed-effect model for my time-variant variables while also estimating the random-effect of my time-invariant variables at the same time. The method I use is commonly referred to in literature as the correlated random-effect model[13].

[13] See Mundlak (1978) for further explanation of the correlated random-effect model.

2.6 Methodology and Hypothesis

2.6.1 Method

There are several other methods to estimating default probabilities, and these include artificial neural networks (ANN), Genetic Algorithm, Forest Tree, et cetera. However, logistic regression is the most widely used method by practitioners and researchers to estimate default probabilities in consumer credit scoring. Traditionally, linear, probit or logit models are used in binary classification problems. However, prior studies have as shown that there are several limitations in using the linear model. These limitations include heteroscedasticity that leads to loss in the efficiency of the estimations, and abnormal distribution of the error terms. The Probit and the Logit are similar, however, both respectively use normal distribution and cumulative logistic, though the latter model has broader tails that result in small difference.

Artificial neural networks (ANN) have also been shown in some empirical studies to provide best outcome in terms of robustness on a larger dataset. I chose logistic regression over artificial neural networks because of the black-box nature of artificial neural networks. This feature of the artificial neural networks contradicts the requirement for lending institutions to be transparent in the credit granting process as per the Basel II and III regulatory frameworks. Further, prior studies that explored amongst others the abilities of ANN and the traditional statistical techniques including logistic regression analysis (LRA) in constructing credit scoring models, finds that ANN shows a promise if the performance measure is the percentage of bad loans accurately classified. However, if the performance measure is the percentage of good and bad loans accurately classified, LRA is as good as ANN.

Additionally, logistic regression has been shown to be capable of successfully creating an effective model for credit scoring and can capture the various characteristics that are specific to developing market economies and capable of detecting features with the most discriminating power to enable lenders to detect default behaviour. Furthermore, it is generally known that the borrower's ex-ante probability of default is unobservable, hence, the application of direct logistic regression technique directly estimates the probability of default, and hence able to avoids this problem. This technique is also capable of handling both continuous and dummy variables. Bagged Logit regression works by sequentially applying my logistic regression classification algorithm in respect to my modified training dataset. Hence, for each sub sample of the training data, I create a classifier.

For chapters two and four of my thesis, I use bagged logistic regression by successively applying my selected predictive classification algorithm in respect to my modified train data set. I chose the bootstrapping aggregation approach by selecting random subset of the train dataset with replacement. To achieve my bagged logistic regression results, I first split my dataset into train sample (80%) and test sample (20%). Second, I divided my train sample into two sub-samples (Train 1 and 2). Third, I randomly draw samples with the same proportions from Train 1 and 2 using bootstrapping (with replacement). Fourth, I mixed the randomly selected samples in Train 1 and 2 to obtain my new train dataset.

By using this approach, all the training datasets will be of equal proportions and same as the classes in the original dataset. Fifth, I train a particular classification algorithm (Logit regression) using the sub-sample dataset. Sixth, I repeated this process ten (10) times to obtain ten (10) classifiers. In this way I build classifiers with samples that are not identical, and at the same time reduce the variance or over-fitting problem. Each sub-sample (Bag) consists of approximately 4,900 samples, and for each of the sub-samples derived from my training dataset, I fit a classifier. After raining each classifier independently using the Logit algorithm, I aggregated the results using an appropriate combination approach.

I use the average of the estimated probabilities method to aggregate my result after obtaining the final classifier by averaging the coefficients of the combined ten (10) classifiers. I obtain the bagging ensemble by averaging the estimated parameters over all bootstrap replicated sub-samples from my training sample. Finally, I use the average of the probabilities from the ten (10) models as the final probability prediction for the test set. Prior studies show that bagging is one of the most effective but computationally intensive procedures that improves unstable estimates. By using this approach, continuous-valued outputs like posteriori probabilities are available and Logit regression support such estimated probabilities, hence my strategy. Furthermore, the use of logistic, or Logit, regression for classification in credit scoring is often very successful in determining low and high-risk loans. Additionally, my bagged Logit model has direct interpretation.

Further, I test the significance of Fintech on the default likelihood of borrowers over time, and I examine the impact of my time-variant independent variable on loan performance. To achieve this, I use a second balanced micro panel dataset. The micro panel dataset that I use consists of borrowers who were granted second loans after paying off their first loans respectively. The second dataset consist of borrowers who were in default or had repaid their second loan. Both the first and second loans were granted in different time periods. That is, first loans in 2018 and second loans in 2019 respectively. By using panel data regression, I am able to control any endogeneity caused by unobserved heterogeneity in my regression result by acknowledging heterogeneity as either fixed or random. The objective is to evaluate the effect of both the time-variant and non-time variant regressors on my time-varying dependent variable.

The total sub-sample consists of 749 borrowers who were in receipt of first and second loans across the two time-periods, 2018 and 2019 respectively. That is, the same 749 borrowers who were granted loans in 2018 also received second loans in 2019 after the repayment their first loans respectively. I performed two panel data analysis using the fixed and random-effect methods. Thereafter, I perform the Hausman static to determine which of the two models best suit my dataset. This procedure enables me to account for individual heterogeneity and for variables that can't be observed.

The fixed effect model eliminates the effect of the time-invariant characteristics to enable me to assess the net effect of the time-variant independent variables on my explanatory variable. Another central assumption of the fixed-effect model is that my time-invariant characteristics are unique to each individual borrower, and hence should not be correlated with other individual borrower characteristics. That is, every borrower is different and hence the error terms associated with each borrower and the constant which captures individual borrower characteristics should not be correlated with other borrowers.

In the random-effect model, the central assumption is that variations across individual borrowers are uncorrelated with the independent variables. Also, the error terms are not correlated with the independent variables and allow the time-variant variables to play a role as independent variables. If there are differences across borrowers that influence their default or non-default status, then the random-effect model is appropriate. I compared my fixed-effect and random-effect models using the Hausman test static where the null hypothesis is that the preferred model is random-effect versus the alternative, and that the unique errors are uncorrelated with the independent variables. Hence, a result that indicates significant differences in the coefficient means that the fixed-effect model is the best model to use.

2.6.2 Hypothesis

In Africa, the absence of credit reference bureau or in some cases where this exists, it provides basic information on borrowers, and at most only help lending institutions to meet their 'Know-Your-Customer' requirement imposed by central banks and regulators. This phenomenon, that is, absence of credit reference bureau, is an important feature of many African countries and is driving loan losses for investors and lending institutions in particular because screening credit applicants in such an environment becomes extremely difficult task to undertake. Furthermore, in such circumstance, a borrower doesn't consider default to be associated with any risk, and hence creates moral hazard and adverse selection problem for lenders operating in this market environment. Andrianova et al., (2014) investigated what inhibit bank lending in Africa using dynamic panel model across 16 selected African countries and find that default and weak regulations are the dominant factors.

Equally, the difficult challenge of distinguishing good credit applicant who becomes an asset to the lender from bad ones can create an adverse selection effect. My theoretical model adds to the existing literature on adverse selection and loan default by exploring in detail how borrowers' adoption of Fintech, that is, mobile money wallet, and the extent of it usage in a signalling framework combine to help determine the type of equilibrium prevailing in the loans market in the developing world. This provides the basis for my empirical model of borrower behaviour in in the loans market, particularly in African economies.

The theoretical foundations of this section of my thesis is grounded on the work of Spence (1973 and 2002); Grossman and Hart (1980); Grossman (1981); Milgrom (1981). These authors argued that verifiable disclosure can mitigate the adverse selection problems. On the empirical side, there is a diverse literature on both the rational for the adoption of Fintech, and the use of Fintech as a channel to achieve financial inclusion in the developing world. Specifically, I refer to the works of Blumenstock, Callen, and Ghani (2018); Björkegren, Blumenstock, Folajimi-Senjobi, Mauro, and Nair (2022); Blumenstock, Cadamuro & On (2015); Björkegren (2010); Björkegren and Grissen (2015, 2017, 2018 and 2020); and Jack, Ray and Suri, T. (2013). These authors also investigated the adoption of cell phones and mobile money impact on economic, financial, and social transactions and find positive effect. These reasoning leads to my three hypotheses that I examine in this second chapter of my thesis, and they are:

$H1_0$: Across all borrowers, ceteris paribus, Fintech signal borrower credit risk and lead to lower loan risk.

$H2_0$: Across all borrowers, ceteris paribus, borrowers' adoption of Fintech reduces cost of debt to the borrower.

$H3_0$: Across all borrowers, ceteris paribus, Female borrowers who adopt Fintech have lower loan default risk.

Table 7. Variables and their measurements

VARIABLES	MEASUREMENT AND SPECIFICATION
1. Borrower Age	Log of client age in years
2. Gender (Female)	1 if client is a female, otherwise male
3. Income Category (Formal Salary)	1 if the client's source of income is salary, otherwise 0
4. Employer	1 if client is employed in public sector, otherwise 0
5. Profession	1 if client has a job that require professional qualification, otherwise 0
6. Loan Amount	Log of loan amount disbursed in local currency (GHC) Converted to US$ at prevailing exchange rate when loans were disbursed.
7. Loan Tenor	Log of the maturity of loan in months
8. Borrower Identity Document (More than 1)	1 if client has more than one identity document, otherwise 0
9. Borrower affordability (=35%]	1 if clients' loan affordability is 35% of disposable income, otherwise 0
10. Mobile phone account ownership (=2)	1 if client has two mobile phone account, otherwise 0
11. Bank Account ownership (Yes)	1 if clients own a bank account, otherwise 0
12. Loan status	I if client defaulted on loan, otherwise 0
13. FinTech	1 if clients have an active mobile money account, otherwise 0
14. Interest Rate	Log of the interest rate charged by lender per annum
15. Gross Domestic Product (GDP)	Log of one period Lag of Gross Domestic Product growth rate
16. Inflation Growth Rate	Log of one period Lag of the annual inflation growth rate
17. Region	1 if branch is in Accra, otherwise 0
Region	1 if branch is in Kumasi, otherwise 0
Region	1 if branch is in Kumasi, otherwise 0

2.7 Empirical Results

2.7.1 Results of Bagged Logit Model

I present my main results using bagged Logit regression model represented by equation (3) in table (X) which is estimated to examine the effect of the adoption of financial technology, Fintech, on loan risk. To aid the interpretation of my results, I present in table (7) above, the measurement of my variables.

$H1_0$: My empirical results in table (8) confirm my first hypothesis. That is, Fintech reduces the likelihood of loan loss faced by lending institutions when providing credit to smooth household consumption. The results in table (8) columns (2) and (4) shows that for every borrower that adopt Fintech as an information enhancing tool and to signal to be 'good' credit risk, and condition on the lender confirming this signal to be 'true' via the transactional information generated from the borrowers' mobile money account (Appendix 3), the likelihood of default is significantly reduced by $100\times(e\beta\hat{}-1)\approx$ -81.6170 percent compared to non-adopters[14]. This is statistically significant at the 1% level.

I briefly review the estimated coefficients on the control variables. One striking result in table (8) is the relationship between interest rate and default likelihood. I anticipated finding higher default associated with higher interest rate and as shown in many literatures and empirical studies. However, my results show that default likelihood is significantly reduced by 49.36% for every percentage increase in interest rate. This suggests a loan pricing anomaly, and that lenders are pooling both risky and non-risky borrowers together when pricing loans. Borrowers who are granted loans, and who's loan sizes are determined on the basis of having 35% affordability are associated with higher default likelihood. Also, a percent increase in older clients is associated with 90% increase default likelihood, and these results are statistically and economically significant.

[14] This result is statistically significant and economically important and show that an 87.70% likelihood for the lender to reduce the total loan portfolio of USD 2, 520.763.32 granted to borrowers who were non-adopters of Fintech and were in default. [(GHS₵ = Ghana Cedis. 1 USD ~ 3.511 GHS₵, (Average mid-rate between 1 Jan. 2011 to 31 December 2019)].

For every borrower who is a female, default likelihood is decreased by more than half compared to their male counterparts. Further, my empirical results provide economically and statistically significant evidence to show that default likelihood is reduced by 43.60% for every borrower who is a professional with full technical skills or education. Default likelihood increases by 5.63% for every ten percent increase in the loan maturity period. Also, I find that for every borrower that has a formal bank account, default likelihood is reduced by more than half which is economically and statistically significant. When bank account is compared to mobile money account and default rate, the reduction in default likelihood is 30.92% lower for adopter of Fintech, that is mobile money wallet accounts.

Taken together, this suggests that although borrowers use their bank account to signal transparency in their finances to the lending institution, the information value generated from the borrowers' use of mobile money account has a higher economic significance in reducing default rate. Another striking result in table (8) is the controlling effect of borrower opacity, which is measured as the number of identification documentations provided by loan applicants at the loan underwriting stage. The results show that borrowers who present more than one identification documents are associated with much higher default likelihood. This is statistically significant. Additionally, I find that borrowers with ownership of two mobile phones accounts are associated with 36.95% reduction in default likelihood compared to their counterparts with one or more than two accounts.

Being employed in the public sector is associated with 89.75% decrease in default likelihood compared to the private sector. Also, relying on formal income (salary) as the main source for the repayment of loans reduces default by 26.97% compared to borrowers who rely on both formal and informal income to repay their loans. This is statistically significant, and the finding was not anticipated, but suggests that borrowers who rely on business and other source of income in addition to their formal salary to repay their debt obligation may not be managing their finances well. Another explanation could be that these cohort of borrowers are diverting more funds to their informal or formal business.

My empirical results in table (9) show that borrowers who adopt Fintech, that is mobile money, and are in the age category of 20 to 40 years are associated with a reduced likelihood of default on their loan contracts. That is, a ten percent increase in borrowers within the age group 20-30 years are associated with a $100\times(1.10^{\hat{\beta}}-1)$ 1)$\approx$-1.673 percent lower default likelihood. Similarly, a ten percent increase in borrowers within the age group 31-40years are associated with a $100\times(1.10^{\hat{\beta}}-1)$ $\approx$-2.131 percent decline in default probabilities. However, the result is statistically significant for borrowers who adopted Fintech and are within the age category of 31 to 40 years.

Further, my results show that for every ten percent increase in borrowers who adopt Fintech and were in receipt of loan amounts between approximately US$142 to US$284, there is a $100\times(1.10^{\hat{\beta}}-1)$ 1) $\approx$-5.657 percent lower propensity to default. Similarly, a ten percent increase in borrowers who adopted Fintech and were in receipt of loan amounts between approximately between US$285 to US$1,424, the probability of defaulting on their loan contract decreases by $100\times(1.10^{\hat{\beta}}-1)$ 1)$\approx$-0.219 percent, and for borrowers who received loan between US$1,425-US$2,563, there is a $100\times(1.10^{\hat{\beta}}-1)$ 1)$\approx$1.073 percent higher likelihood to default. However, the result is only statistically significant for loan amounts that ranges from US$142 to US$284 (Table 10).

Figures (2) and (3) show the performance of my logit model using the receiver operating curve (ROC) and examining the area-under the curve (AUC). The Receiver Operating Characteristic (ROC) curve is a graphical plot of the sensitivity (correctly classifying good credit risk clients) against specificity (correctly classifying bad credit risk clients) for all possible thresholds. My selected threshold of 0.5 for my estimated scores aligns with industry practice and is frequently used in literature. An Area under the Curve (AUC) of 1 suggests a perfect classification and 0.5 is considered a random average prediction result from the model. My model achieved a ROC-AUC score greater than 0.9 which is excellent.

Table 8. Coefficients of the Bagged Logit Model (Cohort I)

$$\text{Log}\left(\frac{\text{Pd}}{(1-pd)}\right) = \alpha 0 + \Sigma\, \text{X}1\beta 1 + \text{X}2\beta 2 + \text{X}3\beta 3 + \cdots \text{Xn}\beta\text{n} + FinTechi\varphi \ + \varepsilon_i \qquad (3)$$

(Default is the explained Variable)

INDEPENDENT VARIABLES	**Likelihood Ratio Chi-Square =1060.730, df=13, sign. =0.000**	
	COEFF.	**STAND. ERROR**
Fintech	-2.2650***	0.1584
Control Variables		
Borrower Age	0.5820*	0.3399
Gender (Female)	-0.7050***	0.1533
Mobile phone account ownership (=2)	-0.3610*	0.2239
Borrower Identity Document (More than 1)	2.2980***	0.1970
Profession (Professionals)	-0.5490*	0.2191
Employer (Public sector)	-1.6290***	0.2821
Income Category (Formal Salary)	-0.9550***	0.3246
Borrower affordability (=35%]	na	na
Loan Amount	0.3120***	0.0924
Tenor	0.5770***	0.1123
Interest Rate	-0.1310*	0.3832
Bank Account ownership (Yes)	-0.9410**	0.3138
GDP	12.7480***	0.8075
(Intercept)	-37.6980***	3.1625
a= Model classification accuracy	a= 89.10, R^2 = 0.597	

Asterisks: ***Indicates a coefficient significantly different from zero at the 1%, ** at the 5% level, and * at 10% level.

Table 9. Coefficient of Logit regression (Fintech Account Ownership by Client Age)

(Default is the explained variable)

Independent Variables	Coefficient	Std. Error
Fintech_Age [20-30]	-0.1770	0.1782
Fintech_Age [31-40]	**-0.2260****	**0.1149**
Fintech_Age [> 40]	na	na
Control Variables		
Gender [Female]	-0.4690***	0.1122
Loan Tenor	0.8380***	0.0962
Interest Rate	-0.8100***	0.2791
Loan Amount	0.1800***	0.0647
Income (Salary)	-0.2840	0.2937
Employer (Public sector)	-1.9160***	0.2175
Profession (Professional)	-0.8500***	0.1426
Borrower Identity Document (More than 1)	1.9200***	0.1442
Mobile phone account ownership (=2)	-0.1990	0.1521
Borrower Affordability [35%]	2.9050***	0.6648
Bank Account ownership (Yes)	-0.3810	0.2448
GDP	14.0530***	0.6055
(Intercept)	-39.6420***	0.2064
Likelihood Ratio Chi-Square	1454.352	Model class accuracy = 0.8710
Sig. of Chi-Square	0.0000	R-Square = 0.5570
df	14	

Asterisks: ***Indicates a coefficient significantly different from zero at the 1%, ** at the 5% level, and * at 10% level.

Table 10. Coefficient of Logit regression(Fintech Account Ownership by Loan Category)

(Default is the explained variable)

Independent Variables	**Coefficient**	**Std. Error**
Fintech_Loan Category 1[US$142-US$284]	-0.6110***	0.2242
Fintech_ Loan Category 2 [US$285-US$1,424]	-0.0230	0.1786
Fintech_Loan Category 3 [US$1,425-US$2,563]	0.1120	0.2158
Fintech_Loan Category 4 [US$>2,5634]	na	na
Control Variables		
Borrower Age	0.3060	0.2541
Gender [Female]	-0.4700***	0.1123
Loan Tenor	0.8460***	0.0963
Interest Rate	-0.7900***	0.2793
GDP	14.1290***	0.6072
Income (Salary)	-0.2820	0.2943
Employer (Public sector)	-1.9210***	0.2178
Profession (Professional)	-0.8570***	0.1427
Borrower Identity Document (More than 1)	1.9050***	0.1442
Mobile phone account ownership (=2)	-0.2010	0.1523
Borrower Affordability [35%]	2.8350***	0.6644
Bank Account ownership (Yes)	-0.3980	0.2458
(Intercept)	-39.6200***	0.4300
Likelihood Ratio Chi-Square	1460.089	Model accuracy = 0.8710
Sig. of Chi-Square	0.0000	R-Square = 0.565
df	15	

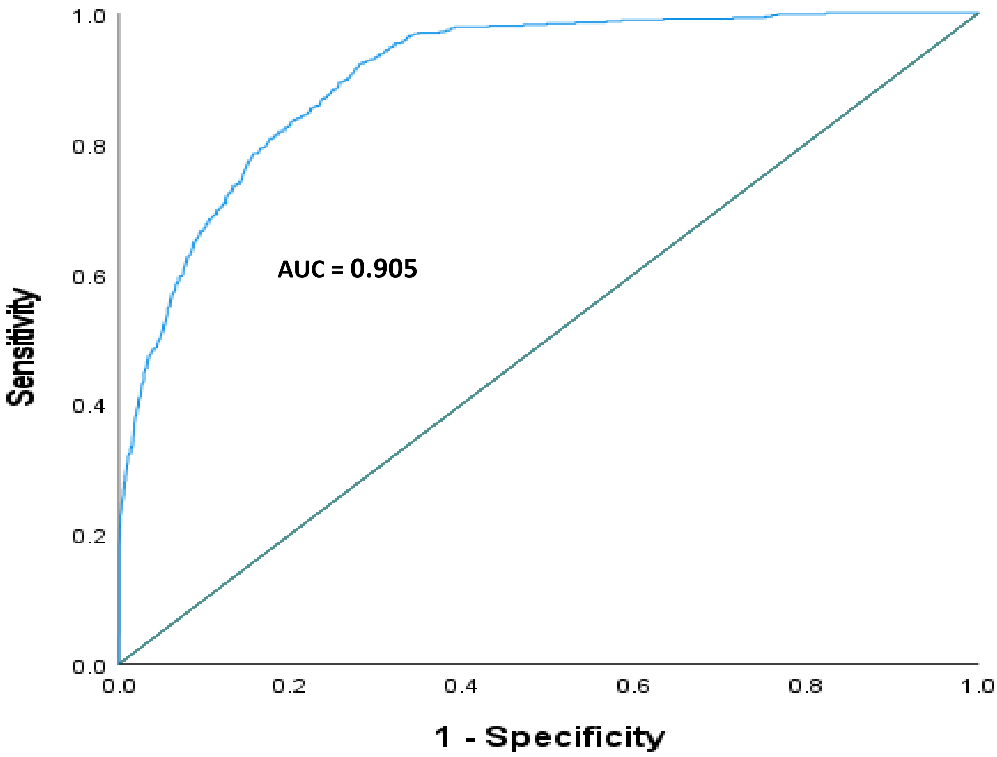

Figure 2. ROC-AUC Curve for Fintech by Age

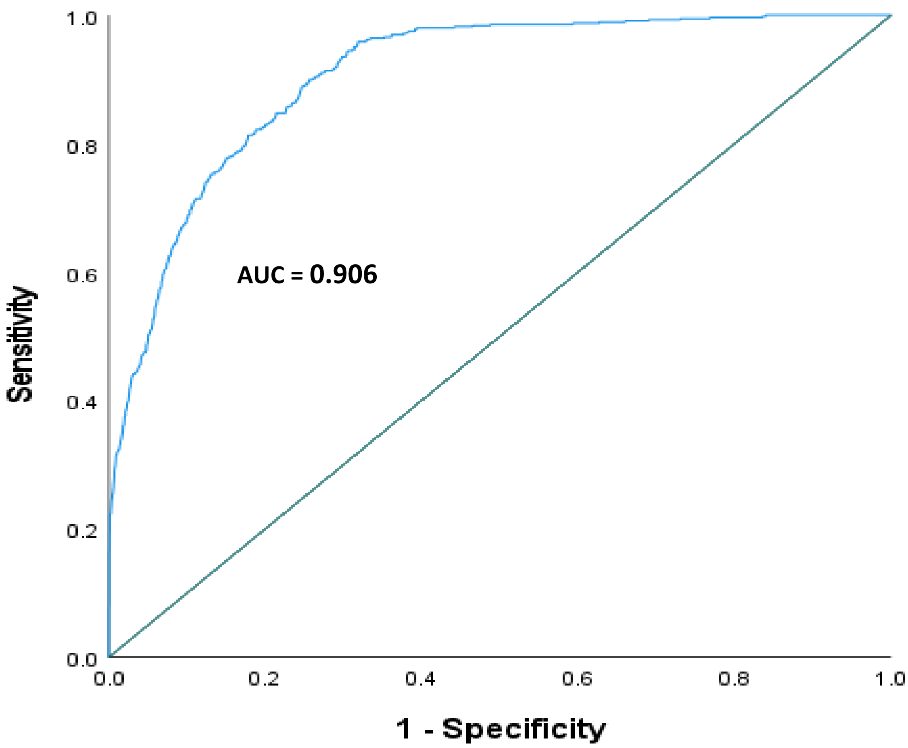

Figure 3. ROC-AUC Curve for Fintech Loan Amount

2.7.2 Panel Regression results: Repeat borrowers.

I present the results of my panel regression that examine the effect of Fintech on loan risk among repeat borrowers over time using the correlated random-effect model in table (11). I find a statistically significantly evidence that borrowers' adoption of Fintech can signal credit risk and mitigate loan losses. That is for every borrower that adopts Fintech prior to their second loan (Cohort II), the likelihood of default is further reduced by $100\times(e\hat{\beta}-1)\approx$ -6.6767 percent compared to their non-adopting counterparts. This finding corroborates with my earlier result using the Logit model in table (8). I briefly discuss some control variables. Borrowers who present more than one identity document to the lender are associated with higher default likelihood of 3.92% compared to their counterparts who had only one acceptable identification document.

Borrowers who received loans on the basis of having an affordability of 35% of their disposable income are also associated with higher default likelihood of 47.83%. Further, GDP growth has negative impact on default likelihood. That is, the likelihood of default increases by 5.674% with a ten percent increase in GDP. Clients who are professionals and have technical skills or education are associated with 11.03% lower propensity to default compared to their non-professional counterparts. Additionally, being employed in the public sector reduces default likelihood by 3.76% compared to being employed in the private sector. These findings are significant at 1% and 5% levels.

Also, it is worth noting that, the likelihood of default among new borrowers as shown in my main results in table (8) increases for a percentage increase in the loan amount and tenor. On the contrary, I find that a percentage increase in loan amount and tenor reduces the likelihood of default by 1.03% and 1.99% but is insignificant. Also, unlike new borrowers, I find an elastic relationship between interest rate and default likelihood among repeat borrowers. That is, a one percent increase in interest rate is associated with a $100\times(1.01\hat{\beta}1-1)\ 1)\approx$0.085 percent change in default likelihood. This is significant at the one percent level (Table 11).

Table 11. Coefficients of the panel regression using Correlated Random Effect (Cohort II)

(Default is the explained variable)

Independent variables	**Coefficient**	**Std. Err.**	**z**	**P>z**	**[95% conf. interval]**	
Fintech	-0.0691	0.0112	6.1800	0.0000	-0.0910	-0.0471
Control Variables						
Borrower Identity Document (More than 1)	0.0206	0.0127	1.6200	0.1050	-0.0043	0.0456
Borrower Age	-2.1738	1.8608	1.1700	0.2430	-5.8208	1.4733
Gender (Female)	-0.0037	0.0115	0.3200	0.7500	-0.0262	0.0189
Income Type (formal salary)	-0.0335	0.0250	1.3400	0.1810	-0.0825	0.0155
Employer (Public sector)	-0.0427	0.0190	2.2500	0.0250	-0.0798	-0.0055
Profession (Professional)	-0.1159	0.0240	4.8200	0.0000	-0.1630	-0.0687
Borrower Affordability (35%)	0.3834	0.1429	2.6800	0.0070	0.1033	0.6635
Mobile phone account ownership (=2)	-0.0057	0.0120	0.4800	0.6350	-0.0291	0.0177
Bank account ownership (Yes)	-0.0240	0.0308	0.7800	0.4360	-0.0845	0.0364
Loan Amount	-0.0104	0.0199	0.5200	0.6030	-0.0495	0.0287
Loan Tenor	-0.0201	0.0223	0.9000	0.3670	-0.0638	0.0236
GDP growth	0.5790	0.1798	3.2200	0.0010	0.2266	0.9314
Interest rate	0.0848	0.0219	3.8700	0.0000	0.0418	0.1277
Intercept	-1.8124	0.4927	3.6800	0.0000	-2.7781	-0.8466
sigma_u	0.0000	R-squared:				
sigma_e	0.2112	Within	0.1021			
rho	0.0000	Between	0.2082			
Wald chi2(17)	266.0700	Overall	0.1524			
Prob > chi2	0.0000					

Asterisks: ***Indicates a coefficient significantly different from zero at the 1%, ** at the 5% level, and * at 10% level.

2.7.3 Gender, Fintech, and Loan Risk

Motivated by extant theoretical and empirical studies that show females are good credit risk, but are less likely to use Fintech, in this section I examine the interaction of gender, particularly female, and their adoption of Fintech on loan performance. To achieve this, I use my two cohort of borrower samples and different methodologies to investigate the use of Fintech by females and their loan performance. First, I use my sample of borrowers in cohort (I) and bagged logit regression. Additionally, I use borrowers in cohort (II) in a balanced panel regression to investigate how the continuous use of Fintech by females and their repeated interaction with the lending over time impact on loan performance. I present my results for both cohorts (I) and (II) in tables (12) and (13) respectively.

My results in table (12) show, that for every female borrower who adopt Fintech prior to the credit contract and loan disbursement in cohort (I), the probability of loan default is significantly reduced. That is, an increase in one (1) female borrower in cohort (I) who adopt Fintech is associated with a $100\times(e\hat{\beta}-1)$ ≈ -82.0575 percent change in the likelihood of default. This is significant at the 1% level. Additionally, in table (13) my results show that the continuous use of Fintech by female borrowers who receive their second loan in a repeated interaction with the same lending institution over time reduces the probability of loan default. That is, for everyone additional repeat client who adopt Fintech and is a female is associated with a $100\times(e\hat{\beta}-1)$ ≈ -3.7576 percent change in the likelihood of default. This is significant at the 1% level.

My results suggest that female borrowers are tech savvy and are able to use Fintech to manage their finances well to ensure that they meet their debt servicing obligation to the lender. Furthermore, my results suggest that in cohort (I), the likelihood of default for the total loan portfolio of US$1,011,421 that were granted to female clients that did not adopt Fintech and were in default could have been significantly reduced by 82.0575%. That is, the likelihood of the lender loosing US$1,011,421 could have been only 17.9425% if the female borrowers who were in default adopted Fintech, *ceteris parabus*. Similarly, for repeat clients, the likelihood of the lender loosing US$34,178 of the loans granted to repeat borrowers who were females but did not adopt of Fintech and in default could have reduced by a further 3.7576%, ceteris parabus.

My results (tables 12) further show, that a ten percent increase in the loan amount and tenor for female clients with Fintech is associated with a $100\times(e\beta\hat{}1-1) \approx 2.529$ percent, and $100\times(e\beta\hat{}-1) \approx 5.865$ percent increase in the likelihood of default respectively. Also, for every female client who adopt Fintech and present more than two (2) borrower verification identity documents to the lender are associated with an increase in the likelihood of default. Further, I find an inverse relation between female borrowers who adopt Fintech and employed in the public sector with only formal source of income. That is, for everyone additional female client who adopt Fintech and is employed in the public sector with formal income, the likelihood of default is significantly reduced. Similarly, being a professional, with two mobile phone and a bank account reduces default by 38.553%, 41.374% and 62.054% respectively. This is significant at the 1% level.

Table 12. Coefficient of Logit regression (Cohort I)

(Default is the explained variable)

Explanatory Variables	**Coefficient**	**Std. Error**
Gender*Fintech	-1.7180***	0.1807
Control Variables		
Borrower Age	0.4430	0.3164
Loan Amount	0.2620***	0.0851
Loan Tenor	0.5980***	0.1057
Interest Rate	-0.1360	0.3602
GDP	12.1070***	0.7593
Income (Salary)	-1.1130***	0.3018
Employer (Public sector)	-1.6910***	0.2726
Profession (Professional)	-0.4870*	0.2023
Borrower Identity Document (More than 1)	2.2940***	0.186
Mobile Phone Account (=2)	-0.5340**	0.2096
Bank Account ownership (Yes)	-0.9690***	0.2857
(Intercept)	-36.0020***	2.917
Likelihood Ratio Chi-Square	896.3050	Model accuracy = 0.8710
Sig. of Chi-Square	0.0000	R-Square = 0.5260
df	12	

Table 13. Coefficients of the panel model using Correlated Random Effect (Cohort II)

(Default is the explained variable)

Independent variables	**Coefficient**	**Std. err.**	**z**	**P>z**	**[95% conf. interval]**	
Fintech*Gender (Female)	-0.0383	0.0142	2.6900	0.0070	-0.0662	-0.0104
Control Variables						
Borrower Identity Document (More than 1)	0.0230	0.0129	1.7900	0.0740	-0.0022	0.0482
Borrower Age	-2.1738	1.8800	1.1600	0.2480	-5.8586	1.511
Gender (Female)	0.0216	0.0152	1.4200	0.1550	-0.0082	0.0514
Income Type (formal salary)	-0.0365	0.0253	1.4400	0.1490	-0.086	0.013
Employer (Public sector)	-0.0446	0.0192	2.3300	0.0200	-0.0821	-0.007
Profession (Professional)	-0.1192	0.0243	4.9100	0.0000	-0.1668	-0.0716
Borrower Affordability (35%)	0.4263	0.1442	2.9600	0.0030	0.1436	0.7089
Mobile phone account (=2)	-0.0054	0.0121	0.4500	0.6550	-0.0291	0.0183
Bank account ownership (Yes)	-0.0233	0.0312	0.7500	0.4550	-0.0844	0.0378
Loan Amount	-0.0104	0.0202	0.5200	0.6060	-0.0499	0.0291
Loan Tenor	-0.0201	0.0225	0.8900	0.3720	-0.0642	0.024
GDP	0.5790	0.1817	3.1900	0.0010	0.223	0.9351
Interest rate	0.0852	0.0222	3.8400	0.0000	0.0417	0.1286
Intercept	-1.8696	0.4978	3.7600	0.0000	-2.8452	-0.894
sigma_u	0.0000	R-squared:				
sigma_e	0.2112	Within	0.1021			
rho	0.0000	Between	0.1710			
Wald chi2(17)	230.4800	Overall	0.1347			
Prob > chi2	0.0000					

2.7.4 The unlocking opportunities of Fintech to improve Loan Risk

I investigate the substitution and or complementary role that borrowers' adoption of Fintech and bank account ownership play on loan risk. My results in tables (14) show clients who haven't adopted Fintech but have a formal bank account and their loan performance. I find that these clients are associated with higher default likelihood. That is, a $100\times(e\hat{\beta}1-1) \approx 6.51$ percent increase in default likelihood. I find similar results for clients who have no bank account and are non-adopters of Fintech. That is, an increase of one additional client who received cash-cheques[15] for their loan is associated with a $100\times(e\hat{\beta}1-1) \approx 19.94$ percent change in default likelihood, table (15).

When I examined borrowers who have formal bank account and were adopters of Fintech, the likelihood of default is significantly reduced. That is, every additional borrower who has a bank account and adopted Fintech is associated with a $100\times(e\hat{\beta}1-1) \approx -6.10$ percent in default likelihood, table (16). Similarly, the propensity to default is lower for clients who do not have bank account but have adopted financial technology. That is, for every additional client who adopt financial technology, Fintech, and do not have a formal bank account is associated with a $100\times(e\hat{\beta}1-1) \approx -3.98$ percent change in default likelihood, table (17).

In summary, my results show that borrowers' adoption of financial technology, that is, mobile money wallet account, can signal borrower credit risk. Default likelihood is reduced for clients who have both formal bank account and mobile money account. Clients who have only bank account and those with no bank or mobile money account are associated with high default probabilities. My results show that the information value of financial technology is higher when compared to bank account. My findings suggest that Fintech can substitute bank account ownership, and this can significantly impact on loan risk. Furthermore, Fintech can unlock opportunities for adopters to improve their credit score by linking their mobile money account to formal bank account.

[15] This is where the lender issues a cheque to the borrower that can be cashed over-the-counter by the client after presenting an acceptable personal identity document and doesn't require the client to have a bank account.

Table 14. Coefficients of the panel regression using Correlated Random Effect (Bank Account Only)

(Default is the explained variable)

Independent Variable	**Coefficient**	**Std. err.**	**z**	**P>z**	**[95% conf.**	
Bank Account_NoFintech	0.0631	0.0113	5.6000	0.0000	0.0410	0.0852
Control Variable						
Borrower Age	-2.1738	1.8646	1.1700	0.2440	-5.8284	1.4809
Loan Amount	-0.0104	0.0200	0.5200	0.6030	-0.0496	0.0288
Loan Tenor	-0.0201	0.0223	0.9000	0.3680	-0.0639	0.0237
GDP	0.5790	0.1802	3.2100	0.0010	0.2259	0.9322
Interest rate	0.0850	0.0219	3.8800	0.0000	0.0420	0.1280
Gender (Female)	-0.0046	0.0115	0.4000	0.6870	-0.0272	0.0179
Income Type (formal salary)	-0.0332	0.0251	1.3200	0.1860	-0.0823	0.0160
Employer (Public sector)	-0.0432	0.0190	2.2700	0.0230	-0.0805	-0.0060
Profession (Professional)	-0.1150	0.0241	4.7700	0.0000	-0.1621	-0.0678
Borrower Identity Document (More than 1)	0.0211	0.0128	1.6500	0.0990	-0.0039	0.0461
Borrower Affordability (35%)	0.3850	0.1432	2.6900	0.0070	0.1043	0.6656
Mobile phone account ownership (=2)	-0.0058	0.0120	0.4900	0.6250	-0.0293	0.0176
Intercept	-1.9086	0.4927	3.8700	0.0000	-2.8743	-0.9429

	R-squared:		
	Within = 0.1021		
sigma_u = 0.0000	Between = 0.1996	Wald chi2(16)	257.8400
sigma_e = 0.2112	Overall = 0.1483	Prob > chi2	0.0000

Table 15. Coefficients of the panel regression using Correlated Random Effect (Cash Cheque)

(Default is the explained variable)

Independent Variable	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
NoBank_NoFintech	0.1818	0.0590	3.0800	0.0020	0.0661	0.2975
Control Variables						
Borrower Age	-2.1738	1.8783	1.1600	0.2470	-5.8551	1.5076
Loan Amount	-0.0104	0.0201	0.5200	0.6060	-0.0498	0.0291
Loan Tenor	-0.0201	0.0225	0.8900	0.3720	-0.0642	0.0240
GDP	0.5790	0.1815	3.1900	0.0010	0.2233	0.9347
Interest rate	0.0844	0.0221	3.8200	0.0000	0.0411	0.1277
Gender (Female)	-0.0034	0.0116	0.2900	0.7720	-0.0261	0.0194
Income Type (formal salary)	-0.0378	0.0252	1.5000	0.1340	-0.0873	0.0116
Employer (Public sector)	-0.0446	0.0191	2.3300	0.0200	-0.0822	-0.0071
Profession (Professional)	-0.1213	0.0242	5.0000	0.0000	-0.1688	-0.0737
Borrower Identity Document (More than 1)	0.0217	0.0129	1.6900	0.0910	-0.0034	0.0469
Borrower Affordability (35%)	0.4285	0.1441	2.9700	0.0030	0.1461	0.7109
Mobile phone account ownership (=2)	-0.0076	0.0121	0.6300	0.5300	-0.0312	0.0161
Intercept	-1.8723	0.4963	3.7700	0.0000	-2.8450	-0.8995

	R-squared:	
	Within = 0.1021	
sigma_u = 0.0000	Between = 0.1732	Wald chi2(16)= 232.72
sigma_e = 0.2112	Overall = 0.1358	Prob > chi2 = 0.0000

Table 16. Coefficients of the panel regression using Correlated Random Effect (Fintech Account and Bank Account)

(Default is the explained variable)

Independent Variable	Coefficient	Std. err.	z	P>z	[95% conf.	
Fintech_Plus Bank_ Account	-0.0629	0.0110	5.7100	0.0000	-0.0845	-0.0413
Control Variables						
Borrower	-2.1738	1.8638	1.1700	0.2440	-5.8268	1.4793
Loan Amount	-0.0104	0.0200	0.5200	0.6030	-0.0495	0.0288
Loan Tenor	-0.0201	0.0223	0.9000	0.3680	-0.0638	0.0237
GDP	0.5790	0.1801	3.2100	0.0010	0.2260	0.9320
Interest rate	0.0827	0.0219	3.7700	0.0000	0.0397	0.1256
Gender (Female)	-0.0038	0.0115	0.3300	0.7390	-0.0264	0.0187
Income Type (formal salary)	-0.0335	0.0251	1.3400	0.1810	-0.0826	0.0156
Employer (Public sector)	-0.0433	0.0190	2.2800	0.0230	-0.0806	-0.0061
Profession (Professional)	-0.1166	0.0241	4.8500	0.0000	-0.1638	-0.0695
Borrower Identity Document (More than 1)	0.0215	0.0128	1.6900	0.0910	-0.0035	0.0465
Borrower Affordability (35%)	0.3876	0.1431	2.7100	0.0070	0.1071	0.6681
Mobile phone account ownership (=2)	-0.0048	0.0120	0.4000	0.6870	-0.0283	0.0186
Intercept	-1.8447	0.4925	3.7500	0.0000	-2.8100	-0.8793
	R-squared:					
	Within = 0.1021					
sigma_u = 0.0000	Between = 0.2011		Wald chi2(16)	259.3100		
sigma_e = 0.2112	Overall = 0.1490		Prob > chi2	0.0000		

Table 17. Coefficients of the panel regression (Client with Fintech Ownership but No Bank Account)

(Default is the explained variable)

Independent Variable	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
Fintech_NoBank	-0.0406	0.0365	-1.1000	0.2660	-0.1122	0.0310
Control Variables						
Borrower Age	-2.1738	1.8835	-1.1000	0.2480	-5.8653	1.5178
Loan Amount	-0.0104	0.0202	-0.5000	0.6070	-0.0500	0.0292
Tenor	-0.0201	0.0226	-0.8000	0.3730	-0.0643	0.0241
GDP growth	0.5790	0.1820	3.1800	0.0010	0.2223	0.9357
Interest Rate	0.0849	0.0222	3.8300	0.0000	0.0414	0.1285
Gender (Female)	-0.0052	0.0116	-0.4000	0.6570	-0.0280	0.0176
Income Category (Formal Salary)	-0.0366	0.0253	-1.4000	0.1480	-0.0862	0.0130
Employer (Public sector)	-0.0453	0.0192	-2.3000	0.0180	-0.0830	-0.0077
Profession (Professional)	-0.1188	0.0243	-4.8000	0.0000	-0.1664	-0.0711
Borrower Identity Document (More than 1)	0.0223	0.0129	1.7300	0.0830	-0.0029	0.0476
Borrower Affordability (35%)	0.4243	0.1445	2.9400	0.0030	0.1411	0.7075
Mobile phone account ownership (=2)	-0.0076	0.0121	-0.6000	0.5300	-0.0313	0.0161
Intercept	-1.8831	0.4977	-3.7000	0.0000	-2.8585	-0.9077
	R-square:					
	Within = 0.1021					
sigma_u = 0.0000	Between = 0.1631		Wald chi2(16)	223.2400		
sigma_e = 0.2112	Overall = 0.1310		Prob > chi2	0.0000		

2.7.5 Fintech and Cost of Debt

$H2_0$: I test this hypothesis using the borrowers' cost of debt as my dependent variable and controlling for other independent variables. Tables (18) and (19) presents my result investigating the effect of Fintech on the risk premium charged by the lender. The results provide evidence to reject my second hypothesis. That is, clients' adoption of Fintech does not lead to the likelihood of interest rate reduction. I find contrary and statistically significant evidence that borrowers in both cohorts (I) and (II) who adopt Fintech are likely to be charged higher interest rate. That is, for one (1) additional client who adopt Fintech in both cohorts (I) and (II) are associated with a $100\times(e\beta\hat{}1-1)$ ≈1.6129 percent and $100\times(e\beta\hat{}1-1)$ ≈3.5620 percent change in interest rate increases respectively. This result suggests two things. First, Fintech may be revealing borrowers' 'true' risk and leading to efficient loan pricing, or second, that the lender is pooling both risky and non-risky borrowers together and leading to pricing anomaly.

When the results in table (8) are taken together with the results in tables (18), and (19), the findings support my loan pricing anomaly proposition. That is, the lender is pooling both risky and non-risky borrowers together when pricing loans. This further suggests that, although Fintech reduces the likelihood of loan losses, the lender is not pricing loans to reflect the risk associated with borrowers who adopt Fintech. However, this may equally suggest that Fintech in performing an effective role. That is, Fintech reveals borrowers' 'true' risk, and that the lender is pricing loans to reflect the risk identified in the verification of the clients signal. Whichever way these results are viewed, Fintech can be seen to be performing a critical function in loan pricing. Given the inelastic relationship between interest rate and default, the lender is able to charge this additional interest rate without deteriorating the quality of the loan portfolio, ceteris paribus.

I briefly review the estimated coefficients of some control variables in table (XXII). Older borrowers who adopt Fintech are more likely to be charged higher interest. That is, a one percent increase in older borrowers is associated with a $100\times(1.01\beta\hat{}1-1)$ 1) ≈0.020 percent change in interest rate compared to their younger counterparts, and for every additional female client who adopts Fintech, there is a likely reduction of interest rate by 0.020%. These results reflect my main findings that show that older borrowers in cohort (I) are associated with higher likelihood of default compared to their younger counterparts, and females have lower default frequencies.

Also, for every borrower who is granted a loan on the basis of having affordability rate of 35%, the likelihood of being charged higher interest rate increase by five (5) percent. The result reflects the higher risk of default associated with borrowers with thirty-five (35) percent affordability. Table (18) show, that for every additional personal identification document presented by the borrower to the lender as verification of 'true' identity, the likelihood of being charged higher interest rate is increases by 8.56%. That is, for every borrower who seeks to be more transparent to the lender by providing additional acceptable identification document at the loan application stage, this is associated with the likelihood of being charged higher interest rate. The most straightforward explanation for the likelihood of higher interest rate charge associated with borrowers with more than one acceptable personal identification document is that they are associated with high default likelihood as observed in table (8).

Furthermore, borrowers with more than one acceptable identification documents are able to and may be taking on additional debt from other lenders with different identification documents. This creates over-indebtedness and may be the cause of the high default rate associated with more than one acceptable personal identification documents across the two cohorts of borrowers. This result is statistically and economically significant. The explanation that lenders may be misinterpreting the borrowers' pursuit to be transparent would have been valid if my empirical results showed an inverse relationship between the likelihood of default and the additional personal identification documents provided by the borrower at the loan application stage.

Additionally, I find a striking result in table (18), that is, higher inflation is negatively associated with lower interest rate. This finding is contrary to what I anticipated. This suggest that interest rates are lower than inflation rate, hence, there is higher incentive to borrow than to save. This result can partly explain why in table (8), higher interest is associated with lower likelihood of default. Also, this result can partly explain why ownership of a bank account is associated with lower default but higher interest rate. This finding corroborates my proposition borrowers had higher incentive to borrower than save.

Table 18. Coefficients of the Bagged Logit Regression (Cohort I)

(Interest Rate is the explained Variable)

INDEPENDENT VARIABLE	**Likelihood Ratio Chi-Square =4357.918, df=13, sign. =0.000**	
	COEFF.	**STAND. ERROR**
Fintech	0.0160**	0.0039
Control Variables		
Borrower Age	0.0210**	0.0086
Gender (Female)	-0.0210***	0.0040
Mobile phone account ownership (=2)	0.0270***	0.0051
Borrower Identity Document (More than 1)	0.0820***	0.0042
Profession (Professional)	-0.0040	0.0067
Employer (Public sector)	0.0260***	0.0051
Income Category (Formal Salary)	0.0050	0.0100
Borrower Affordability (35%)	0.0480*	0.0221
Loan Amount	0.0090***	0.0024
Loan Tenor	0.0790***	0.0027
Bank Account ownership (Yes)	0.0550***	0.0098
Inflation Rate	-0.4570***	0.0100
Intercept	3.7160***	0.0476
Asterisks: ***Indicates a coefficient significantly different from zero at the 1%, ** at the 5% level, and * at 10% level.		

Table 19. Coefficients of the Logit Model (Cohort II)-Fintech and Loan Spread

(Interest rate is the explanatory variable)

Independent Variable	**Likelihood Ratio Chi-Square =166.661, df=12, sign. =0.000**	
	COEFF.	**STAND. ERROR**
Fintech	0.0350*	0.0186
Control Variables		
Borrower Age	-0.0190	0.0380
Gender (Female)	0.0400**	0.0189
Mobile phone account ownership (=2)	0.2220****	0.0184
Borrower Identity Document (More than 1)	0.0360*	0.0197
Profession (Professional)	-0.0280	0.0400
Employer (Public sector)	0.0810***	0.0314
Income Category (Formal Salary)	-0.0220	0.0415
Borrower Affordability (35%)	-0.0970	0.2377
Loan Amount	0.0050	0.0130
Loan Tenor	0.1130****	0.0247
Bank Account ownership (Yes)	-0.0240	0.0513
GDP	na	na
Intercept	0.2330	0.1826

Asterisks: ***Indicates a coefficient significantly different from zero at the 1%, ** at the 5% level, and * at 10% level.

2.7.6 Robustness test results

A concern in my primary analysis is that my results may be sensitive to alternative algorithms, hence I perform a series of robustness test using three different algorithms, that is, the Classification and regression tree (CRT), probit, and random forest models to my dataset. Further, I control for the various branches of the lending institution where the loans were originated and disbursed.

First, I use Breiman et al. (1984) Classification and Regression Trees (CRT) method. This is because the algorithm generates results and rules that can be easily understood and explained. Further, the in-built function allows it to perform attribute selection as shown in the work of Breiman et al. (1984). By so doing, I am able to compare my set of selected attributes obtained and compare the result to my main findings using the bagged Logit regression and panel regression models respectively. However, I anticipated that the three set of algorithms will not perfectly coincide, which suggest that the three approaches quantify the importance of a given feature (or subset of features) differently and that the three methods learn the data differently.

The results from my CRT classification method show the number of total and terminal nodes, the depth of the tree and the independent variables that were included in my final model. I use the CRT model because it can overcome any limitations that may be associated my Logit model in which the dependent variable is forced to fit a single linear model throughout the entire input space. Further, in comparison to the Logit and probit model, the CRT model can detect non-linear interactions between my input variables, which significantly increase the number of independent variables that can be used and the types of effect that can be captured. Also, using the CRT model enables me to interpret the decision rules shown in the trees produced in my analysis. This is an outcome that is significantly transparent compared to artificial neural networks (ANN) which is ‘black box’ in nature and used in prior studies with scepticism.

Similar to my bagged logit model, I train the Classification and regression tree (CRT) model using 80% of my sample dataset, and I evaluated the classification performance on the test sample. That is, the remaining 20% of total dataset is used as test sample. The correlation and collinearly of the variables were checked before the analysis, and the misclassification rate resulting from this was always almost identical to the voting misclassification rate (Breiman, 1996). I briefly discuss the results of my robustness test using alternative models, that is, the Classification and Regression Tree (CRT), Probit and Random Forest models across the two borrower groups.

I present my robustness test result using the classification and regression tree algorithm model with Gini impurity measure in figures (4) and (5). My results show from the variable importance graph and the regression tree that Fintech is the best predictor of default likelihood. This confirms my main empirical results using bagged logistics and panel regression in tables (8) and (9). In addition to Fintech, the model selected the following 10 attribute as the best in classification (listed in decreasing order of their importance): Borrower Identity, GDP, Gender, Loan Tenor, Affordability, Loan Amount, Employer, Income Type, Formal bank Account Ownership, Borrower Age.

The errors associated with the tree is 12.90%. My result show that the likelihood of default for borrowers who adopt Fintech is 7.30% compared to 38.90% for their counterparts who do not adopt Fintech. The classification and regression tree model result achieved a classification accuracy of 87.10% and is significant. I perform an additional robustness test by controlling for the branch of the lending institution where each loan is disbursed, and I present the result in figures (6) to (11) for Accra, Kumasi and Takoradi branches respectively. The results controlling for branch-effect show that for borrowers in Accra, Kumasi, and Takoradi the default likelihood is 6.60%, 7.10% and 11.30% respectively for adopters of Fintech, compared to 41.30%, 34.40% and 48.20% for non-adopters.

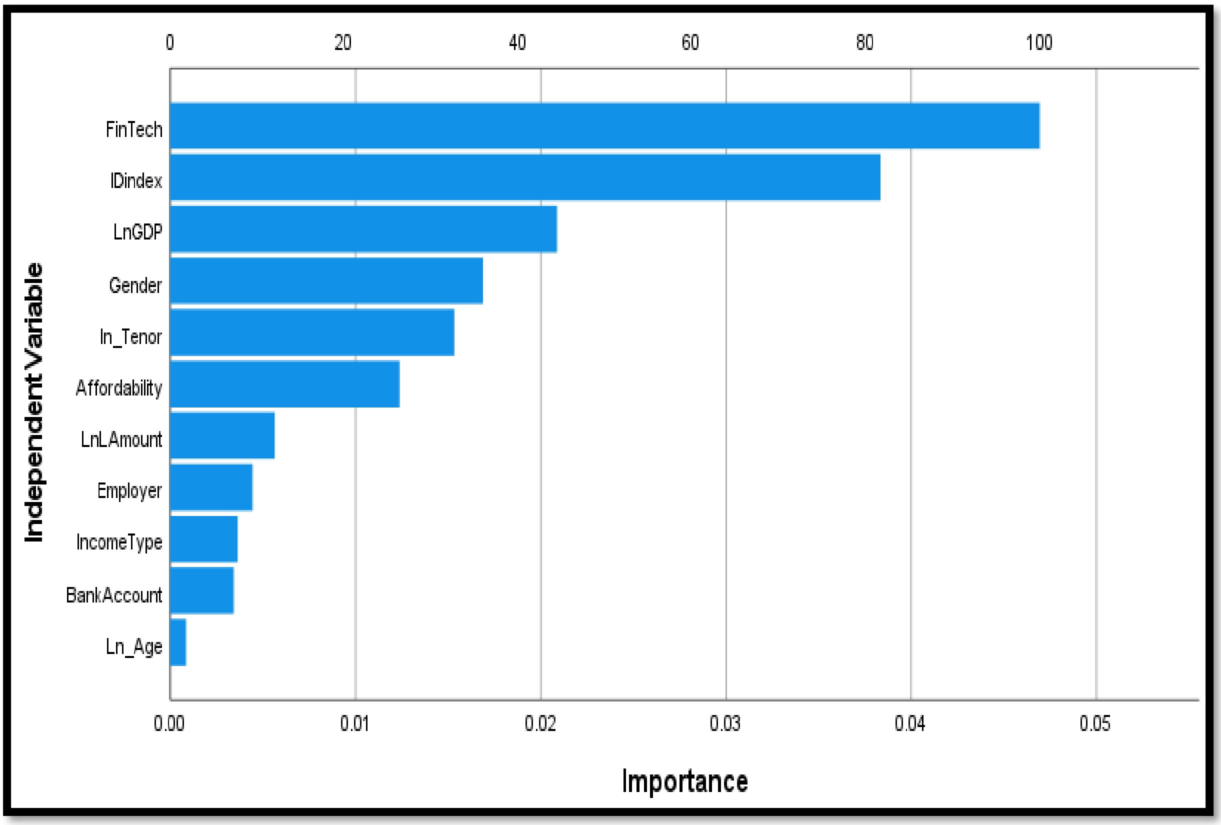

Figure 4. Variable importance graph using the CRT model.

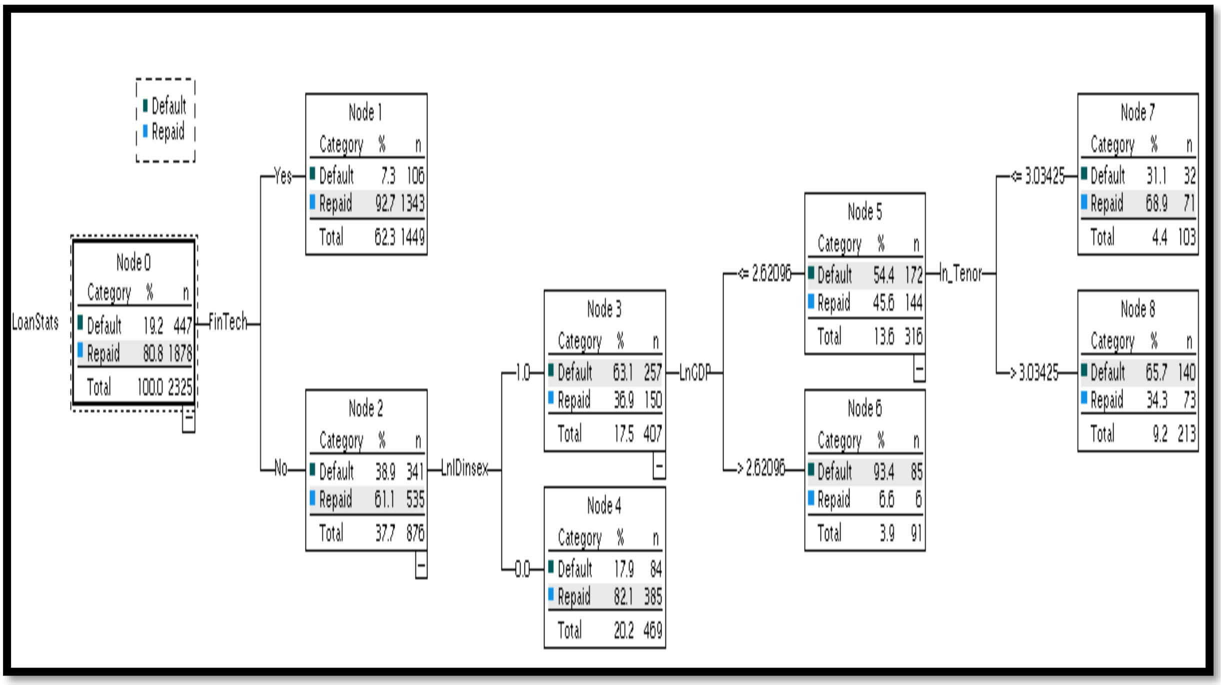

Figure 5. Classification and Regression Tree Result (CRT) Test result for Fintech on Loan Risk

Estimated Risk= 0.129, Model accuracy= 87.10%, Stand. Error =0.007

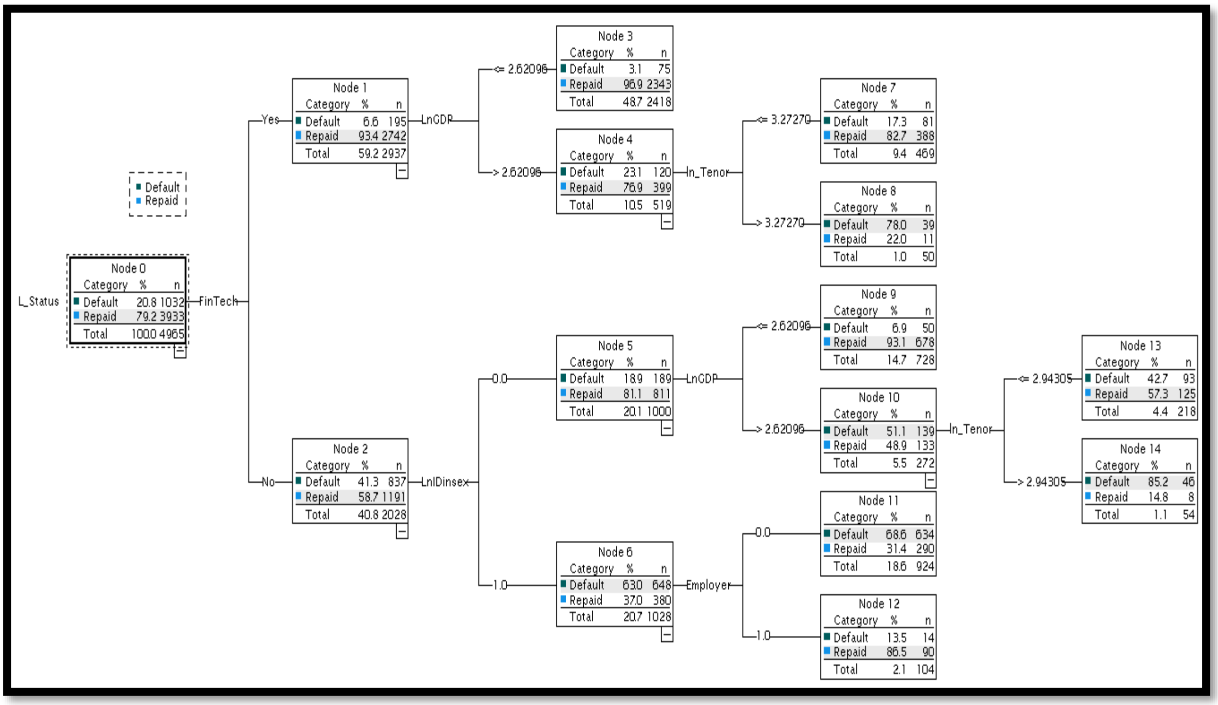

Figure 6. Class and Regression Tree Result (CRT) results for Fintech and Loan Risk (Cohort I): Accra

Estimated Risk= 0.125, Accuracy= 87.50%, Stand. Error =0.006, R^2 =0.435

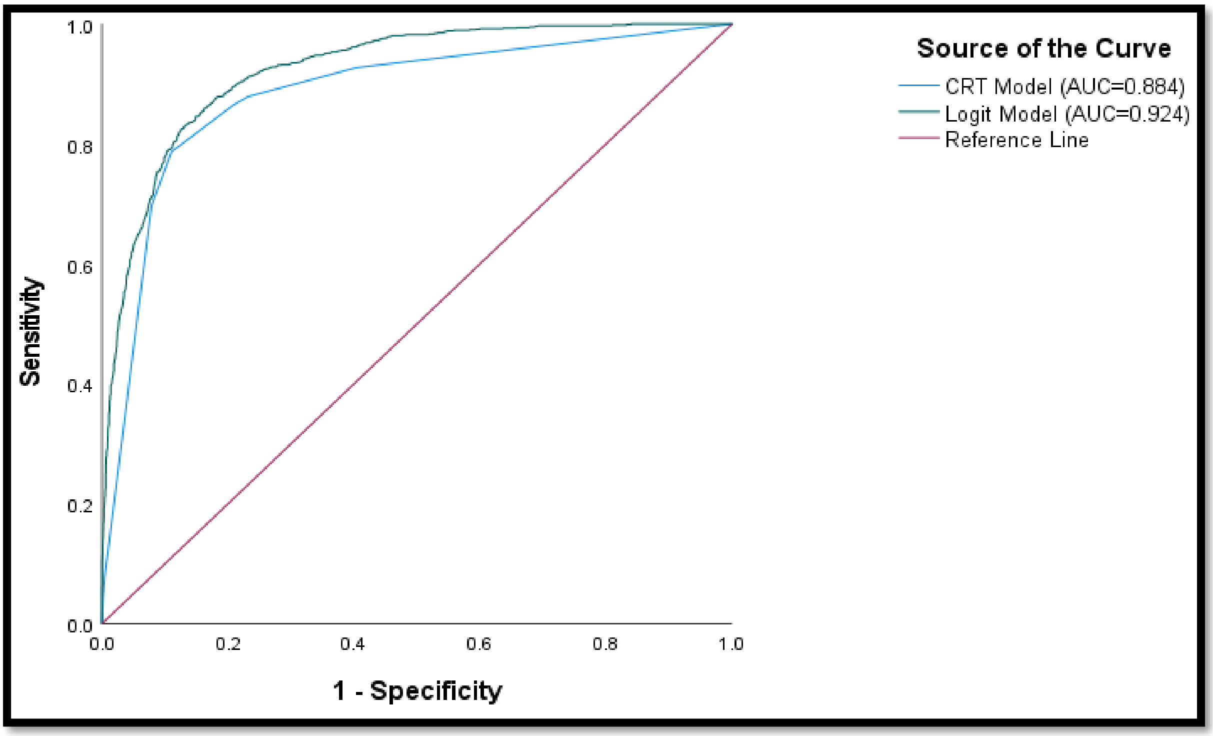

Figure 7. ROC Graph for Fintech on Loan Performance using Classification and Regression Tree and Logit Models: Cohort I- Accra Branch

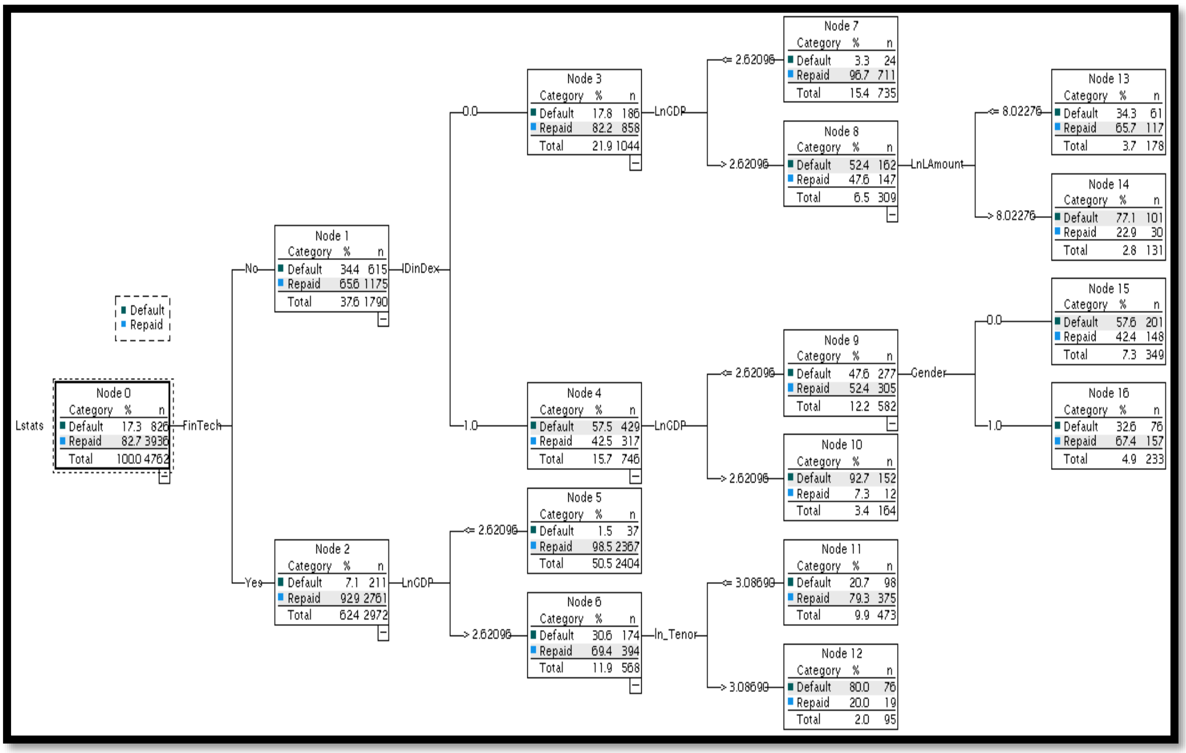

Figure 8. Class and Regression Tree Result (CRT) results for Fintech and Loan Risk (Cohort I): Kumasi

Estimated Risk= 0.106, Accuracy= 89.40%, Stand. Error =0.004, R^2 =0.445

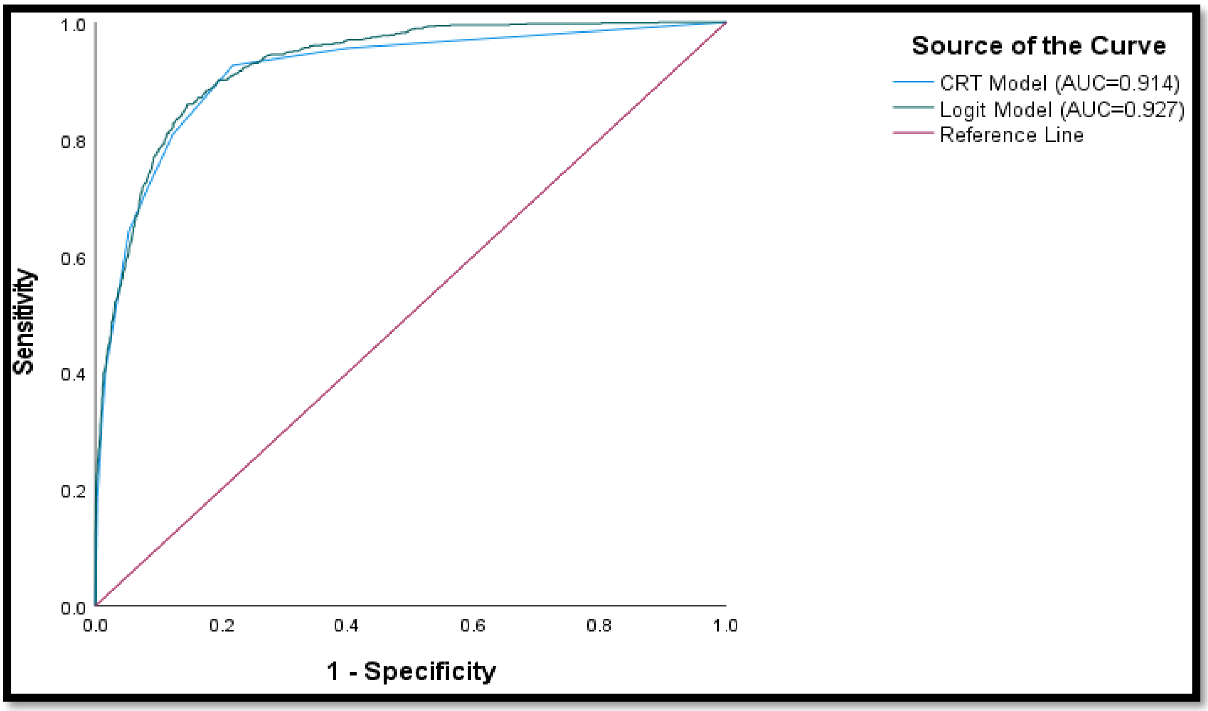

Figure 9. Figure 6. ROC Graph for Fintech on Loan Performance using Classification and Regression Tree and Logit Models: Cohort I- Kumasi Branch

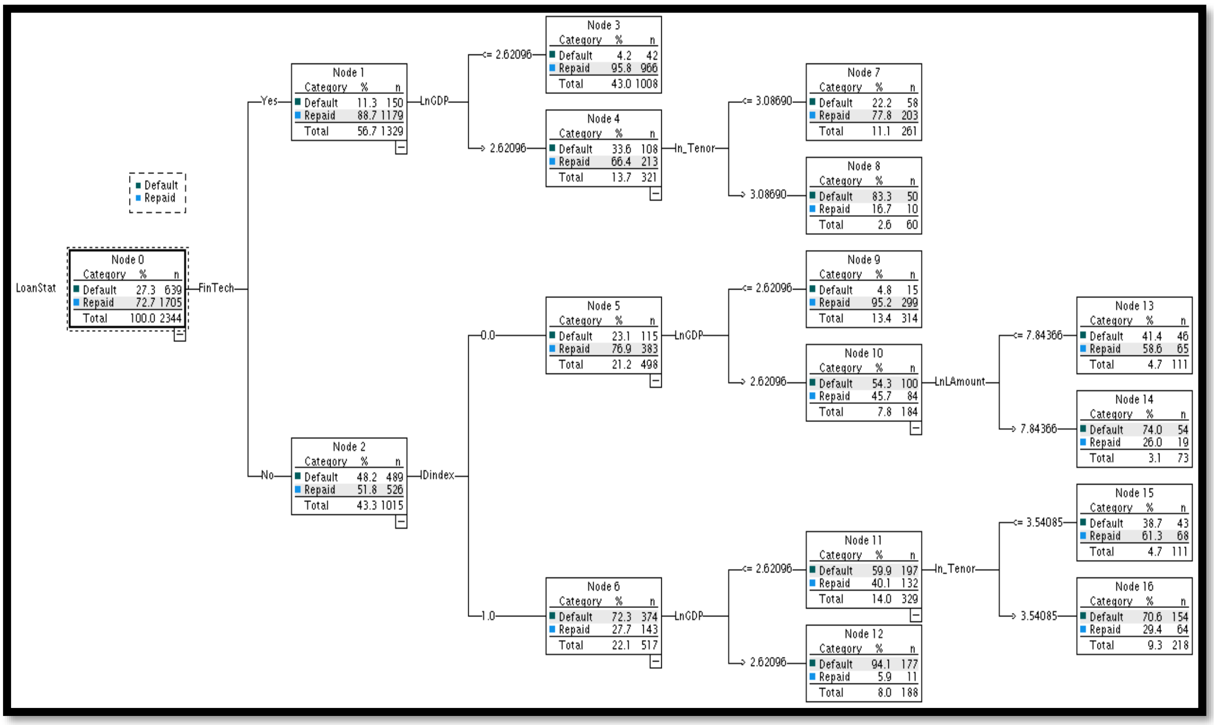

Figure 10. Class and Regression Tree Result (CRT) results for Fintech and Loan Risk (Cohort I): Takoradi

Estimated Risk= 0.131, Accuracy= 86.90%, Stand. Error =0.007, R^2 =0.460

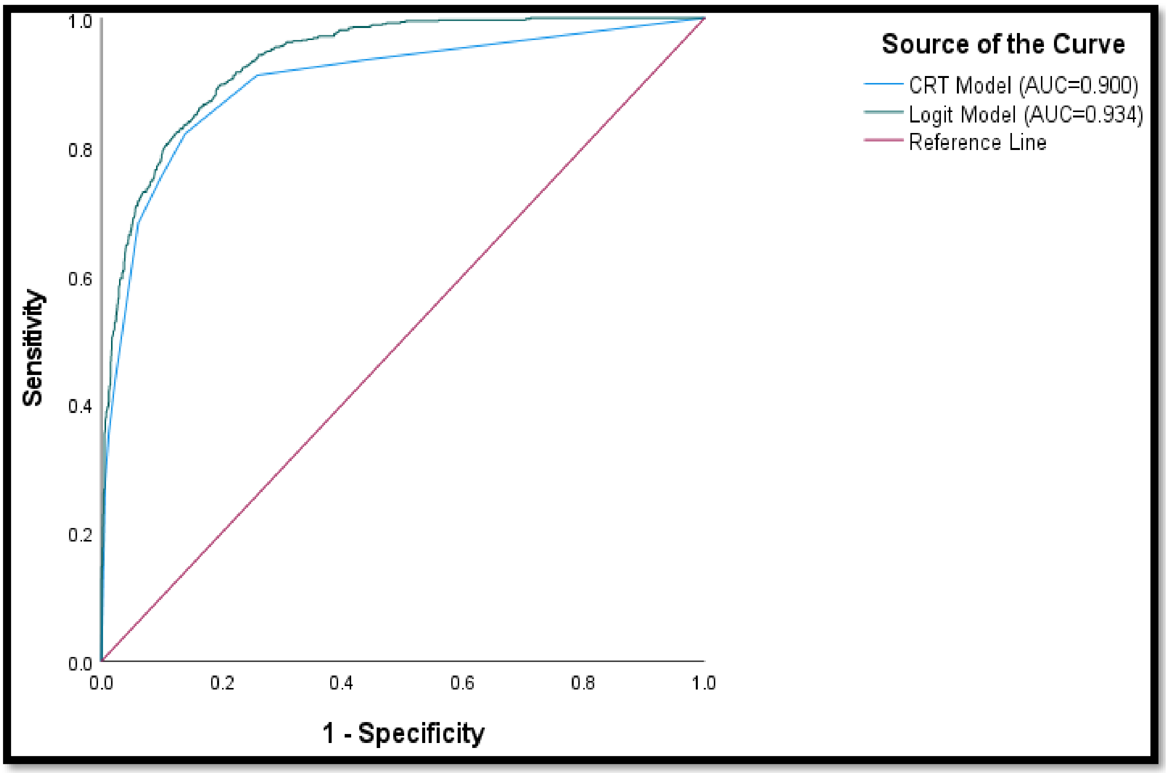

Figure 11. ROC Graph for Fintech on Loan Performance using Classification and Regression Tree and Logit Models: Cohort I- Takoradi Branch

Using the logit model and controlling for the branch effect, I present the results for borrowers in cohort (I) in table (20) and figure (12). I find that the likelihood of default varies across regions. Accra the national capital has the highest, 89.80%, reduction in the propensity to default, followed by Kumasi, 87.50% and Takoradi, 85.30% respectively, albeit it in the same direction. For repeat borrowers, that is cohort (II), I present my results in tables (21), (22) and (23) for the Accra, Kumasi and Takoradi branches respectively. I find similar varying results. That is, Accra the national capital has the highest reduction of 6.65%, followed by Kumasi, 3.66% and Takoradi, 2.59% respectively. However, the result for borrowers in cohort (II) and specifically the Takoradi branch is statistically insignificant.

Further, my probit model results in table (24) confirm that adopters of Fintech in cohort (II) are less likely, 55%, to default. My logit model's robustness test results controlling for branch effect for borrowers in cohort (I), panel regression and my probit robust test results using repeat borrowers provides additional evidence to confirm that Fintech reduces default likelihood for both new and repeat borrowers. My results show that the likelihood of default varies significantly across the two cohorts of borrowers, albeit in the same direction. The performance of classification and regression tree (CRT), bagged logit and probit models using the receiver operating curve and area under the curve (ROC-AUC) and controlling for branch effect are presented in figures (7), (9), (11) and (13). The ROC-AUC associated with the CRT algorithm results are 0.884, 0.914 and 0.900 compared to the logit model's performance of 0.924, 0.927 and 0.934 for Accra, Kumasi and Takoradi branches respectively. These are higher compared to 0.827 for the probit algorithm.

Table 20. Coefficient of Logit regression controlling for branch effect (Cohort I)

Dependent Variable: Log (Default/Non-Default)

INDEPENDENT VARIABLE	**Likelihood Ratio Chi-Square =2363.818, df=14, sign. =0.000**		**Likelihood Ratio Chi-Square =2062.8, df=14, sign. =0.000**		**Likelihood Ratio Chi-Square =1408.255, df=14, sign. =0.000**	
	Accra (Cohort I) sample regression		**Kumasi (Cohort I) sample regression**		**Takoradi (Cohort I) sample regression**	
	COEFF.	**STAND. ERROR**	**COEFF.**	**STAND. ERROR**	**COEFF.**	**STAND. ERROR**
Fintech	-2.2850***	0.1075	-2.0770***	0.1141	-1.9180***	0.145
Control Variables						
Borrower Age	0.6360**	0.2283	0.4310***	0.2416	0.8530***	0.332
Gender (Female)	-0.8570***	0.1019	-0.6430***	0.112	-0.6530***	0.1466
Mobile phone account ownership (=2)	-0.4670***	0.1437	-0.4560***	0.159	-0.303	0.201
Borrower Identity Document (More than 1)	2.2470****	0.1244	2.3920***	0.1463	2.6760***	0.1902
Profession (Professional)	-0.4390***	0.1506	-0.7860***	0.1565	-0.5680***	0.2135
Employer (Public sector)	-2.1680***	0.2076	-1.8970***	0.2194	-1.7530***	0.2521
Income Category (Formal Salary)	-0.7230***	0.2434	-0.3380	0.2546	-0.1760	0.3293
Borrower Affordability (35%)	2.8330***	0.5317	3.6940***	0.7908	3.2600***	0.9834
Loan Amount	0.2590***	0.0615	0.2950***	0.0643	0.2610***	0.088
Loan Tenor	0.6230***	0.0765	0.2610***	0.0788	0.8180***	0.1124
Interest Rate	-1.4160***	0.2551	0.3570	0.2808	-0.6540**	0.3066
Bank Account ownership (Yes)	-1.1310***	0.2090	-0.4780	0.3568	-0.3600*	0.2208
GDP	9.7790***	0.5574	14.0210***	0.6389	13.2780***	0.803
Intercept	-25.8500***	2.1903	-42.0750***	2.5036	-40.2910***	3.1005
a= Model classification accuracy	a= 88.00, R^2 = 0.592		a= 88.80, R^2 = 0.583		a= 8.30, R^2 = 0.654	
Asterisks: ***Indicates a coefficient significantly different from zero at 1%, ** at 5%; and *at the 10% level						

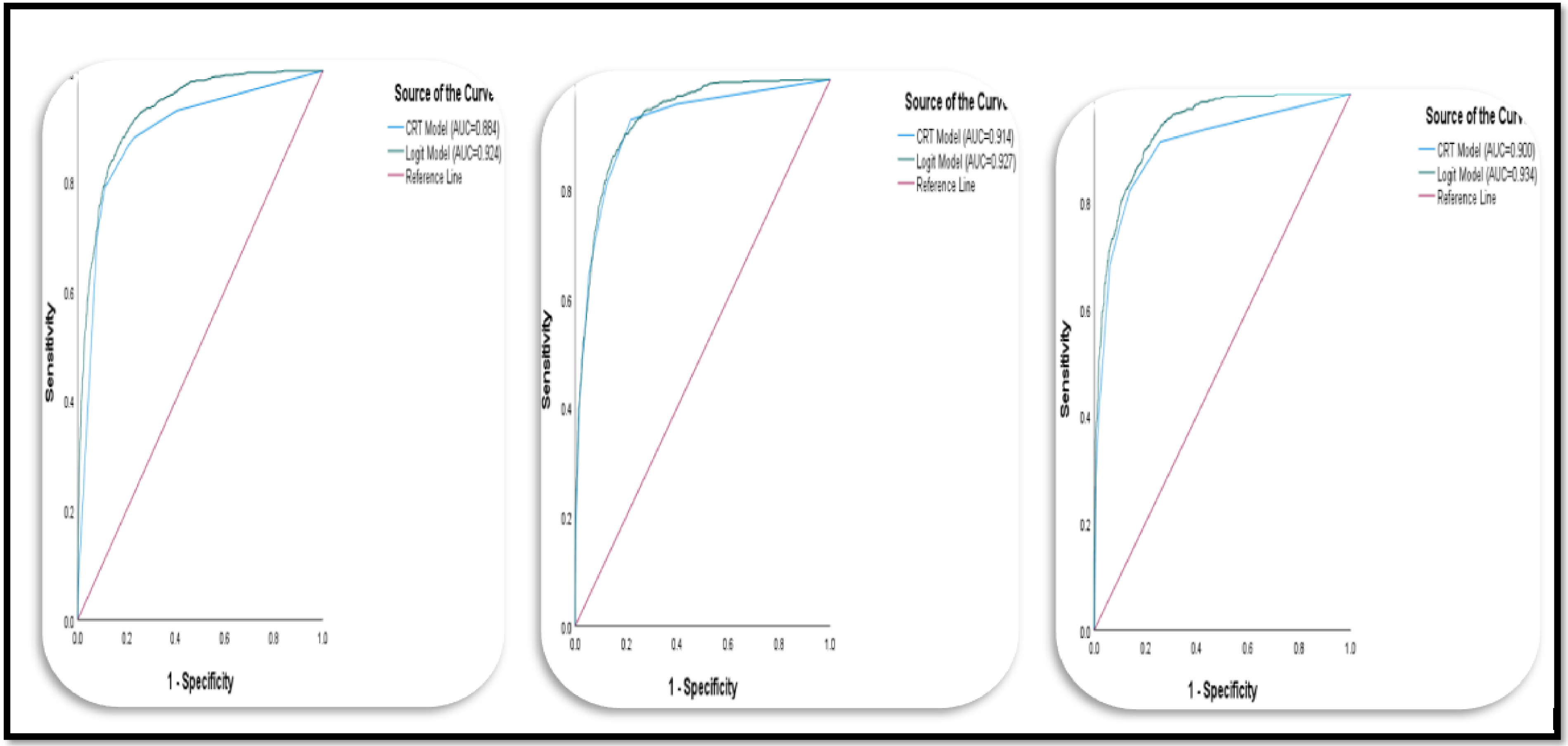

Figure 12. ROC Graphs for Fintech on Loan Risk for Accra, Kumasi and Takoradi branches respectively (left to right).

Table 21. Coefficients of the panel model (Cohort II): Accra Branch

(Default is the explained variable)

Explanatory variables	Coefficient	Std. Err.	z	P>z	[95% conf. interval]	
Fintech	-0.0688	0.0186	3.7000	0.0000	-0.1053	-0.0324
Control Variables						
Mobile phone account ownership (=2)	0.0208	0.0200	1.0400	0.3000	-0.0185	0.0600
Borrower Age	-5.2386	3.1487	1.6600	0.0960	-11.4098	0.9327
Gender (Female)	0.0092	0.0184	0.5000	0.6170	-0.0269	0.0453
Income Type (formal salary)	0.0228	0.0436	0.5200	0.6020	-0.0627	0.1083
Employer (Public sector)	-0.0271	0.0324	0.8400	0.4030	-0.0905	0.0364
Profession (Professional)	-0.1315	0.0354	3.7100	0.0000	-0.2008	-0.0621
Borrower Affordability (35%)	0.3977	0.1514	2.6300	0.0090	0.1009	0.6945
Mobile phone account ownership (=2)	-0.0031	0.0193	0.1600	0.8730	-0.0408	0.0346
Bank account ownership (Yes)	-0.0300	0.0398	0.7600	0.4500	-0.1080	0.0479
Loan Amount	-0.0415	0.0324	1.2800	0.2000	-0.1051	0.0220
Loan Tenor	0.0400	0.0383	1.0400	0.2970	-0.0352	0.1151
GDP	0.9305	0.3061	3.0400	0.0020	0.3305	1.5305
Interest rate	0.0365	0.0358	1.0200	0.3070	-0.0336	0.1066
Intercept	-2.6831	0.8362	3.2100	0.0010	-4.3220	-1.0441
sigma_u	0.0000	R-squared:				
sigma_e	0.2201	Within	0.1197			
rho	0.0000	Between	0.2065			
Wald chi2(17)	116.3500	Overall	0.1606			
Prob > chi2	0.0000					

Table 22. Coefficients of the panel model (Cohort II): Kumasi Branch

(Default is the explained variable)

Explanatory variables	**Coefficient**	**Std. Err.**	**z**	**P>z**	**[95% conf. interval]**	
Fintech	-0.0747	0.0178	4.2000	0.0000	-0.1096	-0.0399
Control Variables						
Borrower Identity Document (More than 1)	0.0292	0.0215	1.3500	0.1760	-0.0131	0.0714
Borrower Age	-0.0358	0.0182	1.9700	0.0490	-0.0714	-0.0001
Gender (Female)	-0.9203	2.8325	0.3200	0.7450	-6.4719	4.6313
Income Type (formal salary)	-0.0781	0.0398	1.9600	0.0500	-0.1561	-0.0001
Employer (Public sector)	-0.0398	0.0310	1.2800	0.1990	-0.1006	0.0209
Profession (Professional)	-0.0869	0.0419	2.0700	0.0380	-0.1690	-0.0048
Borrower Affordability (35%)	na	na	na	na	na	na
Mobile phone account ownership (=2)	-0.0011	0.0191	0.0600	0.9540	-0.0386	0.0364
Bank account ownership (Yes)	0.0542	0.0835	0.6500	0.5170	-0.1095	0.2178
Loan Amount	-0.0125	0.0325	0.3800	0.7020	-0.0762	0.0513
Loan Tenor	-0.0440	0.0317	1.3900	0.1650	-0.1061	0.0182
GDP	0.4598	0.2746	1.6700	0.0940	-0.0785	0.9980
Interest rate	0.1196	0.0361	3.3200	0.0010	0.0489	0.1903
Intercept	-1.5450	0.7560	2.0400	0.0410	-3.0267	-0.0633
sigma_u	0.0000	R-squared:				
sigma_e	0.2099	Within	0.1041			
rho	0.0000	Between	0.2366			
Wald chi2(17)	116.4600	Overall	0.167			
Prob > chi2	0.0000					

Table 23. Coefficients of the panel model (Cohort II): Takoradi Branch

(Default is the explained variable)

Explanatory variables	Coefficient	Std. Err.	z	P>z	[95% conf. interval]	
Fintech	-0.0755	0.0239	3.1600	0.0020	-0.1224	-0.0287
Control Variables						
Borrower ID document (More than 1)	0.0102	0.0282	0.3600	0.7190	-0.0452	0.0655
Borrower Age	0.0325	0.0268	1.2100	0.2260	-0.0201	0.0850
Gender (Female)	0.1765	3.9215	0.0400	0.9640	-7.5094	7.8624
Income Type (formal salary)	-0.0235	0.0487	0.4800	0.6300	-0.1190	0.0720
Employer (Public sector)	-0.0426	0.0379	1.1200	0.2610	-0.1168	0.0317
Profession (Professional)	-0.0912	0.0631	1.4500	0.1480	-0.2147	0.0324
Borrower Affordability (35%)	na	na	na	na	na	na
Mobile phone account ownership (=2)	-0.0167	0.0267	0.6300	0.5310	-0.0691	0.0356
Bank account ownership (Yes)	-0.0801	0.0668	1.2000	0.2310	-0.2111	0.0509
Loan Amount	0.0449	0.0404	1.1100	0.2670	-0.0344	0.1242
Loan Tenor	-0.0840	0.0552	1.5200	0.1280	-0.1921	0.0242
GDP	0.2390	0.3725	0.6400	0.5210	-0.4911	0.9690
Interest rate	0.0857	0.0461	1.8600	0.0630	-0.0047	0.1762
Intercept	-0.9723	1.0285	0.9500	0.3440	-2.9880	1.0434
sigma_u	0.0000	R-squared:				
sigma_e	0.1930	Within	0.0993			
rho	0.0000	Between	0.2831			
Wald chi2(17)	59.2500	Overall	0.1874			
Prob > chi2	0.0000					

Table 24. Coefficient of Probit Regression (Cohort II)

(Default is the explanatory variable)

INDEPENDENT VARIABLES	Likelihood Ratio Chi-Square =109.26, df=12, sign. =0.000	
	COEFF.	STAND. ERROR
Fintech	-0.8050***	0.1477
Control Variables		
Borrower Age	-0.1830	0.3271
Gender (Female)	-0.1330	0.1566
Mobile phone account ownership (=2)	0.1140	0.1748
Borrower ID document (More than 1)	0.4840***	0.1594
Profession (Professional)	-0.9860***	0.2449
Employer (Public sector)	-0.5910*	0.3318
Income Category (Formal Salary)	-0.3880	0.3010
Borrower Affordability (35%)	na	na
Loan Amount	0.5380***	0.0998
Loan Tenor	-0.3550**	0.1600
Interest Rate	0.1700	0.3038
Bank account ownership (Yes)	-0.1560	0.4221
GDP	Na	na
Intercept	-2.2600	1.5192
	R2 = 0.731	
*** significantly at the ***1%, ** at 5%; and *at the 10% level		

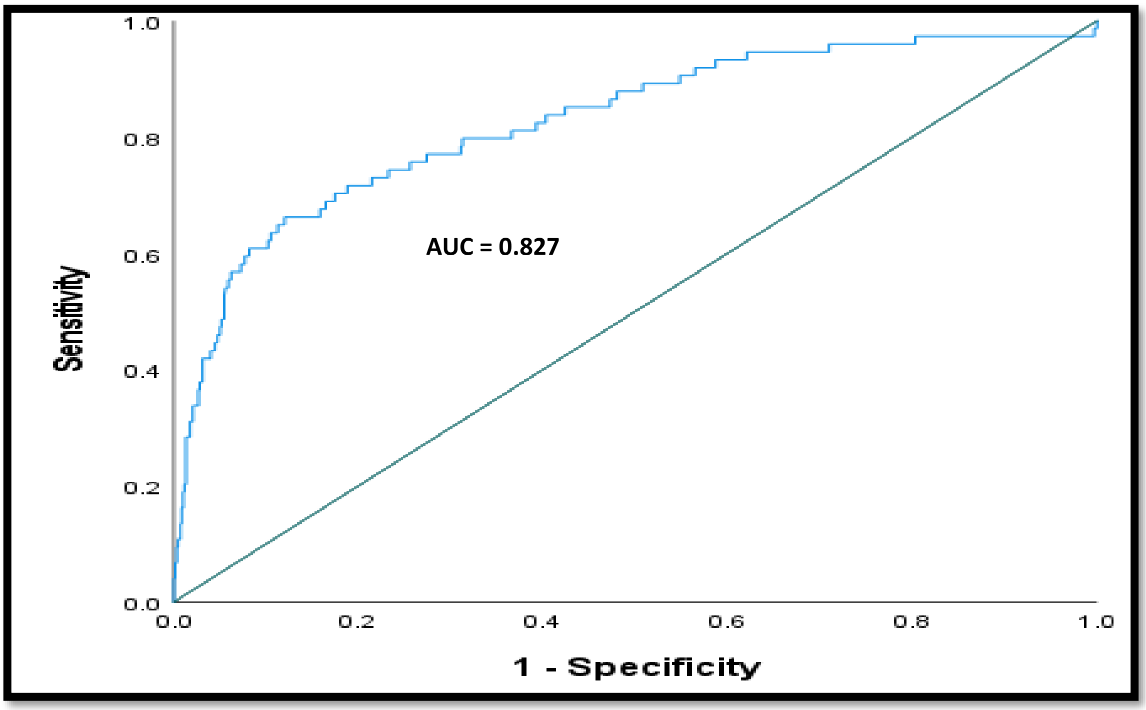

Figure 13. ROC Graph for Fintech on Loan Performance using Probit Model (Cohort II)

Additionally, I use the random forest model to re-examine my main results for Fintech and Loan risk. In my Random Forest model setting, I use the bootstrap method and I set the number of trees grown to 400, the maximum possible depth of each tree was set to 4, and the maximum features is 5, so only a maximum of 5 features were selected in each tree. These parameters generated the highest accuracy rate and ROC-AUC after previously setting it incrementally between 100 trees to a maximum of 500 trees to avoid any over-fitting problem that may occur. The result for my random forest model is presented in figures (14), (15) and (16) below. Similar to the classification and regression tree model, the results from the random forest algorithm show that Fintech is the most important features that predict default likelihood.

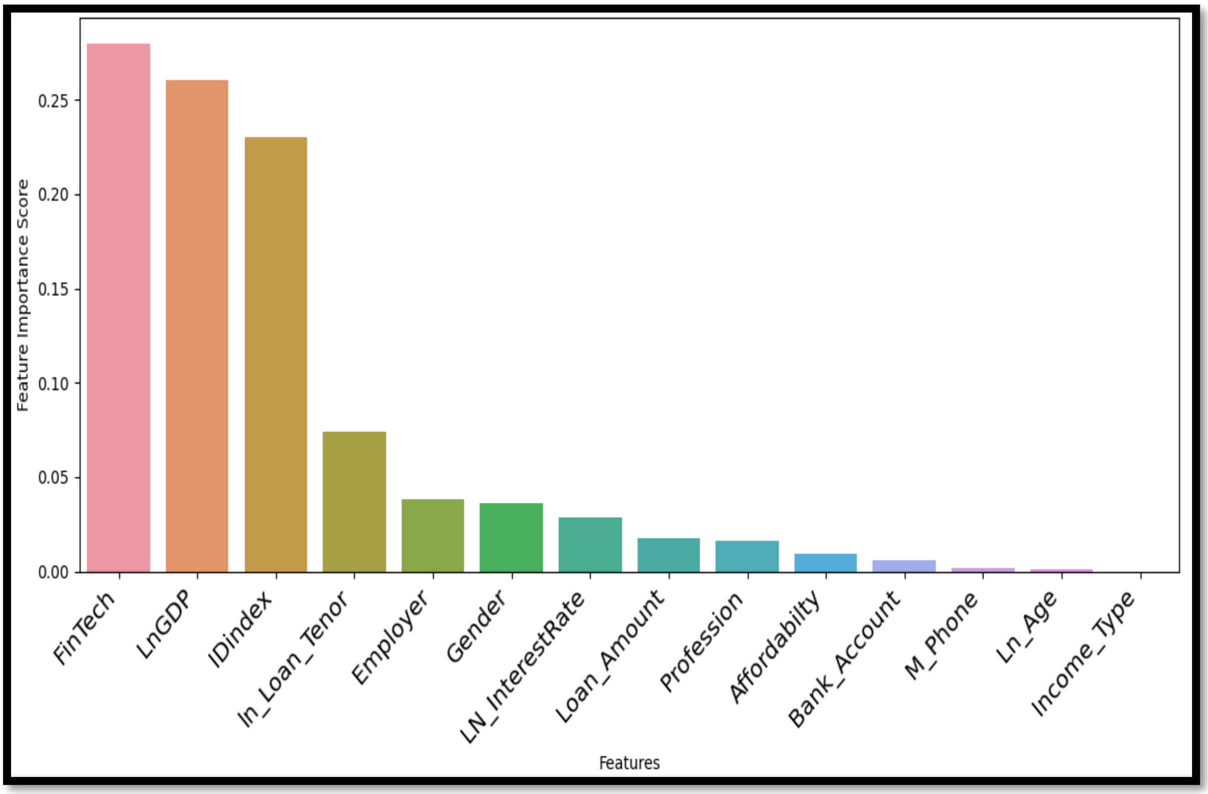

Figure 14. Variable importance graph for Fintech on Loan Risk using Random Forest model.

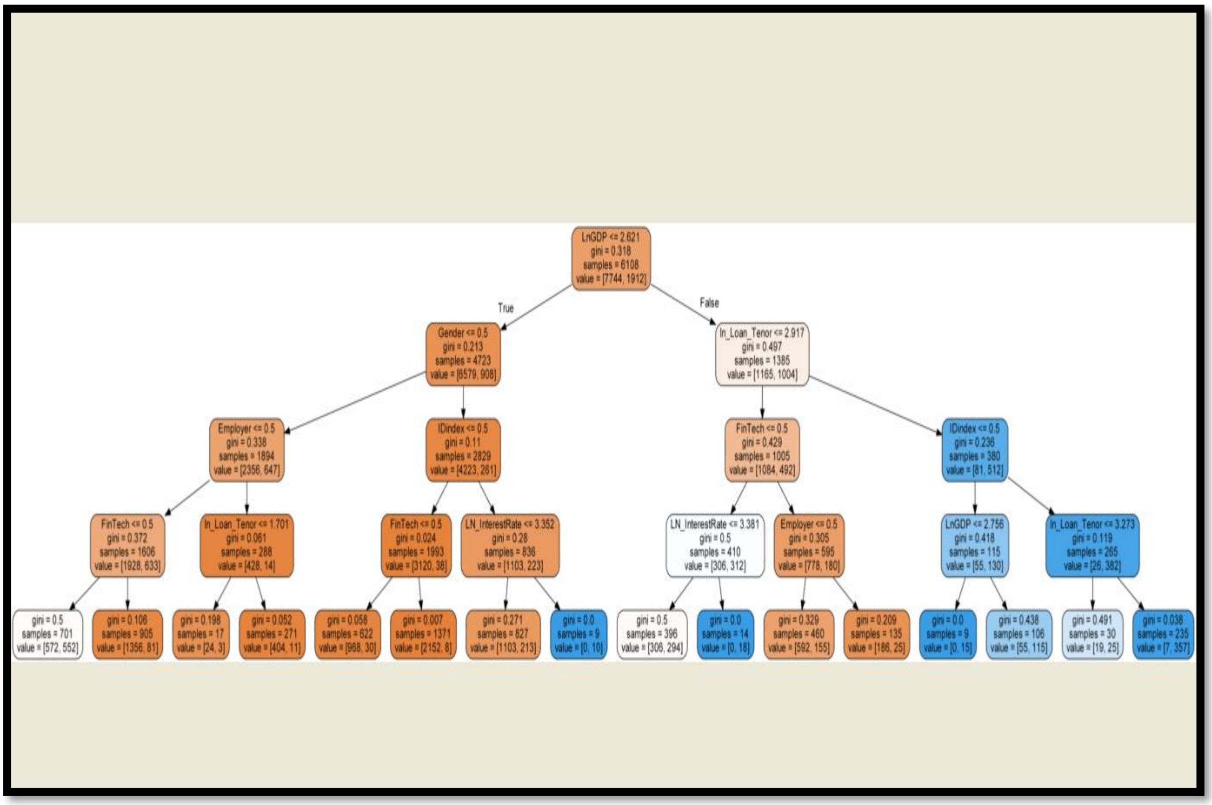

Figure 15. Random Forest tree for Fintech on Loan Risk

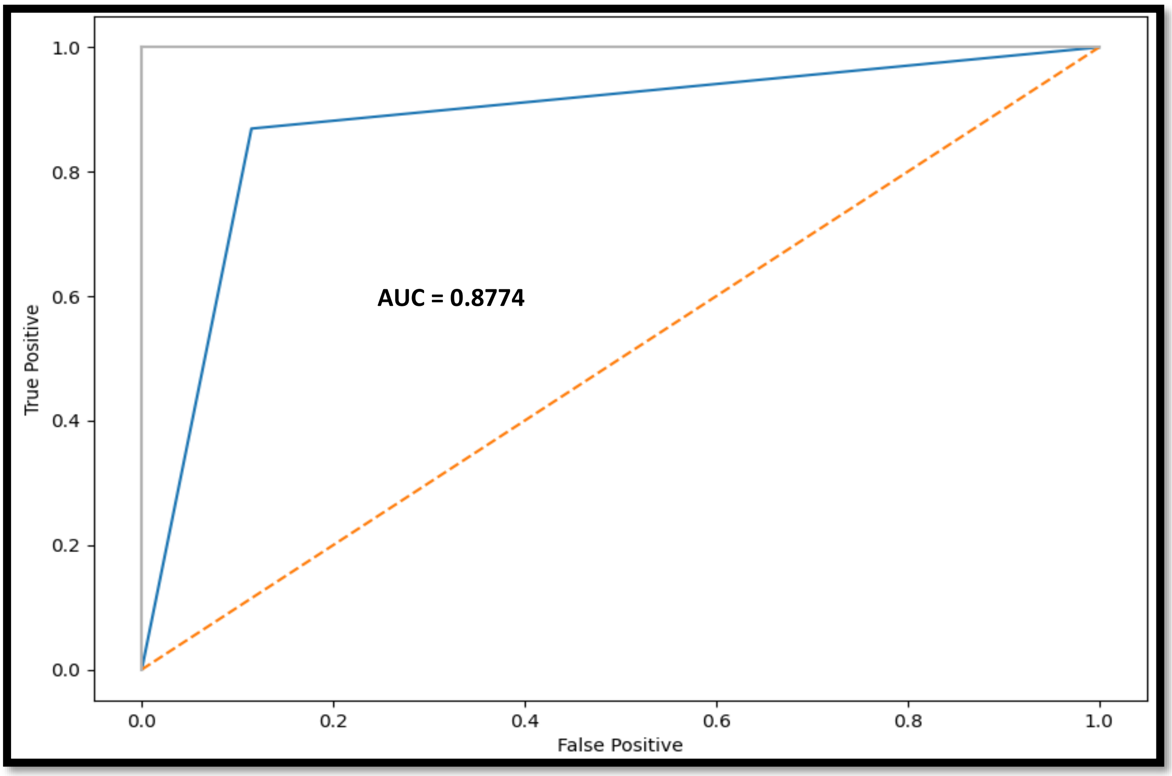

Figure 16. ROC graph for Fintech on Loan Risk using Random Forest Model

I provide a robustness test for my main result in tables (12) and (13) that examined the relationship between female borrowers in cohorts (I) and (II) who adopted Fintech, and their likelihood of loan default. First, I use classification and regression tree (CRT) model. My results show that the likelihood of default for female borrowers in cohort (I) who adopt Fintech is 3.88% compared to 28.70% for their non-adopting counterparts, figure (17). The model's classification accuracy for this result is 87.10%. The receiver operating curve and the area under the curve (ROC-AUC) curve which also measures the performance of my model for this result is 0.880, compared to the Logit model's 0.901, figure (18).

Second, using the random forest regression model, my results in figures (19) and (20), show similar results. That is, Fintech significantly impact loan risk. The ROC-AUC measuring the performance of my random forest classification model is 0.8683 which is significantly higher compared to the random average prediction of 0.5. Also, the algorithm achieved an accuracy rate of 0.8650. Third, using the panel regression, I provide the robustness test results for repeat female borrowers in Cohort II who adopted Fintech and their loan performance controlling for various branch-effects in tables (25), (26) and (27) for Accra, Kumasi and Takoradi branches respectively. My results from the estimated coefficients, show that an increase of one additional female borrower located in Accra is associated with $100\times(1.01\hat{\beta}1-1)$ $\approx$-1.8330 percent. I find similar results for Kumasi, $100\times(1.01\hat{\beta}1-1)$ $\approx$-3.661 percent, and Takoradi, $100\times(1.01\hat{\beta}1-1)$ $\approx$-2.586 percent. However, the result is significant for the Kumasi branch.

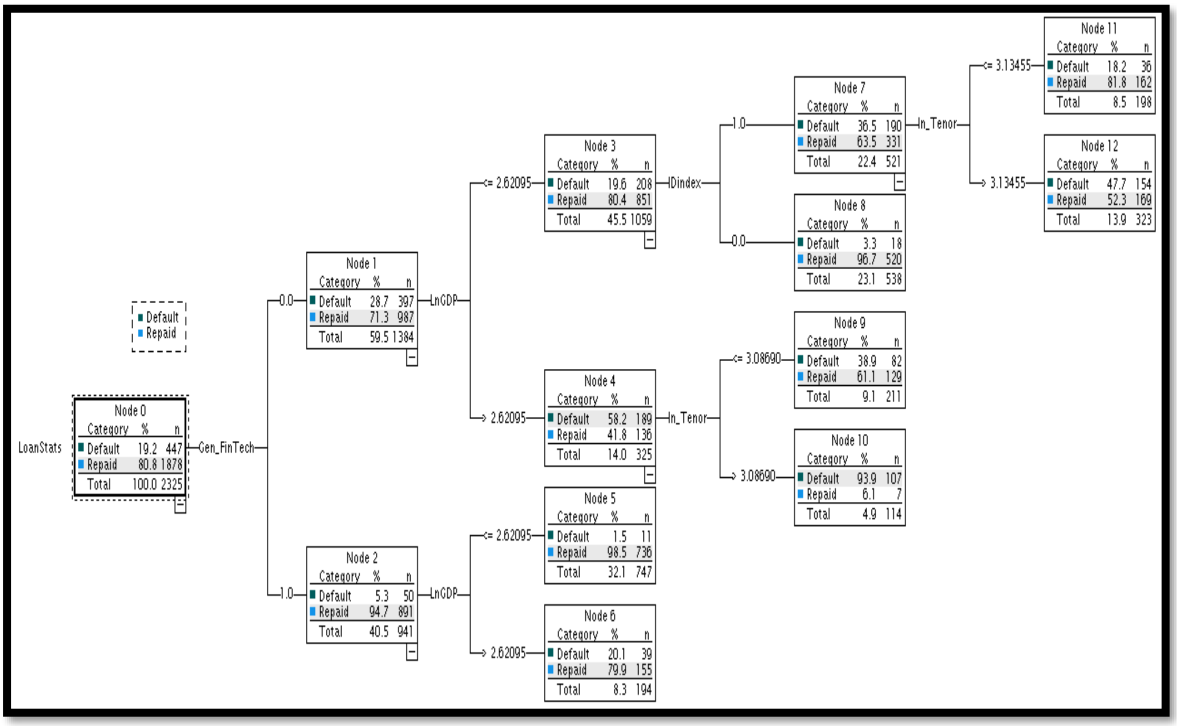

Figure 17. Classification and Regression Tree model result for females and Fintech on Loan Risk (Cohort I)

Estimated risk = 0.149, standard error = 0.007, and Model Classification Accuracy =0.851, R2 =0.543

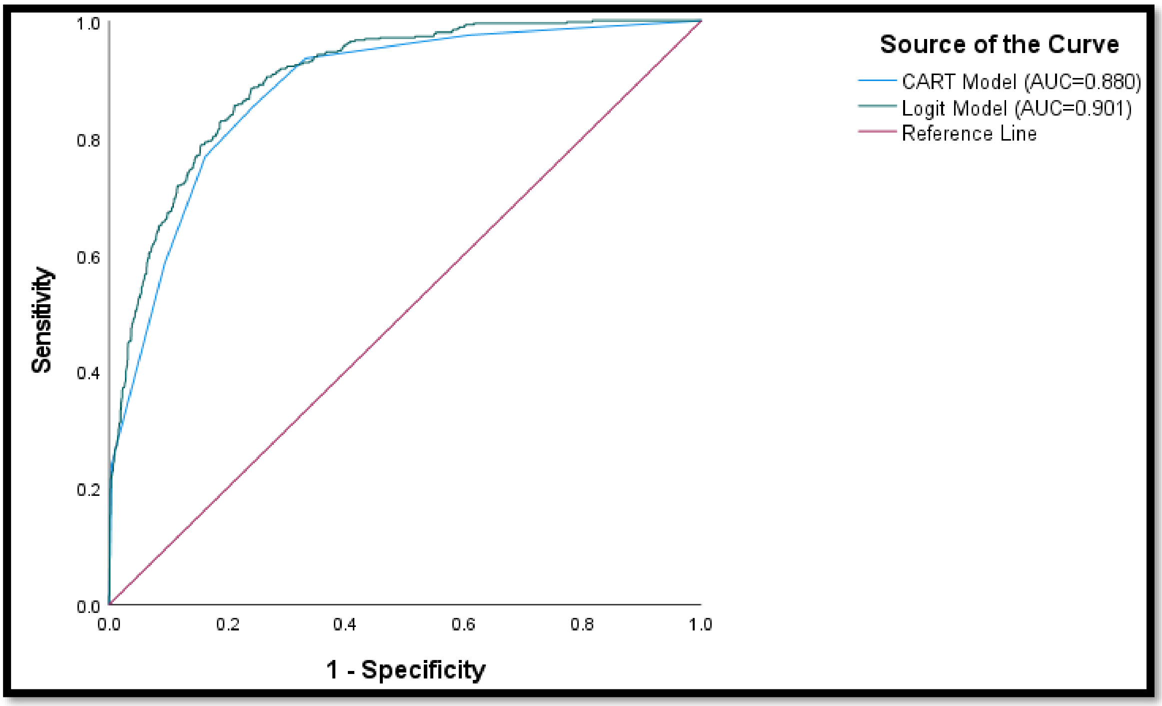

Figure 18. ROC-AUC graph for the regression of Gender (Female) and Fintech on Loan Risk using Classification and Regression Tree and Logit Models

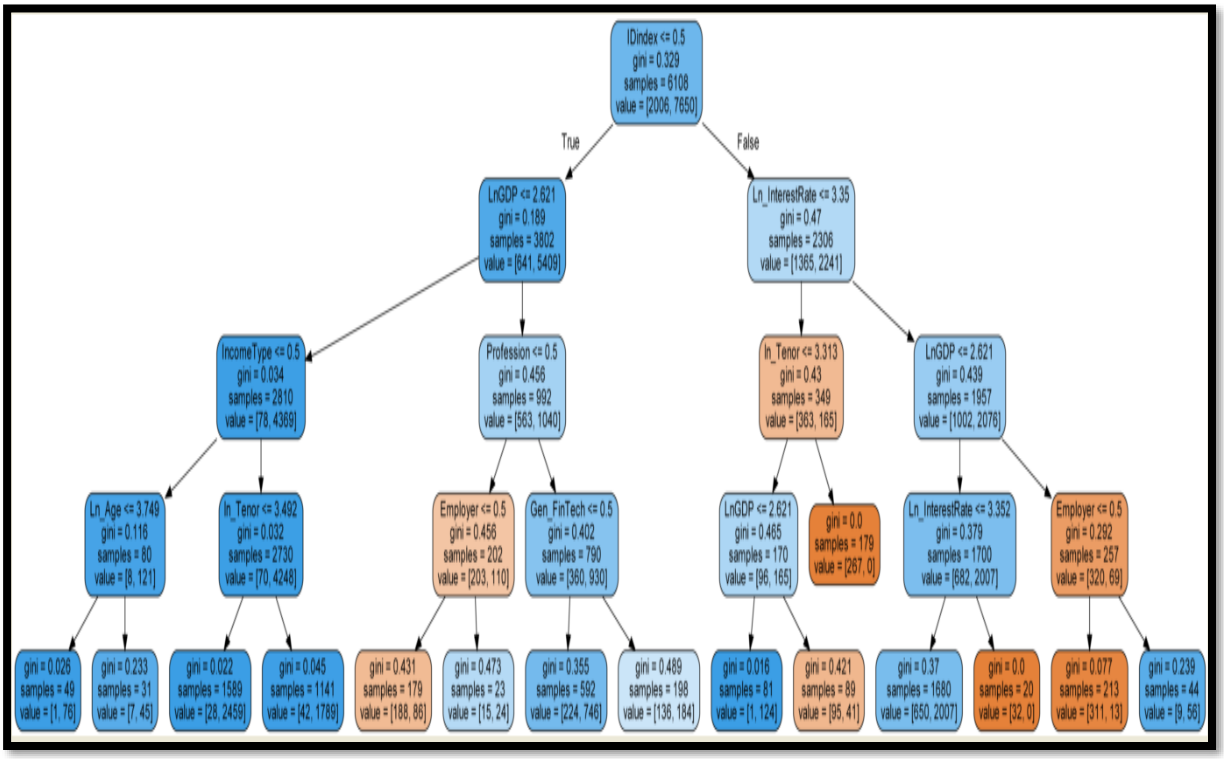

Figure 19. Random Forest tree for the Interaction between Gender (Female) and Fintech on Loan Risk (Cohort I).

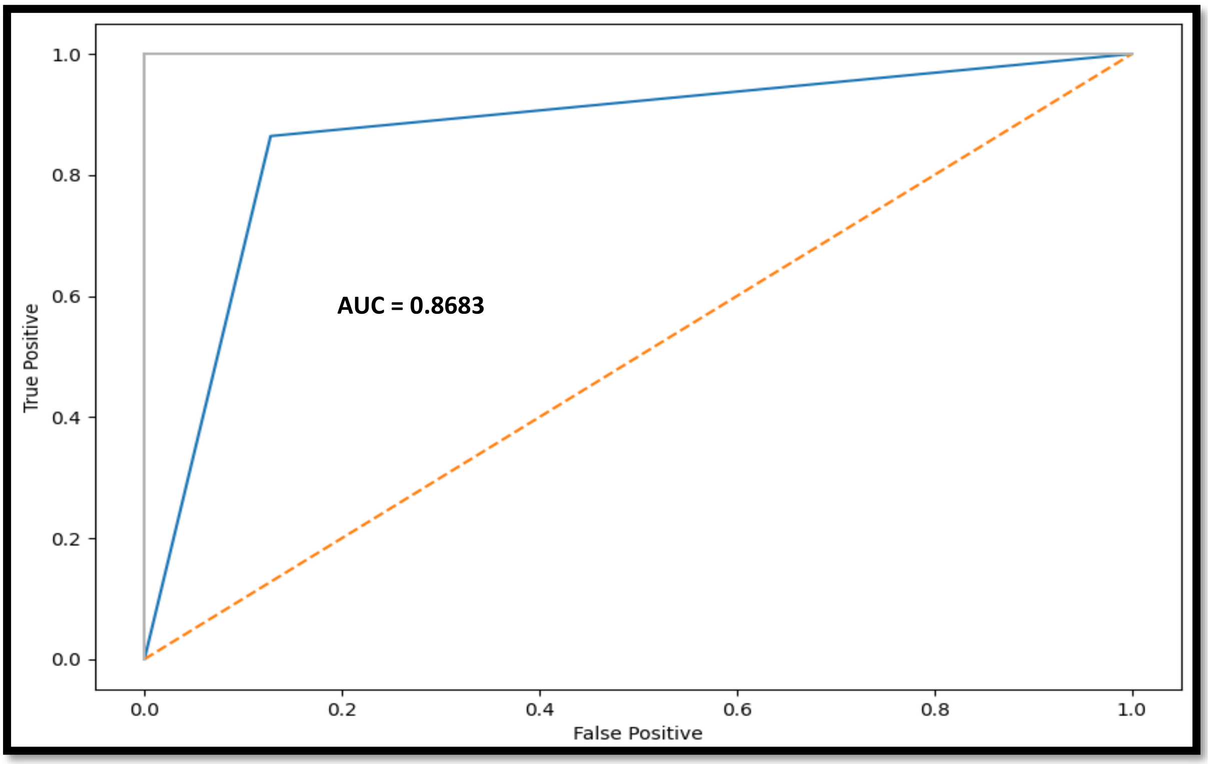

Figure 20. ROC Graph for the interaction between Gender and Fintech on Loan Risk using Random Forest Model (Cohort I)

Table 25. Coefficients of the panel model (Cohort II): Accra Branch

(Default is the explained variable)

Explanatory variables	Coefficient	Std. Err.	z	P>z	[95% conf. interval]	
Fintech*Gender (Female)	-0.0185	0.0175	1.0600	0.2900	-0.0529	0.0158
Control Variables						
Borrower Identity Document (More than 1)	0.0200	0.0201	0.9900	0.3210	-0.0194	0.0594
Borrower Age	-5.2386	3.1785	1.6500	0.0990	-11.4684	0.9913
Income Type (formal salary)	0.0276	0.0440	0.6300	0.5300	-0.0586	0.1138
Employer (Public sector)	-0.0188	0.0326	0.5800	0.5630	-0.0827	0.045
Profession (Professional)	-0.1341	0.0357	3.7600	0.0000	-0.2040	-0.0641
Borrower Affordability (35%)	0.4295	0.1522	2.8200	0.0050	0.1311	0.7279
Mobile phone account ownership (=2)	0.0039	0.0193	0.2000	0.8400	-0.0339	0.0417
Bank account ownership (Yes)	-0.0284	0.0401	0.7100	0.4790	-0.1069	0.0502
Loan Amount	-0.0415	0.0327	1.2700	0.2040	-0.1057	0.0226
Loan Tenor	0.0400	0.0387	1.0300	0.3020	-0.0359	0.1158
GDP	0.9305	0.3090	3.0100	0.0030	0.3248	1.5361
Interest rate	0.0393	0.0361	1.0900	0.2760	-0.0314	0.1101
Intercept	-2.7763	0.8437	3.2900	0.0010	-4.4300	-1.1227
sigma_u	0.0000	R-squared:				
sigma_e	0.2201	Within	0.1197			
rho	0.0000	Between	0.1696			
Wald chi2(17)	101.7900	Overall	0.1432			
Prob > chi2	0.0000					

Table 26. Coefficients of the panel model (Cohort II): Kumasi Branch

(Default is the explained variable)

Explanatory variables	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
Fintech*Gender (Female)	-0.0373	0.0174	2.1500	0.032	-0.0714	-0.0033
Control Variables						
Borrower Identity Document (More than 1)	0.0344	0.0217	1.5800	0.1130	-0.0082	0.0769
Borrower Age	-0.9203	2.8688	0.3200	0.7480	-6.5431	4.7025
Income Type (formal salary)	-0.0749	0.0403	1.8600	0.0630	-0.1539	0.0041
Employer (Public sector)	-0.0482	0.0313	1.5400	0.1240	-0.1096	0.0132
Profession (Professional)	-0.1004	0.0423	2.3700	0.0180	-0.1833	-0.0175
Borrower Affordability (35%)	na	na	na	na	na	na
Mobile phone account ownership (=2)	-0.0058	0.0193	0.3000	0.7630	-0.0436	0.0320
Bank account ownership (Yes)	0.0717	0.0844	0.8500	0.3950	-0.0936	0.2371
Loan Amount	-0.0125	0.033	0.3800	0.7050	-0.0771	0.0521
Loan Tenor	-0.0440	0.0321	1.3700	0.1710	-0.1069	0.0190
GDP	0.4598	0.2781	1.6500	0.0980	-0.0854	1.0049
Interest rate	0.1145	0.0360	3.1900	0.0010	0.0441	0.1850
Intercept	-1.5945	0.7653	2.0800	0.0370	-3.0944	-0.0945
sigma_u	0.0000	R-squared:				
sigma_e	0.2099	Within	0.1041			
rho	0.0000	Between	0.1882			
Wald chi2(17)	97.9100	Overall	0.144			
Prob > chi2	0.0000					

Table 27. Coefficients of the panel model (Cohort II): Takoradi Branch

(Default is the explained variable)

Explanatory variables	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
Fintech*Gender (Female)	-0.0262	0.0248	1.0600	0.29	-0.0748	0.0224
Control Variables						
Borrower Identity Document (More than 1)	-0.0019	0.0277	0.0700	0.9460	-0.0563	0.0525
Borrower Age	0.1765	3.9912	0.0400	0.9650	-7.6461	7.999
Income Type (formal salary)	-0.0383	0.0492	0.7800	0.4370	-0.1346	0.0581
Employer (Public sector)	-0.0533	0.0383	1.3900	0.1640	-0.1284	0.0218
Profession (Professional)	-0.0919	0.0642	1.4300	0.1520	-0.2177	0.0339
Borrower Affordability (35%)	na	na	na	na	na	na
Mobile phone account ownership (=2)	-0.0078	0.0265	0.2900	0.7690	-0.0597	0.0441
Bank account ownership (Yes)	-0.0857	0.0684	1.2500	0.2100	-0.2197	0.0483
Loan Amount	0.0449	0.0412	1.0900	0.2750	-0.0358	0.1256
Loan Tenor	-0.0840	0.0562	1.4900	0.1350	-0.1941	0.0261
GDP	0.239	0.3791	0.6300	0.5280	-0.5040	0.9820
Interest rate	0.0923	0.0469	1.9700	0.0490	0.0003	0.1842
Intercept	-1.0539	1.0469	1.0100	0.3140	-3.1057	0.9980
sigma_u	0.0000	R-squared:				
sigma_e	0.1930	Within	0.0993			
rho	0.0000	Between	0.2155			
Wald chi2(17)	47.3000	Overall	0.1549			
Prob > chi2	0.0000					

I test the robustness of my results in tables (18) and (19) that show borrowers' adoption of Fintech does not lead to the likelihood of interest rate reduction. I provide my robustness test result for Fintech on cost of debt for cohort of borrowers in Figures (21) to (22) using the classification and regression tree (CRT) model. From my results, I find that, an increase of one borrower in cohort (I) who adopt Fintech is associated with a 3.880% percent change in interest rate compared to 3.853% for their counterparts who have not adopted Fintech prior to singing their respective individual liability credit contracts. For repeat borrowers, my results in figure (22) show similar results. That is, an increase of one borrower in cohort (II) who adopt Fintech is associated with a 0.616% percent change in interest rate compared to 0.570% for their counterparts who don't own a Fintech account prior to singing their loan contracts.

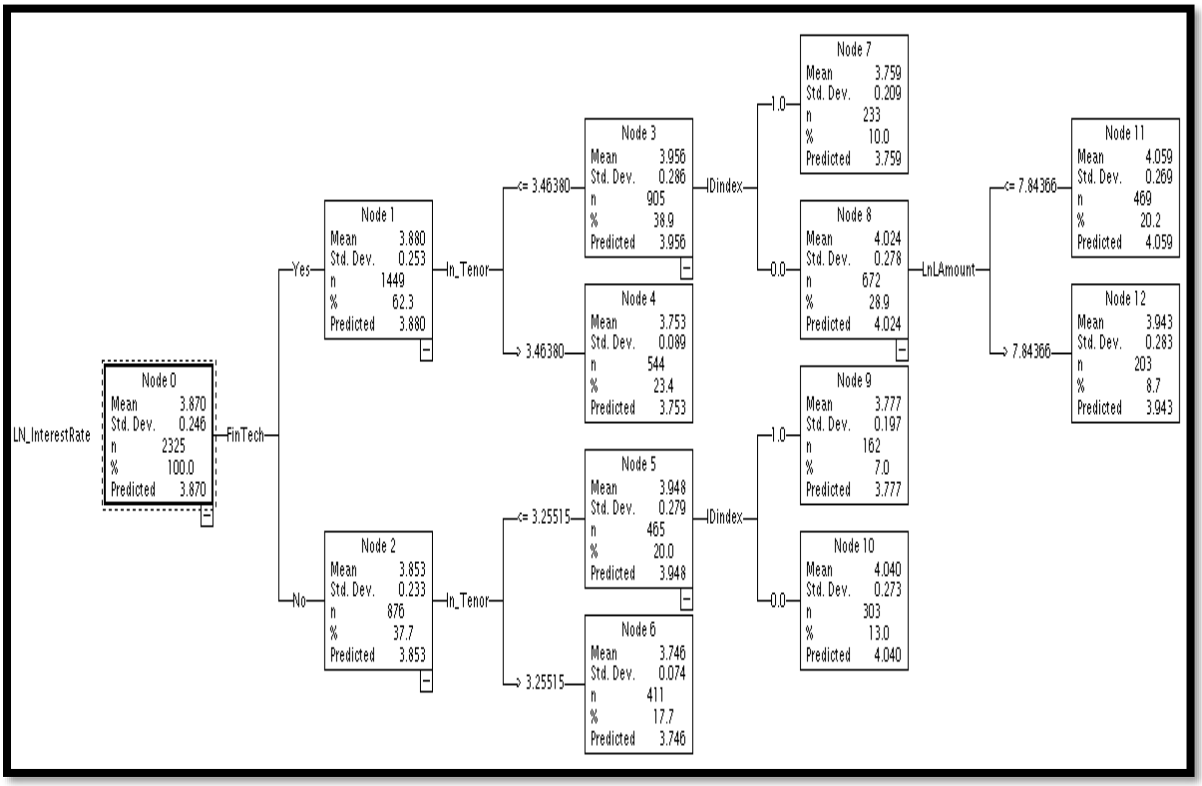

Figure 21. Regression of Fintech on cost of debt using the Classification and Regression tree model (Cohort I)

Note: Estimated Risk= 0.034, Standard Error =0.001

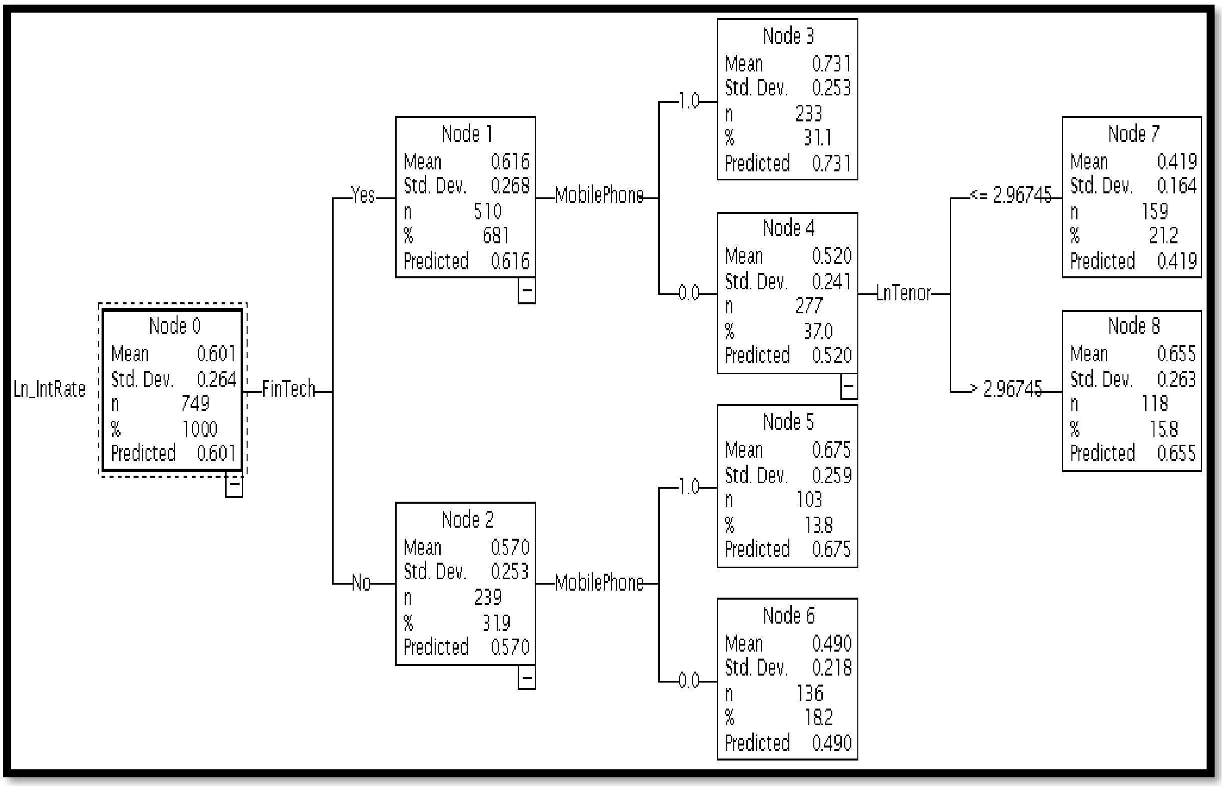

Figure 22. Regression of Fintech on cost of debt using the Classification and Regression tree model (Cohort II)

Note: Estimated Risk= 0.054, Standard Error =0.002

2.8 Performance measurement

I review the performance of my models using the ROC-AUC, F-1, precision, and classification accuracy score. Additionally, I check the error rate for the different statistical models that I used for my empirical analysis. The Receiver Operating Characteristic (ROC) curve is usually summarised through the Area under the Curve (AUC) to measure the performance and discriminatory ability of my models. Further, the Receiver Operating Characteristic (ROC) curve is a graphical plot of the sensitivity (correctly classifying good credit risk clients) against specificity (correctly classifying bad credit risk clients) for all possible thresholds. I selected a threshold of 0.5 for my estimated scores. This aligns with industry practice and is frequently used in literature.

An Area under the Curve (AUC) of 1 suggests a perfect classification and 0.5 is considered a random average prediction. All my empirical results show a ROC-AUC greater than 0.5. Also, my bagged Logit regression model achieved the highest F-1 score and precision rate of 93.34% and 91.90% respectively. This performance is better when compared to the F1 scores of 92.28% and 92.91%, and precision 89.02%, and 88.54% for our classification and regression tree (CRT) model and the random forest models respectively, figure (23). Further, my result show that bagged logistic regression has the lowest error rate of 0.1665 compared to 0.1930 and 0.2069 for the classification and regression tree (CRT) and Random Forest models respectively as presented in figure (24). Also, our bagged Logit model achieved a classification accuracy rate of 89.10% compared to the CRT and random forest models' 87.10% and 87.83% respectively. Overall, our bagged logistic regression outperformed the CRT and random forest models.

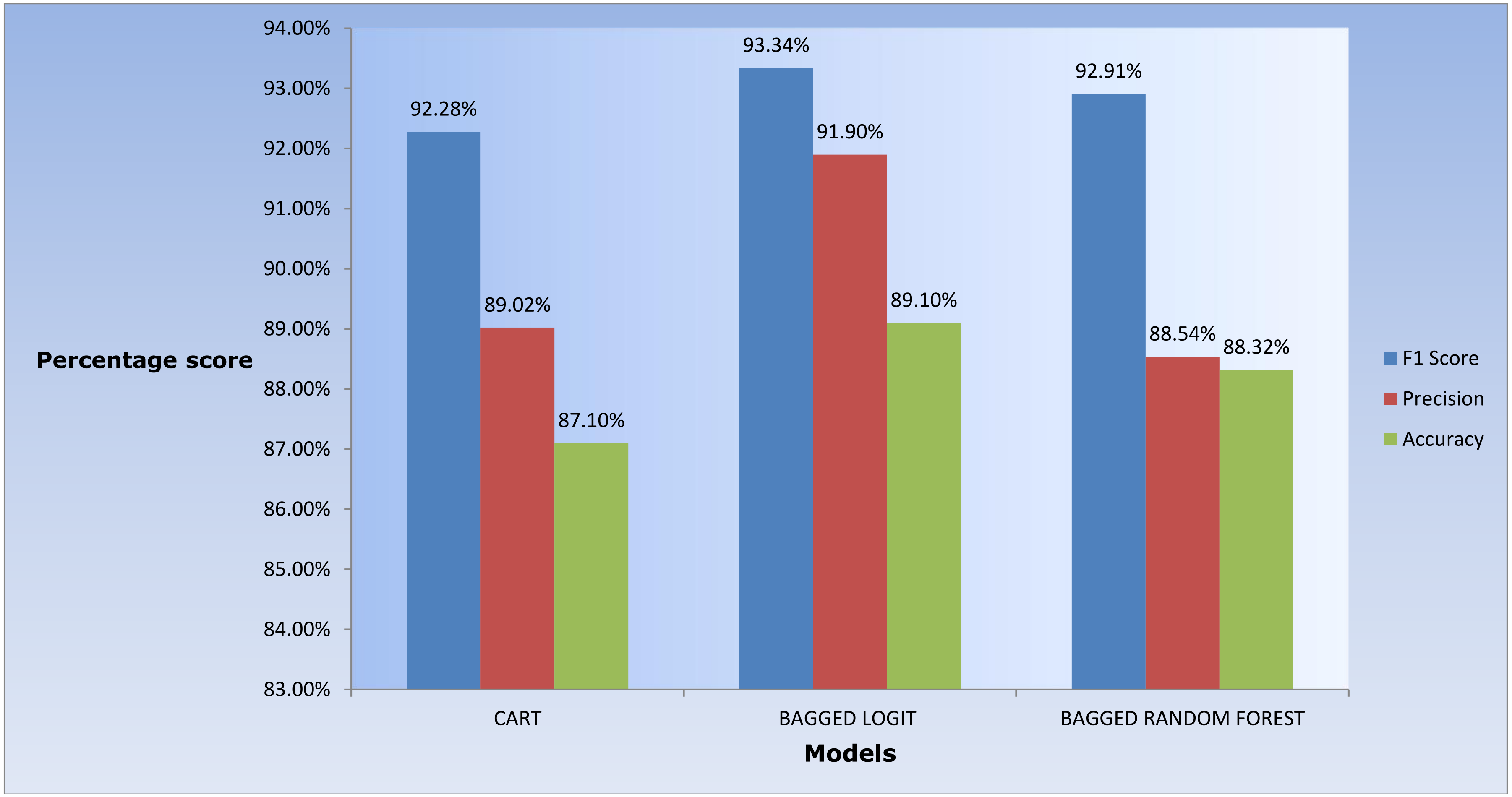

Figure 23. Graph of model performance using F1 score, Precision and Accuracy metrics.

Figure 24. Graph of error rate for individual algorithms.

2.9 Conclusion

The primary goal of this section, that is, chapter 2 of my thesis is to determine whether the use of financial technology (Fintech), that is, mobile money account ownership, can signal borrower credit risk, and to contributes to the reduction of adverse selection in the loans market. Particularly in consumer credit. I find empirical evidence to show that borrowers' adoption of Fintech, that is, mobile money, can signal credit risk. This in turn can reduce loan risk. My finding is statistically and economically significant. My empirical results show that, for repeat borrowers who continues to adopt Fintech, the likelihood of default is further reduced compared to their non-adopting counterparts.

Further, female clients across the two cohorts of borrowers who adopted financial technology, that is, new clients and repeat clients are associated with a significant reduction in their likelihood of loan default. My results suggest that female borrowers are tech savvy and are able to use Fintech to manage their finances well to ensure that they meet their debt servicing obligation to the lender. Additionally, I find a significant inelastic relationship between first-time borrowers who adopt mobile money wallet and the interest rate charged by the lender. I find opposite results for repeat borrowers who adopted Fintech to signal credit risk.

CHAPTER 3 RELIGIOSITY AND LOAN RISK: DOES SELF-DECLARED RELIGIOSITY MATTER?

3.1 Introduction

Religion and religiosity have been shown in prior studies to play a significant role in a person's way of life and in business decision making. According to Statista (2023) report, In Africa, the Christian belief represents the largest proportion, 62%, of the population. The Islamic religion followed with a 31.40%, and other religions accounts for 6.60%. Further, Bank loans have also been shown to have a positive co-movement with the economic growth of several countries, and social finance literatures asserts that the religious environment that a firm is located shape the organisations' culture and way of doing business ((Levine and Zervos (1998)), Hilary and Hui (2009)).

There is several evidence to show, that social and cultural beliefs, for example, religion, reduce the risk appetite and increase the profitability of firms located in high religious countries (Hilary and Hui, 2009). Hence, religiosity can be said to signal that a borrower is trustable; and as such, financial institutions including banks may experience less default rate among religious borrowers. Also, in a study that investigated the rationale for choosing financial product using consumer survey data in Indonesia, and the demand for Islamic banking, Pepinsky (2010) find that Individuals' religiosity, that is, Islamic belief, play a significant role in a person's decision-making process.

Further, Abedifar et al. (2013) investigated 553 small banks in four different countries, predominantly Muslims, to examine their loan risk and stability, and find that small Islamic banks are associated with lower credit risk and are more stable than conventional banks. The work of Baele et al., (2014) that examined Islamic loans and conventional business loans from a lender in Pakistan, a Muslim dominated country, find that Islamic loans are associated with lower default likelihood. Similarly, Abedifar et al. (2013) studies customers at two different banks in Pakistan who opened bank accounts and find that individuals' religiosity and religious belief matters when clients decide to open a bank account.

While research supports consensus on a weak-to-moderate and sometimes strong relationship between religiosity, religious intensity, and bank lending, especially in business and sovereign debt market, there are still several major points of controversy. Most of these studies are undertaken in a predominantly Muslim community where Islam is a state preferred religion, to examine the impact of the religious environment on bank risk taking, stability, and loan default. Others use survey data at the country level to infer borrower religiosity. This raises an important question: Does borrowers' self-declared, not inferred, religiosity and religious connectedness influence the performance of loans in an individual liability credit contract, and in an environment where there is no state preferred religion. I empirically investigate this fundamental question by comparing the likelihood of loan default on conventional loans across the two main religious groups using a comprehensive dataset from a major lender in Ghana, a developing open market economy.

Similar to the works of Iannaccone (1998) and Guiso et al., (2006), my hypotheses which I develop in detail in section 3.2 is that borrowers who signal their credit risk to the lender by voluntarily self-declaration of their religiosity and religious connectedness at the loan application stage and prior to the loan contract are associated with lower default likelihood and spread. Further the work of Bolton and Scharfste (1996) show in a similar framework, that mixed borrowers may default on their individual liability loan contract because of their own personal actions that may not be correlated with, for example, their religious belief. I contend that religious adherents would provide consistent incentives for individuals to behave ethically, and thus, lower default rate among borrowers who voluntarily signal their credit risk using their association with religion than non-religious peers. This assertion concurs with the findings that being honest is a fundamental requirement in religious social norms (Weaver and Agle, 2002).

I find robust prima facie evidence of higher default likelihood across religious individual borrowers. The evidence comes from a variety of specifications that contain pertinent information on individual borrower and loan-specific characteristics, as well as macroeconomic control variables. Also, I find that religious connectedness has no significant on loan performance and cost of debt. However, when branch effect is controlled, the impact of religiosity on the individuals' loan performance varies and suggests that religiosity has diverse impact on loan performance across different regions, even within the same country. My work complements those ideas bringing focus to the role of religion in lending activity, specifically in the area of consumer loan quality and economic exchange.

3.2 Study Objectives

The primary purpose of this section of my thesis is to revisit the question whether religion positively impact economic transactions, specifically, in individual liability credit contract. That is, how individuals' self-declared religiosity and religious connectedness impact on a person's behaviour when it comes to honouring their debt obligations. Further, I investigate how likely an individual borrowers' self-declared religiosity and religious connectedness prior to the loan contract impact on the cost of debt charged by the lending institution in a consumer loan setting.

The specific objectives are to:

1. Estimate the probability of default for borrowers who self-declared their religiosity to signal their credit risk and evaluate the effect of the signal on loan risk.
2. Estimate the impact on cost of debt for borrowers' who self-declared their religiosity to signal their credit risk and evaluate the effect on loan risk.
3. Estimate the probability of default for female borrowers who self-declared their religiosity prior to the loan contract and evaluate the impact on the loan risk.
4. Estimate the probability of default and the impact on cost of debt for borrowers who repeat their self-declared religiosity as signal of their credit risk in a repeat loans' transaction.
5. Estimate the probability of default for female borrowers' who self-declare their religious connectedness prior to the loan contract and evaluate the impact on loan risk in a repeat loans' transaction.

3.3. Significance of the study

Successful lending relationships are built on, and sustained by, the expectations of mutual trust and ethical conduct. This is true whether the lending relationships are business-to-consumer or business-to-business. Moreover, this is true whether the lending relationships are confined to a single country or are multinational in scope and nature. As exemplified by existing research, it is therefore important to study the relation between traits, such as trust, and trustworthiness embedded in the various religious beliefs and how this impact on individuals' loan performance in an individual liability credit contract, and in the consumer loans market. Particularly in the developing where religion has a significant influence in the lives of many residents.

Unlike many prior studies in this area that have investigated the relationship between religion and loan performance that rely on country specific level and general population survey data to infer an individual borrowers' religious belief and religiosity to generalise, I depart from this approach by using a unique characteristic in my dataset that is, the individual borrowers' self-declared religiosity and religious connectedness at the loan application stage. I argue that a country's level of religiosity which is used as proxy to measure individual citizens' religiosity and by extension that of borrowers in many prior studies, can be an over-simplification. This is because a country's level of religiosity is an amalgamation of different religions, and although one religion may dominate, this doesn't necessarily mean that borrowers are members of the dominant religion. Hence, this can lead to spurious result.

However, there are challenges that inhibits empirically examining the various consequences of borrowers' self-declared religiosity, and religious affiliation on loan performance in an individual liability contract. As a result, distinguishing among the various explanations underlying their effect on loan outcomes is difficult. First, it requires information that identifies the individuals' own declaration of belonging to a specific religious belief and this information is in some jurisdictions, such as the US, barred. That is, the lender is legally prohibited from soliciting the information and or prevented from using the data to inform lending decisions. Also, prior studies, for example the work of Guiso et al., (2009) focused on high level of aggregation at the country level, while others have in some cases relied exclusively on survey data collected on the religion or race of specific segment of the population. This, at most has been set up to segregate and discriminate against specific group rather than to reflect the religious beliefs of the entire market.

Furthermore, this can confound any improvement in empirical outcomes from the different individual religious group interactions using statistical based discriminatory analysis. Especially when the excluded religious group are significantly prevalent within the entire population. Also, even when dyadic data covering the individuals' religiosity are available, most studies have investigated the interaction between religiosity and loan performance at the country level or at on corporate and sovereign debt and excluded the consumer loans market. I fill this gap in literature, and I provide the first empirical evidence of the interaction between borrowers’ self-declared religiosity and religious connectedness at the loan application stage and its impact on loan risk in an individual liability credit contracts, and in consumer loans setting.

My thesis adds to our understanding and contribute to the extant literature by studying the effects of religious beliefs on loan performance in individual liability credit contract in two ways. First, my study complements the body of extant research that examines the relationship between religiosity and corporate decisions and individual decision-making process (Stulz and Williamson, 2003; Hilary and Hui, 2009; Renneboog and Spaenjers, 2012; Adhikari and Agrawal, 2016). However, my primary is different and focuses on individual liability contracts and individuals’ borrowers’ self-declared religiosity and religious connectedness at the loan application stage. This is a contrast to most prior studies.

Second, my results add to the extant empirical evidence on the impact of religiosity on loan performance. Unlike extant studies such as the works of Chen et al., (2016), and He and Hu, 2016) that focused on how religious borrowers appear trustworthy to lenders and secure favourable credit terms, I provide new evidence on the loan repayment behaviour of religious borrowers who self-declared their religiosity to the lender at the loan application stage and with individual liability contracts. My evidence suggests that religiosity does improve the loan performance of religious borrowers with individual liability credit contracts. My finding confirms the widespread view that religiosity impacts positively on a person's decision making, that is, borrowers are less likely to default on their loan repayments.

To achieve my research objectives, I leverage on my unique dataset covering individual liability credit contracts issued by a major lender in Ghana. I applied the highest Logit regression model as my main approach and alternative algorithm in a credit scoring model to investigate the implication of borrowers' religiosity and religious connectedness on loan default rate and cost of debt. That is, I use the individuals' self-declared religiosity and religious affiliation as proxy for religion. Additionally, I use the individual borrowers repeated self-declaration of their religiosity prior to the loan contract as well as their repeated interaction with the lender as proxy for religious connectedness to investigate the impact of religiosity on loan performance in individual liability credit contract. Further, I use three groups of control variables: loan-specific characteristics, borrower-specific characteristics, and country-level macroeconomic variables on the basis of the secularization hypothesis as contended by Weber (1930).

3.4 Literature

3.4.1 Religion, Religiosity and Economic Development

The social identity theories of Tajfel and Turner (1979) and the later work of Akerlof and Kranton (2000) who posit that many economic events can be explained by a person's sense of self-identity. Furthermore, the Weberian school of thought argues that individuals associated with the Protestant-Christian belief and worship worked harder and had greater economic behaviours and attitudes than people of other religious beliefs and practice (Weber, 1930). The Weberian argument stimulated further studies that investigate the relation between individuals' religiosity and their attitudes and behaviours. Furthermore, the social identity theory's suggestion as contended by Abrams and Hogg, (1988) argue that one's identity is derived from group membership and association.

Based on these classical arguments, many studies have investigated the impact of religion, a person's religiosity and religious connectedness on economic outcomes, ethical behaviours, and attitudes. Extant studies show that there are two main streams of research in the area of religiosity and economic development. The first stream of research provides evidence to show that when organisations are located in a more religious geographical area, the firm is less exposed to the risk associated with doing business (Hilary and Hui, 2009). Also, firms located in a more religious environment are seen to be involved in few unethical behaviours (Grullon et al., 2010), and are not over optimistic when reporting their financial position (Dyreng et al., 2012, McGuire et al., 2012).

The second stream of literature relates religiosity to economic growth (Weber, 1930; Barro and McCleary, 2003). In Weber (1930), the author compared Marxist and utilitarianism in the role of capitalism in production, and contends that religious believe, social norms and ethics played a dominant role. In Barro and McCleary (2003), the authors empirically examined the role of religiosity on economic development using a cross-country survey data that included individuals' church attendance and find a positive association between economic growth and a country's religious beliefs. The authors also find negative association between church attendance and economic growth. The findings of the authors provide additional evidence on religiosity and economic development with a perspective in which the individual's religious belief influences their traits to enhance economic performance.

Further prior studies also document a positive relation between religious favouritism and the level of individuals' religiosity within society. Driessen (2014) investigated this phenomenon in Muslim dominated countries and find that the proportion of religious citizenship is not the only measure of individuals' religiosity but also by their level of tolerance to secularism. In an empirical study that examined the relation between ethics and religion using cross-country data, Parboteeah et al. (2008) built their hypothesis on the work of Cornwall et al. (1986) and posit that a person's religiosity can be defined by three dimensions, cognitive (knowing), affective (feeling) and behavioural (doing).

Parboteeah et al. (2008) also find, that a person's religiosity has no relation with their ethics, but the individuals' psychology and behaviour to religion has a negative relation with ethics. An individuals' religiosity, that is, the extent that an individual perceives and live in accordance with their beliefs, has been shown to influence economic outcomes (Barro and McCleary (2003). The work of Conroy and Emerson (2004); Wong and Vinsky (2008) using survey data, also finds further evidence that religion improves individuals' ethical behaviour. Closely related is the work of Dyreng et al. (2012) that used the geographical location of US firms to examine the link between religiosity and corporate reporting.

Related is the empirical study of Callen and Fang (2015) that analysed the impact religiosity on equity market performance in crisis period. The authors find that organisations located in a higher religious society exhibit better equity returns during periods of financial crisis. The work of Hilary and Hui (2009) contend that organisations do not make choices, people do, and peoples' behaviours are influenced by culture and norms of the environment they operate. This view is consistent with the empirical work of Barro and McCleary (2003); and Guiso et al, (2003) who find that managers of firms located in a highly religious environment take decisions that are significantly influenced by the religious norms and culture of their environment. This is to avoid any potentially costly consequence of deciding to withhold negative news that may be at odds with the believe system of the society in which these firms operate.

Miller and Hoffmann (1995), Maltby (1999), Smith (2003), Waite and Lehrer (2003), and Lehrer (2004) in their psychology study that investigated the relationship between religion and peoples' personality in both business and non-business context find, that religiosity has a significant constructive impact on individuals' behaviour and are positive in addressing ethical actions. Related are the work of Longenecker, McKinney, and Moore (2004), McCullough and Willoughby (2009), and Vitell (2009) that find significant strong relationship between individuals with stout religious beliefs and their ability to question unacceptable business behaviours. Additionally, they find positive relationship between religiosity and individuals' ability to exhibit self-control and self-regulation in business.

Weaver and Agle (2002) corroborated these findings in an organisational research and social structural theory that analysed relationship between peoples' level of religiosity and ethical behaviour and finds that religiosity encourages socially acceptable ethical behaviours and moral judgment in business relationships. However, studies in sociology and psychology such as the work of Cochran and Akers (1989); Linden and Currie (1977); McIntosh et al., 1981; and Tittle (1980) finds thin evidence that religious denomination significantly influence individuals' moral behaviour. Other related studies that followed have equally provided empirical evidence to show that religious denomination 'makes a difference' (Bock et al., (1987); Cochran et al., (1988); Hadaway et al., (1984); Nelson and Rooney, (1982). These studies provide inconclusive and mixed results on the subject.

In an empirical study that specifically investigated religious denominations and risk-taking behaviour of selected investment banking firms, Shu et al. (2012) finds, that some specific religious denominations such as the Catholic church belief is associated with high risk taking compared to Protestant church belief. The authors argue that this is because these firms are geographically located in areas where the Catholic belief is dominant. Further, Demirgüç-Kunt (2013) in a related study that investigated how individuals' religious belief influences their relationship with bank in Sub-Saharan Africa find that Muslims are less inclined to have banking relationship or open a bank account.

In a study that investigated the impact of religion on the productivity of entrepreneurs using survey data that captured responses across China, Zhang and Liu (2021) finds that religious entrepreneurs focus more resources and time to build social ties and network than their non-religious counterparts and suggest that religious entrepreneurs divert business resources into non-business and unproductive activities. These findings present a moral hazard challenge to lending institutions that attempt to reduce risk in extending credit to individual entrepreneurs. Holm et al., (2013) and Koudstaal et al., (2016) corroborated these findings and show that religious entrepreneurs are no different from non-religious peers in their behaviour towards standard risk.

Related is the study of Evans et al., (1995) that used self-reported survey data to investigate the impact of religious beliefs on adult criminality and find negative association between religion and adult behavior. Further, in a study that reviewed religiosity as a function of earnings, Tomes (1985) finds among other findings that individual diligence, honesty, and reliability is associated with religion. Closely related, is the work of Renneboog and Spaenjers (2012) that examined the association between Dutch Christians and how they conduct their finances. The authors find that religious households are positively associated with savings. The authors also find that households affiliated to the Catholic denomination are less likely to commit funds to long-term risky investment such as equities compared to their Protestant peers.

Halek and Eisenhauer (2001) undertook similar work and finds large variations in the risk appetite of Christians and Jews. Further, Noussair et al. (2013) finds evidence to show that people who are religious have significant low financial risk appetite. In a study that used survey data across 99 market economies in Asia, North and South America and Europe to investigate the link between religiosity and risk taking in financial institutions, Kanagaretnam et al. (2015) finds that financial institutions located in more religious societies tend to take less risk and are less opportunistic in their earnings management approach compared to their counterparts located in less religious places. Additionally, Wong (2008) find, that ethical behaviours and attitudes varies across different Christian entrepreneurs depending on their level of religiousness. However, the authors did not examine how the declared religiosity and religious connectedness among Christian entrepreneurs' impact on loan performance.

Further empirical study that is closely related to the work of Harjoto and Rossi (2019); Rossi et al. (2019) and Kanagaretnam et al. (2015) is the work of Cebula and Rossi (2021) that investigated the link between corporate decision making and religiosity among unregulated and non-financial firms listed on the Italian capital market. The authors find that decision making at the corporate level has significant inverse relationship with religiosity. The empirical work of Du (2012) also investigated the relationship between religiosity in a principal-agent context among firms listed on the Chinese capital market and find a significant inverse but positive association between religion and owner-manager agency costs.

Additionally, Guiso et al., (2003) in an empirical study that used cross-country data to examine peoples' level of religiosity and their economic behaviours, show that religiously inclined individuals exhibit a high 'sense of individual responsibility' and 'good' economic management at the country level compared to their non-religious peers. Stulz and Williamson (2003) provided confirmatory evidence to show that this high 'sense of responsibility' exhibited among religious people are more prevalent in Protestantism believe system because 'each individual determines on his own what is right'. Further, lenders are less protected in countries that are predominantly Catholic because in these countries anti-usury culture prevails (Stulz and Williamson, 2001).

Similarly, in an experimental study that investigated the relation between religiosity, trust and trustworthiness in a dyadic interaction setting, Tan and Vogel (2008) find that religiosity breeds trust and trustworthiness. Also, the authors find that highly religious inclined individuals were found to be more trustworthy. The empirical work of Grullon et al., 2010 accord to this finding in a study that investigated religion and corporate behaviour. The authors find that managers of firms headquartered in US counties with high concentration of religion are less inclined to engage in unethical behaviours that will make the firm a target of class action lawsuit.

Miller (1992) in a study that sought to examine the effect of religiosity in Japan using traditional theories of sociology on individuals' behaviour, the author find that a person's religious belief influences their behaviour and attitude similar to that exhibited in western countries in America and Europe. Related is the work of Miller and Hoffmann (1995) that investigated how gender differences in risk preferences impact on differences in individuals' religiosity, they find that individual risk preference also is a significant determinant of religiosity within gender, and further argue that religious individuals exhibit 'risk-averse' behaviours and attitudes compared to their non-religious counterparts.

Further, Miller and Hoffmann (1995) compared males and females' attitude to religion and religiosity in a gender analysis, and contend that, males are less likely to be religious and be actively involved in religious practice than their female counterparts. The authors argue that this is because men are more like to be engaged in high-risk behaviours. Miller and Stark (2002) and, Walter and Davie (1998) empirically investigated gender and religiosity and document that females are more religious than their male counterparts, and that failure to be religious is tantamount to risk taking. Peterson et al., (2010) in a cross-country study that investigated nationality and business-related ethical behaviour, find that individuals' religiosity and gender are key determinant of ethical behaviours and attitudes.

Using survey data and a definition of religiosity based on individuals' church attendance to investigate how ethical attitudes is influenced by religiosity, and whether knowledge on religion affect attitude, Conroy, and Emerson (2004) find that individual religiosity is a statistically significant predictor of ethical behaviours. In a meta-analysis that sought to investigate the relationship between gender, age and course majors on ethical behaviours and attitudes among undergraduate, Borkowski and Ugras (1998) find that females are more ethical than their male counterparts. In an empirical study to examine individual characteristics that might influence ethical judgments, Hunt and Vitell (1993) included consumer religiosity as a variable in a 'general theory of marketing ethics, and document that a person's religiosity and religious belief can influence decision making process.

In a follow up study, Vitell and Paolillo (2003) investigated how individuals' religiosity and religious belief influence their ethical behaviour. The authors find that individuals' religiosity and belief influence their ethical behaviour. However, because of the instrument used in measuring religiosity, their result shows a weak influence. Kurpis et al., (2008) in a study that surveyed 242 business students to investigate morality and religiosity, the authors find that individuals' religiosity has a positive impact on a person's ethical behaviour and commitment to self-improved morality. Campbell and Viceira (2005), and Porteous (2006) show that based on the risk-return trade-off, lenders have two main options. First, they may decline high-risk borrowers, or second, charge borrowers with high interest rate, depending on lenders risk appetite and borrowers' profile.

However, in the empirical works of Adhikari and Agrawal (2016), the authors show that banks located in a densely populated religious areas are less likely to be exposed in times of financial crises. The authors further contend that, this is the case because local religiosity play a significant role in shaping the decision-making process of managers and investor when taking risk. Clark and Dawson (1996) empirically investigated the relationship between individuals' personal religiosity on ethical behaviours and social norms. The authors find that an individuals' self-declared religious belief and religiosity motivates ethical behaviours and actions that aligns with societal norms.

Giannetti and Yafeh (2012) in a cross-country empirical study investigated how differences in culture influences financial contract and how repeated interactions impact on the performance of contractual obligation between two parties using large sample of syndicated loans. The authors find that, cultural differences between lenders and borrowers' impact on loan terms. Specifically, the authors find that borrowers that are culturally distant from the lender are charged higher interest rate but are not different on their loan performance compared to others. However, my study differs from Giannetti and Yafeh (2012); Giannetti and Yafeh (2012) and Hilary and Hui (2009), in two important ways.

First, most extant studies failed to demonstrate the effect of religiosity directly on individuals' loan performance in the consumer loan market. I measure religiosity as declared by individual borrowers at the loan application stage. Second, unlike other studies that have focused on corporate loans, I focus on the effect of individual borrowers' religiosity on asymmetric information and loan interest rate in the consumer loans market. Third, unlike other studies that are focused on developed economies in America, Asia and Europe, I focus on Ghana, a developing market economy where the problem of asymmetric information in the lender-borrower relationship is severe. This helps to compare the effect of religiosity on loan contracts across different continents and people.

3.4.2 Religiosity, Lending Risk and Loan Performance

Extant literatures and empirical studies appear to have a general consensus that the presence of strong religiosity is associated with corporate borrowers' creditworthiness, and that lending institutions recognise this by offering religious borrowers favourable credit terms. According to this stream of theoretical and empirical literature, religiously inclined borrowers exhibit good personal traits, and this, in turn, positively impact on the loan performance of firms. Furthermore, Bank loans have also been shown to have a positive co-movement with the economic growth of several countries, and social finance literatures asserts that social norms such as religious beliefs, the surrounding a firm's environment equally shape the firms' culture and way of doing business ((Levine and Zervos (1998), Hilary and Hui (2009)).

On the economic front, the empirical work of Barro and McCleary (2006) used broad cross-country dataset to investigate the impact of religiosity on the economic performance of countries and finds that church attendance has an inverse relationship with economic growth, however, individuals' religiosity has positive relation with economic growth. Similarly, in an experiment using a sample of credit card customers for a major Islamic lender in Indonesia, Bursztyn et. al (2019) investigated the association between borrowers' moral ethics and their incentive to repay outstanding debt obligations by sending borrowers a mobile text with reference to the holy Quran. The authors find that, the borrowers' incentive to repay loans is significantly influence by their level of religiosity, and that such religious reference serves as a reminder and incentivised borrower to fulfil their debt obligation to the lender.

The findings of Bursztyn et. al (2019) accord with the related empirical work of Baele et al. (2014) that investigated the performance of borrowers across multiple lending institutions including Islamic lenders in Pakistan and find evidence to show that loans granted to borrowers on religious grounds performed better in default rates compared to non-Islamic or conventional loans. This is because borrowers are made aware of the religious requirements associated with signing a religious loan contract, plus the societal expectations that ensued. Duarte et al. (2012) also find that, trust is fundamental in lending decisions and religiosity nurtures trust and loan applicants who appear to be trustworthy are more likely to have their loan request sanctioned by finance providers.

The work of Burtch et al. (2014) investigated the impact of proximities between lenders and borrowers on lending activities in the online platform Kiva. The authors find that geographically proximate borrowers' impact on lending activities, and that lenders are motivated to lend to culturally and religiously similar borrowers. Sabzehzar et al., (2020) in a related empirical work investigated religious differences in a pro-porr online lending platform, and document that religion distance between borrowers and lenders has a negative and significant impact on lending. The authors also find that state bias towards specific religious beliefs significantly increases the negative effect of religion on lending activity.

Related are the works of Williamson (2000), and Guiso et al., (2003) that show in their empirical studies that an individuals' religiosity can influence their ethics and values, as well as self-impose some constraints on their preferences and behaviours toward economic choices and decisions. The authors further show that this can include a person's commitment to repay loans. Baela et al., (2014) compared conventional loans to Islamic loans in Pakistan using monthly dataset and document that, higher ethical standards associated with religiosity suggest that borrower are less motivated to break the terms of the loan contract or to default on their loan.

In a study that investigated the relation between religion and risk taken by banks, Agrawal et al. (2016) finds that banks located in a religiously dominated geographical area have lower default rate, low risk on their equity returns and are better insulated against financial crisis. Further, Agrawal et al. (2016) show in their empirical work that, indigenous religiosity significantly influences banks' risk appetite. Related is the work of Adhikari and Agrawal (2016) that investigated whether religiosity have any impact on bank risk taking level and finds among others that banks located in a religious geographic area have less default rate as measured by the banks' financial risk level. However, in similar field of study, Zhao et al. (2017) find a significant inverse relation in bank total risk and local religiosity.

Extant studies that have focused on the relationship between the lending business and religiosity, such as the empirical work of Chen et al., (2016) in a cross-country study finds, that religiosity leads to lower interest rate charged by lenders, larger loan amount and a relaxed lending requirement. Kim et al. (2014) corroborated this finding and showed, that lenders relax their loan application requirements in favour of religion and ethical behaviour of loan applicants in a study that employed over 12,000 syndicated credit facility from 19 different countries. Related is the empirical work of Gyapong et al. (2021) that investigated the association between religiosity and loan repayment in 770 micro-financial institutions across 65 countries using survey data. The authors find an inverse relationship between religiosity and loan losses of micro-financial intuition. However, Gyapong et al. (2021) finds that religiosity does not induce repayment behavior of borrowers.

Furthermore, in the empirical work of Baele et al., (2014) that examined both Islamic and conventional business loans in Pakistan and default rate, the authors find that Islamic loans are less likely to default than conventional loans. Also, the authors find that during religious festive periods and in large cities dominated by religious political leadership, default is less likely to occur. However, the work of Baele et al., (2014) is similar to prior work done in an environment where the Islamic religion is predominant and beckons the question, whether a study on consumer loans to borrowers affiliated to Islamic belief will yield similar results in the same or differently religious setting or where the Islamic culture and belief is less dominant.

Similarly, in the work of Barro and McCleary (2003) the authors also investigated the effect of individuals’ church attendance and belief on economic growth, that is, per capita GDP. This beckons the question, whether these characteristics and trait across the diverse religious beliefs translate positively into the individuals’ loan performance. Fishman et al., (2017) investigated individuals' cultural proximity to the lender and credit outcome using quarterly data on loan characteristics and loan status in India. The authors find that cultural proximity improves the number of loans disbursed, the quality of the loan underwriting and cost of lending. Ashraf et al., (2016) used international sample of banks from 75 different countries to investigate the impact of religion as part of national culture on loan default rate. The authors find a statistically significant positive between religion on loan default probabilities.

Additionally, the works of Abedifar et al., (2013); Beck et al., (2013); Pappas et al., (2013) and Van Wijnbergen and Zaheer (2013) all show that Islamic banks may be less exposed to credit risk than conventional banks and that many of such banks are associated with high-quality assets that enables them to withstand financial and economic shocks compared to their conventional counterparts. For example, in the work of He and Hu (2016) that empirically examined the effect of religion on bank loan terms among 1500 U.S. companies located in 45 states, the authors find that borrowers of business loans receive favourable credit terms when the firm is located in a county that is more religious compared to counterparts located in less religious counties. This finding suggests that lenders offer favourable credit terms to religious borrowers in the United States.

The work of Liu et al. (2012) provided evidence using Kiva, an online lending platform to show that lenders provide more loans on the platform based on the religiosity, and that individual religiosity play an important motivating factor in online lending decisions. The finding of Liu et al. (2012) is in accord with the work of Batson (1976) and Saroglou et al. (2005). The related work of Jiang et al. (2018) examined small bank lending and finds that, the relation between religiosity and cost of borrowing is significantly strong in an environment where the problem of asymmetric information is severe and hard information about borrowers is less reliable in determining the likelihood of default.

Also directly related to my study is the works of Ibrahim et al., (2008) and Wong (2008). In Ibrahim et al., (2008), the authors empirically examined the impact of religion and religious connectedness on individuals' state of mind and social behaviours across diverse religious groups in Malaysia and find homogenous behavior across different ethnic and religious groups towards social norms. Wong (2008) also investigated the relationship between church attendance and ethical behaviours among Christian entrepreneurs using survey data solicited from individual church attendees from three large churches in Malaysia. The author finds that religious connectedness among Christian entrepreneurs are positively related to ethical behaviour and attitudes.

3.5 Empirical strategy, Hypotheses and Method

3.5.1 Determinants of Religiosity

My dataset consists of borrowers who voluntarily self-declared their religiosity and religious connectedness to two main religions, that is, Christianity and Islam, to the lender. Further, my data show borrowers affiliated to Jewish and Hindu, however, the numbers were insignificant to be treated as independent variables to be investigated. Hence, I excluded the Jewish and Hindu religious beliefs in this my empirical analysis, and I focus of the two main religions and those borrowers who did not declare their religiosity. My thesis builds on the work of McCleary and Barro (2006) that investigated the relation between religion and economic development.

Like many residents in Africa, religion, and religiosity play an important role in the lives of many Ghanaians and in society. During the loan application stage, borrowers declare various personal information to the lender, that is, both personal and financial information on their loan application form. When completing the required loan application form from the lending institution, clients voluntarily provide their individual respective religious affiliation with the objective of appearing trustworthy to the lender at the beginning of the lending relationship. Similar to the work of McCleary and Barro (2006), I measure religiosity and religious connectedness as self-declared by individual borrowers.

My analysis of the determinants of loan risk uses the borrowers' self-declared religiosity and religious connectedness as the independent variable. My choice is motivated by prior studies that individuals' religious belief, that is, Christianity and Islam require strict adherence to religious responsibility and that includes honouring financial obligations. With religiosity and religious connectedness viewed as an independent variable in this second part of my thesis, a key challenge is how religiosity affects individual characteristics, such as honesty, and thereby influences their loan performance in an individual liability credit contract. Furthermore, religion prescribes high ethics and norms, and hence borrowers who declare their religiosity to signal their credit risk are less likely to intentionally default on their individual liability loan contracts.

This is because individuals who declare their religiosity and religious connectedness to the lender are expected to act honestly, and hence, are less likely to be dishonest to secure a loan. This will in turn have a positive effect on loan risk. Furthermore, Dehejia et al. (2005) investigated religion and economic activities using survey data and find that individuals who declare affiliation to a religion and identify themselves to be religious are associated with less volatile sources of income. In my thesis, I sketch this two-way interaction in a consumer loan loans market setting, and I use religiosity and religious connectedness as my independent variables respectively.

Similar to the empirical strategy in the first part of my thesis, that is, Fintech and Loan Risk, I use borrowers' religiosity in a signalling framework to investigate the relation between self-declared religiosity and religious connectedness on loan risk. For simplicity, let us suppose that there are just two groups of borrowers. Group (A) declare their religiosity to the lender to signal their credit risk at the loan application stage and prior to signing the loan contract. This group of borrowers are assigned the value of 1 to the lender for being for self-declaring their religiosity. The second group of borrowers, that is., group (B) do not declare their religiosity or are not religious at the loan application stage, and or for some reason these borrowers believe the information will have no effect or adverse effect on their risk profile and are assigned a value of 0.

In this framework, and as in the case for the lender, the borrowers' religion or religiosity is not a loan eligibility requirement and form no basis for loan decision making as shown in all the loans disbursed by the financial institution. That is, the lender does not discriminate on the basis of religion. Clients voluntarily disclose their religious beliefs and affiliations, and their level of commitment and religious connectedness to the lender at the loan application stage. The rationale for such self-declaration is unknown, however in this framework, it is reasonably assumed based on prior studies that borrowers believe such self-declaration show that they are honest and can be trusted to repay their debt when granted. Further, if this belief is true, then this signal by borrowers to the lender prior to the loan disbursement should impact positively on the performance of the loan contract.

The probability of default is determined by the independent featured variables, and here it is assumed that this is linear and additive and of the form:

$$\mathrm{Log}\,(\mathrm{Pd}/\,(1\;-\;\mathrm{Pd})) = \alpha 0 + \mathrm{Relig}\psi + \Sigma\,\mathrm{X}1\beta 1 + \mathrm{X}2\beta 2 + \mathrm{X}3\beta 3 + \cdots \mathrm{Xn}\beta\mathrm{n} + \varepsilon_i \qquad (1)$$

The left-hand-side variables are measures of the loan status, i.e., default or non-default. The key right-hand-side variable of interest is *Religiosity* which measures the borrowers' religiosity and religious connectedness, and represents measures, described above. The key coefficients of interest are ψ which is, how religiosity impact on loan risk in an individual liability credit contract. In equation (1), *Relig* measures borrowers' self-declared religiosity to the lending institution at the loan application stage and prior to the disbursement in the first individual liability credit contracts (Cohort I) using consumer loans. Furthermore, I investigate the impact religious connectedness and it impact on loan risk over time, I use my panel data, that is, cohort (II) and Mundlak's correlated random effect model of the form:

$$Y_{it} = \alpha + \beta_i X_{it} + \overline{x}_i + \alpha + RelegConn\,\delta_{it} + u_i^{residual} + \varepsilon_{it} \quad (2)$$

In equation (2) the left-hand-side variable is a measure of the loan status, i.e., default or non-default, over time. The key coefficient of interest is δ, which is, how religious connectedness impact on loan risk in an individual liability credit contract. In equation (2), *ReligConn* measures borrowers' religiosity over time. That is, religious connectedness as self-declared by clients to the lending institution at the first and second loan application stage and prior to the disbursement in the first and second individual liability credit contracts (Cohort I and II) using consumer loans. The right-hand-side variable, Y_{it} is the loan status of each borrower over time, that is in first and second loan periods respectively.

3.5.2 Hypotheses

If religiosity and religious connectedness signal that a borrower is trustable; then financial institutions such as banks may experience less default rate among religious borrowers. In this section of my thesis, I contend that religious adherents would provide consistent incentives for individuals to behave ethically, and thus, lower default rate among borrowers who voluntarily self-declare their religiosity to the lender prior to the loan contract than their non-religious peers or those who do not self-declare. This assertion concurs with the findings that being honest is a fundamental requirement in religious social norms (Weaver and Agle, 2002). The authors find that religion positively influence transparency in corporate reporting by managers. This suggest that financial institutions can rely on accurate and reliable information about the borrower to aid quality loan underwriting when dealing with honest and relatively transparent loan applicants who are religious. This in turn, can mitigate the moral hazard problem for the lender.

Despite a wide body of related work that theoretically and empirically examined the effect of religiosity on lending activity in business loans, corporate and sovereign debt market, it's direct influence on information asymmetry and loan quality in the dynamic consumer loans market are not immediately obvious. Hence, I fill this gap literature in my thesis. Bearing these issues in mind, and unlike most prior studies that has examined the role of religiosity on corporate and sovereign loans, I aim to investigate how individual borrowers' self-declared religious affiliations, religiosity, and religious connectedness impact on their respective loan performance in the dynamic consumer loans market.

In summary, the outlined literature on religion, a person's religiosity and traits, and credit risk in corporate and sovereign debt suggests the following four testable null hypotheses:

$H1_0$: Across all first-time borrowers, *ceteris paribus*, borrowers who voluntarily self-declare their personal religiosity to signal their credit are associated the likelihood of lower default and interest rate.

I surmise that Individual borrowers' religiosity induces positive traits and this in turn leads to a reduction in loan risk and cost of debt. That is, individual borrowers associated with a religious belief system are positively influenced to be conservative, takes less risk by borrowing what they can afford and are associated with good traits such as honesty in declaring their true credit risk to the lender and are trustworthy to repay their loans. Further, it follows that this will in turn positively impact on the borrowing cost for borrowers.

$H2_0$: Religious connectedness is associated with lower likelihood of loan default and cost of debt.

I surmise that the longer the duration of interaction and connectedness between the lender and the individual religious borrowers, the less severe the problem of information asymmetry becomes. That is, individual borrowers' religious connectedness through repeated interactions leads to a significant reduction in asymmetric information, and this in turn, positively impact on borrowing cost.

Hypothesis 3: Female borrowers who self-declare their religiosity and religious connectedness to signal their credit risk are less likelihood to default compared to their male counterparts, *ceteris paribus*.

3.5.3 Empirical data and Method

I describe my data that I use to empirically investigate the impact of self-declared religiosity and religious connectedness on loan performance and cost of debt. I examine the differences among the features of default, non-default, borrowers' self-declared religiosity and undeclared religious affiliation, and their impact loan performance under this theme. Additionally, I discuss the socio-economic and loan-specific features to examine their differences, and comparisons are made between their means and frequencies. Further, I computed the unconditional probabilities of default for the nine categorical variables used in my thesis. The objective is to examine how these features on their own impact on default probabilities, and to show the ability of categorical independent features to discriminate between defaulted, non-defaulted borrowers who are religious and non-religious.

I use two categories of datasets for my empirical analysis. The first cohorts of borrowers I use consist of a total sample size of 12,071 individual liability credit contracts issued to borrowers who were first time clients to the lender and had received their first loan (Cohort I). The second cohorts consist of 749 borrowers who repaid their first debt and had received their second loans from the same lender (Cohort II). The first cohort of borrowers self-declared their religiosity and religious belief to the lender at the loan application stage and prior to the loan disbursal. The second cohort of clients repeated their self-declaration of being religious and to show their religious connectedness to the lender at second loan application stage and prior to signing the second loan contract.

I present a description of the variables that I use for this section of my thesis in tables (28) to (30) below. In total, I use fourteen (14) variables. The variables I use consists of borrower-specific and loan-specific characteristics. The borrower-specific characteristics that I use as control variables are age, gender, profession, employer, income category, mobile phone account ownership, number of identification documents presented by each borrower to the lender and ownership of formal bank account. The loan-specific characteristics are loan amount, interest rate, loan tenor, loan affordability-to-income ratio for each client. Furthermore, I include economic variables, that is, annual gross domestic product (GDP) growth rate and annual inflation rate. Additionally, I use the empirical method in chapter 2, that is, bagged logistic regression and Mundlak's Correlated Random-Effect model for my empirical analysis in this section of my thesis.

In my first sample dataset, that is cohort I, the who were in receipt of their first loan from the lender. Clients in cohort II received their second loan after successfully repaying their first loan. In both cohort I and II of borrowers, more than half (59.48%) and (63.55%) were female compared their male counterparts that constituted 40.52% and 36.45% respectively as shown in table II. When analysed together with the unconditional probability of default in table VI, female borrowers are less likely, 13.73%, to default compared to their male counterparts, 30.89%. In both cohorts I and II of borrowers in my dataset, majority of clients either have at least one (1) or no mobile phone account (83.18% and 55.14%) compared to 16.82% and 44.86% of their counterparts who own two (2) mobile phone accounts.

From my dataset, majority of borrowers, 8,985, representing 74.44% of the total 12,071 clients did not voluntarily self-declare their religious belief or religiosity at the loan application stage. However, 1,979 and 1,107 of the clients declared their religiosity to be associated with the Christian belief and Islamic faith, representing 16.39% and 9.17% respectively. 23.18% of the total borrowers who did not self-declare their religious belief and affiliation defaulted on their loan contracts compared to 15.62% and 0.24% for the Christian and Islam beliefs. When analysed together with the unconditional default probabilities in table II**,** borrowers who self-declared their religiosity to be affiliated to the Islam faith are less likely to default, 2.17%.

The mean age for borrowers who self-declared their religiosity to the lender to be affiliated with the Christian belief, and clients who did not declare their religious affiliation is 40years. This class of borrowers are two (2) years older compared thirty-eight (38) years for borrowers who self-declared their religiosity to be affiliated to the Islam faith. The mean age for female borrowers in this cohort is forty (40) years compared to thirty-nine (39) years for their male counterparts. Additionally, the mean interest rate for female clients is higher, 50.91%, compared to 46.84% for their male counterparts. Borrowers who own bank accounts are less likely to default, 19.83%, compared to 42.45% for clients who do not have a formal bank account, table 50.

Also, even though majority of borrowers own a bank account, significant proportion were in default as shown in table (28). Significant proportion of borrowers in my two datasets are professionals and are employed in the public sector. Being employed in the private sector is associated with a 23.54% likelihood of default compared to 5.89% for borrowers engaged in engaged in the public sector (table 31). Further, borrowers who are professional are less likely, 19.33%, to default on the loan contract compared to 34.37% for their non-professional counterparts. Additionally, majority of borrowers have formal salary as the main source of income to service their debt and are associated with 20.26% likelihood to default when compared to 31.83% for their counterparts who are receipt of formal and informal sources of income.

Branch is the location of the lender's premises where the loans were originated and disbursed. The lender has three (3) branches and located in the three main capital cities, that is, Accra, Kumasi and Takoradi. Majority (41.13%) of borrowers are in the national capital city, followed by Kumasi (39.45%) and Takoradi (19.42%) respectively in the first cohort of borrowers, table (28). This is similar to the second cohorts of borrowers who are repeat clients. Also, majority of borrowers in my dataset have one acceptable document that they use to validate their personal identity to the lender as shown in table (28). When analysed with table (31), clients who have more than one (1) form of acceptable identification documents are more likely to default, 38.86%, compared to 9.91% for their counterparts who possess only one (1) form of personal identification document.

Affordability is a measure used by the lender to determine the loan amount that each borrower may be granted and is determined by the amount of disposable income that each borrower has from their income, both formal and informal. This ranges from a minimum of thirty-five (35) percent to sixty (60) percent in my dataset. More than 99% of the borrowers in my two datasets have affordability ratio greater than thirty-five (35) percent. In analysing this with the unconditional default in table (31), clients with affordability of thirty-five (35) percent are associated with a higher, 88.76% likelihood of default. The minimum age for borrowers who defaulted on their loan is twenty-two (22) years compared to twenty (20) years for non-defaulters.

The loan maturity is essentially how long the loan is approved for. It ranges from a month to ninety-six (96) months. The mean loan maturity for defaulters is thirty-four (34) months compared to twenty-eight (28) months for non-defaulting borrowers as presented in table I. The minimum and maximum loan tenor for clients who self-declared their religiosity to be affiliated to the Christian faith and those who did not disclose their religiosity to the lender is one (1) and ninety-six months for both categories respectively. The average loan tenor for borrowers who self-declared their religiosity at the loan application stage is higher, thirty-three (33) and thirty-five (35) months for clients affiliated to the Christian and Islamic beliefs respectively, compared to twenty-eight (28) months for borrowers who did not declare their religious believe.

The interest rate is the risk premium charged by the lender for taking on the risk of lending. Defaulters were associated with a mean interest rate of 45.68% per annum, compared to 50.19% for their non-defaulting counterparts. borrowers who subscribe to the Christian and Islam believe have mean interest rate of 46.61302% and 44.9045% respective. This is lower when compared to clients who did not declare their religiosity, 50.37948%. When the minimum interest rate charged by the lender is examined, borrowers whose self-declared religiosity is affiliated to the Christian faith is lower, 8.4111%, compared to 29.8659% for Islam, and 13.95354% for clients who did not declare their religiosity to the lender prior to the loan disbursement. This could be due to differences in risk profile.

Loans are in Ghana Cedis (GH¢) which is the local currency. However, for ease of interpretation and comparison I convert the loan amount into United States dollars (US$). The minimum loan offered by the lender is US$142.41. However, when the maximum amount disbursed is compared across the three categories of borrowers, borrowers who did not declare their religiosity received a higher maximum loan amount of US$24,209.63 compared to US$11,677.58and US$9,968.67 for clients who self-declare their religious belief to be affiliated to the Christian and Islam faith respectively. Conversely, the mean loan amount for clients affiliated to the Christian and Islam belief is higher, S$1.314.10 and

US$1,131.45 compared to US$ 1,035.22 who did not declare their religious believe to the lender (table 30).

Table 28. Descriptive statistics for clients in Cohort (I)

VARIABLES	TOTAL SAMPLE (12 ,071) PERCENTAGE	DEFAULT CLIENTS (2,497) PERCENTAGE	NON-DEFAULT CLIENT (9,574) PERCENTAGE
GENDER			
Male	40.52 (4,891)	30.89 (1,511)	69.11 (3,380)
Female	59.48 (7,180)	13.73 (986)	86.27 (6,94)
INCOME CATEGORY			
Salary	96.33 (11,628)	20.68 (2,356)	79.74 (9,272)
Other	3.67 (443)	31.83 (141)	68.17 (302)
EMPLOYER			
Private	16.18 (1,953)	5.89 (115)	94.11 (1,838)
Public	83.82 (10.118)	23.54 (2,382)	76.46 (7,736)
PROFESSION			
Professional	90.96 (10,980)	19.33 (2,122)	80.67 (8,858)
Other	9.04 (1,091)	34.37 (375)	65.63 (716)
IDENTITY INFO.			
>1 Identity Info.	37.22 (4,493)	38.86 (1,746)	61.14 (2,747)
=1 Identity Info.	62.78 (7,578)	9.91 (751)	90.09 (6,827)
AFORDABILITY			
35% (1)	0.74 (89)	88.76 (79)	11.24 (10)
Other (0)	99.26 (11,982)	20.18 (2,418)	79.82 (9,564)
MOBILE PHONE			
2 Phones =1	16.82 (2,030)	13.40 (272)	86.60 (1,758)
Other = 0	83.18 (10.041)	22.16 (2,225)	77.84 (7,816)
BANK ACCOUNT			
Yes	96.12 (11,614)	19.83 (2,303)	80.17 (9,311)
No	3.79 (457)	42.45 (194)	57.55 (263)
BANK BRANCH			
Accra	41.13 (4,965)	20.79 (1,032)	79.21 (3,933)
Kumasi	39.45 (4,762)	17.35 (826)	82.65 (3,936)
Takoradi	19.42 (2,344)	27.26 (639)	72.74 (1,705)

Table 29. Descriptive statistics for clients in Cohort (II)

VARIABLES	TOTAL SAMPLE (749) PERCENTAGE	DEFAULT CLIENTS (74) PERCENTAGE	NON-DEFAULT CLIENT (675) PERCENTAGE
GENDER			
Male	36.45 (273)	13.19 (36)	86.81 (237)
Female	63.55 (476)	92.02 (438)	7.98 (38)
INCOME CATEGORY			
Salary	95.33 (714)	9.52 (68)	90.48 (646)
Other	4.67 (35)	17.14 (6)	82.86 (29)
EMPLOYER			
Private	8.54 (64)	3.13 (2)	96.88 (62)
Public	91.46 (685)	10.51 (72)	89.49 (613)
PROFESSION			
Professional	94.93 (711)	8.44 (60)	91.56 (651)
Other	5.07 (38)	36.84 (14)	63.16 (24)
IDENTITY INFO.			
>1 Identity Info.	31.11 (233)	16.31 (38)	83.69 (195)
=1 Identity Info.	68.89 (516)	6.98 (36)	93.02 (480)
AFORDABILITY			
35% (1)	0.13 (1)	100 (1)	0.00 (0)
Other (0)	99.87 (748)	9.76 (73)	90.24 (675)
MOBILE PHONE			
2 Phones =1	44.86 (336)	9.23 (31)	90.77 (305)
Other = 0	55.14 (413)	10.41 (43)	89.59 (370)
BANK ACCOUNT			
Yes	97.06 (727)	9.77 (71)	90.23 (658)
No	2.94 (22)	13.64 (3)	86.36 (19)
BANK BRANCH			
Accra	41.79 (313)	10.86 (34)	89.14 (279)
Kumasi	79.84 (598)	4.85 (29)	95.15 (569)
Takoradi	18.29 (137)	3.51 (11)	96.49 (302)

Table 30. Descriptive statistics for clients by religiosity, age, and loan terms

RELIGIOSITY	VARIABLES	MINIMUM	MAXIMUM	MEAN	STAND. DEVIATION
Christian belief					
	Age	22	67	40.9146	8.6088
	Loan amount	142.4096	11677.5847	1314.0971	1186.5372
	Loan tenor (months)	1	96	33.0207	21.0953
	Annual Interest Rate	8.4111	72.6594	46.6130	11.9890
Islamic belief					
	Age	25	61	38.88799	8.8052
	Loan amount	142.4096	9968.6699	1131.4549	1026.806
	Loan tenor (months)	4	60	35.2963	21.0677
	Annual Interest Rate	29.8659	72.6594	44.9045	8.9891
Other					
	Age	20	68	40.1488	9.1187
	Loan amount	142.4096	24209.6269	1035.2233	1150.1085
	Loan tenor (months)	1	96	28.43728	20.1186
	Annual Interest Rate	13.95354	72.6594	50.37948	13.8516

Table 31. Unconditional default probabilities for selected variables

VARIABLES	PROBABILITY OF DEFAULT
1. Religiosity	
Christianity	19.71%
Islam	2.17%
Other	23.18%
2. GENDER	
Male	30.89%
Female	13.73%
3. INCOME CATEGORY	
Salary	20.26%
Other	31.83%
4. EMPLOYER	
Public	5.89%
Private	23.54%
5. PROFESSION	
Professional	19.33%
Other	34.37%
6. IDENTITY INFO.	
>1 Identity Info.	38.86%
=1 Identity Info.	9.91%
7. LOAN AFORDABILITY	
35% (1)	88.76%
Other (0)	20.18%
8. MOBILE PHONE OWNERSHIP	
2 Phones =1	13.40%
Other = 0	22.16%
9. BANK ACCOUNT OWNERSHIP	
Yes	19.83%
No	42.45%

3.6 Empirical results and Analysis

I present my main results using bagged Logit regression and Correlated Random-Effect models represented by equation (1) and (2) in tables (32) to (35), which estimate the effect of religiosity on loan performance.

$H1_0$: My empirical results in table (32) and (33) confirm my first hypothesis. That is, borrowers in cohort I who signal their credit risk by voluntarily declaring their religiosity to the lender at the loan application stage, and prior to the loan contract are associated with lower default frequencies across the two main religious beliefs. That is, for the Christian belief, the likelihood of default is reduced by $100\times(e^{\hat{\beta}}-1)$ ≈ -11.6620%. Similarly, for borrowers' who's declared religiosity is affiliated with the Islam belief, the probability of defaulting is reduced by $100\times(e^{\hat{\beta}}-1)$ ≈ -9.3170%. However, the result is significant for borrowers affiliated with the Islam belief.

When borrowers who signal their credit risk by voluntarily declaring their religious connectedness to any of the two beliefs when they apply for second loans are examined, my results in tables (34) and (35) show that the likelihood of default is lower. That is, for every borrower who declare their religious connectedness to the Christian belief at the second loan application stage to signal credit risk, default likelihood is reduced by $100\times(e^{\hat{\beta}}-1)$ ≈ -0.499%, and for Islam belief, the propensity to default is reduced by $100\times(e^{\hat{\beta}}-1)$ ≈ -9.317% respectively. However, the result is only significant for borrowers whose religious connectedness is affiliated to the Islam belief.

I briefly review some of my control variables in table (32) and (33) across the two religious' beliefs. Gender, that is female clients affiliated to both religious beliefs are associated with lower default likelihood for repeat borrowers ((Islam, $100\times(e^{\hat{\beta}}-1)$ ≈ -7.494%, and for Christianity, $100\times(e^{\hat{\beta}}-1)$ ≈ -0.050%)). This result is significant for clients affiliated to the Islam belief. Across the two religious' beliefs, being employed in the public sector, and having a profession with technical skills significantly reduces the likelihood of default. However, borrowers who received loans based on affordability rate of 35% are associated with higher probability to default. This result is significant across the two religious' beliefs. Further, having more than one nationally acceptable personal identification document is associated with higher default. Additionally, a one percent increase in interest rate is associated with an increase in default likelihood by a $100\times(1.01\beta\hat{}1-1) \approx 0.016$ percent, and $100\times(1.01\beta\hat{}1-1) \approx 0.0159$ percent for repeat borrowers whose religious connectedness is affiliated to the Islam and Christian beliefs respectively. However, this is only significant for the Christian belief.

With interest rate as a control variable, my empirical results show that first-time borrowers who signal their credit risk by voluntarily declaring their religiosity to the lender at the loan application stage and prior to the loan contract are associated with the likelihood of higher cost of debt across the two main religious beliefs. That is, for Christian belief, the impact on cost of debt for self-declaring their religiosity to the lender is a likelihood of receiving higher, $100\times(e\beta\hat{}-1) \approx 1.8160\%$ interest rate. I find similar results for borrowers who voluntarily self-declared their religiosity to be affiliated with the Islam belief by $100\times(e\beta\hat{}-1) \approx 8.9810\%$. However, the result is statistically significant for borrowers affiliated with the Islam belief.

$H2_0$: I test my second hypothesis using interest rate charged by the lender as the dependent variable. My results in tables (36) and (37) rejects my second hypothesis that religiosity and religious connectedness (Cohort II) are associated with lower interest rate across the two main religious beliefs. I find contrary evidence, that is, for borrowers who voluntarily self-declare their religiosity to be affiliated to the Christian or Islam belief are more likely to receive higher interest rate on their individual liability credit contracts. For every additional borrower whose religiosity is affiliated to Christian belief, interest rate is likely to increase by $100\times(e\beta\hat{}1-1) \approx 1.816$. Similarly, for the Islam belief, interest rate increases by $100\times(e\beta\hat{}1-1) \approx 8.981\%$ per annum respectively. However, the result is statistically significant for clients affiliated with the Islam belief.

Further, I find a negative impact of religious connectedness on interest rate. That is, borrowers who signal their credit risk by voluntarily declaring their religious connectedness prior to the loan decision and contract are associated with the likelihood of being charged higher interest rate across the two main religious beliefs. That is for one additional client affiliated to the Christian belief, Interest rate is likely to increase by $100\times(e\hat{\beta}1-1) \approx 1.0000\%$ compared to the results for borrowers affiliated with the Islam belief $100\times(e\hat{\beta}1-1)\approx 25.4830\%$, table (38). When all my results are taken together, I find that although voluntary self-declaration of religiosity and religious connectedness across the two main beliefs to signal credit risk prior to the loan contract by borrowers reduces the likelihood of default, this has an inverse impact on the interest rate charged.

I briefly review the effect of some control variables for religiosity on interest rate across the two religious' beliefs. Older borrowers are associated the likelihood of higher interest but is only significant for the Islam belief by $100\times(1.01\hat{\beta}-1) \approx 0.593$ percent. An increase in the loan amount is associated with higher interest rate charge. For example, a 1% increase in the average loan amount for borrowers whose religiosity is affiliated with the Christian belief, US$13, is associated with the likelihood of increase in interest rate by $100\times(1.01\hat{\beta}-1) \approx 0.008$ percent. Similarly, for borrowers whose religiosity is affiliated to the Islam belief, a one percent increase in the average loan amount, US$11, is associated with the likelihood of increase in interest rate by $100\times(1.01\hat{\beta}-1) \approx 0.015$ percent.

borrowers who own a formal bank account are associated with likelihood of higher interest rate, but this significant for the Christian belief by $100\times(e\hat{\beta}-1) \approx 5.760$ percent. This may suggest that the information value of owning a bank account is insignificant in reducing borrower opacity or credit risk to positively impact on loan risk and interest rate. A one percent increase in the loan maturity period is associated with a $100\times(1.01e\hat{\beta}-1) \approx 0.088$ percent, and $100\times(1.01e\hat{\beta}-1)$ ≈ 0.079 percent increase in interest rate for borrowers affiliated to the Islam and Christian beliefs respectively. For one additional client whose loan amount and tenor are determined by an affordability rate of 35%, there is a $100\times(e\hat{\beta}-1) \approx 4.600$ percent, and $100\times(e\hat{\beta}-1) \approx 9.527$ percent increase in loan spread for the Christianity and Islam beliefs respectively.

Being employed in the public sector is associated with a $100\times(e\hat{\beta}-1)\approx 2.737$ percent, and $100\times(e\hat{\beta}-1)\approx 2.942$ percent increase in loan spread for the Christianity and Islam beliefs respectively. Further, across the two religious' beliefs, that is Christian and Islam, an increase in one borrower who is a professional or has technical skills is associated with lower interest rate. However, this is only significant for borrowers affiliated to the Christian belief, $100\times(e\hat{\beta}1-1)\approx$-0.300 percent. For borrowers whose religiosity and religious connectedness is affiliated with the Christian and Islam belief and have more than one nationally acceptable personal identity documents, the interest rate associated with these borrowers is higher across the two religions. The rationale for such increase could be that these borrowers are able to apply for additional credit from different lenders using alternative personal identity document and can lean lead to over indebtedness and higher loan risk.

Both repeat and first-time borrowers employed in the public sector are associated with higher cost of debt. That is, for one additional client employed in the public sector, and who's religiosity is affiliated with the Christian or Islam belief is associated with a $100\times(e\hat{\beta}1-1)\approx 2.737$, and $100\times(e\hat{\beta}1-1)\approx 2.942$ percent respectively when compared to their counterparts in the private sector. Additionally, self-declared religious connectedness to the Christian or Islam belief is associated with a $100\times(e\hat{\beta}1-1)\approx 8.220$, and $100\times(e\hat{\beta}1-1)\approx 8.220$ percent increase in annual interest rate, table (VIII). This result show that though borrowers employed in the public sector are associated with lower default likelihood, their cost of debt is higher compared to their counterparts employed in the private sector.

$H3_0$: Using gender as my independent variable, my result confirms that female borrowers whose religious connectedness is associated with the Christian belief are less likely to default by $100\times(e\hat{\beta}1-1)\approx$ -7.3000%, compared to their male counterparts, table (40). This is significant at the one percent level and confirm prior studies that female clients are more likely to be religious compared to their male counterparts, and hence, this follows that they are less likely to default on their loan contract. Further, I find that male borrowers who voluntarily self-declared their religious connectedness to the Islam belief are associated with a lower default propensity by $100\times(e\hat{\beta}1-1)\approx$ -2.5960%, table (41). This result is significant at five percent level. Female borrowers across both religious groups in Cohort (I) who signal their credit risk by self-declaring their religiosity prior to the loan contract are associated with lower likelihood of default by $100\times(e\beta\hat{}1-1)\approx$ -39.8300%, table (39) and figure (25) is the ROC-AUC that show that my model's performance is 0.886 in correctly classifying borrowers.

I briefly discuss some control variables for borrowers in cohort (II). Females repeat clients who signal their credit risk by voluntarily self-declaring their religious connectedness to be affiliated to the Christian belief and are employed in the public sector are associated with lower loan risk. That is, for one additional female borrower who's declared religious connectedness is affiliated to the Christian belief is associated with a $100\times(e\beta\hat{}1-1)\approx$ -4.084 percent likelihood of loan default. Whether they voluntarily self-declare their religiosity or not, one additional female borrower is associated with a $100\times(e\beta\hat{}1-1)\approx$-0.300 percent decline in the likelihood of default across the two cohorts.

Table 32. Coefficients of the Bagged Logit Model-Christian belief

(Default is the explained Variable)

INDEPENDENT VARIABLES	**Likelihood Ratio Chi-Square = 843.634, df=14, sign. =0.000**	
	COEFF.	**STAND. ERROR**
Religiosity [Christian belief]	-0.1240	0.1784
Control Variables		
Borrower Age	0.2910	0.3044
Gender (Female)	-0.7450****	0.1380
Mobile phone account ownership (=2)	-0.5650***	0.2043
Borrower Identity Document (More than 1)	2.3510****	0.1854
Professionals	-0.5710***	0.1974
Employer (Public sector)	-1.6940****	0.2689
Income Category (Formal Salary)	-1.2060****	0.2925
Borrower Affordability=35%	na	na
Loan Amount	0.2870****	0.0830
Loan Tenor	0.5980****	0.1038
Interest Rate	-0.0810	0.3482
Bank Account ownership	-0.9650****	0.2739
GDP	11.8940****	0.7373
Intercept	-35.2230****	2.8221
a= Model classification accuracy	a= 86.20, R2 = 0.637	

Asterisks: ****Indicates a coefficient significantly different from zero at the <1%,***1%, ** at 5%; and *at the 10% level

Table 33 Coefficients of the Bagged Logit Model-Islam belief

(Default is the explained variable)

INDEPENDENT VARIABLES	Likelihood Ratio Chi-Square =973.538, df=14, sign. =0.000	
	COEFF.	STAND. ERROR
Religiosity [Islamic belief]	-2.3360****	0.4881
Control Variables		
Borrower Age	0.5940**	0.3014
Gender (Female)	-0.9680****	0.1369
Mobile phone account ownership (=2)	-0.3560*	0.1965
Borrower Identity Document (More than 1)	2.2050****	0.1753
Professionals	-0.3990**	0.197
Employer (Public sector)	-1.7380****	0.244
Income Category (Formal Salary)	-0.7920***	0.2849
Borrower Affordability=35%	3.8040****	0.8151
Loan Amount	0.3300****	0.0812
Loan Tenor	0.5410****	0.1012
Interest Rate	-0.4020	0.3241
Bank Account ownership (Yes)	-0.4800*	0.2924
GDP	10.8870****	0.7188
Intercept	-33.5940****	2.8663
a= Model classification accuracy	a= 85.60, R^2 = 0.587	

Asterisks: ****Indicates a coefficient significantly different from zero at the <1%,***1%, ** at 5%; and *at the 10% level

Table 34. Coefficients of the panel model-Christian belief

(Default is the explained variable)

Independent Variable	**Coefficient**	**Std. Err.**	**z**	**P>z**	**[95% conf.**	
Religious Connectedness (Christian Belief)	-0.005	0.0218	-0.2300	0.8190	-0.0480	0.0378
Control Variables						
Borrower Identity Document (More than 1)	0.0229	0.0129	1.7800	0.0750	-0.0020	0.0482
Borrower Age	-2.1738	1.8846	-1.1500	0.2490	-5.8680	1.5199
Gender	-0.0005	0.0219	-0.0200	0.9810	-0.0430	0.0424
Income Type (Formal)	-0.0363	0.0254	-1.4300	0.1520	-0.0860	0.0134
Employer (Public sector)	-0.0455	0.0192	-2.3700	0.0180	-0.0830	-0.008
Profession (Professional)	-0.1198	0.0243	-4.9200	0.0000	-0.1680	-0.072
Borrower Affordability=35%	0.4256	0.1446	2.9400	0.0030	0.1423	0.709
Mobile phone account ownership (=2)	-0.0062	0.0121	-0.5100	0.6090	-0.0300	0.0176
Bank Account	-0.0206	0.0313	-0.6600	0.5110	-0.0820	0.0407
Loan Amount	-0.0104	0.0202	-0.5100	0.6070	-0.0500	0.0292
Loan Tenor	-0.0201	0.0226	-0.8900	0.3730	-0.0640	0.0242
GDP	0.579	0.1821	3.1800	0.0010	0.2221	0.9359
Interest Rate	0.0822	0.0222	3.7000	0.0000	0.0387	0.1257
Intercept	-1.8666	0.4991	-3.7400	0.0000	-2.8450	-0.888
Wald chi2(17)	206.62		Number of obs.	1498		
Prob > chi2	0.0000		Number of groups	749		
R-squared:						
Within	0.1021					
Between	0.1452					
Overall	0.1225					

Table 35. Coefficients of the panel model-Islam belief

(Default is the explained variable)

Explanatory variables	**Coefficient**	**Std. Err.**	**z**	**P>z**	**[95% conf. interval]**	
Religious Connectedness (Islam)	-0.0978	0.0213	-4.6000	0.0000	-0.1394	-0.0561
Control Variables						
Borrower	-2.1738	1.8800	-1.1600	0.2480	-5.8584	1.5109
Loan Amount	-0.0104	0.0202	-0.5200	0.6060	-0.0499	0.0291
Loan Tenor	-0.0201	0.0225	-0.8900	0.3720	-0.0642	0.0240
GDP	0.5790	0.1817	3.1900	0.0010	0.2230	0.9351
Interest Rate	0.0159	0.0226	0.7000	0.4810	-0.0284	0.0603
Gender (Female)	-0.0779	0.0191	-4.0700	0.0000	-0.1154	-0.0404
Income (Salary)	-0.0156	0.0259	-0.6000	0.5470	-0.0663	0.0351
Employer (Public sector)	-0.0417	0.0192	-2.1800	0.0300	-0.0794	-0.0041
Profession (Professional)	-0.1239	0.0243	-5.1000	0.0000	-0.1715	-0.0763
Borrower Identity Document (More than 1)	0.0153	0.0132	1.1600	0.2460	-0.0106	0.0412
Borrower Affordability=35%	0.3831	0.1446	2.6500	0.0080	0.0997	0.6665
Mobile phone account ownership (=2)	0.0107	0.0126	0.8500	0.3970	-0.0140	0.0353
Bank account ownership (Yes)	-0.0153	0.0312	-0.4900	0.6240	-0.0765	0.0459
Intercept	-1.5745	0.4942	-3.1900	0.0010	-2.5431	-0.6058
sigma_u	0.0000					
sigma_e	0.2112					
rho	0.0000					
Wald chi2(17)	230.6100		Number of obs	1498		
Prob > chi2	0.0000		Number of groups	749		
R-square: Within = 0.1021 Between = 0.1712 Overall = 0.1348						

Table 36. Coefficients of the Logit Model -Religiosity (Christian belief) and Loan spread.

(Interest Rate is the explained Variable)

INDEPENDENT VARIABLES	Likelihood Ratio Chi-Square =4353.63, df=13, sign. =0.000	
	COEFF.	STAND. ERROR
Religiosity [Christian belief]	0.0180****	0.0051
Control Variables		
Borrower Age	0.0190**	0.0086
Gender (Female)	-0.0200****	0.0040
Mobile phone account ownership (=2)	0.0270****	0.0051
Borrower Identity Document (More than 1)	0.0790****	0.0042
Professionals	-0.0030****	0.0067
Employer (Public sector)	0.0270****	0.0051
Income Category (Formal Salary)	0.0060	0.0100
Borrower Affordability=35%	0.0450**	0.0220
Loan Amount	0.0080****	0.0024
Tenor	0.0790****	0.0027
Bank Account ownership	0.0560****	0.0098
Inflation Rate	-0.4610****	0.0100
Intercept	3.7450****	0.0473

Asterisks: ****Indicates a coefficient significantly different from zero at the <1%,***1%, ** at 5%; and *at the 10% level

Table 37. Coefficients of the Logit Model -Religiosity (Islam belief) and Loan spread

(Interest rate is the explained variable)

Independent Variable	**Likelihood Ratio Chi-Square =1043.903, df=13, sign. =0.000**	
	COEFF.	**STAND. ERROR**
Religiosity [Islamic belief]	0.0860****	0.0158
Control Variables		
Borrower Age	0.0190	0.0185
Gender (Female)	-0.011	0.0095
Mobile phone account ownership (=2)	0.0540****	0.0112
Borrower Identity Document (More than 1)	0.0880****	0.0092
Professionals	-0.0020	0.0143
Employer (Public sector)	0.0290***	0.0106
Income Category (Formal Salary)	-0.0250	0.0202
Borrower Affordability=35%	0.0910***	0.0465
Loan Amount	0.0150****	0.0052
Tenor	0.0880***	0.0058
Bank Account ownership	0.034	0.0217
GDP	-0.4330****	0.0213
Intercept	3.6380****	0.1009
	R^2 = 0.345	
Asterisks: ****Indicates a coefficient significantly different from zero at the <1%,***1%, ** at 5%; and *at the 10% level		

Table 38. Coefficient of Logit regression: Religious connectedness on Loan spread.

(Interest rate is the explained variable)

Independent Variable	Likelihood Ratio Chi-Square = 156.026, df=12, sign. =0.000	Likelihood Ratio Chi-Square =219.125, df=12, sign. =0.000
	Christian belief	Islamic belief
	Coefficient (Stand. Error)	Coefficient (Stand. Error)
Religious Connectedness	0.0100 (0.0361)	0.2270**** (0.0298)
Control Variables		
Borrowers Age	0.0030 (0.0392)	0.0030 (0.0368)
Gender (Female)	0.0240 (0.0363)	0.0020 (0.0190)
Mobile phone account ownership (=2)	0.2330*** (0.0192)	0.2030**** (0.0179)
Borrower Identity Document (More than 1)	0.0470** (0.0199)	0.1160**** (0.0217)
Professionals	-0.0250 (0.0401)	-0.0170 (0.0386)
Employer (Public sector)	0.0790*** (0.0317)	0.0800**** (0.0303)
Income Category (Formal Salary)	-0.0180 (0.0419)	-0.1950**** (0.0462)
Borrower Affordability=35%	-0.1190 (0.2391)	-0.0150 (0.2296)
Loan Amount	0.0120 (0.0131)	0.0150 (0.0126)
Loan Tenor	0.0780**** (0.0210)	0.0910**** (0.0240)
Bank Account ownership	-0.0360 (0.0517)	-0.0540 (0.0496)
GDP	na	na
Intercept	0.2120 (0.1899)	0.1670 (0.1764)

Asterisks: ****Indicates a coefficient significantly different from zero at the <1%,***1%, ** at 5%; and *at the 10% level

Table 39. Coefficient of Logit regression results for Religiosity (Christian belief) and Gender on Loan Risk.

(Default is the explained variable)

Independent Variable	**Likelihood Ratio Chi-Square =4512.882, df=13, sign. =0.000**	
	COEFF.	**STAND. ERROR**
Religiosity_(Female)	-0.5080***	0.1030
Control Variables		
Borrower Age	0.5990***	0.1330
Mobile phone account ownership (=2)	-0.5530***	0.0850
Borrower Identity Document (More than 1)	2.4970***	0.0780
Professionals	-0.5860***	0.0870
Employer (Public sector)	-2.0910***	0.1240
Income Category (Formal Salary)	-0.5850***	0.1380
Borrower Affordability=35%	3.6490***	0.3880
Loan Amount	0.2660***	0.0350
Loan Tenor	0.5300***	0.0450
Interest Rate	-0.3370**	0.1490
Bank Account ownership (Yes)	-0.9220***	0.1200
GDP	11.9380***	0.3120
Intercept	0.2120	0.1899

a= Model classification accuracy	a= 84.80, R^2 = 0.6190

Asterisks: ***Indicates a coefficient significantly different from zero at the <1%,**1%, and *at the*at 5% level

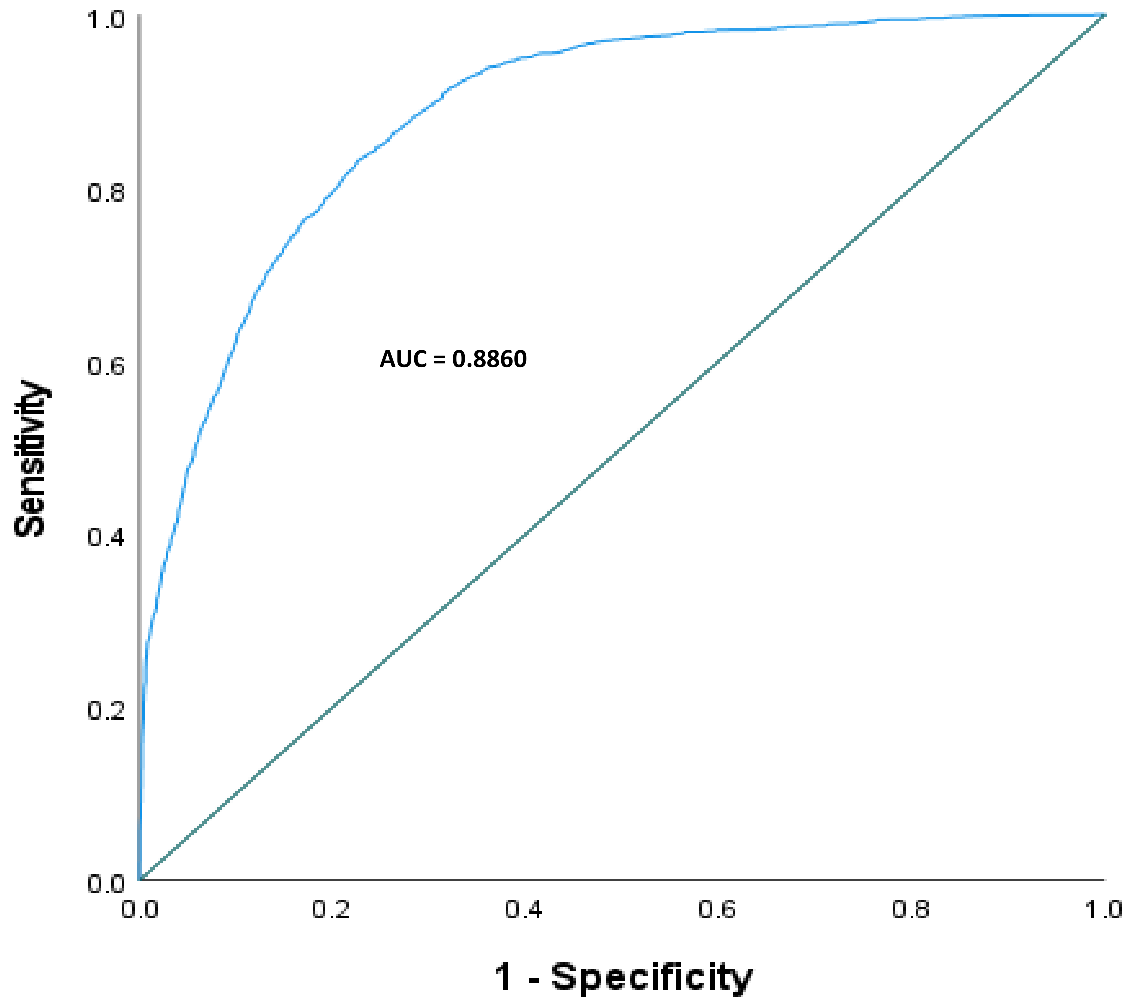

Figure 25. ROC-AUC Graph for female religious clients (Cohort I) and Loan Risk using Logit Model

Table 40. Coefficients of the panel model- Religious Connectedness (Christian belief) and Gender on Loan Risk.

(Default is the explained variable)

Independent Variable	**Coefficient**	**Std. err.**	**z**	**P>z**	**[95% conf. interval]**	
RelCH_Gender(Female)*	-0.0758	0.0185	4.0900	0.0000	-0.1121	-0.0394
Control Variables						
Borrower Identity Document (More than 1)	-0.0002	0.0139	0.0100	0.9900	-0.0275	0.0271
Borrower Age	-2.1738	1.8735	1.1600	0.2460	-5.8458	1.4983
Income Category (Formal Salary)	-0.0109	0.026	0.4200	0.6750	-0.0618	0.0400
Employer (Public sector)	-0.0417	0.0191	2.1800	0.0290	-0.0791	-0.0043
Profession (Professional)	-0.1234	0.0242	5.1000	0.0000	-0.1709	-0.0760
Borrower Affordability=35%	0.3855	0.144	2.6800	0.0070	0.1032	0.6677
Mobile phone account ownership (=2)	0.0075	0.0124	0.6100	0.5450	-0.0168	0.0317
Bank Account ownership (Yes)	-0.0118	0.0311	0.3800	0.7040	-0.0728	0.0492
Loan Amount	-0.0104	0.0201	0.5200	0.6050	-0.0497	0.0290
Loan Tenor	-0.0201	0.0224	0.9000	0.3710	-0.0641	0.0239
GDP	0.579	0.181	3.2000	0.0010	0.2242	0.9338
Interest Rate	0.0597	0.0227	2.6300	0.0090	0.0151	0.1042
Intercept	-1.7694	0.4966	3.5600	0.0000	-2.7426	-0.7961
Wald chi2(17)	241.35		Number of obs.	1498		
Prob > chi2	0		Number of groups	749		
R-squared:						
Within	0.1021					
Between	0.1824					
Overall	0.1401					

Note: *Female borrowers who voluntarily self-declared their religious connectedness to the Christian belief.

Table 41. Coefficients of the panel model- Religious Connectedness (Islam belief) and Gender on Loan Risk (Default is the explained variable)

Independent Variable	Coefficient	Std. Err.	z	P>z	[95% conf. interval]	
Relig [ISlam]*	-0.0263	0.0129	-2.0400	0.0410	-0.0516	-0.0011
Control Variables						
Borrower Identity Document (More than 1)	0.0220	0.0127	1.7300	0.0830	-0.0029	0.0470
Borrower Age	-2.1738	1.8814	-1.1600	0.2480	-5.8613	1.5138
Income Type (Formal)	-0.0314	0.0254	-1.2300	0.2170	-0.0812	0.0185
Employer (Public sector)	-0.0474	0.0192	-2.4800	0.0130	-0.0850	-0.0099
Profession (Professional)	-0.1195	0.0243	-4.9200	0.0000	-0.1671	-0.0719
Borrower Affordability=35%	0.4241	0.1442	2.9400	0.0030	0.1415	0.7068
Mobile Phone Account Ownership (=2)	-0.0083	0.0119	-0.7000	0.4870	-0.0316	0.0150
Bank Account ownership (Yes)	-0.0205	0.0312	-0.6600	0.5110	-0.0816	0.0406
Loan Amount	-0.0104	0.0202	-0.5100	0.6070	-0.0499	0.0291
Loan Tenor	-0.0201	0.0225	-0.8900	0.3730	-0.0643	0.0241
GDP	0.5790	0.1818	3.1800	0.0010	0.2227	0.9353
Interest Rate	0.0805	0.0221	3.6400	0.0000	0.0372	0.1239
Intercept	-1.8459	0.4982	-3.7100	0.0000	-2.8224	-0.8695
Wald chi2(17)	226.9300		Number of obs	1498		
Prob > chi2	0.0000		Number of groups	749		
R-squared:						
Within	0.1021					
Between	0.1671					
Overall	0.1329					

Note: *Male borrowers who declared their religious connectedness to the Islam belief.

3.6.1 Robustness test results

I perform a series of robustness test using three different algorithms. First, I use the classification and regression tree (CRT) method to examine my main results. That is, the impact of borrowers voluntary self-declared religiosity and religious connectedness on loan risk and cost of debt in individual liability credit contracts. Additionally, I evaluate the robustness of my results for gender, religion, and loan performance. I present my results using the CRT model in figures (26) to (29). The dependent variables in each of my decision tree is the default status of each borrower across the two cohorts which has two classes, default (1) or non-default (0). The root of my tree contains all the total observations for each cohort of borrowers in my dataset.

The pruned decision tree obtained using classification and regress tree (with Gini impurity measure is shown in Figures (26) and (27) for borrowers' whose affiliated religiosity is with the Christian belief and figures (28) and (29) for Islam. The errors associated with classification and regress tree (CRT) model is 0.152 and 0.167 for both religious beliefs, that is, Christianity and Islam respectively. My results show that there is no significant difference in the likelihood of default for borrowers who declared their religiosity, and religious affiliation with the Christian belief compared to borrowers affiliated to other religious affiliations or those who did not signal their credit risk using self-declared religiosity to the lender. I find contrary evidence for borrowers affiliated to Islam. That is, the difference in default likelihood is significant, 2.30% for clients whose self-declared religiosity is affiliated to the Islam faith compared to borrowers who did not declare their religiosity, 22.30%. These results confirm my main finding.

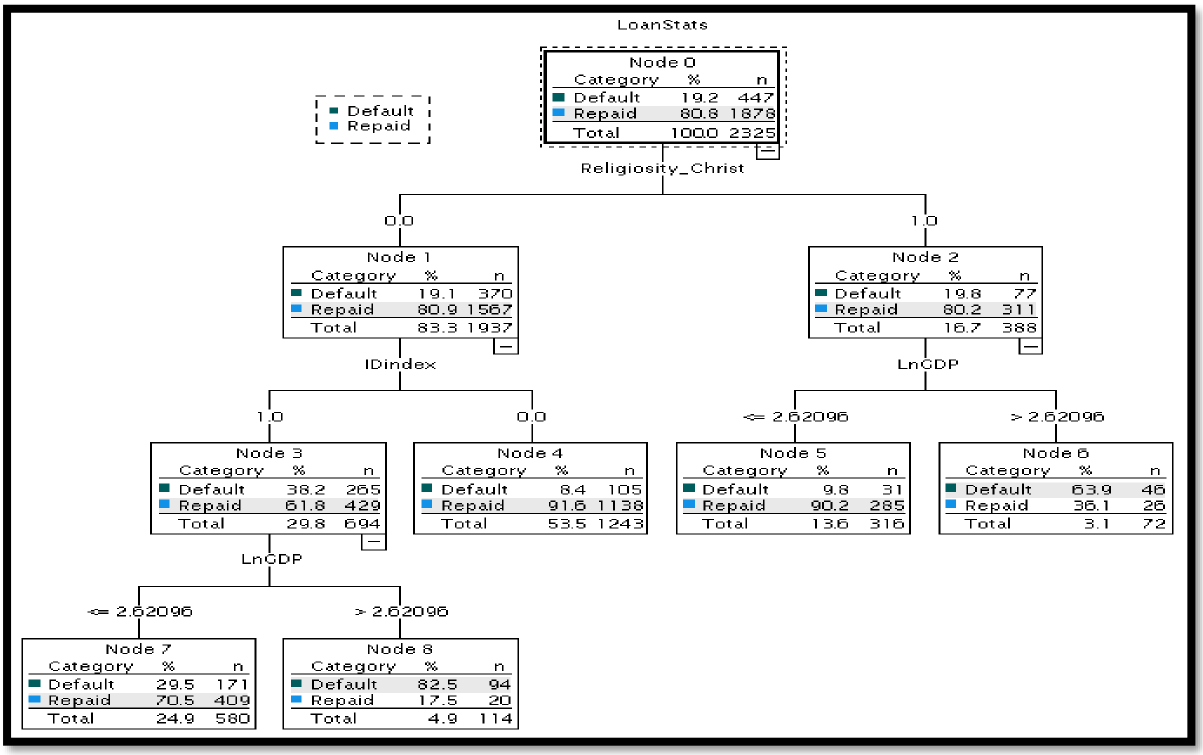

Figure 26. Classification and regression tree model result for Religiosity (Christian belief) on Loan Risk

Estimated Risk= 0.152, Accuracy= 84.80%, Standard Error =0.007, R^2 =0.772

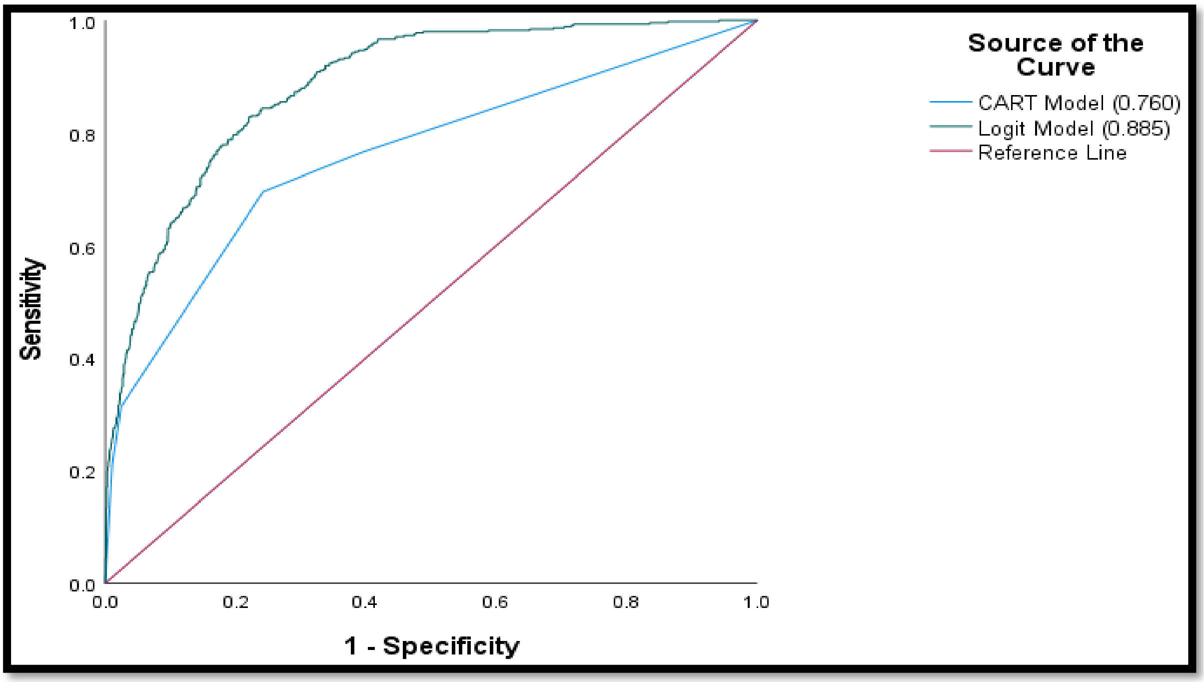

Figure 27. ROC Graph for regression of Religiosity (Christian belief) on Loan Risk using the Classification and regression tree and Logit Models

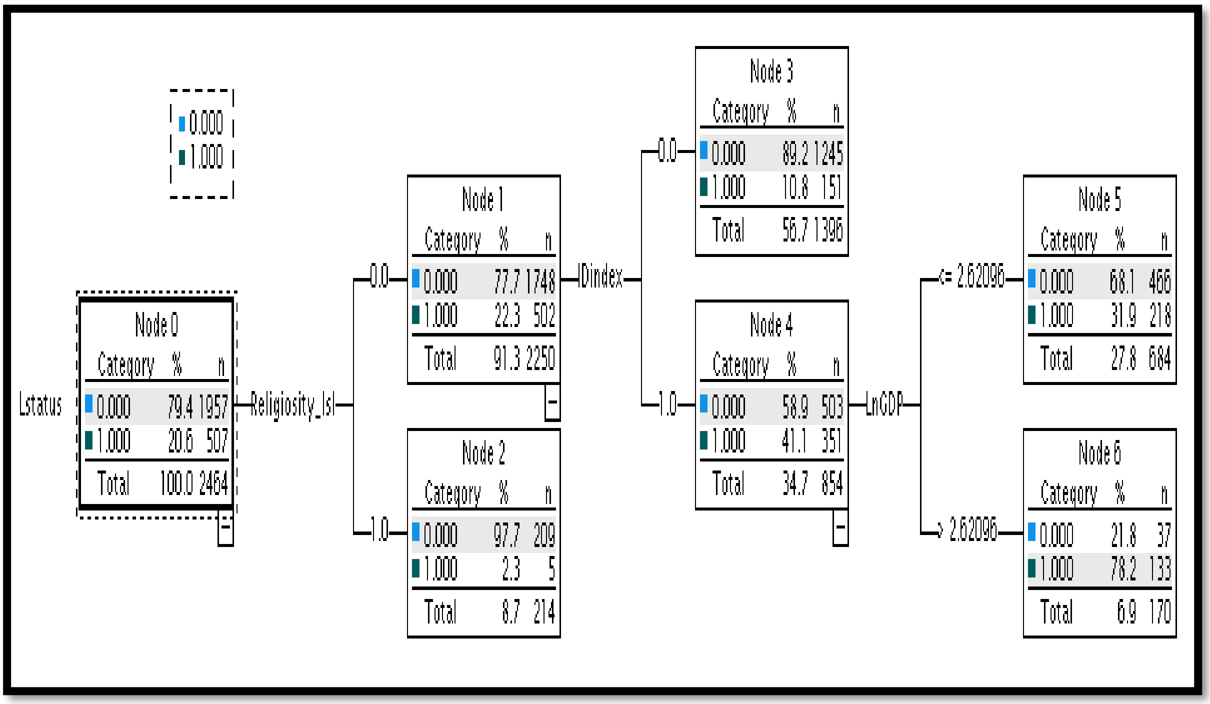

Figure 28. Classification and regression tree model result for Religiosity (Islam belief) on Loan Risk

Estimated Risk= 0.167, Accuracy= 83.30%, Standard Error =0.008, R^2 =0.851

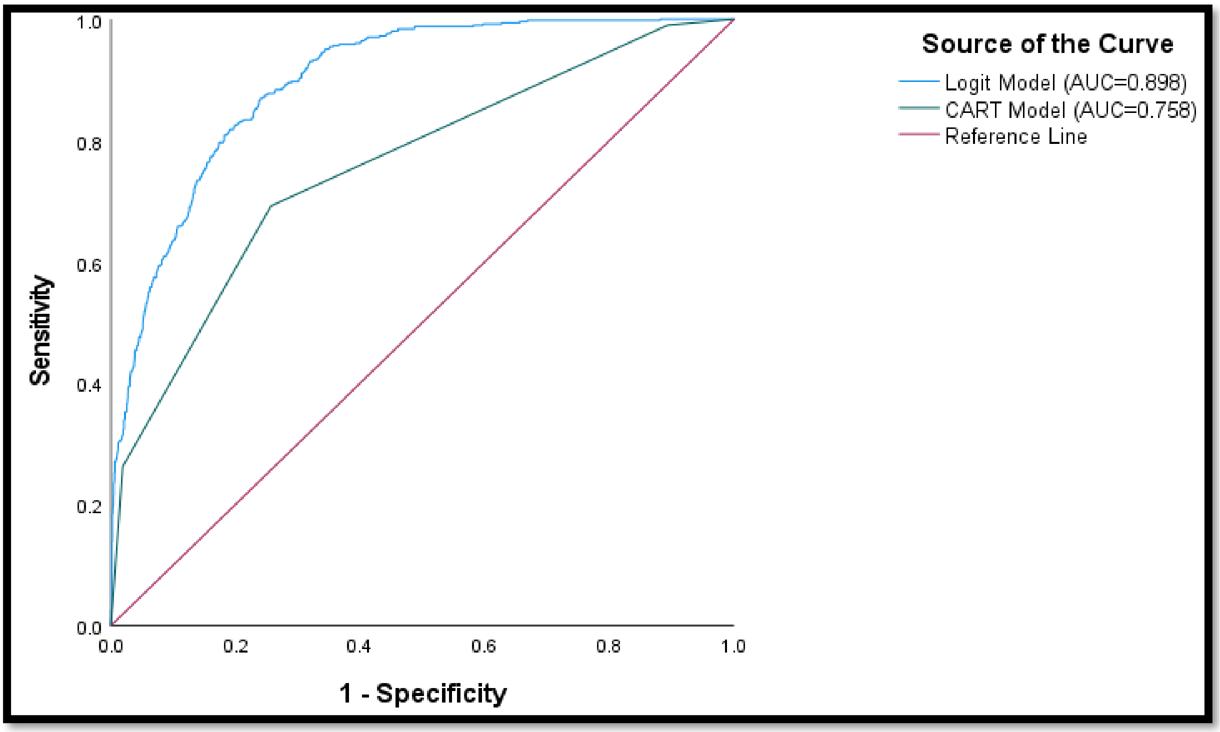

Figure 29. ROC Graph for regression of Religiosity (Islam belief) on Loan Risk using the Classification and regression tree and Logit Models

Second, I robust test my main results in tables (32) and (33) that show that religiosity positively impacts on loan risk by controlling for branch-effect. I use the logit regression model and I present my results in appendix (B) supplementary tables (62) and (63). I find that default likelihood is reduced for one additional borrower who voluntary self-declare their religiosity to signal their trust worthiness at the loan application stage. That is, for every increase of one client who self-declare their religiosity to be is affiliated to the Christian belief is associated with a $100\times(e^{\hat{\beta}_1}-1)\approx$ -10.506 percent change in the likelihood of loan default in Accra, $100\times(e^{\hat{\beta}_1}-1)\approx$ -9.787 for Kumasi, and $100\times(e^{\hat{\beta}_1}-1)\approx$ -52.001 for borrowers in Takoradi. For clients affiliated to the Islam belief, I find similar results.

Third, using the classification and regression tree model and controlling for the branch effect, I find that default likelihood for borrowers who voluntarily self-declared their religiosity to be affiliated to the Christian belief is higher, 22.02% in Accra. The associated model accuracy and ROC-AUC are 83.00% and 0.83, figure 34 and 35. However, I find contrary results for borrowers in Kumasi and Takoradi. That is, the propensity to renege on their individual liability credit contract is lower for Kumasi, 16.40%, and Takoradi, 20.90% respectively. The results for Kumasi and Takoradi also achieved model accuracies of 87.20% and 83.00%, and ROC-AUCs of 0.755 and 0.877, appendix (A) supplementary figures (51) to (56).

Additionally, in appendix (A) supplementary figures (57) to (62) I present the result for the impact of religiosity (Islam belief) on loan risk and controlling for branch effect. I find significant positive impact of religiosity (Islam belief) on loan risk across the three main cities. That is, the likelihood of default is 2.30% in Accra, 1.40% in Kumasi, and 3.60% in Takoradi respectively. Compared to 22.70%, 19.00% and 29.40% for their counterparts who’s declared religiosity is not affiliated to Islam or who did not voluntarily declare their religiosity at the loan application stage to signal their trustworthiness. The ROC-AUC for the model in each of the three branches are 0.883, 0.769 and 0.895 for that Accra, Kumasi and Takoradi branches.

3.6.2 Gender and loan risk

I provide a robustness test for my main result in tables (58) and (59) that examined the relationship between female religious borrowers who signalled their trustworthiness by voluntarily self-declaration of religiosity and religious connectedness, and their likelihood of loan default. First, I use probit model and I present my result in table (64) in appendix (B) containing supplementary tables. My results show that the likelihood of default for female borrowers who voluntarily self-declared their religiosity to signal to be 'good' credit risk and trustable are associated with lower propensity to default on their individual liability loan contracts. That is, for an increase of one additional female borrower who voluntarily self-declare their religiosity to signal credit risk is associated with a $100\times(e\beta\hat{}1-1)\approx$-25.40 percent change in default likelihood.

Second, I examine the impact of gender and religious connectedness on loan risk, and controlling for the bank branch where the loans were originated and disbursed. I measure religious connectedness as the repeated self-declaration by borrowers at the second loan application stage, and I present my results in appendix (B) supplementary tables (65) to (67). I find that for females who declared their religious connectedness to be affiliated with the Christian belief to signal their trustworthiness to the lender, the default likelihood is significantly reduced across all the three regional capitals. That is, for an increase of one additional female borrower who voluntarily self-declare their religious connectedness (Christian belief) to signal credit risk is associated with a $100\times(e\beta\hat{}1-1)\approx$-6.049 percent change in default likelihood in Accra, $100\times(e\beta\hat{}1-1)\approx$-12.085 percent in Kumasi, and $100\times(e\beta\hat{}1-1)\approx$-8.323 percent in Takoradi respectively.

Additionally, for male borrowers whose affiliated religious connected is to the Islamic faith, I find similar results across all the three branches of the lender where the loans were originated and disbursed. That is, for an increase of one additional male borrower who voluntarily self-declare their religious connectedness (Islam belief) to signal to be 'good' credit risk and trustable is associated with a $100\times(e\beta\hat{}1-1)\approx$-3.835 percent change in default likelihood in Accra,

$100\times(e\beta\hat{}1-1)\approx$-0.678 percent in Kumasi, and $100\times(e\beta\hat{}1-1)\approx$-5.720 percent in Takoradi respectively. Except for Kumasi branch that the result is statistically insignificant, my findings for the largest capital city of Accra and the third largest city of Takoradi are significant, appendix (B) supplementary tables (68) to (70).

3.6.3 Religiosity and Religious Connectedness on Cost of debt

My machine learning model using the classification and regression tree confirm my main results in tables (51) and (52) that borrowers who voluntary self-declare their religiosity and religious connectedness are associated with the likelihood of higher loan spread. That is, clients who declare their religiosity to be affiliated with the Christian and Islam belief to signal to the lending intstitution to be trustable and 'Good' credit risk at the loan application stage, are associated with the likelihood of being charged an interest rate of 55.00% and 53.90% per annum, compared to 43.60% and 50.06% for loan applicants who do not declare their religiosity or religious connectedness, figures (46) and (47). However, this is lower compared to the maximum interest rate of 72.00% charged by the lender.

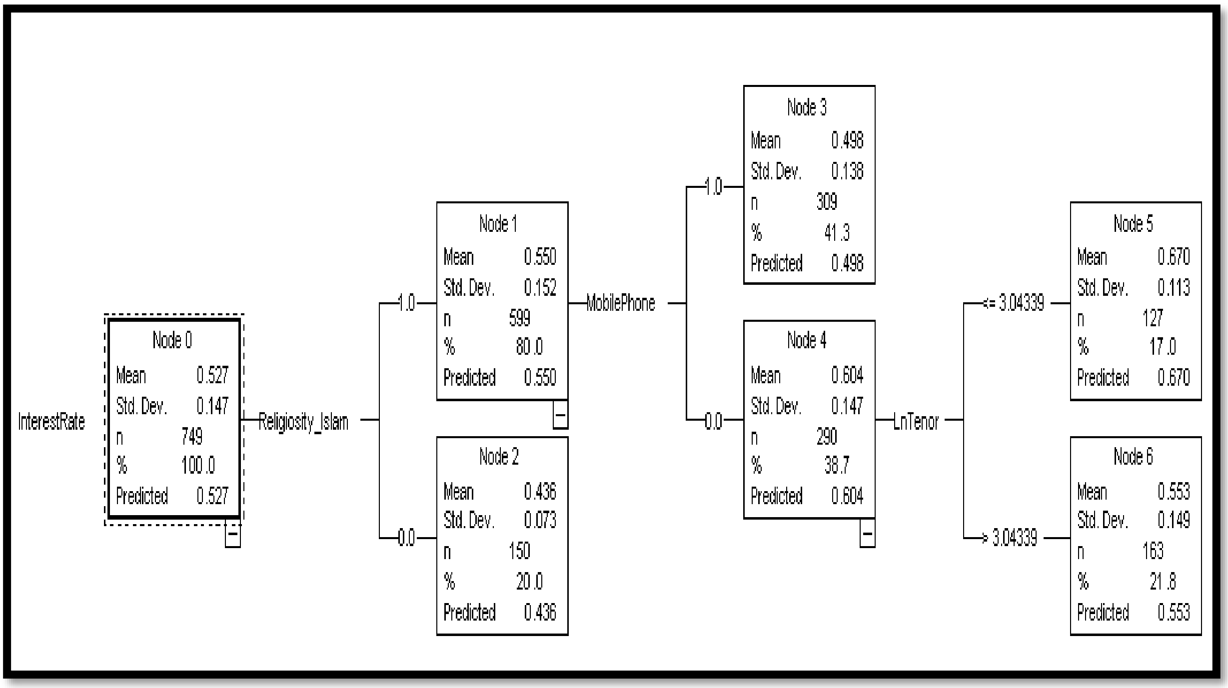

Figure 30. Classification and regression tree model result for Religious Connectedness (Islam belief) on Loan Spread

Estimated risk =0.016 std. error = 0.001

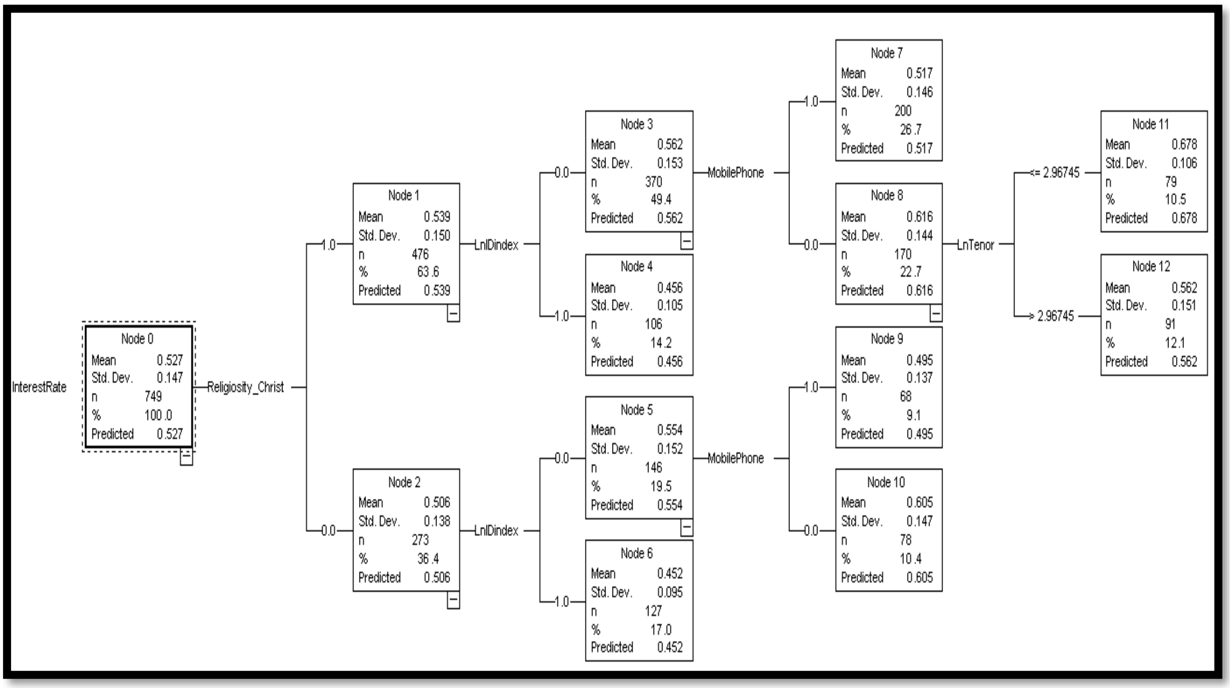

Figure 31. Classification and regression tree model result for Religious Connectedness (Christian belief) on Loan Spread

Estimated Risk= 0.017 Standard Error =0.002.

3.6.4 Performance measurement

I provide the accuracy and precision score for each of the models I use in my analysis to investigate the relation between borrower self-declared religiosity and religious connectedness on loan risk and cost of debt. Precision represents the ratio of defaulted borrowers to be judged correctly and measures how many of my "positive" predictions made by the model were correct. The 'accuracy' metric I use measures how many times my model made a correct prediction across my entire dataset. Finally, I use the F1 score to measure the performance of the machine learning models I use in my analysis. This metric uses the combined harmonic mean of the precision score and recall[16] to maximise the F1 score and has been widely used method to evaluate the performance of scoring models.

[16] This measures how many of the positive class samples present in my dataset were correctly identified by my model.

Additionally, from figure (LII) my Logit model achieved the lowest error rate of 0.1402, followed by the random forest, 0.1474, and 0.1518 for the classification and regression tree (CRT) model. Also, when I examine the accuracy and precision score of my models, I find that my bagged Logit model achieved the highest accuracy and precision score of 0.885 and 0.898 respectively. My random forest model achieved the second-best performance with a score of 0.8526 and 0.8477 for accuracy and precision, Figure (LIII). My logit model achieved the highest F-score 0.9177, followed by bagged random forest and the Classification and regression tree models with F-scores of 0.9131 and 0.9121 respectively. Taken together, the results show that my bagged logistic regression outperformed the classification and regression tree (CRT) and Random Forest Models. Table (XXIII) provides similar results when I control for the branch-effects.

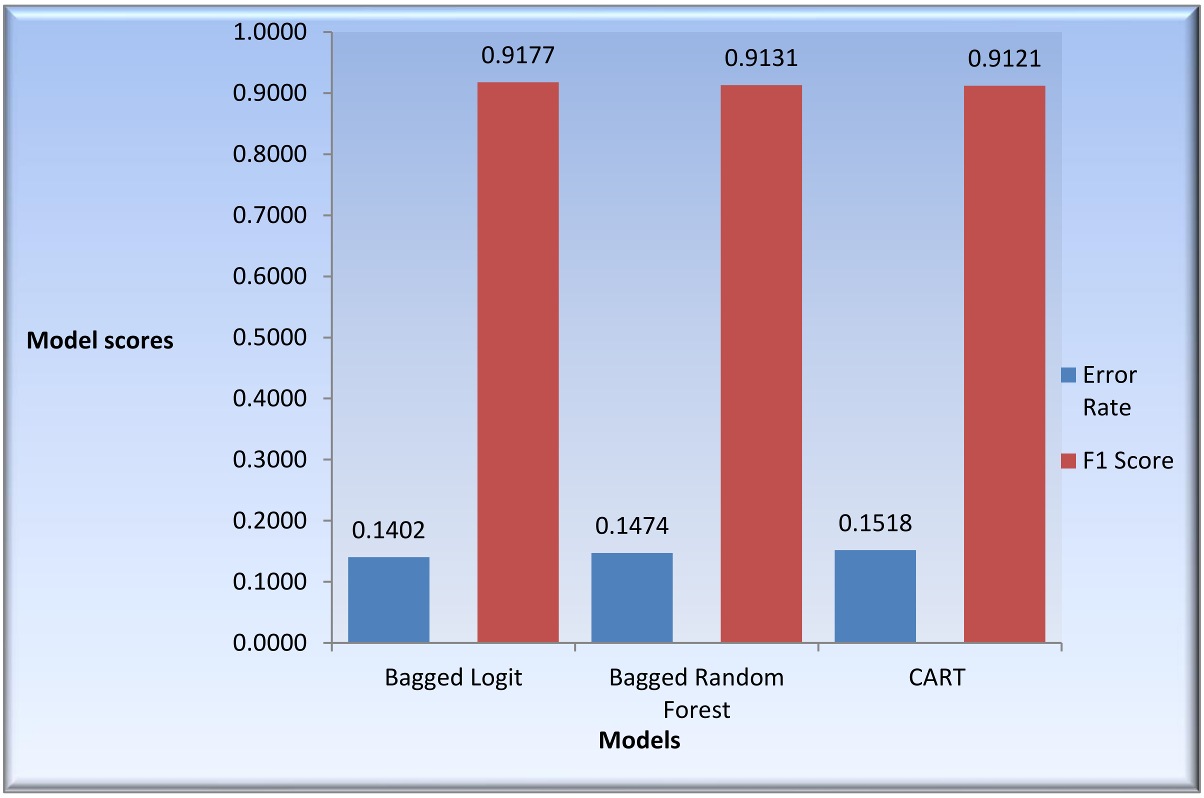

Figure 32. Graph of model performance for religiosity and Loan Risk -Error rate and F1-Score.

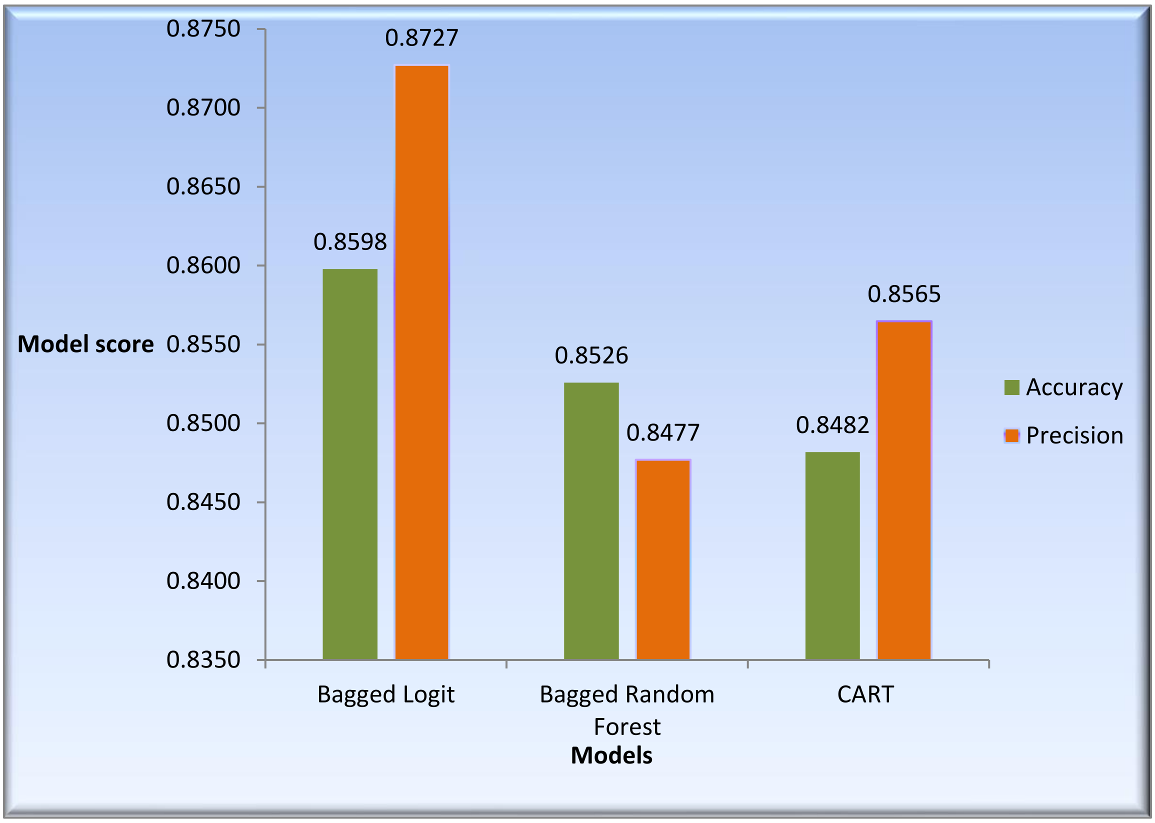

Figure 33. Graph of model performance for religiosity and Loan Risk - Accuracy and Precision.

3.6.5 Conclusion

In this section of my thesis, that is, chapter 4, I have examined the impact of borrowers' voluntary self-declared religiosity and religious connectedness at the loan application stage, and its impact on the performance of their individual liability credit contracts in a consumer loan setting. My empirical results show that individuals' religiosity and religious connectedness positively impact on loan performance. Additionally, my results show that females who declare their religiosity and religious connectedness (Christian belief) are associated with lower default likelihood. I find similar results for males affiliated to the Islam belief. Further, I find that borrowers' self-declaration of their religiosity and religious connectedness to signal to be trustable does not lead to the likelihood of being charged lower interest rate. On the contrary, my results show that self-declared religiosity and religious connectedness are associated with the likelihood of higher loan spread.

CHAPTER 4: FINANCIAL TECHNOLOGY AND PAYMENT SYSTEMS

WHAT IS THE IMPACT OF FINTECH ON PAYMENT SYSTEMS, SIGNIORAGE AND FINANCIAL INCLUSION? EVIDENCE FROM MOBILE MONEY IN KENYA

4.1 Introduction

In the last two decades, Fintech, that is mobile money wallet, have transformed the payment system landscape in developing countries. Further, the rapid digitalization agenda in several developing economies, particularly their financial sector is changing the many residents the developing world access and use financial services. This has allowed individuals and organisations to make payment via a mobile phone and has become enormously popular and competing with traditional payment systems. According to the International Monetary Fund, '*mobile money is a pay-as-you-go digital medium of exchange and store of value using mobile money accounts, facilitated by a network of mobile money agents. It is a financial service offered to its clients by a mobile network operator or another entity that partners with mobile network operators, independent of the traditional banking network. A bank account is not required to use mobile money services—the only pre-requisite is a basic mobile phone'*.

Mobile money providers, who are usually mobile telecom operators, issue mobile money and keep the electronic account on the SIM card in the mobile phone for their customers to use for savings, insurance, and other related financial transactions that meet the needs of mobile money account holders. According to the Global System for Mobile telecommunication Association (2013), speed of payment transactions, convenience, flexibility, and affordability are some of the benefits that accrue to users of Fintech platforms for mobile banking and payments. Electronic payments platforms across a number of developing economies in Africa using financial innovation technologies such mobile money has been on the ascendancy in the past decade, and a well-functioning system of payment is considered vital for ensuring that the financial sector is stable and safe. Further, an improvement in payment systems will reflects in the entire economy via its inter-linkages with the fiscal, external and the real sectors to the benefit of the developing countries and their residents.

Additionally, a country's payment system can significantly impact on its financial market. Robinson and Flatraaker (1995) and Humphrey and Berger (1990) show in their empirical works that a country's payment system is associated with social cost that ranges between two (2) to three (3) percent of gross domestic product (GDP). However, this can be reduced by shifting and promoting electronic forms of payments such as the use of Fintech, that is, mobile money wallet account. Further, this can foster financial inclusion. Particularly for the many residents in the developing world who are unbanked. Cash and traditional forms of electronic payments such as the use of debit card, credit card and charge cards have inverse relationship as expected, but the use of mobile money wallet since its introduction a decade ago and its impact on traditional payment systems at the point of sale is yet, to the best of my knowledge, to be empirically examined.

Also, following the introduction of electronic payment as alternative currency, that is cash, the global payment architecture is gradually adjusting to digital payments because of the numerous benefits, such as the speed of processing payment transactions across payment system participant (Premchand & Choudhry, 2015). Further, according to the 2022 world payment report, electronic commerce payment transactions exceeded USD5.30 trillion in transaction value. Of this, 48.60% is attributable to digital wallet payments. The report also show that electronic payment transactions are expected to exceed USD8.30 trillion by the year 2025, and of this, 52.50% will be attributable to digital wallet payments. In addition, point-of-sale payments increased by 13.40% to nearly USD46 trillion in transaction value in the year 2021 and it is expected to grow by 26.20% to nearly USD59 trillion by the year 2025. On the use of cash at point-of-sale, this is expected to significantly decline from USD8.30 trillion, 17.90% in 2021 to USD5 trillion, 9.80% by the year 2025.

The additional functionalities on mobile phones have inspired the development of value-added mobile services such as mobile banking, mobile money wallet, and mobile payments in developing countries. Further, the use of these additional features has facilitated mobile commerce in general. This has been possible because many residents in developing countries in Africa using mobile phones far exceed any other technical mobile enabled devices that can be used in commerce. However, the impact of Fintech on the national payment systems in Africa has been under-researched. Most prior studies have focused mainly on what motivates people to adopt Fintech, hence, there is scant empirical literature on how Fintech provides financial inclusion and its impact payment system.

4.1.2 Significance of the study

The development of Fintech, that is, mobile money wallet, as an alternative payment system to the traditional use of cash and non-cash payment instrument should not endanger the smooth functioning of payment systems. Mobile money wallet offers a new channel which permit efficiency gains; however, this can only be realised if adequate safeguards are in place to ensure that mobile money is a reliable accepted by all it users. Further, the increased use of mobile money wallet has led to the several different studies seeking to examine the rationale for its adoption. However, most of these studies have focused on the factors that drive its usage, hence, there is scant empirical study that examine how mobile money wallet adoption impact central bank money supply and how this can completely replace currency.

The inability to control broad money supply depend largely on the monetary authority's capability to measure accurately, the behaviour of payment system participant's use of cash and non-cash payment instrument. This is because failure to appropriately gauge how payment system actors behave in the use of currency will significantly impact limit the monetary authority's open market operations and broad money supply target in the economy. Further, if central banks assume money supply to be fixed, when the use of cash decreases as a result of the increasing use of mobile money wallet, this can adversely impact on their balance sheet. This can in turn, also negatively impact on the monetary authority's balance sheet and the central banks' open market operations as shown the work of Tak (2002).

Additionally, the increasing use of mobile money as replacement for cash directly can impact money multiplier. Further, mobile money can lead to loss of income from signiorage[17]. All these impacts of mobile money is contingent, however, on its actual use, and understanding the short and long-run impact of mobile money wallet transactions on the traditional payment system is important. However, despite the growing increasing in the use of Fintech, that is, mobile money wallet in the developing world, particularly in Sub-Saharan Africa, there is dearth of empirical study on the interaction between the use Fintech, that is, mobile money wallet, broad money supply (cash), non-cash payment instruments and financial inclusion to inform policy and investment decisions.

4.1.3 Study Objectives

I fill this gap in literature by showing empirically, that Fintech provides financial inclusion. Further, I investigate whether the use of Fintech, that is mobile money wallet can substitute the use of traditional payment instruments such as cash and non-cash (debit, credit, and charge cards) at the point-of-sale. Additionally, I show using my econometric analysis that by encouraging the widespread and use of Fintech as an alternative payment instrument, central banks in less-developed countries can deepen their financial system, payment eco-system and enhance monetary policy transmission mechanisms. Particularly, in Africa where the use of cash has dominated the medium of exchange for goods and services for decades.

Specifically, I:

1. Estimate the short and long-run impact of Fintech on payment system transactions and evaluate its impact on financial inclusion and physical cash usage.
2. Estimate the forecast error decomposition variance and impulse response functions for Fintech and payment system transaction and evaluate its impact on the stability and efficiency of the payment eco-systems in Kenya.

[17] According to Ely (1996), this is 'the interest savings the government earns by issuing no interest-bearing debt in the form of currency'.

For my contribution, I add to the existing literature on the use of Fintech, that is, mobile money and payment systems in the developing world in three (3) ways. First, I use econometric methods that are less prone to misspecifications problems that is associated with similar methodology such the ordinary least square (OLS)approach when causal relationships are investigated. Second, by using broad money supply as proxy for the use of cash, I am able to examine Kenya's move to become a cashless society in a broad sense; and third, I carefully distinguish between short-run and long-run effects between mobile money wallet transactions, payment system transactions at the point of sales, and the use of cash in the country.

My contribution is structured as follows: Section 2 introduces the theory and empirical evidence on the adoption of financial technologies, Fintech, which form the basis of my analysis. It also provides an overview of the use of Fintech, that is mobile money, in Sub-Saharan Africa and Kenya in particular. Section 3 introduces my empirical and applied data that I use to achieve my research objectives and the source of the data. Additionally, I outline the hypotheses that I test in the second part of my thesis in this section. Section 4 presents descriptive statistics and a discussion about my dataset. In section 5, I discuss the methodology and empirical strategy that I use to achieve my research objective. I present my empirical results and discusses the findings of the causality analyses, and accordingly deduce the implications for economic theory and policy in section 6, and I conclude in chapter 7.

4.2 Literature

The theoretical framework of this second part of my thesis is based on the theory of reasoned action (TRA) by Fishbein (1963), Technology Acceptance Model by Davis (1989) and Innovation Diffusion theories of Rogers (1980, 1983). Davis (1989) shows a person's journey to accepting new technology that encourage economic activity and contend that individuals' perception plays a dominant role when deciding on whether to accept new technology or otherwise. That is, the person's perceived usefulness of the innovation in their everyday life, and the ease with which the innovation can be used to perform a given task. Rogers (1980, 1983) innovation diffusion theory (IDT) contend that the adoption of innovation is a process that reduces uncertainty, and this can be achieved when the potential user gathers and analyse relevant information about the new technology to a point of belief. Subsequently, the individual's belief leads him or her to a rejection or acceptance of the proposed new technology based on the knowledge and information acquired.

In Fishbein (1963) theory of reasoned action (TRA), the author contends that a person's attitude towards innovation is grounded on the individuals' assessment and belief with respect to the specific innovation that the person intends to adopt. According to Fishbein, in the individuals' journey to adopt any proposed innovation, behaviours emerge as a result of several psychological variables interacting in the adoption process, and that the person's social behaviour is under the control of some external factors. According to Ajzen and Fishbein (1975) and, Ajzen and Fishbein (1980), the theory of reasoned action (TRA) generally explains most human behaviour and is dependent on what an individual belief to be important in predicting his or her behaviour.

The Bank of International Settlements (BIS, 2003, p. 38) contends that a payment system '*consists of a set of instruments, banking procedures and, typically, interbank funds transfer systems that ensure the circulation of money*'. In today's modern financial system, purchases of goods and services in most market economies are facilitated by the use of various payment instruments. Hence, a country's national payments systems are the main channel through which payment system participants such as buyers and sellers of goods and services undertake transactions and ensure that financial settlements are made. This usually consists of a set of instruments, banking procedures and, typically, interbank funds transfer systems that ensure the circulation of money.

4.2.1 Electronic payment and cash

When the electronic forms of payment such as debit and credit card was introduced, many payment system participants, such as banks, expected that the introduction of these electronic money transfer system would relieve the cost burden of handling cash. Indeed, with the introduction of electronic payments many industry participants predicted the evolution of a "cashless" payment system whereby cash would be substituted by electronic money transfers. Yet, today a cash-less payment system is far from becoming a reality and cash usage continues to grow among businesses and consumers in many Sub-Saharan countries, and Kenya continue to rely on cash as the main instrument for conducting business (Statista, 2023).

Furthermore, because cash is a familiar and widely accepted form of payment, growth in cash usage is understandable. From an economic perspective, however, the continued growth of cash usage may be undesirable because of the relative amount of resources consumed in the use of cash compared to electronic payments such as debit, credit, and charge cards, and in recent decades, the use of mobile money wallet. The most widely used payment mechanism in many countries, particularly in Sub-Saharan Africa, with the exception of cash is the use of Fintech, that is, mobile money wallet (World Bank 2021 Findex report).

Despite the strong public interest in mobile money wallet and mobile payment eco-systems in developing countries, there is only a small body of empirical academic research that policymakers can draw on to analyse the impact of this alternative payment instrument on the traditional payment systems and financial inclusion. This is all the more surprising given the significant increase in the usage of mobile money wallet and mobile payments in the last decade in developing countries. Across the four regions of Africa, the total value of mobile money transaction stood at USD701.4 billion, and East Africa account for 57.51%, USD403.4 billion in 2021 (Statista, 2022).

The digital revolution in developing countries, particularly in Africa is reshaping how residents in these economies make payments for financial transactions. The usage of mobile phone technology and mobile service have rapidly integrated into people's daily life in developing countries as an alternative payment instrument for ordering good and services and for remittances. Mobile money wallet and payments has come to stay and competes with traditional payment instrument such as cash, credit card, cheques, and debit cards, and can be used almost everywhere and in many situations where mobile phone network exists. The transaction volume of M-Pesa in Kenya, East Africa, increased steadily from 2017 to 2023, and eventually reached twenty-six (26) billion transactions as at the end of the financial year 2022-2023 (Statista, 2022).

According to the Global System for Mobile communication Association (2019), there are over 1billion Mobile Money account holders in Sub-Saharan Africa and rising, and the monetary value of Mobile Money transactions in Africa stood at USD453billion in 2019 and rising. Further, the total value of mobile money transactions reached USD456.3 billion in 2019, higher than any part of the world. The evidence and importance of mobile money wallet to users and providers in Sub-Saharan Africa region is unambiguous. Additionally, the use of Fintech such as mobile banking as channels for distributing credit, making payments, and receiving remittances has and continue to gain grounds, and this will potentially be the default channel for transacting business for many of the population who do not have access to traditional bank account. However, the impact of these new channel of payments on the national payment systems of developing countries is under-researched.

4.2.2 Mobile Payment adoption

Mobile payment is defined as any form of payment that requires the use of mobile enabled device such as mobile phone, tablets, et cetera, and is capable of being connected to a mobile communication infrastructure to initiate, sanction, and confirm a personal or business transaction (Au and Kauffman, 2008). The main motivation for the introduction of mobile money wallet and mobile payments in the 1990s was to provide users and other stakeholders such as merchants, with alternative forms of payment channel that facilitate the settlement of relatively small financial transactions at lower cost to both merchants and the users (Van der Heijden, 2002). Electronic forms of payments such as using mobile money is considered to provide some benefit to users of this payment instrument. These benefits, ranges from ease of accessibility, convenience, fast transaction speed, and offers users control and privacy for conducting financial transactions (Birch and Young, 1997; Daniel, 1999; Ramsay and Smith, 1999).

The empirical work of Thakur and Srivastava (2014) show, that mobile payment adoption remained significantly high in developing countries in Africa and in Asia. However, in some Asian countries, for example in India, where the economy was chiefly driven by cash transactions for small to large purchases, the adoption of mobile payment is relatively low (Thakur and Srivastava, 2014). Contextual factors are important to understand the mobile payment dynamics in developing countries. For example, in Africa, high financial sensitivity influences the adoption of mobile payments, whereas in Asia, cost of mobile payment transactions, internet access, incidence of fraud and the regulatory environment are some of the contextual factors influencing the adoption of mobile payments (Barker et al., 2008; and Curtis and Payne, 2008).

The theoretical work of Shapiro and Varian (1999) show that one of the key characteristics of network enabled products, such as mobile payment is the perceived benefit that such payment systems bring to the users, and in the work of Kauffman & Wang (1999), they show that users of technology enabled mobile payments increases as the benefit to users' increase. In a related empirical work, Dahlberg et. al., 2002 find that customers were unwilling to use mobile payments where the cost of using mobile payments is greater than alternative conventional methods of payment; and that the process for using this new form of payment should be less procedural to complete a transaction.

Similar studies in developing economies in Asia (Yao and Zhong, 2011; and Sripalawat et al., 2011), and South America (Cruz et al., 2010) provides further evidence that monetary risk adversely affect users' intention, perception, benefit, and usage of mobile payment as a new form of payment towards a cash-lite economy. In related empirical studies, Bishop et al, (1999); Butler, (2005); Elijah and Ogunlade, (2006) and Etim, (2011) finds, that there is a relation between the use of mobile money for payments and the number of mobile phone adoption and usage in Sub- Saharan Africa. Furthermore, Financial institutions and mobile payments service providers such as mobile telecom operators, generate income from mobile payment transactions fees and from transactions on float.

Hence, for these mobile payments service providers, the development of mobile technology enabled payment system offers the potential to lower cases of fraud and cost of payment transactions to facilitate the provision of new services to customers. Bold, et al, (2012) finds that in Sub-Saharan Africa, the use of mobile enabled financial technology via mobile phones for mobile money and mobile payment services is the chief driving force behind the progress made towards financial inclusion in recent times. In developing economies, particularly in Africa, these forms of financial technology are used primarily for Person-to-Person transactions and remittances. However, there is a growing trend in the usage of mobile payment as a medium to pay for good from merchants and for irregular and regular bill payments such as school fees, gas, electricity, and water (ITU, 2013).

Mobile money and mobile payments have been found to facilitate payments and the drive to move the unbanked into the mainstream financial systems in developing countries, particularly in Africa, and this has led to an increase in government revenues needed for development and effective market participation (Jenkins, 2008). Ehrbeck et al., (2012) show, that in Sub Saharan Africa, the emerging partnership between financial institutions and mobile telecom and mobile money operators is a striking indication of a positive move towards ensuring that the many residents of Sub-Saharan Africa who are unbanked move into the mainstream financial system. The work of Dias and McKee (2010) further show, that mobile phone users in Sub Saharan Africa who do not have formal bank accounts now use mobile money for bill payment, payroll deposits, remittances, loan receipts and payments, airtime top-up, groceries, payment of transport fares and other financial services related transactions.

Aron (2018) provided a theoretical framework on the economics of mobile money that includes transaction cost. The author finds that mobile money enables households to share risk when they experience financial shock. Further, the works of Suri (2017) and, Alampay and Moshi (2018) investigated the use of Fintech (mobile money wallet) by households selected in Sub-Saharan Africa countries and find that many adopters of mobile money receive more remittances than their non-adopting peers. Although prior studies help to advance our understanding of how mobile money wallet and payment influence the socioeconomic wellbeing of individuals and households, they offer scant evidence of the relationship between the continuous use of rise of mobile money wallet usage on payment systems, particularly in developing countries in Africa.

Mobile money payments can accelerate the reduction in the use of cash in developing countries to become cashless economies. This phenomenon can bring significant benefits to residents, industries, central banks, mobile money and telecom operators, financial institutions and investors doing business in less developed economies. For example, the empirical work of Skaggs (2014) investigated a scenario where the US becomes a cashless society and find that industries, banks, and the government will be the chief beneficiaries of such an environment. However, the author also acknowledges that for example, financial institutions are able to better understand the need of their customer and can best address this in a cashless society where clients transactional footprints are known to the bank for the marketing of financial products and services.

Most of these theories are constructed based on behavioural concept rather than contextual; however, mobile money wallets and mobile payment in developing countries in Africa are technology driven that encompasses the users' acceptance of these new forms of payment, and the risk associated to the everyday usage of cash for financial transactions. This further makes mobile money payments more behaviourally driven as well. According to the Bank for International Settlements' Committee on Payment and Settlement Systems 2003, mobile wallet is "a reloadable multipurpose prepaid card which may be used for small retail or other payments instead of coins". Mobile money and mobile payment are different from cash cards or credit cards that are facilitated by a professional financial intermediary. Financial transactions undertaken using mobile money wallet and mobile payments are done using mobile enabled devices and are transacted off-line at lower cost (Cronin et al., 2000).

In an empirical study that examined the theoretical frameworks on the adoption and usage of technology to understand mobile payments acceptance features, in the context of mobile-based financial services delivery, Thakur and Srivastava (2014) finds, that adoption readiness and perceived risk are critical factors that determine the usage of mobile payment. Yang (2009) also finds that mobile payments adoption and usage is significantly affected by the transaction fees, plus the cost of connecting mobile enabled devices. In Sub Sahara Africa, particularly in Kenya, Mbogo (2010) studied the various drivers that contribute to the success of mobile payments usage among small enterprises. The author concluded that among others, accessibility, and cost of undertaking mobile payment transactions positively influence residents' intention and actual usage of mobile payment and related services in Kenya. Kim et al., (2007) also show that the value of mobile internet service is a positive driver of mobile payment and affiliated services.

My study seeks to fill a gap by providing an analysis of the relationship between Fintech and payment systems in developing countries. I empirically examine the impact of the prevalent use of financial innovation technology services, such as mobile payments and Mobile money wallet services on the national payment system at point of sales, and financial inclusion in Kenya, a developing open market economy in Sub-Saharan Africa. Specifically, I first test for causality between Fintech and financial inclusion. Second, I examine the long-run relationship between the use of Fintech and the traditional payment systems. I finally will investigate the causal relationship between Fintech and financial sector deepening, and a move for the country to become a cashless society.

4.2.3 Mobile Money in Sub-Saharan Africa

In developing countries, Kenya is known to be the pioneer in the delivery of digital financial services that includes mobile money wallet payments and transfers, and mobile banking using third party agents. In Kenya, there are four main providers of mobile money services in the country. That is, Airtel Money, Essar yuCash, Orange Money, and Safaricom M-Pesa. M-PESA, which is a well-known mobile money payment and transfer services launched in 2007 by mobile telecom operator, Safaricom, had the objective of providing financial services to the many unbanked poor population in the rural and urban communities in Kenya. This became possible as a result of the collaboration between financial institutions and the mobile telecom operator.

In Africa, almost 144 mobile money providers operate in the Sub-Saharan region, and three firms, that is, M-Pesa, MoMo and Orange Money, account for the substantial share of the mobile money market (Statista, 2023). Further, subscribers of M-Pesa, a mobile money service provided in seven (7) countries, increased by 28.92% to reach 41.5 million from the financial year 2017 to 2020, and generated US$784.36 million in revenue (Statista, 2023). According to the Global System for Mobile telecommunication Association (2021 and 2022) reports, there are 1.35 billion registered mobile money accounts with transaction volume and value of 53.9 billion and US$1 trillion respectively. Of this, 605million registered mobile money accounts, 36.6 billion volume of transaction, and value of transaction worth US$697.7 billion were exchanged in Sub-Saharan Africa. In Kenya, there is limit to the amount of money that mobile money account holders can transfer, UD$700, and hold as deposit, US$1,000; compared to US$1,500 and US$2,000 in Uganda due to regulations (Suri et. al., 2023).

In Sub-Saharan Africa, specifically in Kenya, the volume of mobile money transactions using MPESA increased steadily from 6.4 billion 2017 to 26 billion in the financial year ending March 2023 (Statista, 2023). In Kenya, the mobile money eco -system is regulated and supervised by the central bank of Kenya and the Kenya communication authority. A 2018 survey conducted in Kenya that show that majority, 94%, of businesses in Kenya use cash as the main method of payment, followed by mobile money, 3.7% (Statista, 2022). Further, the survey shows the among consumers in Kenya, cash and mobile money dominates payments at points of sale, and 40% of Kenya’s gross domestic product (GDP) relies on the use of M-Pesa (Premchand and Choudhry (2015). Further, 97% of households in Kenya have a mobile money account as at 2014 (Jack & Suri 2016).

In Uganda, another East African country witnessed an increasing trend in the total volume and value in the number of mobile money wallet transactions. The total value of mobile money wallet transactions increased from US$442million in 2010 to US$44billion in 2022 (Bank of Uganda,)**.** The increase was higher during the period from 2020 to 2021 when the total value of mobile money transactions increased from US$25.208 billion to US$44.884. Similarly, the total volume of mobile money wallet transactions increased from 28.815million in 2010 to 5.230billion in 2022. Also, the increase was higher during the period 2018 -2019, 962million, and the 2021-22 when the total volume of mobile money transactions increased by 939million (Bank of Uganda,). According to Statista 2023 report on mobile money in Africa, In Sub-Saharan Africa there are 144 mobile money providers operate.

In 2022, 1.2 billion users made US$1.26 trillion mobile money transactions globally. Of this, 45billion transactions volume and value of US$836.5billion were transacted in Sub-Saharan Africa according to the Global System for Mobile telecommunication Association 2023 report on mobile money. In addition, Africa accounts for more than half, 166, of the total 315 mobile money live services. Furthermore, in Africa, East and West Africa account for the significant share mobile money services and transactions. Specifically, West Africa has 65 live services, 290 million registered subscribers, total volume and value of mobile money transaction stood at 12 billion and US$277 billion. In East Africa, there are 56 live services, 390million registered account holders, and 28billion and US$492billion in transaction volume and value respectively.

According to the Global System for Mobile telecommunication Association 2022 report on mobile money, for every $1 cash-in, sixty-six percent, representing $0.66 is cashed-out in 2022. This is higher compared to $0.63 that is withdrawn for every $1 deposited into a mobile money account in 2021. Further, person-to-person payments dominated mobile money transaction, followed by bill payments that increased by thirty-six percent in 2022 and reached transaction value of US$88 billion compared to 2021. On the supply-side, the report shows, that ninety-seven percent of the mobile money providers offered bill payment services to subscribers. The report further shows that, for example, forty-six percent and twenty-seven percent of mobile money users in Kenya and Senegal claimed to have used the service for bill payments respectively.

Mobile money is also used for merchant payment and bulk disbursements such as employee wages and salaries. According to the Global System for Mobile telecommunication Association 2022 report, these two forms of payments increased in 2022 by twenty-three percent to exceed transaction value of US$80 billion, compared to an increase of twenty-six percent in 2021 and fourteen percent in 2019 before the covid-19 global pandemic. In Africa, specifically in Ghana and Kenya, payments from Government institutions to mobile money account holders stood at seventeen and twenty-seven percent respectively, compared to eighteen percent in Bangladesh. Bulk payments transaction volume using mobile money increased by twenty-two percent in 2022 compared to twenty-eight percent in the prior year.

Further, the Global System for Mobile telecommunication Association 2022 report show that West Africa has now outpaced East Africa in the use of mobile money, and Côte d'Ivoire, Ghana and Senegal are the leading champion for this change. For example, in Ghana, retail payments interoperability has enabled the transfer of funds from one mobile money operator's platform to another seamlessly. This includes the transfer of funds from mobile money wallet account to formal bank account and vice versa in real-time and has helped to enhance the overall effectiveness and efficiency of retail payments in the country (Bank of Ghana, 2018).

Additionally, according to the Bank of Ghana 2022 payment system report, the total mobile money on float balance was US$1.52billion at end-December 2022, compared to US$1.14 billion in 2021, reflecting a growth of 34.14 per cent. Total value and volume of mobile money transactions in Ghana was US$14.23 billion and 55.29 million in 2022, an increase of 47.26% and 14.45% from 2021. Furthermore, the mean mobile money wallet transaction value per day increased from US$34.37 in 2020 to US$38.29 in 2021 and represent a 16.30 percent. In the same periods, the cash-in value increased from US$17.39 2021 to US$27.44 and represented a 64.50 percent increase. Similarly, the mean value for cash-out transactions per day stood at US$31.08 in 2021, representing an increase an increase of 18 percent from 2020, US$25.31.

4.3 Empirical Data and Hypotheses

4.3.1 Data

I identified and collected data from the central bank of Kenya covering the total volume of payment system transactions excluding cash, the total value of payment system transactions excluding cash, and broad money supply (M3) from January 2010 to December 2022, except for the use of cheque payments that is continuously declining. Hence, I use debit cards, credit card, prepaid card, and charge cards payments to constitute the volume and value of payment system transactions. Additionally, I collected data on the total volume and value of mobile money wallet transactions, active registered mobile money accounts and agents in Kenya.

However, I do not use the active registered mobile money accounts and agents in my model. This is because individual users can hold multiple mobile money wallet accounts from the same and or different providers, and this may distort my analysis. Further, I analyse cash and noncash payments in terms of their values and volumes because they impact seigniorage and cash redemption policies of central banks and regulatory authorities globally. Furthermore, the issues I am concerned with are connected with the substituting role and the impact of Fintech on traditional payment system transactions at the point-of-sale, financial inclusion, and payment system efficiency and stability.

The ability for any payment system participant to substitute payment instrument depends importantly on the "end use", that is, what the objective is, and the three main uses are, for bill settlement, disbursement (both credit and debit), and point-of-sale transactions (Snellman et. al., 2001). In this second part of my thesis, I focus on the interaction between mobile money wallet transactions, the debit, credit, charge card transactions and the use of cash in Kenya. I empirically examine the impact and substituting role that Fintech, that is, mobile money wallet, play on the traditional payment instruments such as cash, debit, credit, and charge card transactions at the point-of-sale, and financial inclusion.

4.3.2 Hypotheses

A frail payments system can destabilise a country's financial sector and economic development. This can lead to significant losses for payment system participants and confidence in the use of money in any economy. Further, the payments industry is an indisputable flagship sector of financial technology in developing countries, particularly in Sub-Saharan Africa, a region where historically more than ninety percent of the economy is cash-based. I empirically examine Fintech, that is, the use of mobile money wallet at the household and business level, and the impact on traditional payment systems and financial inclusion. Related to my study is the empirical work of Humphrey et al., (1996). The authors investigated the substituting role of non-cash payment across fourteen developed economies and examined the factors accounting for this phenomenon. They find that cultural differences across the countries, payments options and past experience of consumers account for the greater use of electronic forms of payments.

The hypotheses that I test are:

H1: Financial Technology Innovation adoption, that is mobile money wallet provides financial innovation.

I surmise that a cointegration between Kenya's total value and volume of mobile money payment transactions, and cash is an indication that mobile money provides financial inclusion.

H2: Financial Technology Innovation adoption, that is mobile money wallet, transfer informal cash into the formal banking system in a move to become a cashless society.

I surmise that a cointegration between the total value and volume of mobile money payment transactions and the use of cash is an indication that Fintech can substitute cash usage by linking the informal and formal sectors of Kenya's economy together in a drive to become a cashless society.

4.4 Descriptive statistics and analysis

I present descriptive statistics for my dataset in Table (28). The maximum, minimum and mean value of total payment system transactions (Valps) is significantly lower when compared to the total value of mobile money wallet transactions (Valtm). The mean value of total payment system transactions stood at USD$434.2657million, compared to that of the total value of mobile money wallet transactions, USD$2.8681billion. The minimum total volume of mobile money wallet transactions (Voltm) is also significantly higher, 20million, compared to 3million for the total volume of payment system transaction (Volps). Additionally, the maximum and minimum volume of payment system transactions are all significantly lower than the volume of mobile money wallet transactions.

Further, when I analysed the annual trend for the total value of mobile money wallet transactions and compared it to payment system transactions. I find that the latter experienced a significant decline from USD$5.040million in 2010 to USD$4.838million in 2011 and thereafter remains $4.573million on average between 2012 to 2018, then began to significantly increase from 2019 to 2022 with an average of USD$6.463million (figures 25 and 27). During the periods from 2016 to 2021, the value of payment system transactions declined from USD$6.8876million in 2019 to $6.1319millionin 2020 and this may be the result of the impact of Covid-19 global pandemic. Figure (27) show the total value of mobile money transactions and provide evidence of a significant increasing trend from $9.22billion in 2010 to $67.32billion in 2022.

The volume payment system transactions increased from 2010 to 2012 and thereafter began to decline significantly from 2013 although 2015 and 2018 experienced a one-off increase (figure 26). On the contrary, the total volume of mobile money wallet transactions shows an increasing annual trend from 2010 to 2022 (Figure 5). When the volume of payment systems transactions and volume of mobile money transactions are compared in figures (26) and (28), we find a significant increasing volume of transactions from 311.05million in 2010 to 2.28billion in 2022 for the later. This is significantly higher when compared to the volume of payment system of 86.977million in 2010 and 71.743million in 2022.

The volume and value of mobile money transactions suggests that it is the main form of undertaking financial transactions in Kenya compared to traditional payment methods such as the use of debit card, prepaid card, credit card, charge cards and cash. We use the broad money supply in the Kenyan economy as proxy for the use of cash. Figure (29) show an average annual growth rate of 18.96% in the amount of cash available in the Kenyan economy. 2016 experienced a significant decline to 3.8904%, and thereafter maintained an average increase of 8.551% per annum from 2017 to 2022. Figure (30) is the log form of my variables and shows no significant outliers.

Appendix-A, supplementary figures (43) and (44) show an increasing trend in the number of registered mobile money agents and registered mobile money account ownership in Kenya. However, I do not use these two variables in my analysis. This is the case because for example, one person can have multiple mobile money accounts from different providers so as to take advantage of different tariff policies of the competing providers. Further, serving as one of the crucial pillars upon which the mobile money architecture is built, mobile money agents provide cash-in and cash-out service to customers on behalf of mobile money providers, individuals or entities can be agent for multiple mobile money provider. Hence, adding the number of mobile money agents and registered account can distort my results and analysis.

Table 42. Descriptive Statistics-Fintech and Payment System

Variables	Minimum	Maximum	Mean	Std. Dev.	Skewness	Kurtosis
Volps (million)	3.8952	28.1677	8.3731	3.4956	3.1989	12.4105
Voltm (million)	20.0767	207.01	107.9573	54.0559	-0.0168	-1.3082
Valtm ($billion)	0.6395	6.1296	2.8681	1.4491	0.5246	-0.5456
Valps ($million)	223.4965	649.515	434.2657	97.0209	0.3315	-0.5336
Cash (%)	3.8904	26.5213	12.9979	6.8738	0.5527	-0.4697

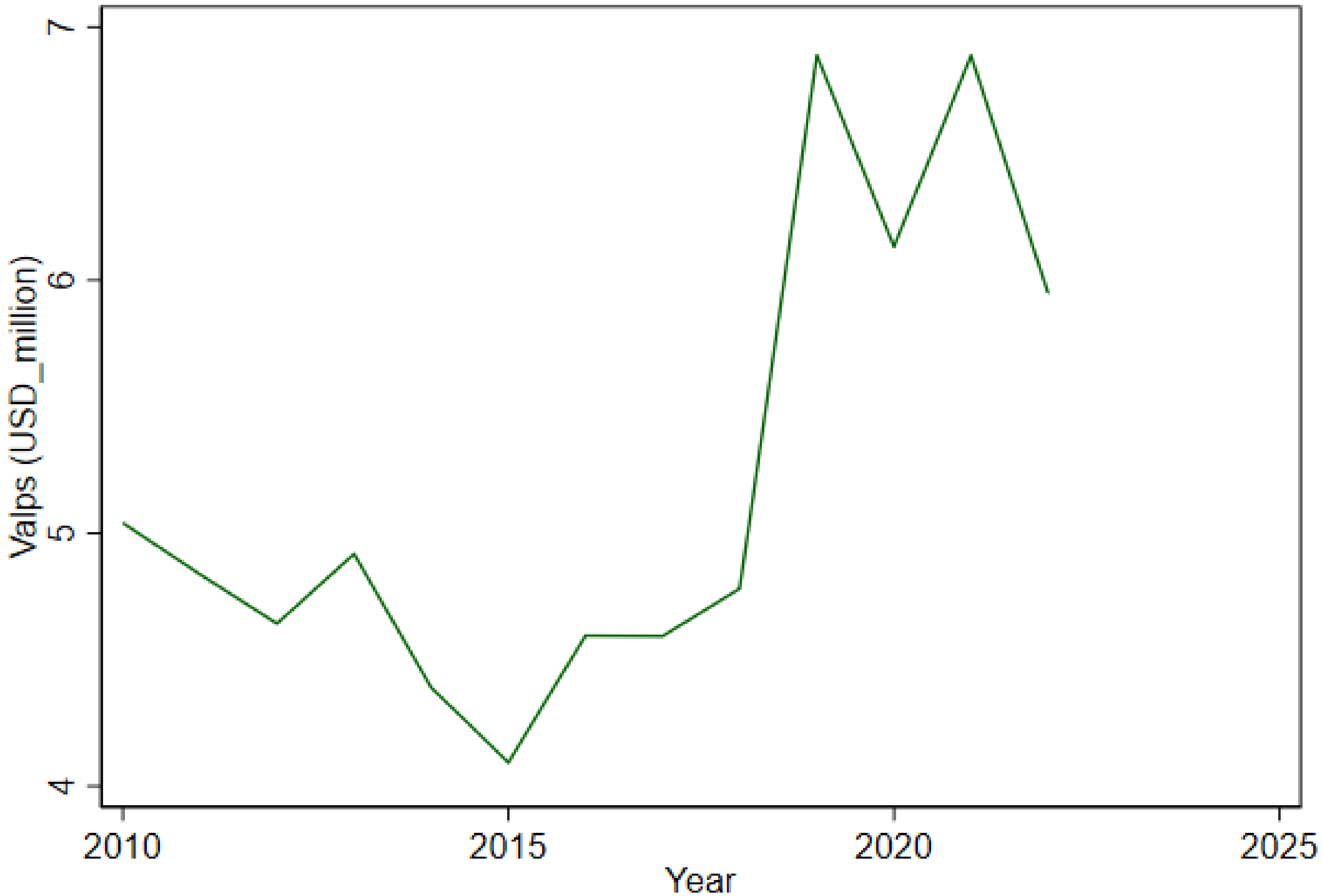

Figure 34. Annual trend of total value of payment system transactions

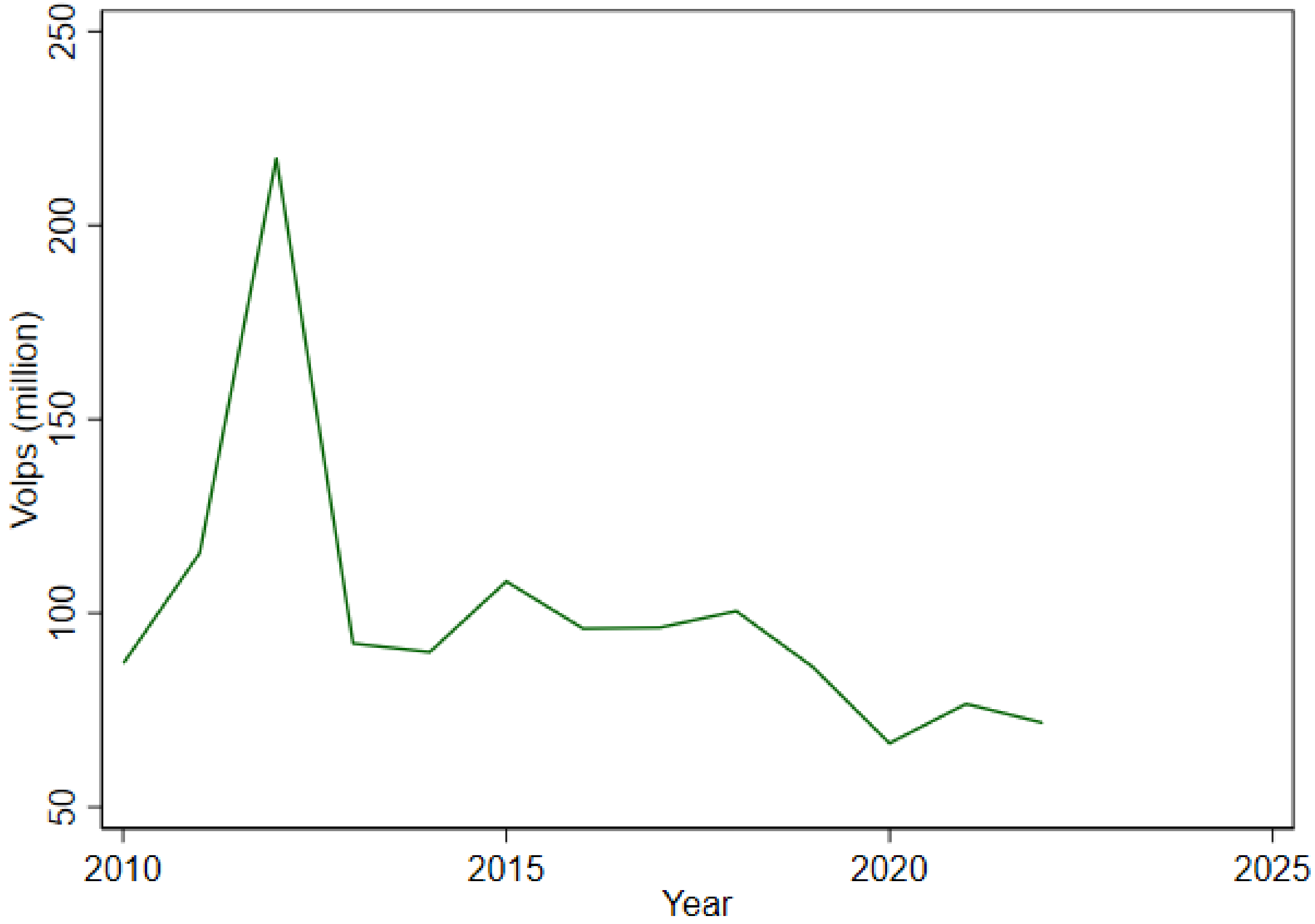

Figure 35. Annual trend of total volume of Payment System transactions

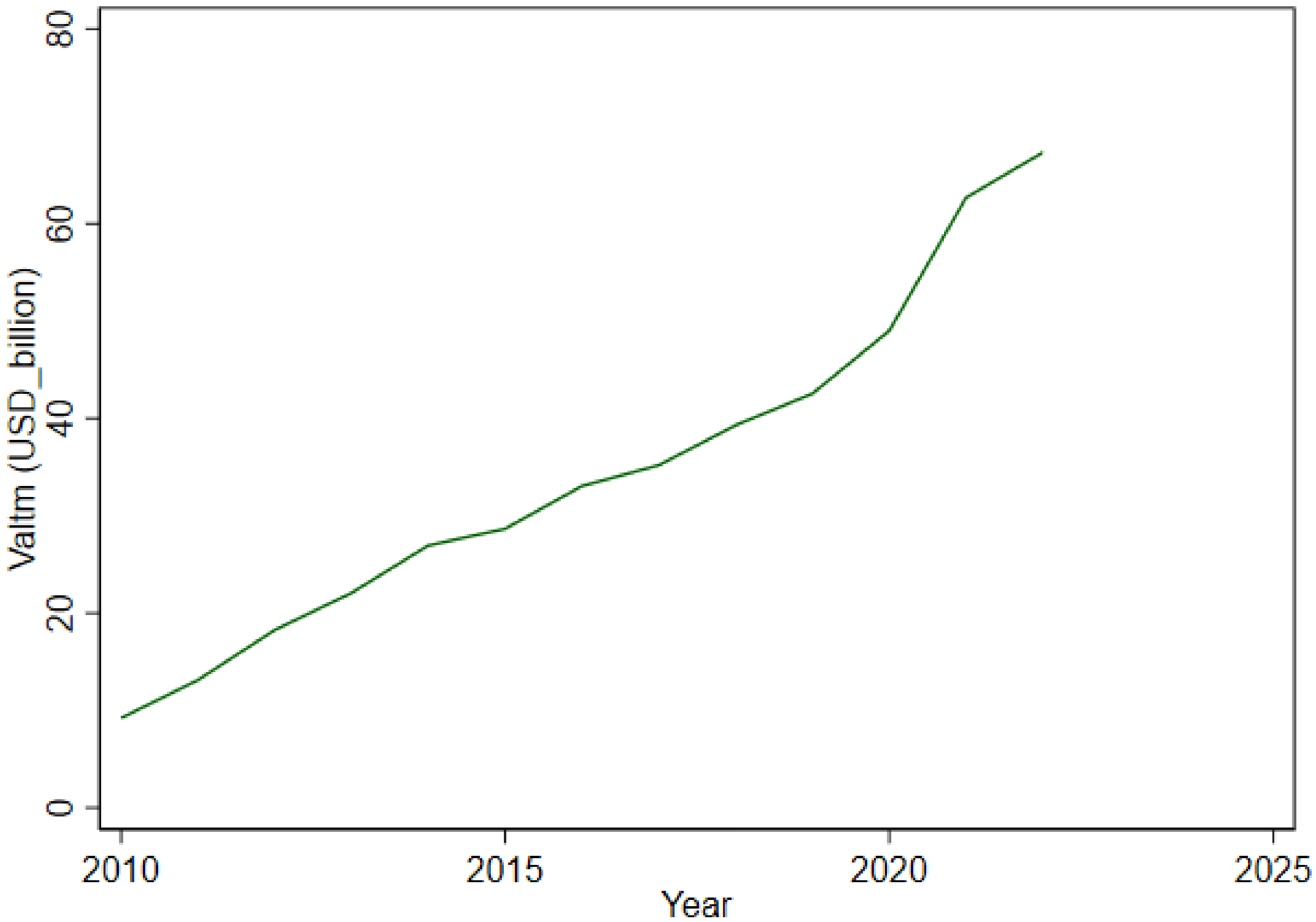

Figure 36. Annual trend of total value of Mobile Money transactions

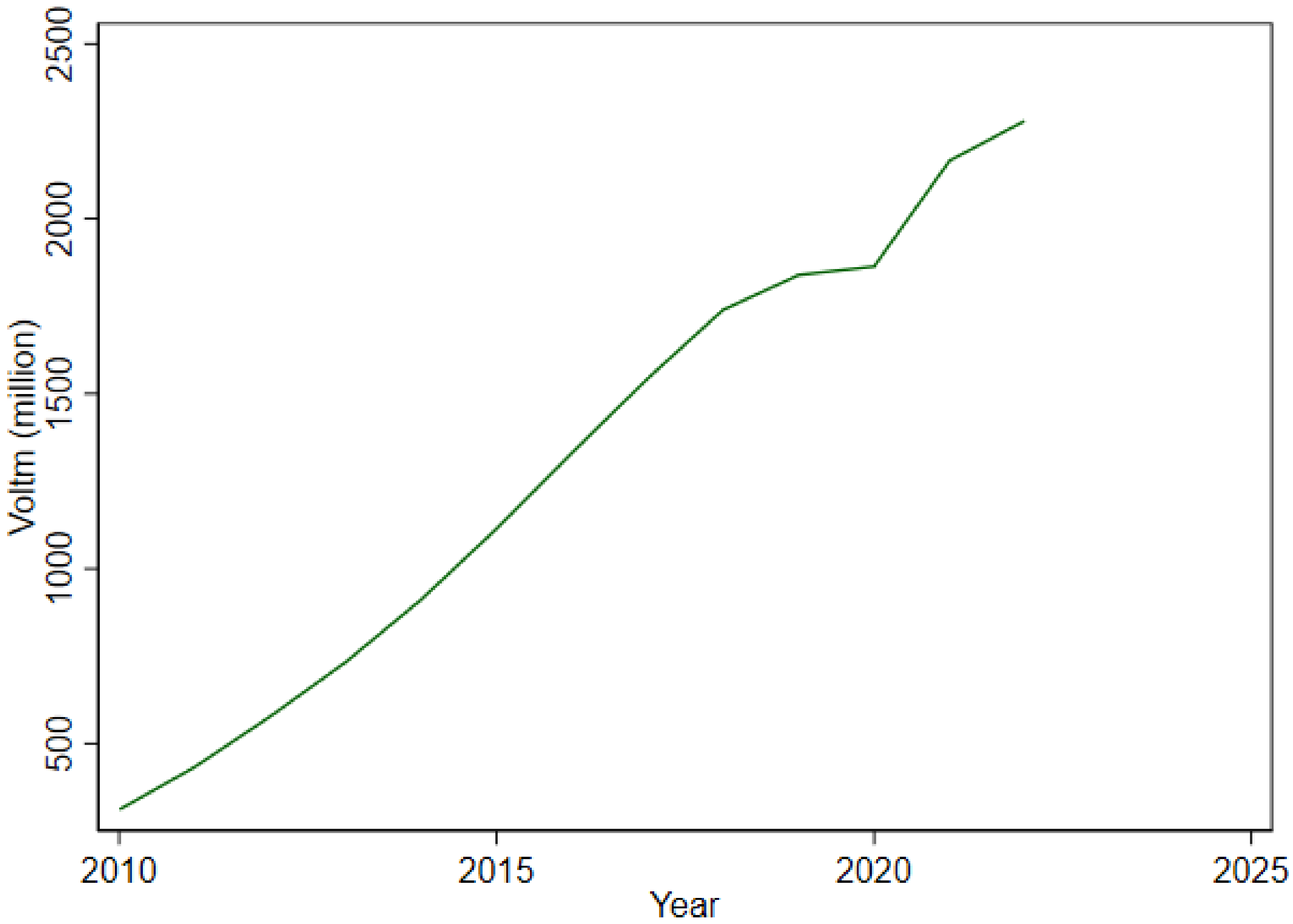

Figure 37. Annual trend of total volume of Mobile Money transactions

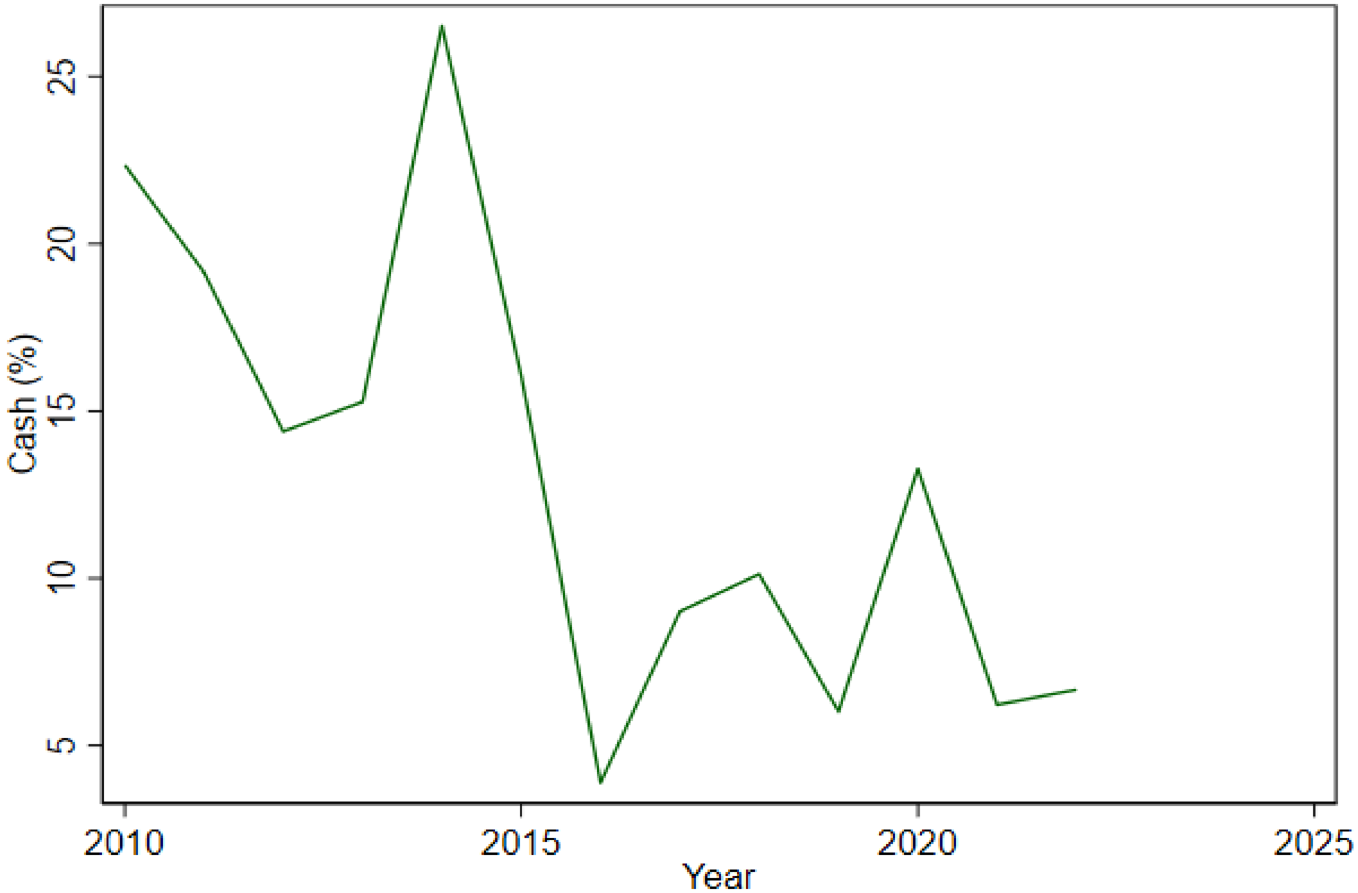

Figure 38. Annual growth rate for Broad Money (M3)

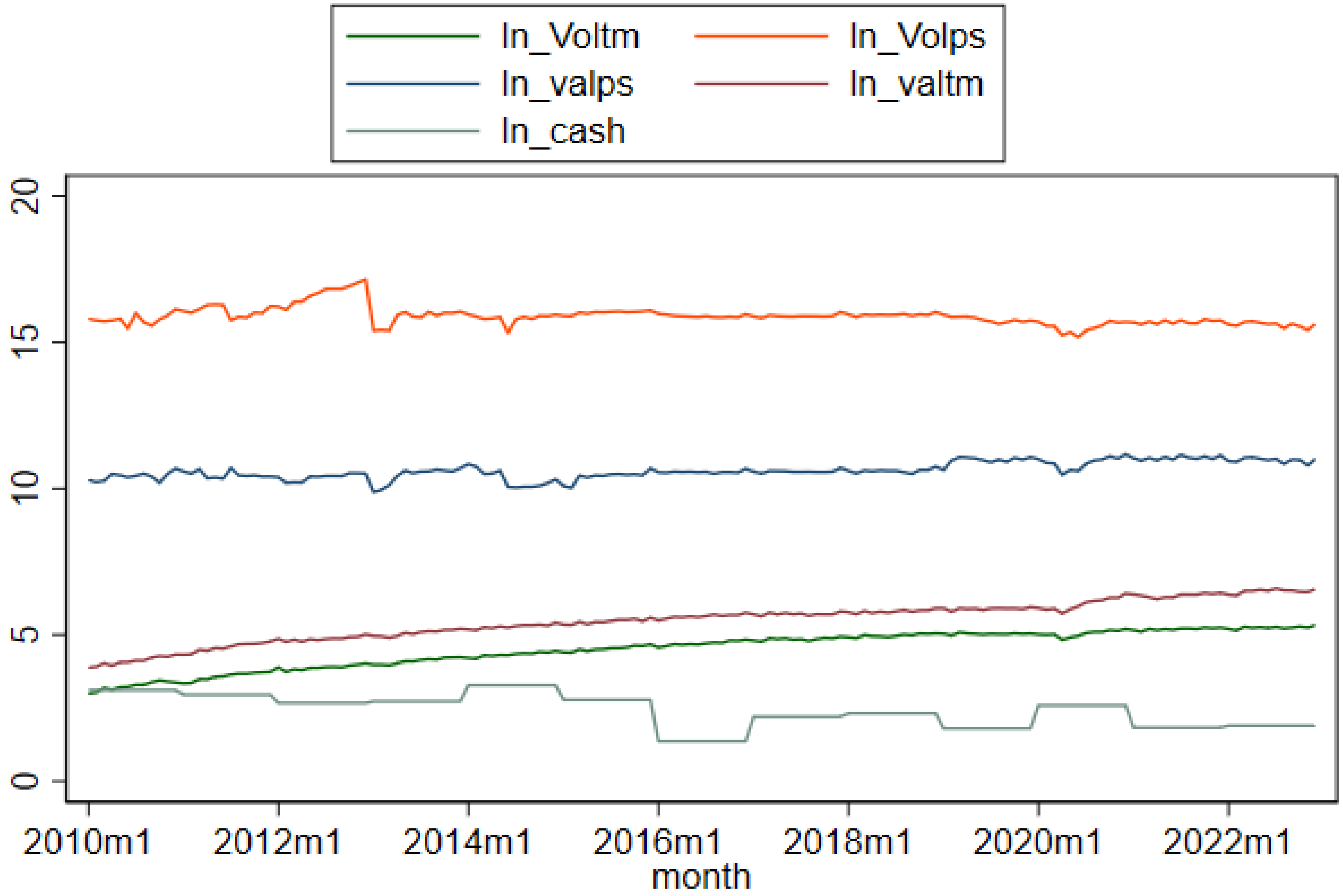

Figure 39. Diagnostic test for outliers in variables

4.5 Method, Empirical Strategy and Model Specification

4.5.1 Method

To develop a comprehensive understanding of the short and long-term impact of Fintech, that is, mobile money wallet, on the payment systems and financial inclusion in developing countries, I use Kenya, a country in east Africa as case study. The rationale for choosing Kenya and using case study approach is based on the fact that the country is the first to introduce mobile money wallet payment popularly known as M-PESA and have a significant uptake in volume and value of transactions since its introduction. Furthermore, in a World Bank report, Sy et al., (2019) examined the use of mobile money in 17 economies in Africa and find that Kenya ranked second, above bigger economies such as Nigeria and South Africa. Additionally, by using a case study approach I am able to provide an insightful and practical understanding of the subject matter (Bryman 2004).

4.5.2 Empirical Strategy

I use the Vector Error Correction Model (VECM) model for my empirical analysis. This is because in the pure Vector Auto Regression (VAR) model, the existence of co-integration between variables leads to model misclassification, and the stationary requirement of time series in the Vector Auto Regression (VAR) model is a further weakness because it distorts the long-run relationship that may exist between the variables due to differencing (Granger. 1981). Further, Granger (1981) extended this work in Engle & Granger (1987) and showed that problem of differencing and non-stationarity of time series can be made stationary by introducing a linear combination of the time series.

The vector autoregression and vector error correction models are the two main approaches used by modern econometricians, economist, and empirical researchers to establish the causal relation among economic variables in a non-structural method. Since its introduction by Christopher Sims in 1980, the vector autoregression (VAR) model has been used widely in economic research. Based on the statistical properties of the data, the vector autoregression method is built, and the system uses the lagged value of each of the endogenous variables in the system to establish causality. Further, by combining the cointegration and the error correction term, Engle and Granger established the error correction model that is traceable.

The vector error correction model can be obtained as long as there is at least one cointegration interaction between the selected variables in the lagged disturbed vector autoregression model. Additionally, since in the vector error correction model (VECM) there is a cointegration relationship among the variables in the system, the presence of a short and long-term dynamic variation, the model can control the long-term component to revert to the initial cointegration relationship. This leads to the identification of any long-run relationship that may exist between variables, commonly referred to as co-integration. Vector error correction model (VECM) is a dynamic cointegration method for forecasting and economic analysis.

This method can address any spurious regression results associated with non-stationary time series data. Further, the vector error correction model (VECM) approach has an advantage of reducing finite sample endogeneity bias problem (Banerjee et al., 1993). However, the vector error correction model has a challenge in identifying individual structural relationships. This relationship requires exact restrictions necessary in the cointegration rank, and Johansen (1988, 1991, 1995) provided a mathematical approach using statistical method to achieve the required restrictions. However, later works by Pesaran and Shin (2001) and Pesaran and Smith (1998) proposed an alternative method based on theory and argued that Johansen's method is not based on theory but purely a convenient arithmetic method.

In Engle & Granger (1987), they showed that by introducing the Vector Error Correction Model (ECM), the dual objective of having a flexible dynamic specification in the short-run and permitting long-run elements of the variables to conform to the equilibrium constraint can be achieved. Hence, they proposed a Vector Error Correction Model (VECM), which is a restricted version of the Vector Auto Regression Model (VAR). I use the Vector Error Correction Model (VECM)[18] model similar to the work of Adam (1992) for my empirical analysis.

[18] Adam (1992) in an empirical work show, that the Vector Error Correction Model (VECM) encompasses all other models.

I use unit root and cointegration tests to identify the stationary properties and possible cointegration relationships of my investigated time series variables. I build on integration and cointegration test results accordingly to establish causality and to avoid spurious regression results. Further, as shown in the work of Braun and Mittnik (1993), standard Granger causal analysis is associated with arbitrary selection of lag length, and this can possibly suffer from model misspecification problems because the variables are constrained and allowed to enter the system at the same lag period. By using the vector error correction model (VECM), my procedure avoids this problem as all variables may enter at different lag lengths.

Additionally, I am able to differentiate between the short-run and long-run causality. In my VECM system, I interpret the estimates for the error correction term as evidence of a short-run causal relationship between my selected variables. Nonetheless, as shown in the work Wickens (1996), my interpretation is possible if the results show that my error correction term is statistically significant and negative. Also, I interpret the Johansen result from my vector error correction model (VECM) as long-term relationship between my considered variables.

4.5.3 Model specification

To achieve my Vector Error Correction Model (VECM), I differenced the vector autoregression (VAR) model. The identified model consists of five variables. I provide below the five (5) variables Vector Error Correction Models (VECM).

$$\Delta lnVolTM_t = \alpha + \sum_{a=1}^{k-1} \beta_i \Delta lnValTM_{t-1} + \sum_{b=1}^{k-1} \Upsilon_i \Delta lnVolTM_{t-1} + \sum_{d=1}^{k-1} \varphi_i \Delta lnCASH_{t-1} + \sum_{d=1}^{k-1} \tau_i \Delta ln\mathrm{ValPS}_{t-1} + \sum_{d=1}^{k-1} \phi_i \Delta ln\mathrm{VolPS}_{t-1} + \psi \Delta lnACTM_{t-1} + \lambda_1 ECT_{t-1} + u_{1t} \ldots (1)$$

$$\Delta lnValTM_t = \omega + \sum_{a=1}^{k-1} \beta_i \Delta lnValTM_{t-1} + \sum_{b=1}^{k-1} \Upsilon_i \Delta lnVolTM_{t-1} + \sum_{d=1}^{k-1} \varphi_i \Delta lnCASH_{t-1} + \sum_{d=1}^{k-1} \tau_i \Delta ln\mathrm{ValPS}_{t-1} + \sum_{d=1}^{k-1} \phi_i \Delta ln\mathrm{VolPS}_{t-1} + \psi \Delta lnACTM_{t-1} + \lambda_2 ECT_{t-1} + u_{2t} \ldots (2)$$

$$\Delta lnValPS_t = \Psi + \sum_{a=1}^{k-1} \beta_i \Delta lnValTM_{t-1} + \sum_{b=1}^{k-1} \Upsilon_i \Delta lnVolTM_{t-1} + \sum_{d=1}^{k-1} \varphi_i \Delta lnCASH_{t-1} + \sum_{d=1}^{k-1} \tau_i \Delta lnValPS_{t-1} + \sum_{d=1}^{k-1} \phi_i \Delta ln\mathrm{VolPS}_{t-1} + \psi \Delta lnACTM_{t-1} + \lambda_3 ECT_{t-1} + u_{3t} \ldots (3)$$

$$\Delta lnVolPS_t = \kappa + \sum_{a=1}^{k-1} \beta_i \Delta lnValTM_{t-1} + \sum_{b=1}^{k-1} \Upsilon_i \Delta lnVolTM_{t-1} + \sum_{d=1}^{k-1} \varphi_i \Delta lnCASH_{t-1} + \sum_{d=1}^{k-1} \tau_i \Delta lnValPS_{t-1} + \sum_{d=1}^{k-1} \phi_i \Delta ln\mathrm{VolPS}_{t-1} + \psi \Delta lnACTM_{t-1} + \lambda_4 ECT_{t-1} + u_{4t} \ldots (4)$$

$$\Delta lnCASH_t = \eta + \sum_{a=1}^{k-1} \beta_i \Delta lnValTM_{t-1} + \sum_{d=1}^{k-1} \Upsilon_i \Delta lnVolTM_{t-1} + \sum_{c=1}^{k-1} \varphi_i \Delta lnCASH_{t-1} + \sum_{d=1}^{k-1} \tau_i \Delta ln\mathrm{ValPS}_{t-1} + \sum_{d=1}^{k-1} \phi_i \Delta ln\mathrm{VolPSS}_{t-1} + \psi \Delta lnACTM_{t-1} + \lambda_5 ECT_{t-1} + u_{5t} \ldots (5)$$

In my above system equations:

K − 1 is the lag length, and this is reduced by 1.

β, Y, φ, τ, and φ are the short-run dynamic coefficient of the model's adjustment to short-run equilibrium

λ_i is the speed of adjustment and should be negative to ensure convergence to long-run equilibrium.

ECT_{t-1} is the error correction term. This is the lagged value of the residuals of the model obtained from the cointegrating regression of the dependent variable on the independent variables.

u_{it} is the stochastic error terms.

4.6 Empirical results

4.6.1 Preliminary diagnostic test.

Prior to performing my vector error correction model (VECM), I perform three main preliminary tests. First, I examined and present the stationarity of my dataset using the Augmented Dickey–Fuller test for unit root at level and at first difference in appendix (B) supplementary table (78) and tables 29 respectively. The Augmented Dickey–Fuller test for unit root result at level show that the value of mobile money transactions and the use of cash were non-stationary. To ensure stability and to avoid the problem of spurious regression results, I performed unit test on first difference and the results suggests that each of the five variables in my model are integrated of first order I(1), table 29. Put differently, the variables in my vector error correction model (VECM) are all stationary at first-order difference and that the test failed to reject the null hypotheses that each of my six series contains a unit root. I plot the first difference of my selected variables and present them in appendix (A) supplementary figures (4) to (8).

Table 43. First-order difference Unit root test results

Variables	ADF test [t-values [Z(t)]	*P*-Values
Voltm	-8.1560	0.0000
Valtm	-7.3060	0.0000
Valps	-7.8990	0.0000
Volps	-6.6760	0.0000
Cash	-7.0520	0.0000

Second, to consistently test for cointegration, I determine the appropriate lags length and I present the results of my lag order selection results in table (30). My results show that the optimal lag for my model based on the widely used Akaike information criterion (AIC) is two (2). Since all my five variables in the system are integrated of order I(1), I use Johansen Cointegration approach to test whether there is a long-run relationship among the variables. Here, it should be understood that if cointegration exists among my selected variables, Vector Error Correction Model (VECM) approach will be used to determine long term relationships.

Table 44. Lag order selection.

Sample: 2010m5 thru 2022m12 **Number of obs = 152**

Lag	LL	LR	p	FPE	AIC	HQIC	SBIC
0	-90.0365			2.40E-06	1.25048	1.29089	1.34995
1	786.339	1752.8	0.000	3.30E-11	-9.95183	-9.70939*	9.35502*
2	816.809	60.94*	0.000	3.1e-11*	-10.0238*	-9.57932	8.92964
3	831.47	29.321	0.251	3.50E-11	-9.88776	-9.24123	8.29625
4	848.756	34.571	0.096	3.90E-11	-9.78626	-8.93769	7.69739

* Indicates lag order selected by each criterion.

Finally, I test for cointegration based on Johansen (1995), and the results of the Johansen cointegration analysis with 2 lags order are presented in Table (31). The results show that there is evidence of a long-run relationship among the five variables in my vector error correction mode (VECM). That is, as reported in table (31), the co-integration test results for the trace test indicates one cointegrating equations at the 5% significance level. Hence, it can be said that there exists a long-run relationship among the five selected variables that I include in my Vector Error Correction Model (VECM). Figure (31) is a graph examining the in-sample values for my cointegrated equation, and the result show stationarity with a peak during the covid-19 pandemic period in 2020.

Table 45. Johansen tests for cointegration

Maximum rank	Params	LL	Eigenvalue	Trace statistic	Critical value at 5%
0	30	785.3081	.	75.1043	68.5200
1	39	803.4348	0.20975	38.8509*	47.2100
2	46	812.1366	0.10686	21.4473	29.6800
3	51	817.8029	0.07095	10.1147	15.4100
4	54	822.046	0.05361	1.6285	3.7600
5	55	822.8602	0.01052		

* Denotes a rejection of the hypothesis at the 0.05 level.

4.6.2 Short and Long-run causality

I present the short and long-run equation results of my vector error correction model with the optimal lags, unrestricted constant and no trend in tables (32) to (39). I find that for the dependent variable, that is, the total volume of mobile money (Voltm), the speed of adjustment for the error correction factor is significant and negative as expected. This suggests that prior month's error or deviation from long-run equilibrium is corrected for within the current month at a converging speed of 3.44% as shown in equation (1) results in table (35). Additionally, I find a significant (at the 5% significance level) negative short-term causal relationship between the dependent variable, that is, the total volume of mobile money (Voltm) and its own shock, [β = -0.2969, SE = 0.1430, Z = -2.0800, P = 0.0380].

The result for equation (2) is shown in table (36). I find no significant causal relationship between the dependent variable, that is, total volume of payment system transactions and the four independent variables (total volume of mobile money transactions, total value of payment system transaction, cash, and total value of mobile money transactions). In equation (3), I find, that for the dependent variable, that is, the total value of payment system transactions (Valps), the speed of adjustment for the error correction factor is significant and negative, [β = -0.1489, SE = 0.0296, Z = -5.0400, P = 0.0000]. Since my dataset is monthly, this suggests that prior month's error or deviation from long-run equilibrium is corrected for within the current month at a convergence speed of 14.89% as shown in equation (3) results in table (37).

I find a significant asymmetric short-term causal relationship between the total volume of payment system transactions [β = 0.1571, SE =0.0632, Z = 2.4900, *P* = 0.0130], total value of mobile money transaction [β = -0.6964, SE =0.3226, Z = -2.1600, *P* = 0.0310], and the dependent variable (total value of payment system transactions) shown in equation (3) results in table (37). However, I find no significant short-term relationship between the total volume of mobile money transactions (Voltm), and the use of cash on the dependent variable, total value of payment system transactions (Valps). From equation (5) results in table (39), I find no significant short-term causal relationship between the dependent variable, that is cash, and the four independent variables ((total volume of mobile money transactions (Voltm), total volume of payment system transactions (Volps), total value of payment system transactions (Valps), total value of mobile money transactions (Valtm)).

In equation (4) I find, that for the dependent variable, that is, the total value of mobile money wallet transactions (Valtm), the speed of adjustment for the error correction factor is significant (albeit at 10% level) and negative, [β = -0.0237, SE = 0.0134, Z = -1.7700, *P* = 0.0770]. This suggests that prior month's error or deviation from long-run equilibrium is corrected for within the current month at a converging speed of 2.37%. Additionally, I find a negative short-term causal relationship between the dependent variable, that is, total value of mobile money wallet (Valtm), and the total volume of mobile money wallet (Voltm), [β = -0.3741, SE = 0.1659, Z = -2.2500, *P* = 0.0770], and is significant at the 5% level in table (38).

I discuss the result of the long-run relationship between the dependent variable and independent variables in tables (33) and (34). I Find a negative long-run causal relationship from the total volume of payment system transactions [β = 0.8755, SE = 0.2062, Z = 4.2500, P = 0.0000], and the total value of payment system transactions [β = 1.3686, SE = 0.2911, Z = 4.7000, P = 0.0000] to the dependent variable, total volume of mobile money transactions (Voltm). Additionally, I find an asymmetric long-run causal impact from the use of cash [β = 0.4419, SE = 0.1434, Z = 3.0800, P = 0.0020] and the total value of mobile money transactions to the dependent variable and is significant at the 1% level.

Mainly, my long-run results show that a 1% increase in the volume of mobile money transaction is associated with 0.88% decrease in the volume of payment system transactions, and a 1.37% reduction in the value of payment system transactions. Additionally, a 1% increase in the dependent variable leads to a 0.80% increase in the value of mobile money transactions. The results show that, *all things being equal*, financial technology innovation adoption, that is, mobile money, provides financial inclusion. My results are statistically significant at the one percent level and confirm my first hypothesis.

Furthermore, a 1% increase in the total volume of mobile money transaction is associated with 0.44% decrease in the use of physical cash in the Kenyan economy, *ceteris parabus*. My result confirms my second hypothesis that financial technology innovation adoption, that is mobile money wallet, can transfer informal cash into the formal banking system by linking the formal and informal sectors of the country's economy in a move to become a cashless society. This can in turn impact on central bank signiorage and facilitate financial sector deepening. Additionally, the error correction term in my long-run equation is significant and show that any deviation in the short-run is corrected in future period, table (34).

Table 46. VEC Model Summary results

Sample period: 2010m3 to 2022m12	**Log likelihood**	**803.4348**			
	Det(Sigma_ml)	**2.02E-11**			
Equation	**Parms**	**RMSE**	**R-sq.**	**chi2**	**P>chi2**
Voltm	7	0.0482	0.3000	62.9960	0.0000
Volps	7	0.1835	0.1668	29.4210	0.0001
Valps	7	0.1239	0.2532	49.8360	0.0000
Valtm	7	0.0559	0.2934	61.0300	0.0000
Cash	7	0.1788	0.0348	5.3049	0.6228

No. of observations=154

AIC = -9.9277

HQIC = -9.6153

SBIC = -9.1586

Table 47. Result of Johansen normalization restriction-imposed test

_ce1	**Coefficient**	**Std. err.**	**z**	**P>z**	**[95% conf. interval]**	
Voltm	1					
Volps	0.8755	0.2062	4.2500	0.0000	0.4713	1.2796
Valps	1.3686	0.2911	4.7000	0.0000	0.7981	1.9390
Valtm	-0.7995	0.1397	-5.7200	0.0000	-1.0734	-0.5256
Cash	0.4419	0.1434	3.0800	0.0020	0.1608	0.7230
Intercept	-29.7377					

Table 48. Results for the Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	4	538.0723	0.000

Table 49. Equation (1) results- VEC Model results for short-run relationship

D_ln_voltm	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
_ce1 L1.	-0.0344	0.0115	-2.9900	0.0030	-0.0569	-0.0118
Voltm LD.	-0.2969	0.1430	-2.0800	0.0380	-0.5771	-0.0166
Volps LD.	0.0259	0.0246	1.0500	0.2920	-0.0223	0.0741
Valps LD.	0.0245	0.0360	0.6800	0.4970	-0.0461	0.0951
Valtm LD.	-0.1641	0.1256	-1.3100	0.1910	-0.4102	0.0820
Cash LD.	0.0213	0.0223	0.9500	0.3410	-0.0225	0.0651
Intercept	0.0191	0.0042	4.5400	0.0000	0.0108	0.0273

Table 50. Equation (2) results- VEC Model results for short-run relationship

D_ln_Volps	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
_ce1 L1.	-0.1888	0.0438	-4.3100	0.0000	-0.2747	-0.103
Voltm LD.	-0.1244	0.5443	-0.2300	0.8190	-1.1912	0.9425
Volps LD.	-0.0503	0.0936	-0.5400	0.5910	-0.2337	0.1332
Valps LD.	0.1732	0.1372	1.2600	0.2070	-0.0957	0.4420
Valtm LD.	-0.4739	0.4779	-0.9900	0.3210	-1.4105	0.4628
Cash LD.	0.0538	0.0851	0.6300	0.5270	-0.1129	0.2205
Intercept	-0.0083	0.016	-0.5200	0.6040	-0.0396	0.0230

Table 51. Equation (3) results- VEC Model results for short-run relationship

D_ln_valps	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
_ce1						
L1.	-0.14890	0.02960	-5.04000	0.00000	-0.20690	-0.09090
Voltm						
LD.	-0.00380	0.36740	-0.01000	0.99200	-0.72380	0.71630
Volps						
LD.	0.15710	0.06320	2.49000	0.01300	0.03330	0.28090
Valps						
LD.	-0.02190	0.09260	-0.24000	0.81300	-0.20340	0.15960
Valtm						
LD.	-0.69640	0.32260	-2.16000	0.03100	-1.32860	-0.06420
Cash						
LD.	0.02630	0.05740	0.46000	0.64700	-0.08620	0.13880
Intercept	0.00420	0.01080	0.39000	0.69700	-0.01690	0.02530

Table 52. Equation (4) results- VEC Model results for short-run relationship

D_ln_valtm	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
_ce1						
L1.	-0.0237	0.0134	-1.7700	0.0770	-0.0498	0.0025
Voltm						
LD.	-0.3741	0.1659	-2.2500	0.0240	-0.6993	-0.0489
Volps						
LD.	0.0175	0.0285	0.6100	0.5400	-0.0384	0.0734
Valps						
LD.	0.0421	0.0418	1.0100	0.3140	-0.0399	0.1240
Valtm						
LD.	-0.1993	0.1457	-1.3700	0.1710	-0.4848	0.0862
Cash						
LD.	0.0030	0.0259	0.1200	0.9070	-0.0478	0.0538
Intercept	0.0238	0.0049	4.8900	0.0000	0.0143	0.0334

Table 53. Equation (5) results- VEC Model results for short-run relationship

D_ln_cash	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
_ce1 L1.	-0.0409	0.0427	-0.9600	0.0380	-0.1245	0.0428
Voltm LD.	0.5155	0.5304	0.9700	0.3310	-0.5240	1.5550
Volps LD.	0.0704	0.0912	0.7700	0.4400	-0.1083	0.2492
Valps LD.	-0.0664	0.1337	-0.5000	0.6190	-0.3284	0.1956
Valtm LD.	-0.6965	0.4656	-1.5000	0.1350	-1.6091	0.2161
Cash LD.	0.0164	0.0829	0.2000	0.8430	-0.1460	0.1788
Intercept	-0.0069	0.0156	-0.4400	0.6590	-0.0374	0.0236

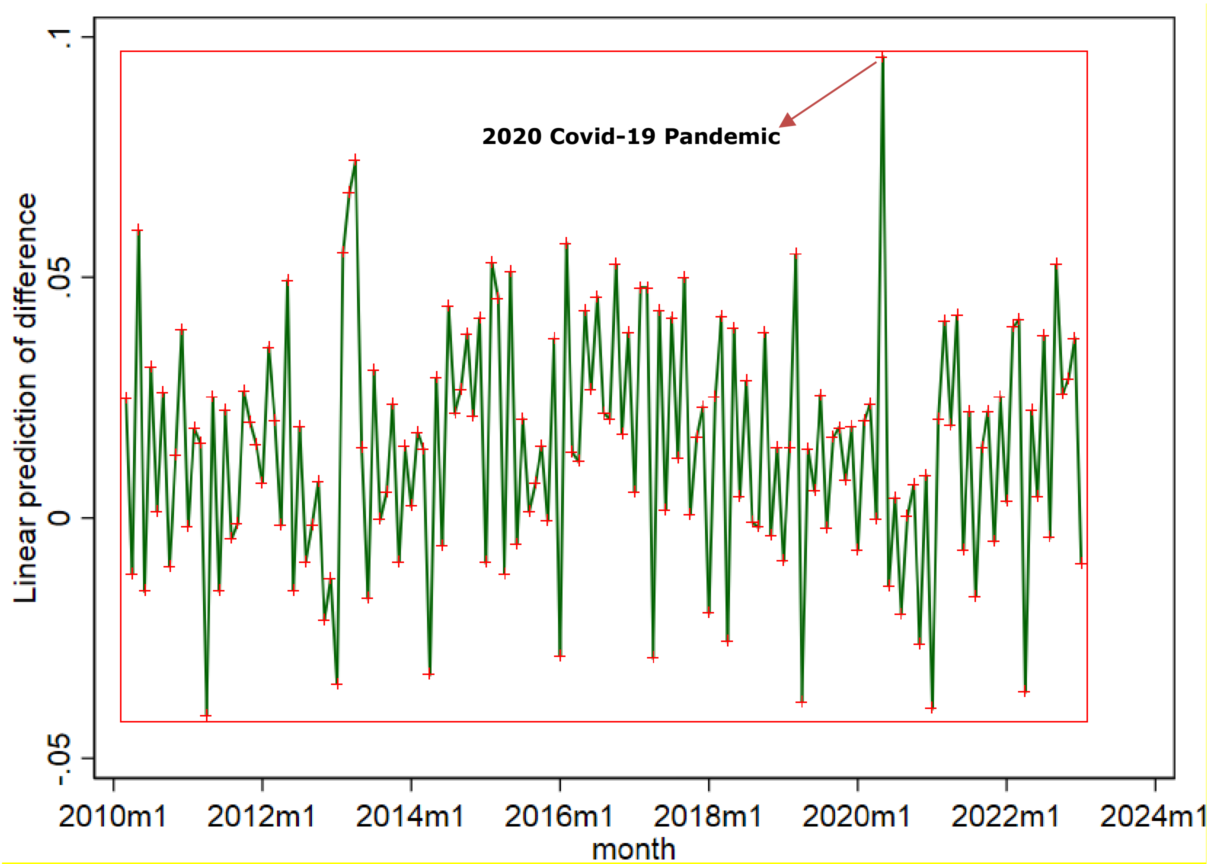

Figure 40. Graph of cointegration equation of VEC Model

4.6.3 Variance Impulse Function

To examine the effect of unanticipated shocks to the value and volume of mobile money wallet payment on Kenya's payment systems stability, I estimate a reduced form vector autoregression (VAR) model and analyse the impulse response function. My result can provide information to central banks to forecast and respond to the impact of any unanticipated shocks on the stability of their payment system. I use Cholesktype of contemporaneous identifying restrictions to draw a meaningful interpretation of my results. The recursive structure assumes that variables appearing first in my variance impulse function graph contemporaneously influence the latter variable. I provide the impulse response functions in figure (32) and discuss the responses as follow:

As seen in the first graph on the top left of figure (32), I find that a one standard deviation positive own shock leads to a nearly 0.2 standard deviation increase in the total volume of payment system transactions in the first period. This is followed by a steady positive decline from period 2 to near equilibrium in the long term. Further, there is a minimal positive impact to the volume of payment system transactions from a unit shock to the volume of mobile money transactions in the initial period before a decline to equilibrium and remained same into the long term, period 18.

Graph number three from the first row as shown in figure (32) is the response of the total volume of payment system transactions to the use of cash, that is, broad money supply (M3). I find a minimal positive first-period impact on the total volume of payment system transactions before a decline in period 3. This is followed by a second positive impact in period 4 and remained stable between period 4 and 5 before returning to equilibrium in period 6 to period 18 from a standard deviation shock to the use of Cash in the economy. Additionally, I find that a one standard deviation positive shock to the total value of payment system transactions leads to a 0.05 standard deviation increase in the total volume of payment system transactions in the first period after the shock. This is followed by a decline between periods 2 to 3 and remained stable in periods 4 to 5 before returning to equilibrium from period 6.

I find that a one standard deviation positive shock to the total value of payment system transactions leads to a 0.05 standard deviation increase in my dependent variable, that is, the total volume of payment system transactions, in the first period after the shock. This declined to equilibrium in period 2 before a second positive impact in period 3. Also, there is a positive first-period impact to a one standard deviation to own shock. This is followed by a negative response in period (2) before returning to equilibrium in period 4, and thereafter remained same to period 18. I find similar results to a one standard deviation shock from the total value of mobile money wallet transaction (Valtm), total value of payment system transactions (Valps), total volume of payment system transactions (Volps), and the use of cash (Cash) to the total volume of mobile money transactions (Voltm).

When I examined the response of the use of cash, I find a negative impact between period 2 to 5 (figure 32). This is followed by a positive impact from period 8 and remained in equilibrium from a unit shock to the total volume of payment system transaction. Further, I find no impact from a one standard deviation to the total volume of mobile money transaction and the total value of mobile money transaction on the use of cash. I find that a one standard deviation positive own shock leads to a nearly 0.2 standard deviation increase in broad money supply in the first period. This is followed by a steady decline in period 2 before returning to equilibrium in the long-term. Also, my results show no first-period impact on the use of cash but remained stable in periods 4 to 6 after a negative in periods 2 to 3. That is, from a unit shock to the total value of payment system transactions.

Row four of figure (32) show the response of the total value of payment system transactions. I find no first-period impact, but this is followed by a negative impact in period 2 to 3 and remained stable in 5 to 6 before a positive impact in periods 6 to 12. Thereafter, it remained in equilibrium into the long-term from a unit shock to the total volume of payment system transactions. I find no impact on the total volume of payment system transactions from a unit shock to the total value and volume of mobile money wallet transactions. On the contrary, I find a negative first-period impact, followed by a positive impact in periods 2 to 6 before returning to equilibrium in the long-term from a one standard deviation shock to the use of cash. Additionally, my result shows a positive first-period impact to own shock before declining steadily to equilibrium in the long-term from period 2.

From row 5 in figure (32), my impulse response function graph shows a negative impact on the total value of mobile money transactions in the first period from a one standard deviation shock to the total volume of payment system transactions. This is followed by a positive impact in periods 2 to 4 and remained in equilibrium from period 5 thereafter into period 18. Further, there is a reverse first-period impact before a positive impact from period 2, and thereafter remained in equilibrium into the long-term from a unit shock to the use of cash, and the total value of payment system transactions. Additionally, there is a minimal negative impact on the value of mobile money transactions from own shock and from volume of mobile money transaction before a positive impact in period 3, and thereafter remained in equilibrium.

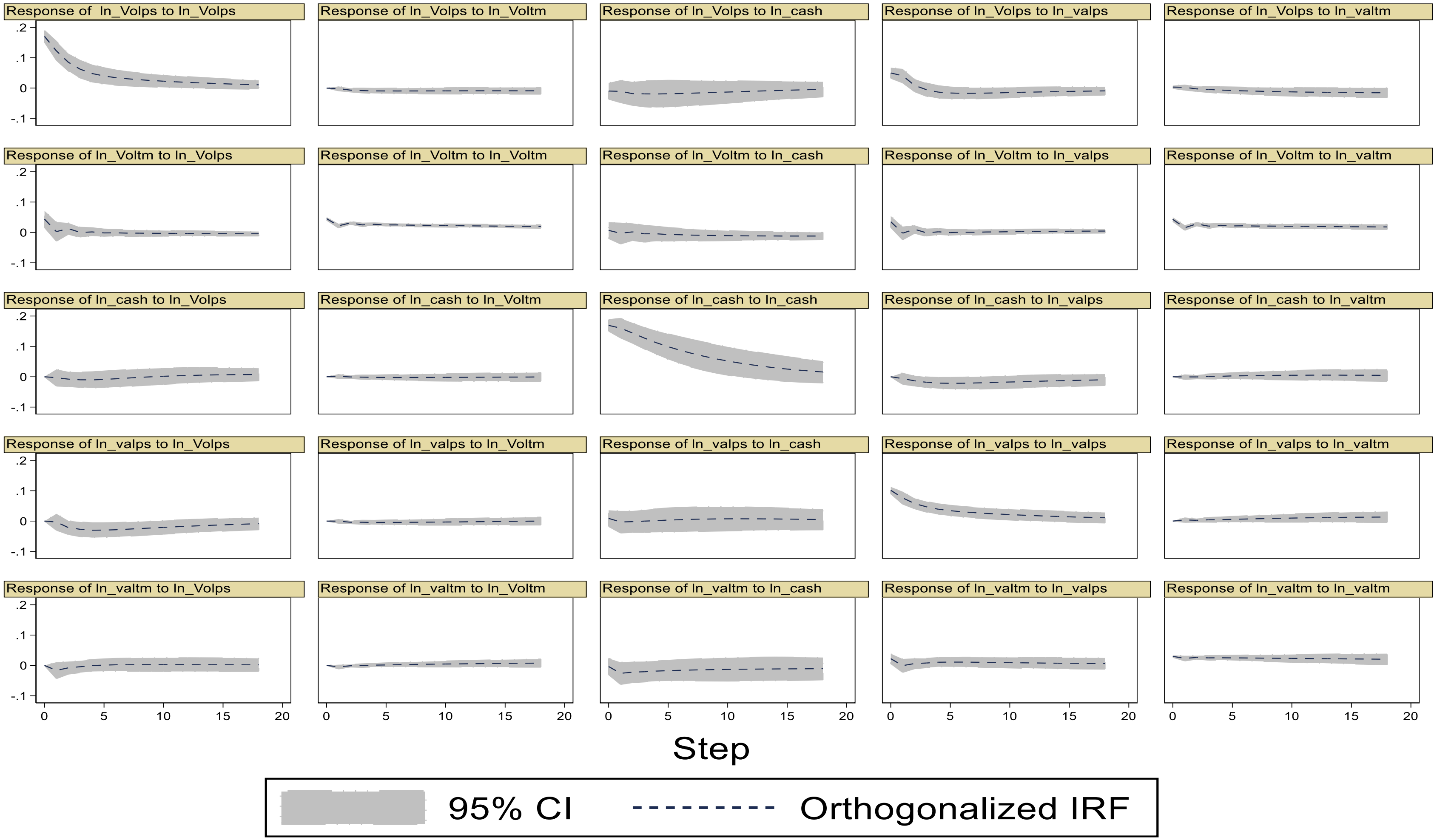

Figure 41. Graph of Impulse Response Functions

4.6.4. Analysis of Variance decomposition

I employ this analysis as evidence presenting more detailed information regarding the variance relations between my selected endogenous variables. It should be noted here that my variance decomposition results determine the amount that the forecast error variance of each of the five (5) variables can be explained by the other variables. That is, the variance decomposition reflects the mean square error contributions of each variable in the system.

In the short-run, that is, in period (12), 88.63% of the forecast error variance of the dependent variable, that is, total volume of mobile money wallet transactions (Voltm), is explained by the variable itself, and 43.53% by the total value mobile money transaction (Valtm). The total value and volume of payment system transactions, and cash exhibited strong exogeneity. That is, these three variables have weak influence in predicting the total volume of mobile money wallet transactions in the future. In the long run, that is, in period 18, 85.83% of the variations in the total volume of mobile money transactions is explained by own shock. This is followed by a 39.17% contribution from the total value of mobile money transactions, table (40).

Table (41) show the result for the variance decomposition forecast of the total volume of payment system transactions (Volps). My results show that own shock dominates and account for 93.8244% in the first period. This is followed by a contribution of 17.09 from the total value of payment system transaction (Valps) of the forecasted variance in the same period. These percentages decline to 87.1608% from own shock, and 15.1851% from the total value of payment system transaction (Valps) at the end of the first year which is period 12. Further, in the long-term, that is, in period 18, 85.7568% and 15.7244% of the forecast variations in the total volume of payment system transactions is from own shock, and from the total value of payment system transactions respectively. The total volume and value of mobile money transactions, and the use of cash are strongly exogenous and have weak influence in predicting the total volume of payment system transactions (Volps), both in the short and long-term.

I present the variance decomposition for the total value of mobile money wallet transactions (Valtm) in table (42) I find that variations in the total value of mobile money wallet transactions can be explained by own shock. The results show an increasing trend, that is, from 32.09% in period 1 to 47.08% in period 8. This is then followed by a decreasing trend, that is, from 47.03% in period 9 to 46.28% in period 12 before declining further to 43.80% in period 18. Additionally, my results also show that the total volume of mobile money transaction (Voltm), total value of payment system transaction (Valps), total volume of payment system transaction (Volps), and the use of cash (Cash) are strongly exogenous and have weak influence in predicting the total value of mobile money transactions (Valtm), both in the short and long-term.

The variance decomposition for the total value of payment system transactions (Valp) is shown in table (43). I find that variations in the total value of payment system transactions can be explained by own shock. The results show an increasing trend, that is, from 70.88% in period 1 to 76.33% in period 4. However, this is then followed by a decreasing trend, that is, from 75.69% in period 5 to 69.07% in period 12 before reducing further to 66.59% in period 18. Additionally, the total volume of mobile money transaction (Voltm), total volume of payment system transaction (Volps), total value of mobile money transactions (Valtm), and the use of cash (Cash) are strongly exogenous and have weak influence in predicting the total value of payment system transaction (Valps) in the short and long-term.

In in table (44), I present the results for the variance decomposition of the forecasted use of cash (Cash). The results show that 99.20% of the variance decomposition forecast can be explained by own shock in the first period. This reduces to 94.89% in the first year, that is period 12, and declined to 93.67% in period 18. The total value of payment system transaction contributed 10.4721% of variations in period 18. Additionally, the total volume of mobile money transaction (Voltm), total volume of payment system transaction (Volps), total value of mobile money transactions (Valtm), are strongly exogenous and have weak influence in predicting the use of cash in the short and long-term.

Table 54. (Cholesky) Variance decompositions for Total Volume of Mobile Money Wallet Transactions (Voltm).

Period	Voltm.	Volps.	Valtm.	Valps.	Cash.
1	1.000000	0.061756	0.674909	0.086188	0.001576
2	0.989800	0.041468	0.58963	0.056981	0.000973
3	0.976184	0.038314	0.571567	0.052853	0.000741
4	0.96064	0.035255	0.540301	0.048028	0.000819
5	0.944897	0.033425	0.522752	0.044623	0.000898
6	0.931678	0.032153	0.504721	0.041858	0.001218
7	0.920670	0.031202	0.490536	0.039676	0.001597
8	0.911592	0.030526	0.477256	0.037931	0.002104
9	0.903962	0.030014	0.465518	0.036565	0.002681
10	0.897387	0.029646	0.454628	0.035489	0.003338
11	0.891563	0.02938	0.444634	0.034666	0.004052
12	0.886255	0.029203	0.435339	0.034046	0.004817
13	0.881296	0.029096	0.426709	0.033604	0.005621
14	0.876558	0.029049	0.41867	0.03331	0.006456
15	0.871950	0.029053	0.411184	0.033146	0.007313
16	0.867406	0.029101	0.404209	0.033092	0.008183
17	0.862877	0.029186	0.397715	0.033136	0.009059
18	0.858330	0.029305	0.391668	0.033263	0.009936

Table 55. (Cholesky) Variance decompositions for Total Volume of Payment Systems Transactions (Volps)

Period	Voltm.	Volps.	Valtm.	Valps.	Cash.
1	0.000000	0.938244	0.004224	0.170929	0.003260
2	0.000970	0.952281	0.004882	0.186585	0.003788
3	0.012942	0.945584	0.004771	0.162618	0.007002
4	0.026178	0.935505	0.007117	0.148589	0.009583
5	0.038829	0.922719	0.011840	0.143446	0.011924
6	0.049362	0.911010	0.017512	0.142606	0.013847
7	0.057794	0.900854	0.023907	0.143754	0.015465
8	0.064621	0.892497	0.030613	0.145470	0.016803
9	0.070165	0.885657	0.037490	0.147287	0.017914
10	0.074794	0.880066	0.044400	0.148980	0.018826
11	0.078727	0.875454	0.051265	0.150503	0.019569
12	0.082157	0.871608	0.058022	0.151851	0.020165
13	0.085207	0.868360	0.064627	0.153040	0.020634
14	0.087976	0.865582	0.071048	0.154091	0.020994
15	0.090532	0.863179	0.077261	0.155025	0.021262
16	0.092927	0.861077	0.083250	0.155857	0.021451
17	0.095198	0.859220	0.089007	0.156603	0.021576
18	0.097373	0.857568	0.094525	0.157274	0.021650

Table 56. (Cholesky) Variance decompositions for Total Value of Mobile Money Wallet Transactions (Valtm)

Table XIV. Variance Decomposition of Valtm

Period	Voltm.	Volps.	Valtm.	Valps.	Cash.
1	0.000000	0.000000	0.320867	0.034091	0.000477
2	0.008265	0.005832	0.401131	0.022458	0.012719
3	0.006259	0.006145	0.419214	0.020718	0.015505
4	0.005353	0.005972	0.445899	0.020983	0.017307
5	0.004651	0.005657	0.456580	0.023059	0.018378
6	0.004491	0.005450	0.465392	0.025198	0.019286
7	0.004881	0.005345	0.469075	0.027363	0.020074
8	0.005668	0.005294	0.470764	0.029227	0.020826
9	0.006842	0.005283	0.470341	0.030859	0.021548
10	0.008327	0.005291	0.468704	0.032250	0.022259
11	0.010100	0.005313	0.466079	0.033455	0.022961
12	0.012120	0.005342	0.462816	0.034503	0.023656
13	0.014362	0.005376	0.459091	0.035426	0.024346
14	0.016797	0.005413	0.455076	0.036248	0.025029
15	0.019403	0.005450	0.450882	0.036987	0.025706
16	0.022154	0.005486	0.446598	0.037659	0.026377
17	0.025029	0.005522	0.442290	0.038274	0.027040
18	0.028008	0.005555	0.438007	0.038843	0.027696

Table 57. (Cholesky) Variance decompositions for Total Value of Payment Systems Transactions (Valps)

Period	Voltm.	Volps.	Valtm.	Valps.	Cash.
1	0.000000	0.000000	0.000000	0.708793	0.002721
2	0.000019	0.000210	0.004280	0.732333	0.001568
3	0.003833	0.008650	0.004353	0.755480	0.001175
4	0.006754	0.020388	0.006461	0.763349	0.000961
5	0.009802	0.033757	0.008279	0.756854	0.000864
6	0.011909	0.045951	0.011109	0.746040	0.000882
7	0.013418	0.056677	0.014271	0.733973	0.000997
8	0.014350	0.065645	0.018003	0.722869	0.001200
9	0.014863	0.073068	0.022053	0.712988	0.001466
10	0.015050	0.079115	0.026409	0.704458	0.001778
11	0.014995	0.084012	0.030947	0.697086	0.002113
12	0.014764	0.087943	0.035614	0.690718	0.002455
13	0.014409	0.091077	0.040336	0.685180	0.002790
14	0.013970	0.093554	0.045066	0.680338	0.003106
15	0.013483	0.095493	0.049758	0.676073	0.003394
16	0.012974	0.096993	0.054376	0.672294	0.003649
17	0.012468	0.098137	0.058894	0.668923	0.003869
18	0.011982	0.098997	0.063288	0.665899	0.004052

Table 58. (Cholesky) Variance decompositions for Broad Money (M3)-Cash

Period	Voltm	Volps	Valtm	Valps.	Cash.
1	0.000000	0.000000	0.000000	0.000000	0.991965
2	0.000946	0.000208	0.000077	0.001643	0.980952
3	0.000782	0.001307	0.000095	0.008332	0.975578
4	0.001074	0.002879	0.000222	0.019050	0.971330
5	0.001821	0.004442	0.000549	0.032018	0.967936
6	0.002560	0.005437	0.001267	0.044298	0.964766
7	0.003237	0.005921	0.002211	0.055234	0.961866
8	0.003769	0.006038	0.003364	0.064503	0.959067
9	0.004167	0.005979	0.004598	0.072302	0.956390
10	0.004442	0.005882	0.005858	0.078823	0.953799
11	0.004615	0.005841	0.007074	0.084291	0.951305
12	0.004704	0.005903	0.008210	0.088882	0.948906
13	0.004726	0.006091	0.009236	0.092750	0.946609
14	0.004699	0.006402	0.010140	0.096013	0.944415
15	0.004633	0.006826	0.010916	0.098769	0.942326
16	0.004540	0.007344	0.011566	0.101098	0.940340
17	0.004429	0.007934	0.012094	0.103064	0.938456
18	0.004306	0.008576	0.012511	0.104721	0.936666

4.6.5 Robustness test results

I present the result of the diagnostic test for my vector error correction model's (VECM) stability in tables 45 and 46 using Johansen (1995) in my vector error correction model and Stata 17 software. First, I test for any serial correlation, and my results in table (45) show that there is no serial correlation in the residuals. Finally, the results of my stability test presented in table (46) and the graph of the eigenvalue in figure (33) show that none of the remaining eigenvalues appear close to the unit circle, hence my stability check does not indicate that my vector error correction model (ECM) is misspecified. My results generally show no sign of autocorrelation or multicollinearity and appears to be stable and statistically significant, particularly with respect to the lag orders that I chose in accordance with the causality testing procedure.

Table 59. Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	28.8532	25	0.2701
2	16.7834	25	0.8895

H0: no autocorrelation at lag order

Table 60. Result of the VECM stability condition

Eigenvalue	Modulus
1	1
1	1
1	1
1	1
0.512112	0.512112
-0.439561	0.439561
0.213249	0.213249
-0.200072	0.200072
-0.120947	0.120947
0.080663	0.080663

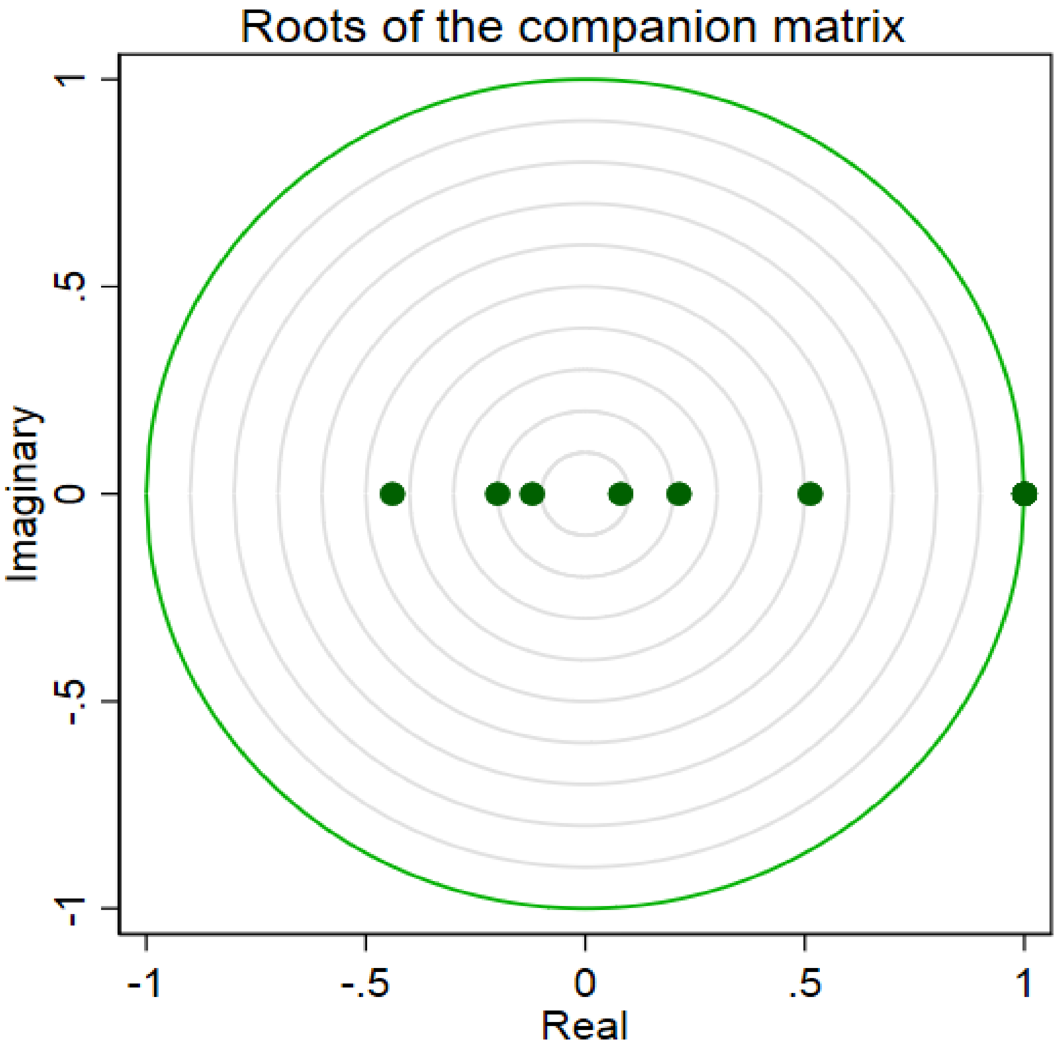

Figure 42. Companion Matrix

4.6.6 Conclusion

In this third section, that is chapter 3 of my thesis, I empirically examined the prevalent use of financial technology, that is, mobile money, which is mostly used for small but high frequency transactions in the developing world, and it impact of the traditional electronic payment systems. Further, this chapter empirically investigated the relationship between Fintech, financial inclusion, and the use of cash. To achieve this, first, I used the total volume and value of mobile money wallet transactions as proxy for Fintech and financial inclusion. Additionally, I used the volume and value of debit, credit, prepaid, and charge cards payments to proxy my payment system transactions.

Second, I performed three diagnostic tests on my dataset. That is, the Augmented Dickey-Fuller test result at level and at first difference to examine the stationarity of my data; test for cointegration to determine the appropriate lags length using the Akaike information criterion (AIC); and I use Johansen Cointegration approach to test for any long-run relationship among the variables. My diagnostics test results show that three of the five selected variables are stationary at level, and all five variables are stationary at first difference. Hence, I use stationarity at first order to ensure stability of my model. My results further show that the appropriate lag is two, and there is a long-run relationships among the variables. Finally, I use Vector Error Correction Model (VECM) to determine the causal relationship among my selected variables.

My results show a negative long-run causal relationship from the total volume and value of payment system transactions to the dependent variable, Volume of mobile money transactions. These findings are significant at the one (1) percent level. This confirm my first hypothesis that, all things being equal, financial technology provides financial inclusion for the many unbanked residents in the developing world. Further, my empirical results show a cointegration between the total value and volume of mobile money payment transactions, and total volume and value of payment system transactions, and the use of cash. That is, there is an asymmetric long-run causal relationship between the volume of transactions using Fintech and the volume of transactions using debit card, credit cards, prepaid cards, charge cards and the use of physical currency. This also confirm my second hypothesis that Fintech provides financial sectors deepening, payment system stability and the country's drive to be a cashless society.

When I performed a variance decomposition analysis of my selected endogenous variables, I find that majority of the forecast error variance of my outcome variable, that is, total volume of mobile money wallet transactions (Voltm), is explained by the variable itself. This is followed by the total value mobile money transaction (Valtm. Further, my empirical results show, that in the long-term the total value and volume of payment system transactions, and the use of cash in the Kenyan economy have weak influence in predicting the total volume of mobile money wallet transactions in the future. Additionally, I find that the total volume of mobile money transaction (Voltm), total value of payment system transaction (Valps), total volume of payment system transaction (Volps), and the use of cash (Cash) are weak predictors of the total value of mobile money wallet transactions (Valtm), in the short and long-term.

The variance decomposition for the total value of payment system transactions (Valp) shows an increasing trend in own shock from period one (1) to four (4). This is followed by a consistent decrease and other variables have a weak influence in predicting changes in the total value of payment system transactions. I find a contribution of 17.09% from the total value of payment system transaction to the total value of payment system transactions. In my forecast error variance decomposition analysis for the use of cash, I find that in the first 18 months, the total value of payment system transaction contributed 10.4721% of the variations in the use of cash. This is after a 94.89% variation due to own shock in the first twelve (12) months. The total volume of mobile money transactions (Voltm), total volume of payment system transaction (Volps), total value of mobile money transactions (Valtm) exhibited weak influence in predicting the use of currency in the short and long-term.

5. Final Conclusion

5.1 Financial Technology and Loan Performance: Can Fintech Adoption Signal Loan Risk?

Signaling and technology adoption theories provides a firm ground to understand how signals can be used by lenders to screen for quality borrowers, reduce uncertainty and facilitate lending. Further, technology adoption theories provide us with basis to examine what drives the use of Fintech and the associated benefit that accrue to users. Additionally, theoretical, and empirical studies have shown that lenders can benefit significantly from acquiring additional information about borrowers. This will reduce the information gap, facilitate lending, and ultimately improve the lending institutions' loan portfolio at risk. Also, extant studies have shown the benefit of Fintech, that is mobile money, on the social and economic well-being of residents in the developing countries. However, no studies have yet, to the best of my knowledge attempted to proof the relationship between borrowers' use of financial technology such as mobile money wallet and its impact on credit using both loan and borrower-specific data.

I modelled the loan default likelihood of borrowers as a function of their adoption and use of financial technology, that is, mobile money wallet, plus borrower and loan specific characteristics, and the branch of the lending institution where each loan was disbursed. My empirical results provide evidence to show, that Fintech can signal borrower credit quality, and this can lower default rate when lending to the many unbanked in the developing world. My results speak to the literature on financial technology adoption and asymmetric information in the consumer loans market. The results of my empirical analysis highlight the importance of investigating the relationship between individuals' adoption of financial technology using standard mobile phone, and its relationship with asymmetric information problem. The approach I used, that is, borrowers' ownership of mobile money account, differ from other studies that mainly focused on clients' mobile phone call records and top-up data to investigate loan repayment.

I find empirical evidence to show that borrowers' adoption of Fintech, that is, mobile money, can signal credit risk. This in turn reduces loan risk. My finding is statistically and economically significant. Further, my empirical results show that, for repeat borrowers who continues to adopt Fintech, the likelihood of default is further reduced compared to their non-adopting counterparts. Also, female clients across the two cohorts borrows who adopted Fintech are associated with a significant reduction in their likelihood of loan default. My results suggest that female borrowers are tech savvy and are able to use Fintech to manage their finances well to ensure that they meet their debt servicing obligation.

Additionally, I find a significant inelastic relationship between first-time borrowers who adopt Fintech and the interest rate charged by the lender. I find opposite results for repeat borrowers. This result suggests two things. First, Fintech may be revealing borrowers' 'true' risk and leading to efficient loan pricing, or second, that the lender is pooling both risky and non-risky borrowers together and leading to pricing anomaly. My results are robust when alternative algorithms were applied, and the bank's branch effects are controlled for. When I examined the substituting and complementing roles that clients' ownership of Fintech and bank account has on loan performance, I find that the propensity to default is significantly reduced for borrowers' who adopted financial technology and own a bank account. However, for clients who have bank account only are associated with higher default likelihood. This suggest that clients actively substituting bank account with mobile money account for their everyday banking and financial transactions.

My thesis provides novel evidence to show, that lenders can provide incentives in the form of lower interest rate to borrowers who adopts and use Fintech as an information enhancing mechanism. This in turn can have amplified effects, at least in reducing the adverse selection problem that lending institutions face when lending to households in the developing world. Furthermore, Fintech can become alternative sorting device for lenders to use for screening loan applicants, and can help reduces credit risk, non-performing assets and improve quality of their loan portfolio. In summary, I find economically and statistically robust evidence that Fintech can mitigates loan risk.

For the impact of my research, First, my results show the critical role that financial technology such as mobile money wallet can play in loan pricing and performance. Further, the sizes of the coefficients from results imply an economically important relationship. Second, my empirical result also show that the continuous use of Fintech can signal borrower credit risk, and significantly reduce the adverse selection problem that lenders face. Particularly, in the lender-borrower relationship, and in the consumer loans market when providing credit to households in the developing world to manage the financial shocks that the face on a regular basis.

5.2 Religion and Loan Performance: Does self-declared religiosity matter?

Prior theoretical and empirical studies in psychology and business have shown that a person's religious belief can have a significant impact on their way of life, both in business and in their personal social lifestyle. This in turn can impact on the individuals' risk-taking attitude. As a result, several studies examining the relationship between religion and individual as well as business decision show that religiosity significantly affect later. For example, Hilary and Hui (2009), document that businesses located in counties in the Unites States with higher religiosity are associated with taking lower risk in business decisions. The authors further contend that businesses don't take this decision, but individual managers within the firm do.

Hence, I investigated the impact of individual borrowers' religion and religious connectedness the performance of their loans. Unlike several prior studies that measure individuals' religiosity based on their location, I use the clients self-declared religiosity and religious connectedness and I examine its impact on loan risk and spread. I find that default likelihood is significantly reduced when individual borrowers signal their credit risk by voluntarily self-declaring their religiosity and religious connectedness at the loan application stage and prior to signing their individual liability credit contract, *ceteris parabus*. However, this is only significant for borrowers whose self-declared religiosity is affiliated to the Islam faith. When I examined the likely effect of self-declared religiosity on loan spread, I find that, *all things being equal*, borrowers who voluntarily self-declare their religiosity to signal their credit risk are likely to be charged higher interest rate. This result is significant across both the Christian and Islamic religious beliefs.

Unlike first-time religious borrowers that exhibited inelastic relation between interest rate and the likelihood of default, when I examined the effect of borrowers' self-declared religious connectedness on loan risk, I find an elastic relationship. Additionally, I find that borrowers who self-declare their religious connectedness are associated with the likelihood of receiving lower interest rate across the two religious' groups, *ceteris parabus*. When I examined the effect of female religious borrowers who signal their credit risk by self-declaring their religiosity and religious connectedness, I find that female borrowers who signal their credit by self-declaring their affiliation to the Christian belief, are associated with lower default likelihood. I find similar results for males affiliated to the Islamic faith. My results show that individuals' religiosity may induce behaviours that have favourable consequences in loan contracting as have been shown in similar prior studies.

5.3 The Impact of Financial Technology on Payment Systems and Financial Inclusion

In this third section, that is chapter 3 of my thesis, the main objective is to empirically examine the use of financial technology, that is, mobile money, which is mostly used for small but high frequency transactions in the developing world, and its impact on the traditional electronic payment systems (debit, credit and charge card payments), financial inclusion and the use of cash. I used time series monthly data spanning from January 2010 to December 2022, and I performed both unit root and cointegration tests to ascertain the stationarity of my variables. Therefore, I used the Johansen's technique to identify the cointegrating vectors and discussed the long-run relationships by setting up my VEC Models. I adopted the VAR-VECM and variance decomposition methods to examine the causal relationship among my five selected endogenous variables.

The results of my unit root test indicate that the variables are non-stationary and hence are integrated of order one to make them stationary. The results of my cointegration test indicate that there is a long run relationship among my five endogenous variables. This implies that the variables included in my VAR-VECM model will have transitory deviations from their long-run common trend but will eventually be driven together again. My vector error correction model (VECM) and variance decomposition results provide evidence on the causal relationships between Fintech and the traditional payment systems variables in the model over the period of study.

My results show a cointegration relation between the volume of mobile money transactions, the use of cash and value of mobile money transaction. This confirms my first hypothesis that Fintech provides financial inclusion. Also, my empirical results show a cointegration between the total value and volume of mobile money payment transactions, and total volume and value of payment system transactions, and the use of cash. This corroborates my second hypothesis that Fintech provides financial sectors deepening, payment system stability and the country's drive to become a cashless society. The coefficients of the five variables in my vector error correction model (VECM) are statistically significant at the one percent level.

I find that a 1% increase in the total value of mobile money wallet transaction, increases the total volume of mobile money transaction by 0.7995%. A 1% percent increase in the use of cash, decreases the total volume of mobile money transaction by 0.4419%. This confirms my first hypothesis that Fintech, that is, mobile money wallet account provides for financial inclusion. Further, a 1% increase in the total value of payment system transactions, reduces the total volume of mobile money transaction by 1.3686%. An increase of 1% in the total volume of payment system transactions reduces the total volume of mobile money wallet transaction by 0.8755%. Further, my results indicate that *all things being equal*, Fintech, that is mobile money, can substitute the use of cash and non-cash payment methods such as debit, credit, and charge cards. This substitute role can in turn, lead to a significant reduction in the social burden of signiorage to central banks.

On the payment systems stability, my orthogonised impulse response functions (OIRF) results provided useful information about the selected variables in my model and their impact on each other. According to my impulse response function analysis, it is found that that except for the use of cash, response to own innovation for all the five variables decline at varying periods in the short-run and thereafter converges to its long-run value before the end of the eighteenth month. This suggests a long-run association between the country's financial sector deepening, and stability in Kenya's payment ecosystem. Further, the analysis of the result of the forecasted error variance decomposition reveals that the variation in individual variables is accounted for by own shock.

My results have policy implications in two ways. First, my findings show that by encouraging and promoting the use of Fintech, that is, mobile money, as an alternative payment system instrument, this can have an amplified effect of providing financial inclusion for the many residents who are unbanked in the developing world. Second, by promoting the use of Fintech, central banks can significantly reduce the monetary and social cost of seigniorage. That is, the cost of producing physical cash in the economy.

Finally, by facilitating the development of the mobile money sub-sector, this will create employment for the many unemployed in the country, particularly the youth and women who act as agents for mobile money operators in Kenya. The impact and future of mobile money as an alternative to traditional payment system depends on its own growth, advancement in technology, and regulations from key stakeholders such a central banks and monetary authorities. This is because as mobile money wallet usage continues to grow, it can significantly impact on the control of monetary policy.

5.4 Research limitation and recommendations.

The recent introduction of electronic transaction levy on mobile money transfers can impact the use of financial technology. Further, this can impact lending decisions and borrower repayment behaviour. Similar to the work of Boyan Jovanovic (1982) that investigated the welfare implications of disclosure costs, my thesis provides an opportunity to undertake further research to capture the influence of this new phenomenon on the use of Fintech. Additionally, the impact of transaction fees was not addressed. This is a limitation associated with my thesis. Additionally, there is a cost associated with borrowers adopting financial technology, that is, mobile money, for their everyday transactions.

These costs include expenses directly related to the use of Fintech, such as the cost of acquiring a mobile phone and the expenditure associated with subscribing to a mobile money provider. For example, the initial cost of acquiring a second-hand mobile phone plus related charges in Ghana is US$60 (Boadi et al., 2007). Further, my unique dataset may suffer from sample selection biases, and even though I perform the Heckman's test to address this potential problem and the results show that that there is no bias, this may not be exhaustive in addressing the challenge. All these can impact on my results in chapter 2 of the thesis, and hence provides an opportunity for future studies.

By using the VAR-VECM method in chapter 3, a limitation may be omitted variable bias. This is because the forecasted error variances of one variable is fully explained only by variables in the model without quantifying the potential influence of variables outside the system. Further, using borrowers' self-declared religiosity at the first-loan application stage and the repeated declaration when the client re-apply for a second loan may not fully reflect actual church attendance or practice. Similarly, self-declaration of individual religiosity to be affiliated to the Islam belief may not necessarily be that the borrower practices the belief by performing all the religious tenets, and this can be a limitation since it was not feasible given the limited time to interact with the over twelve thousand individual clients whose loan and socio-economic information constitute my unique dataset that I use in chapter 4 of my thesis.

6. References

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APPENDIX A-SUPPLEMENTARY FIGURES

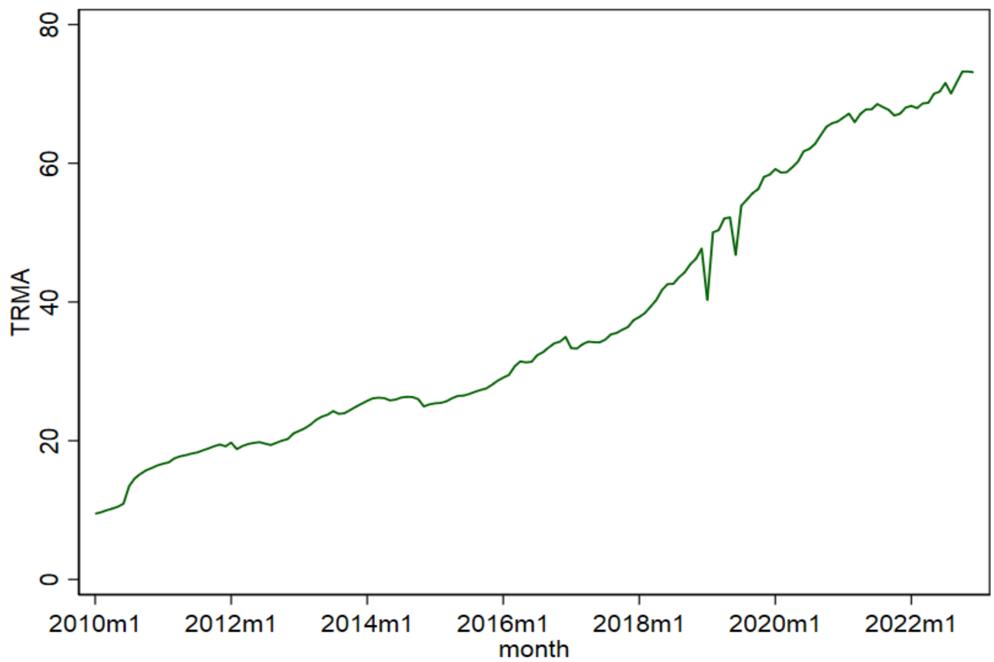

Figure 43. Annual trend of Active Mobile Money Account Ownership in Kenya (2010-2022)

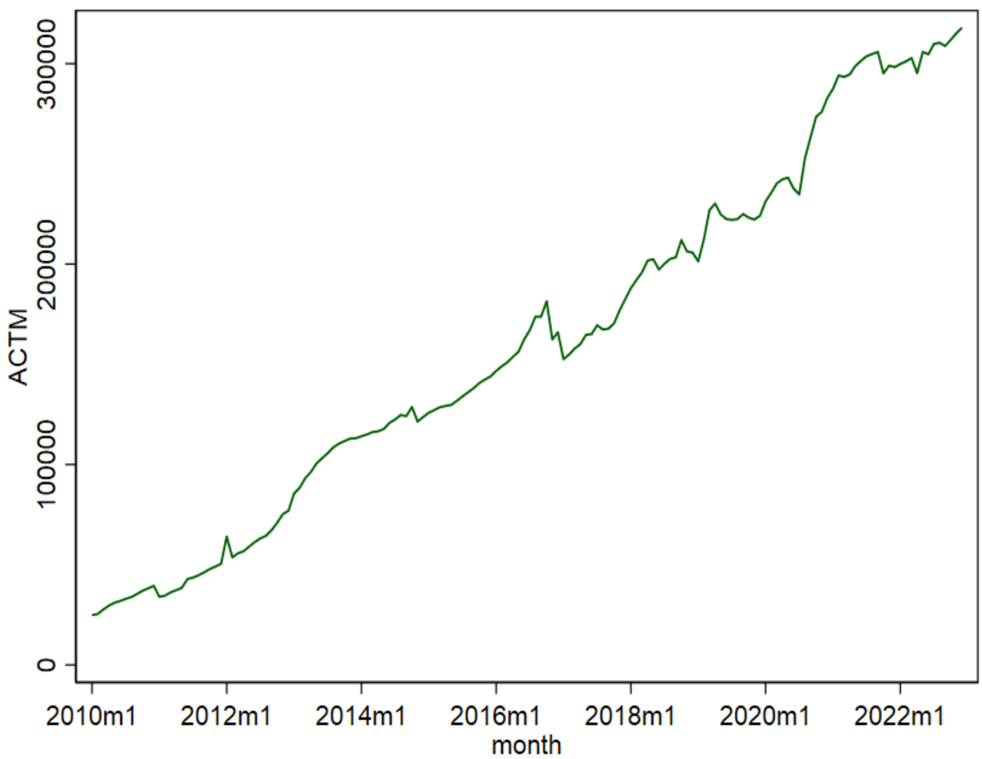

Figure 44. Annual trend of Active Mobile Money Agents in Kenya (2010-2022)

MOBILE MONEY TRANSACTION HISTORY

TIME RUN: 29 Jan,2022 05:43:05AM

From: 01-Aug-2021 To: 25-Jan-2022

MSISDN: [redacted] ACCOUNT HOLDER NAME: [redacted]

TRANSACTION DATE	FROM ACCT	FROM NAME	FROM NO.	TRANS. TYPE	AMOUNT	FEES	BAL BEFORE	BAL AFTER	TO NO.	TO NAME	TO ACCT	F_ID	REF	OVA
23-Jan-2022 07:07:06 AM	[redacted]	[redacted]	[redacted]	DEBIT	28	0	100.13	72.13	[redacted]	Interpay	[redacted]	[redacted]	NATIONAL HEALTH INSURANCE AUTHORITY	interpul2.sp
20-Jan-2022 10:57:52 PM	[redacted]	[redacted]	[redacted]	DEBIT	3	0	103.13	100.13	0	cis	[redacted]	[redacted]	Internet Bundle	cis
20-Jan-2022 09:52:45 PM	[redacted]	[redacted]	[redacted]	TRANSFER	9	0	112.13	103.13	[redacted]	[redacted]	[redacted]	[redacted]	[redacted] rode with you	Internal
18-Jan-2022 09:15:31 PM	[redacted]	[redacted]	[redacted]	TRANSFER	56	0	168.13	112.13	[redacted]	[redacted]	[redacted]	[redacted]	8756	Internal
17-Jan-2022 07:14:55 PM	[redacted]	[redacted]	[redacted]	TRANSFER	100	0	268.13	168.13	[redacted]	[redacted]	[redacted]	[redacted]	Akosua	Internal
16-Jan-2022 11:19:42 AM	[redacted]	[redacted]	[redacted]	PAYMENT	5	0	273.13	268.13	0	MTNONLINEAIRTI [redacted]	[redacted]	[redacted]		MTNONLINEAIRTIMEVENDOR
16-Jan-2022 10:50:45 AM	[redacted]	[redacted]	[redacted]	DEBIT	12	0	285.13	273.13	[redacted]	ONEWALLET	[redacted]	[redacted]	Offering-Yahweh T	apsNmoPs.sp
16-Jan-2022 09:12:35 AM	[redacted]	[redacted]	[redacted]	TRANSFER	10	0	295.13	285.13	[redacted]	[redacted]	[redacted]	[redacted]	000	Internal
15-Jan-2022 05:59:15 PM	[redacted]	[redacted]	[redacted]	TRANSFER	51	0	346.13	295.13	[redacted]	[redacted]	[redacted]	[redacted]	000	Internal
14-Jan-2022 09:27:56 PM	[redacted]	[redacted]	[redacted]	DEBIT	28	0	374.13	346.13	[redacted]	Interpay	[redacted]	[redacted]	NATIONAL HEALTH INSURANCE AUTHORITY	interpul2.sp
11-Jan-2022 09:47:22 AM	[redacted]	[redacted]	[redacted]	PAYMENT	140	1.4	515.53	374.13	[redacted]	INTEROPERABILITY PUSH OVA	[redacted]	[redacted]	[redacted]	mmipush
10-Jan-2022 10:33:59 PM	[redacted]	[redacted]	[redacted]	DEBIT	3	0	518.53	515.53	0	cis	[redacted]	[redacted]	Internet Bundle	cis
10-Jan-2022 06:14:29 PM	[redacted]	[redacted]	[redacted]	CASH_IN	205	0	313.53	518.53	[redacted]	[redacted]	[redacted]	[redacted]	Cashin To- [redacted]	Internal

Figure 45. Sample of Mobile Money statement of account.

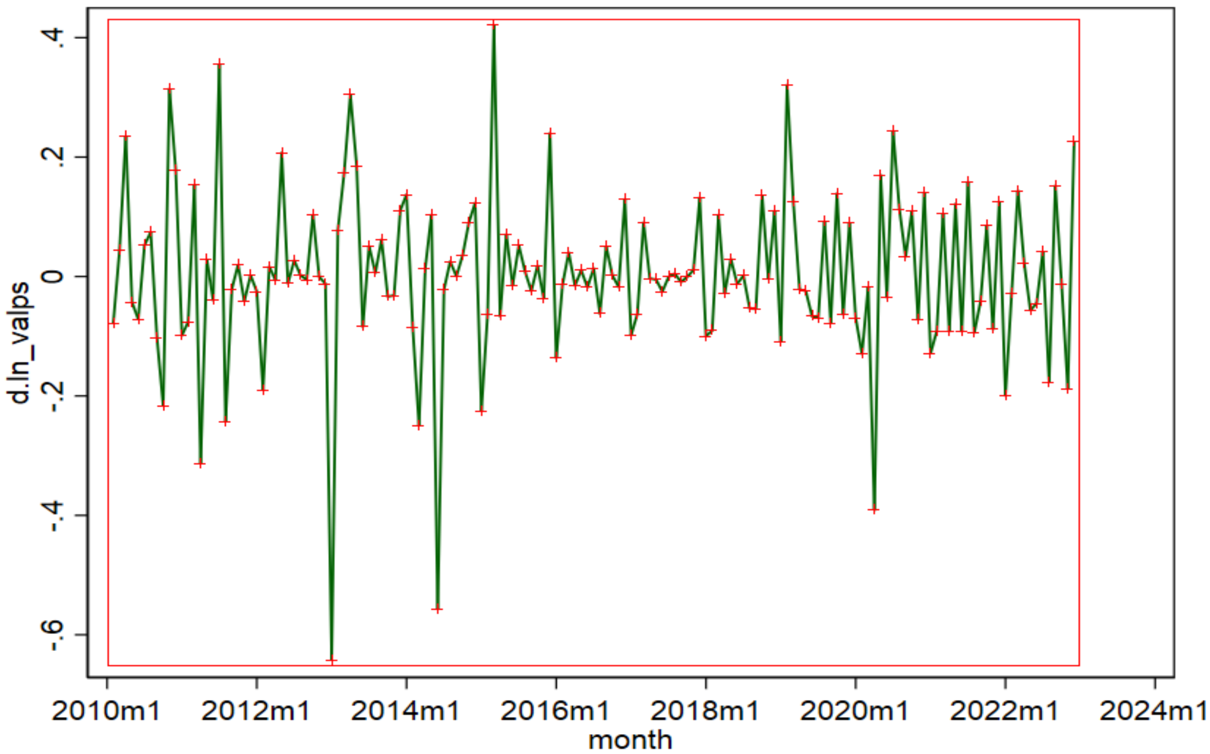

Figure 46. Graph for the first difference of total value of payment system transactions (2010-2022)

Figure 47. Graph for the first difference of total volume of payment system transactions (2010-2022)

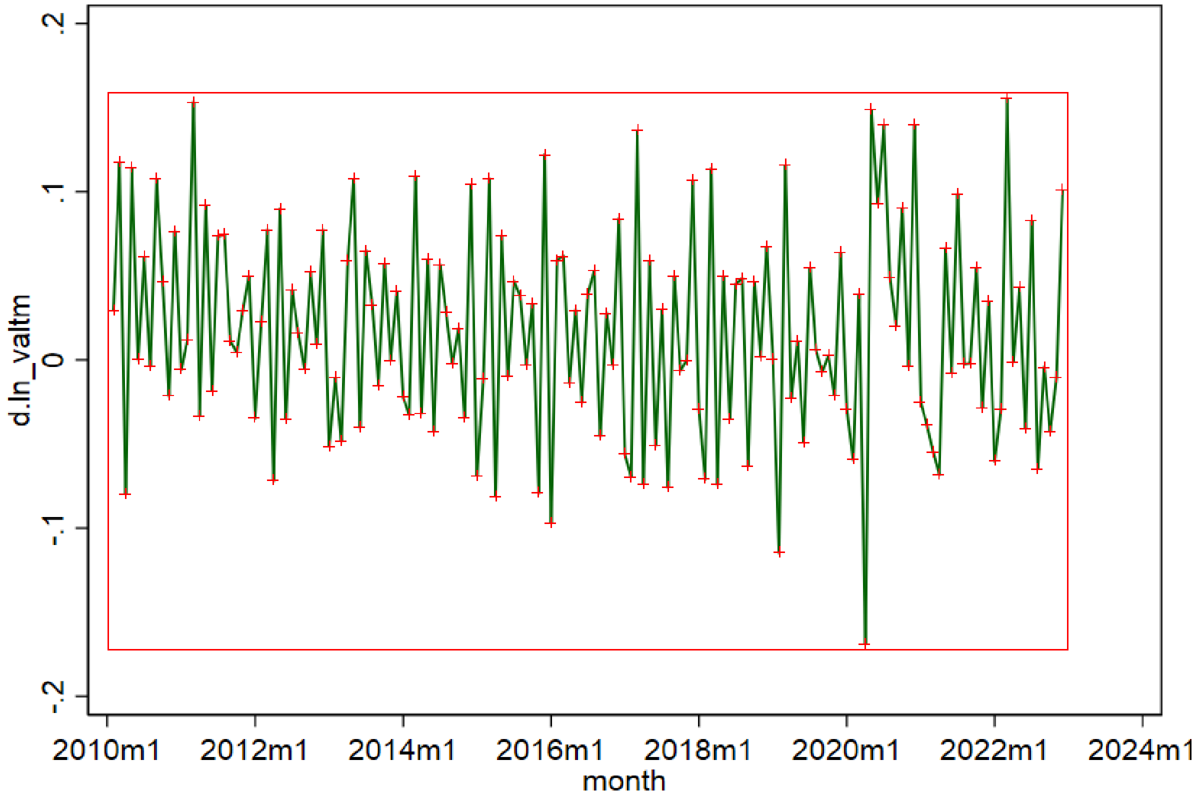

Figure 48. Graph for the first difference of total value of mobile money transactions (2010-2022)

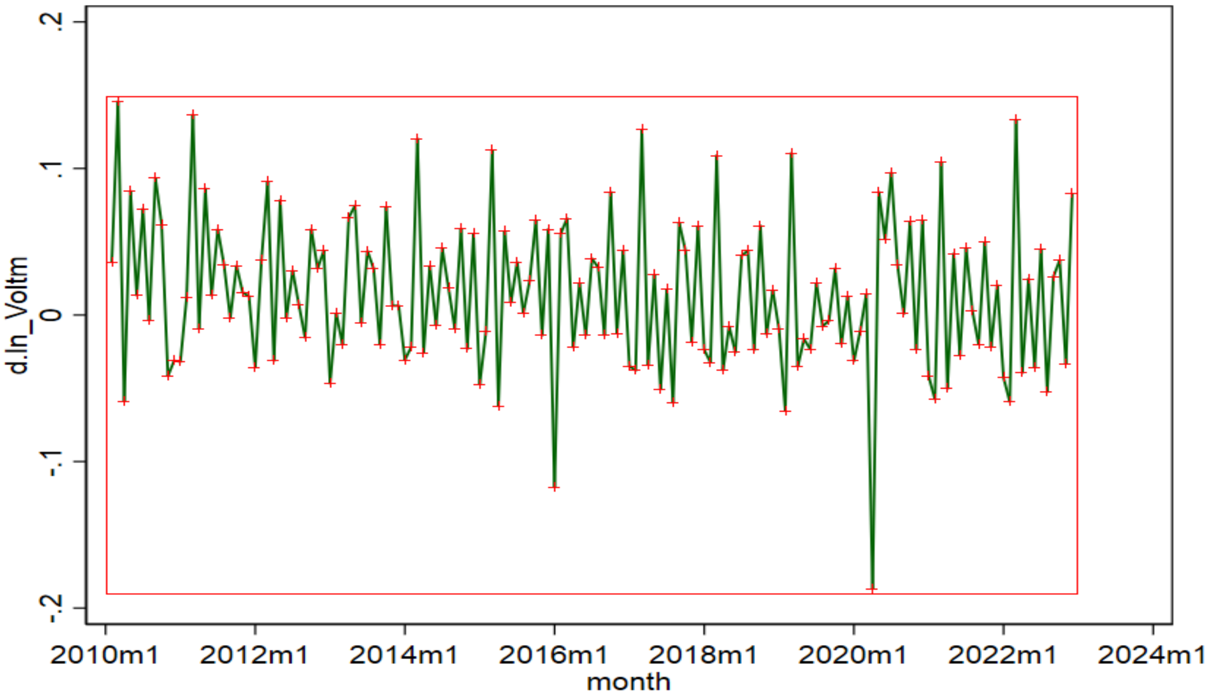

Figure 49. Graph for the first difference of total volume of mobile money transactions (2010-2022)

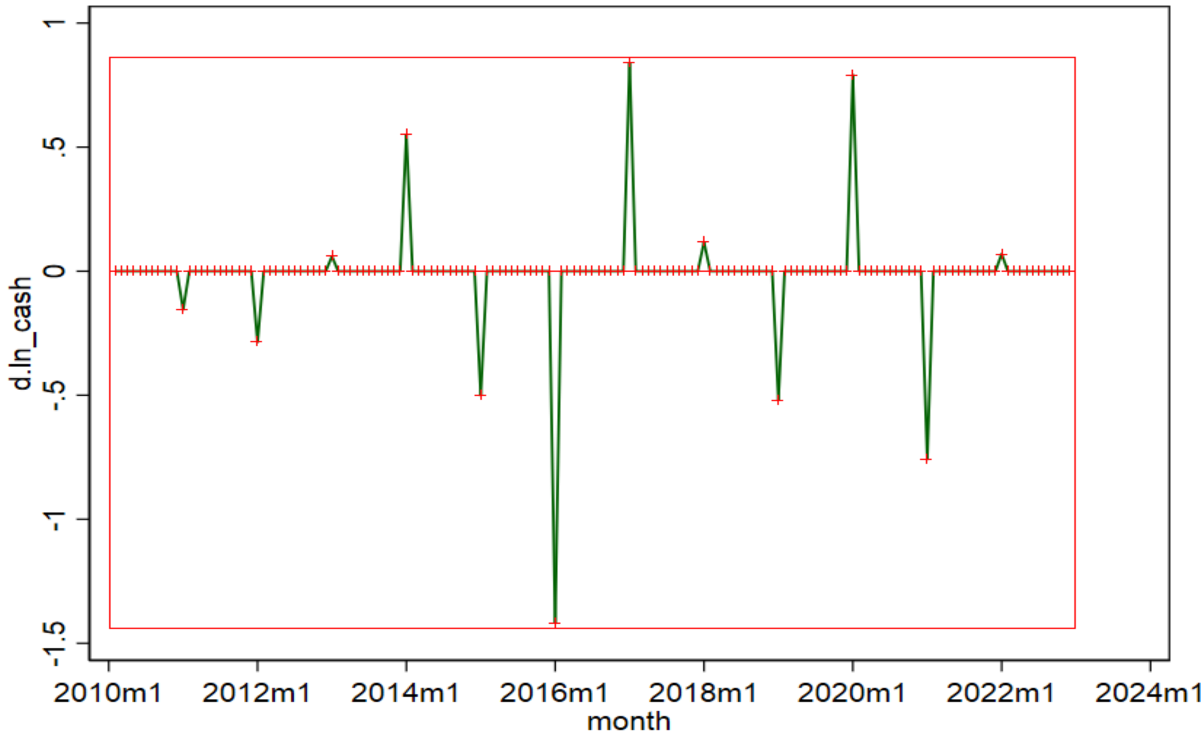

Figure 50. Graph for the first difference of broad money supply (M3)-2010-2022

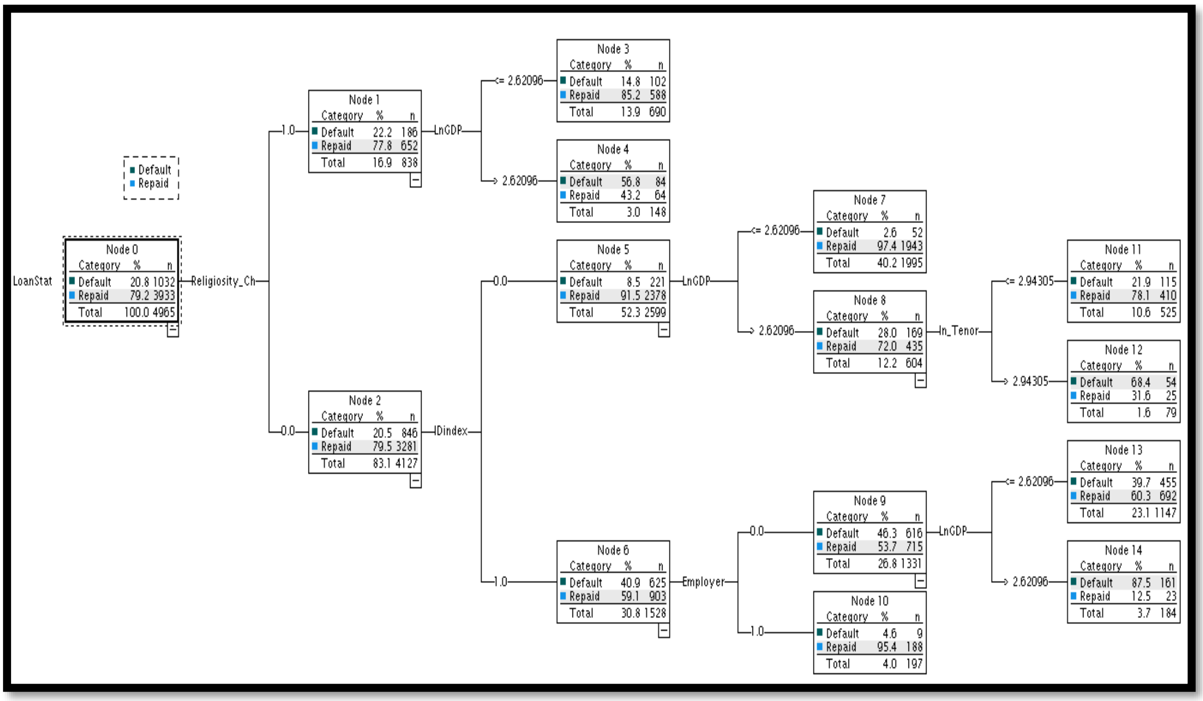

Figure 51. Classification and regression tree model result for Religiosity (Christian belief) on Loan Risk- (Accra branch).

Estimated Risk= 0.170, Accuracy= 83.00%, Stand. Error =0.005, R^2 =0.707

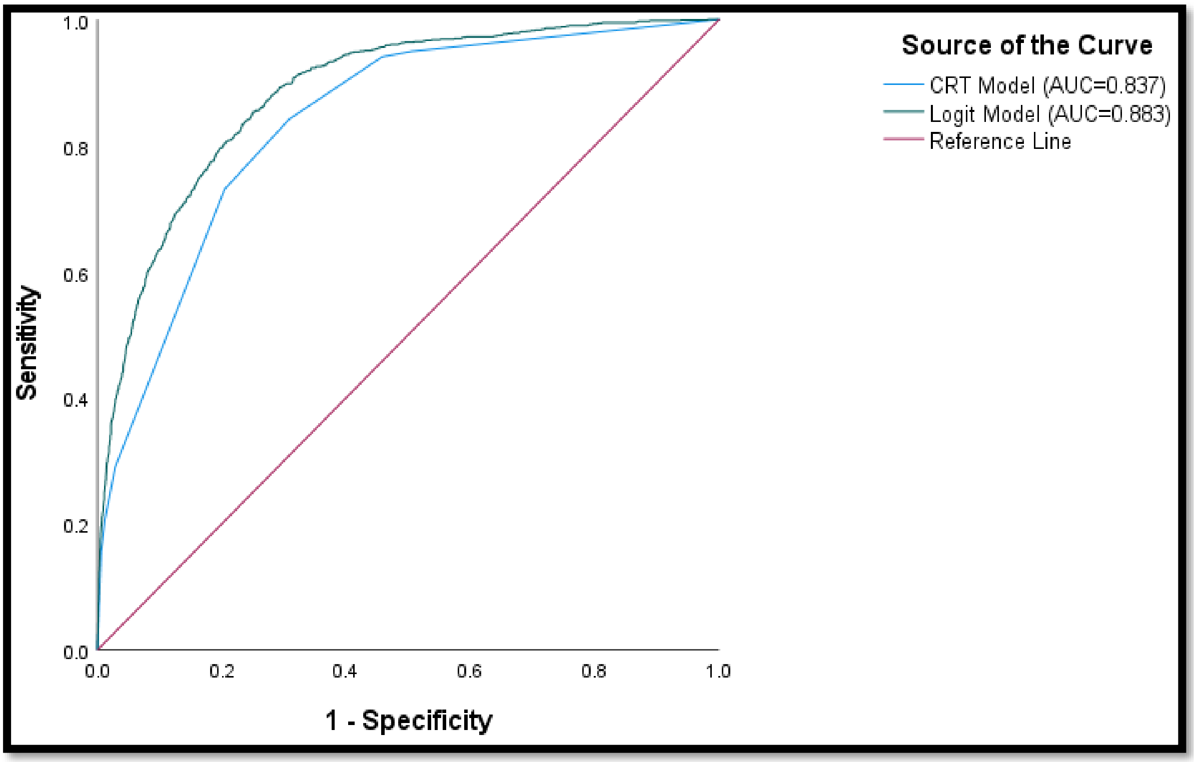

Figure 52. ROC-AUC Graph for Religiosity (Christian belief) on Loan Risk using Classification and regression tree and Logit Models (Accra branch).

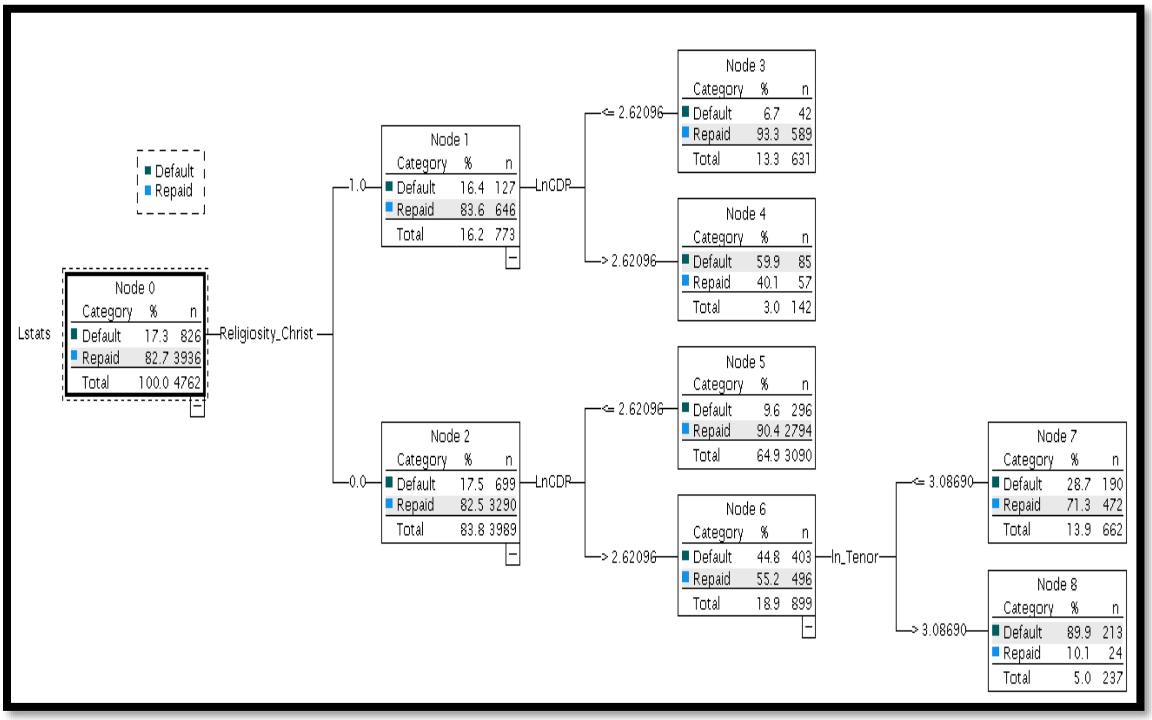

Figure 53. Classification and regression tree model result for Religiosity (Christian belief) on Loan Risk- (Kumasi branch).

Estimated Risk= 0.128, Accuracy= 87.20%, Standard Error =0.005, R^2 =0.839

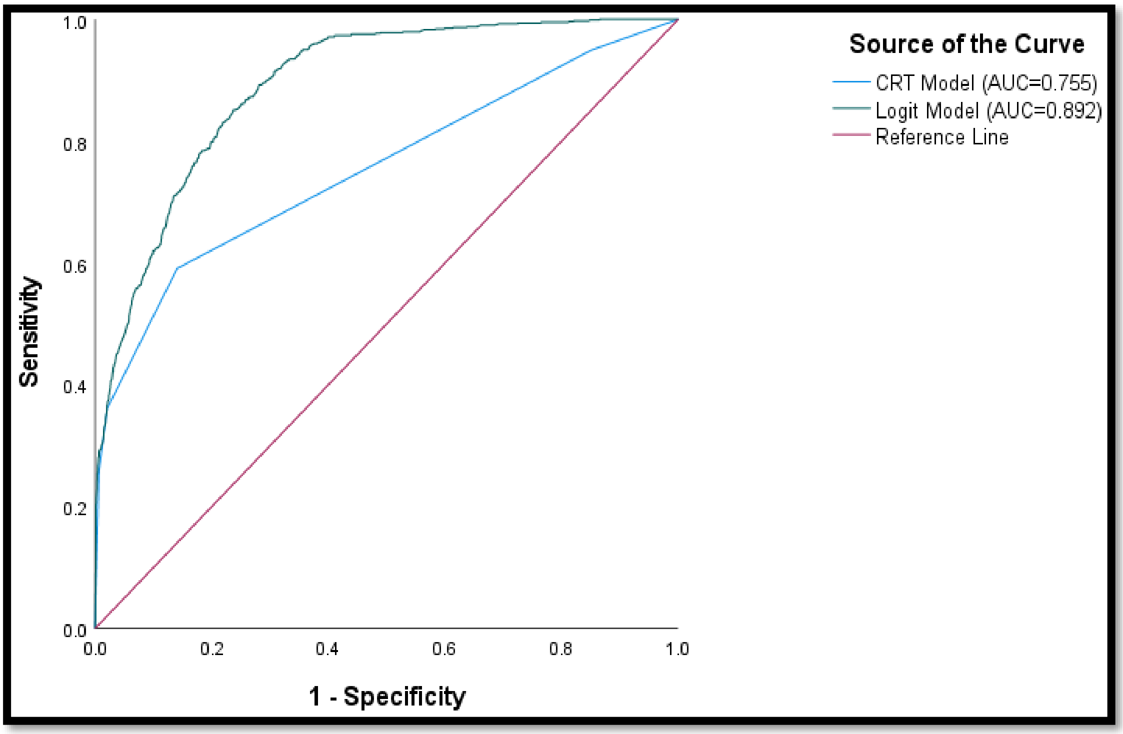

Figure 54. ROC-AUC Graph for Religiosity (Christian belief) on Loan Risk using Classification and regression tree and Logit Models (Kumasi branch).

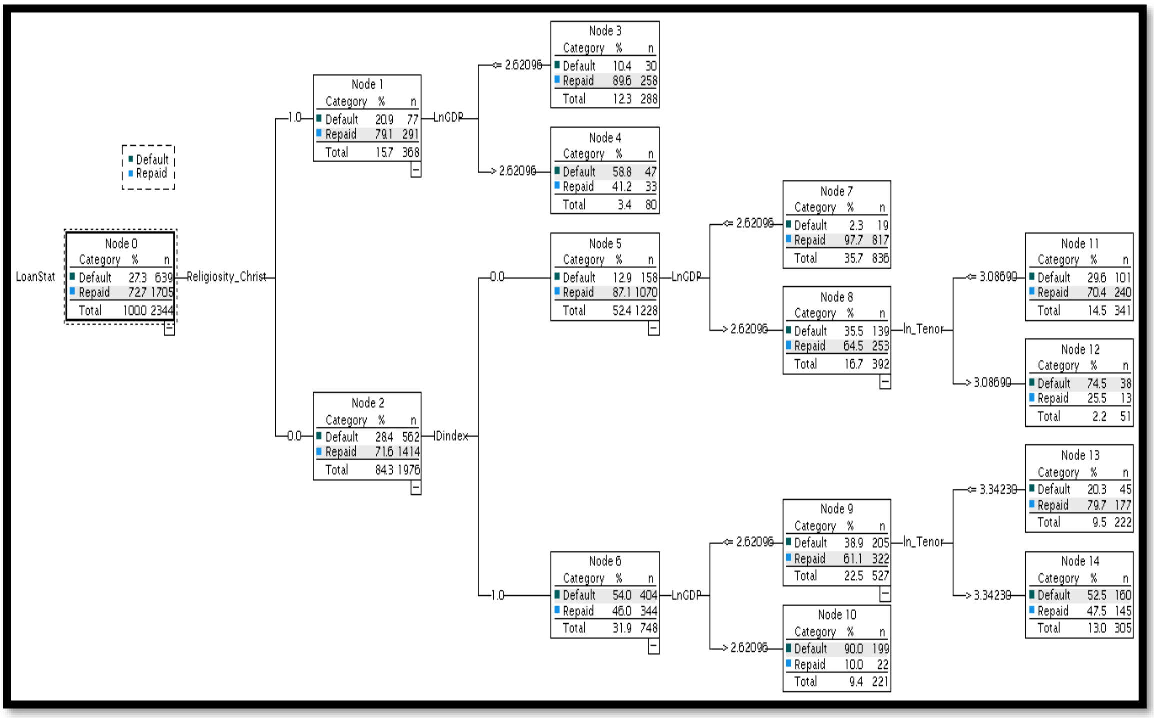

Figure 55. Classification and regression tree model result for Religiosity (Christian belief) on Loan Risk- (Takoradi branch).

Estimated Risk= 0.174, Accuracy= 82.60%, Standard Error =0.008, R^2 =0.615

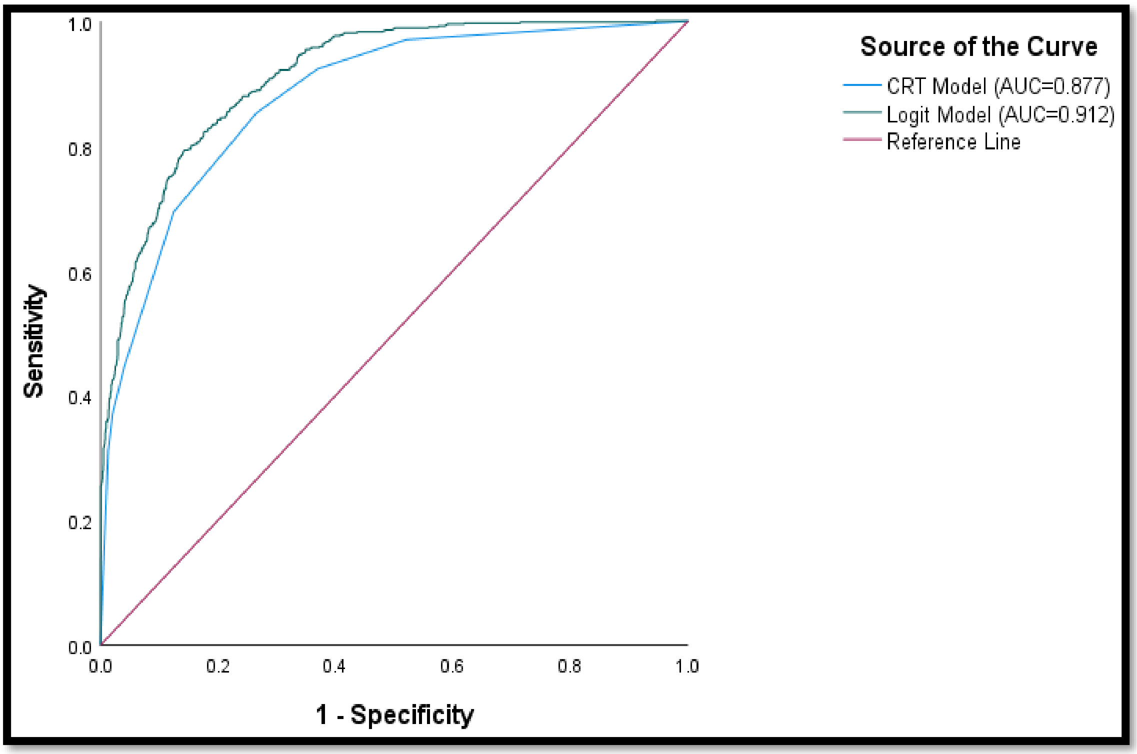

Figure 56. ROC-AUC Graph for Religiosity (Christian belief) on Loan Risk using Classification and regression tree and Logit Models (Takoradi branch).

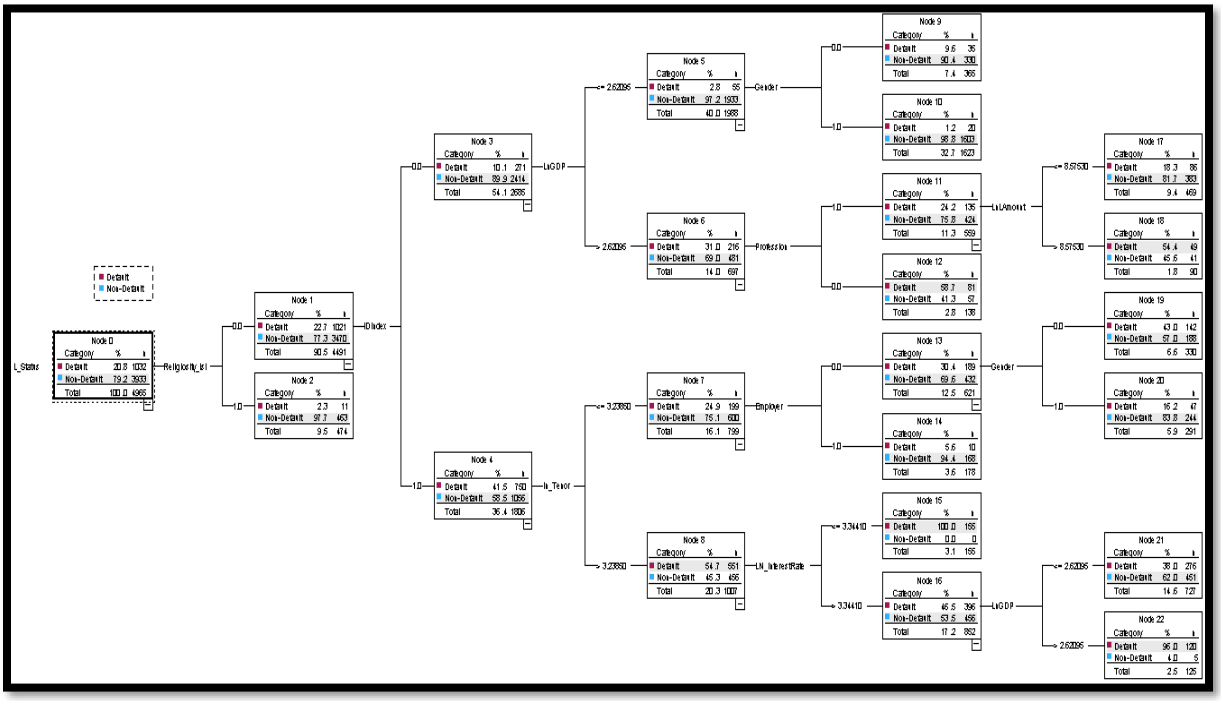

Figure 57. Classification and regression tree model result for Religiosity (Islam belief) on Loan Risk- (Accra branch)

Estimated Risk= 0.149, Accuracy= 85.10%, Standard Error =0.005, R^2 =0.660

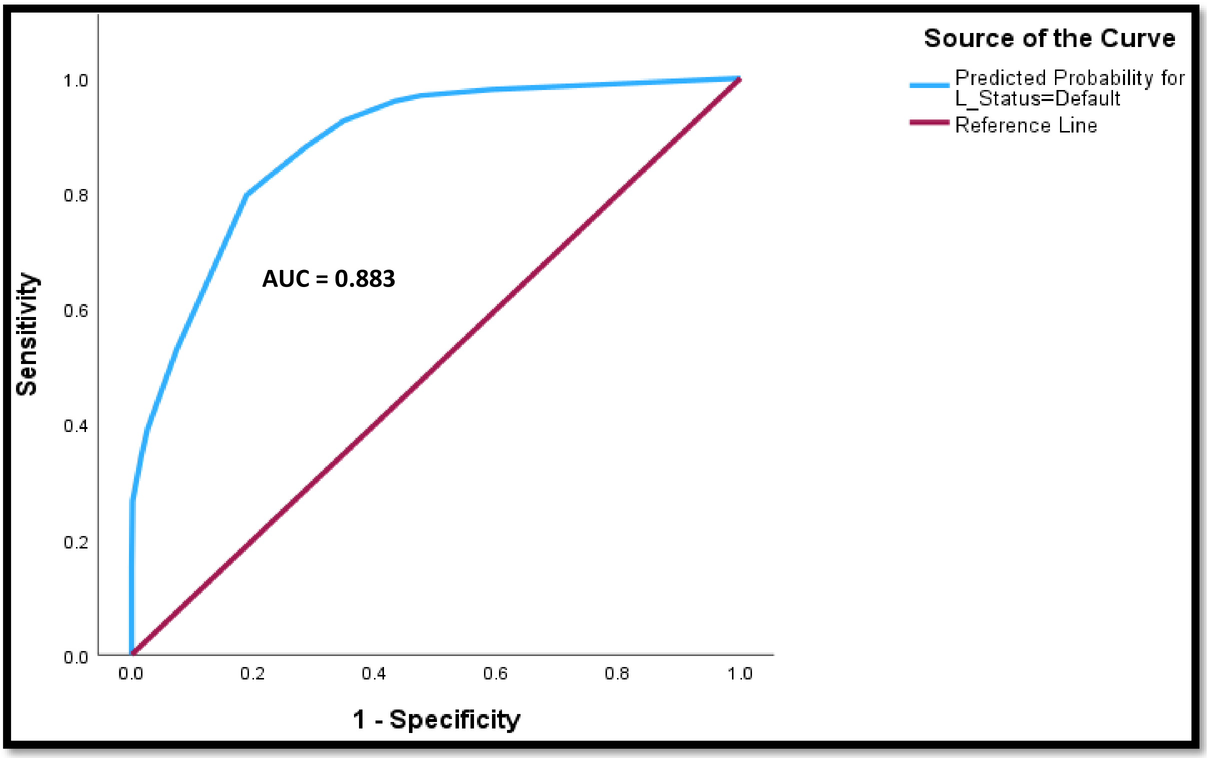

Figure 58. ROC-AUC Graph for Religiosity (Islamic belief) on Loan Risk using Classification and regression tree and Logit Models (Accra branch).

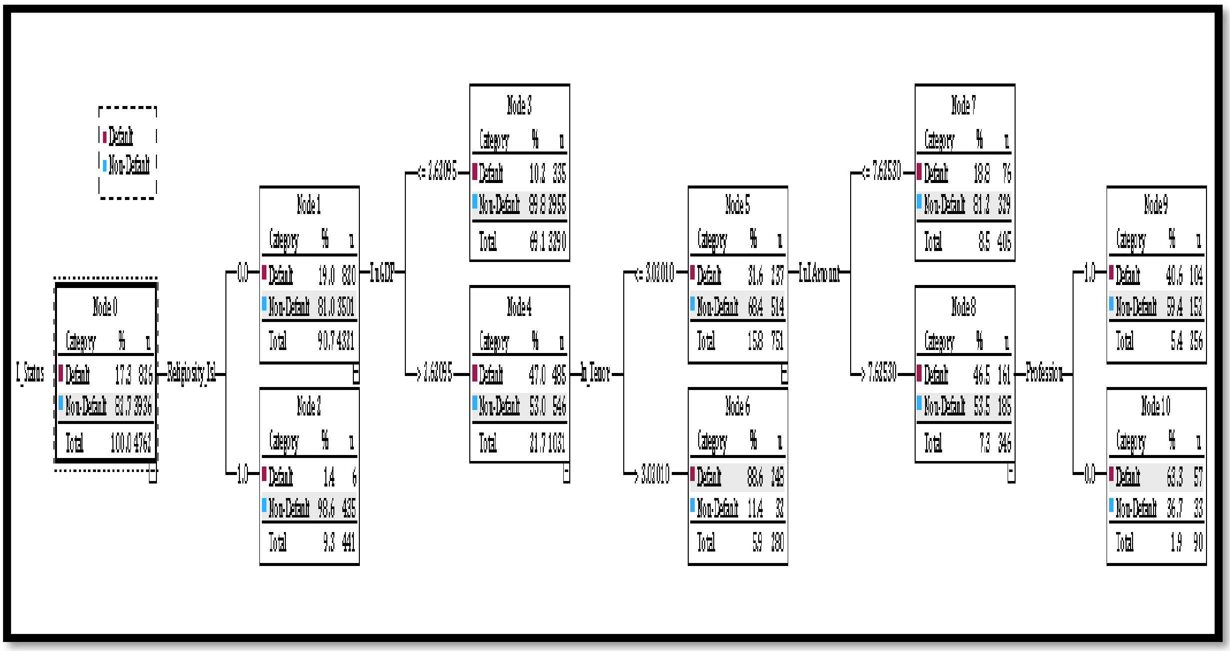

Figure 59. Classification and regression tree model result for Religiosity (Islam belief) on Loan Risk- (Kumasi branch).

Estimated Risk= 0.123, Accuracy= 87.70%, Standard Error =0.005, R^2 =0.809

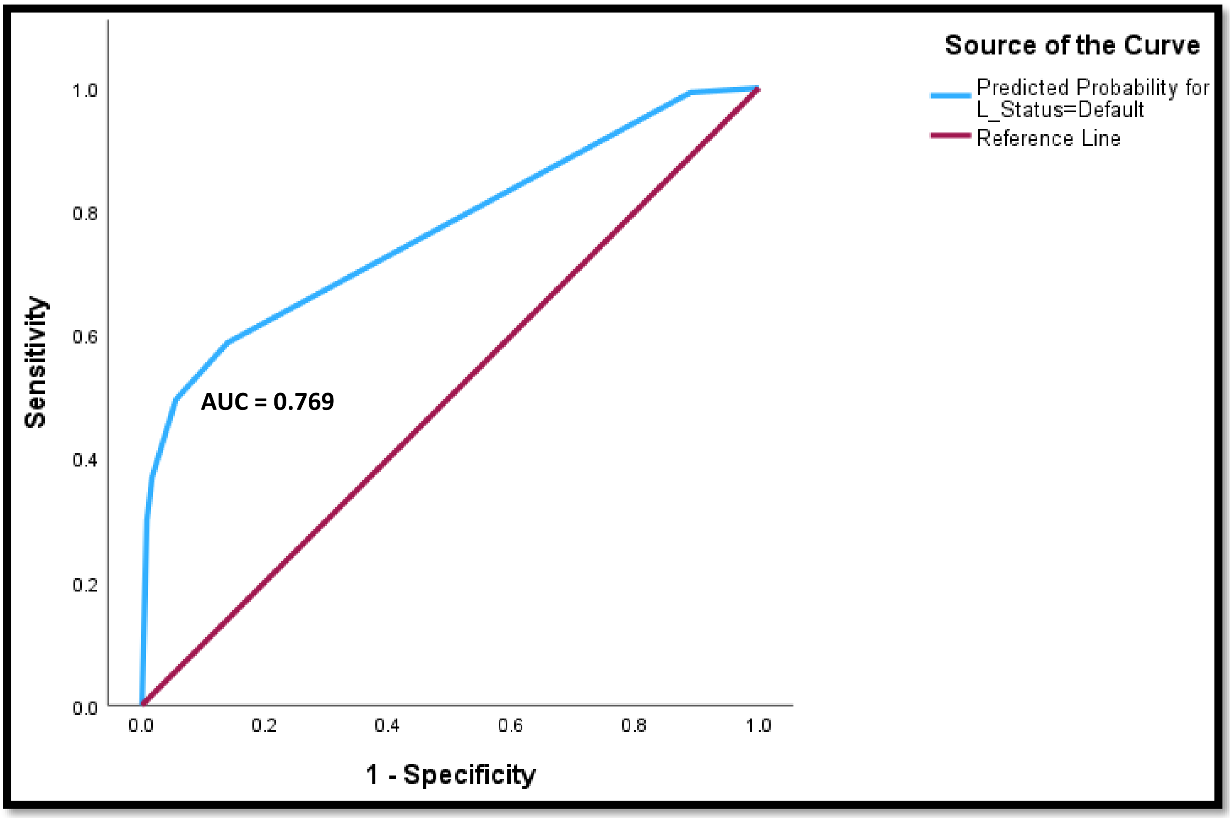

Figure 60. ROC-AUC Graph for Religiosity (Islamic belief) on Loan Risk using Classification and regression tree and Logit Models (Kumasi branch).

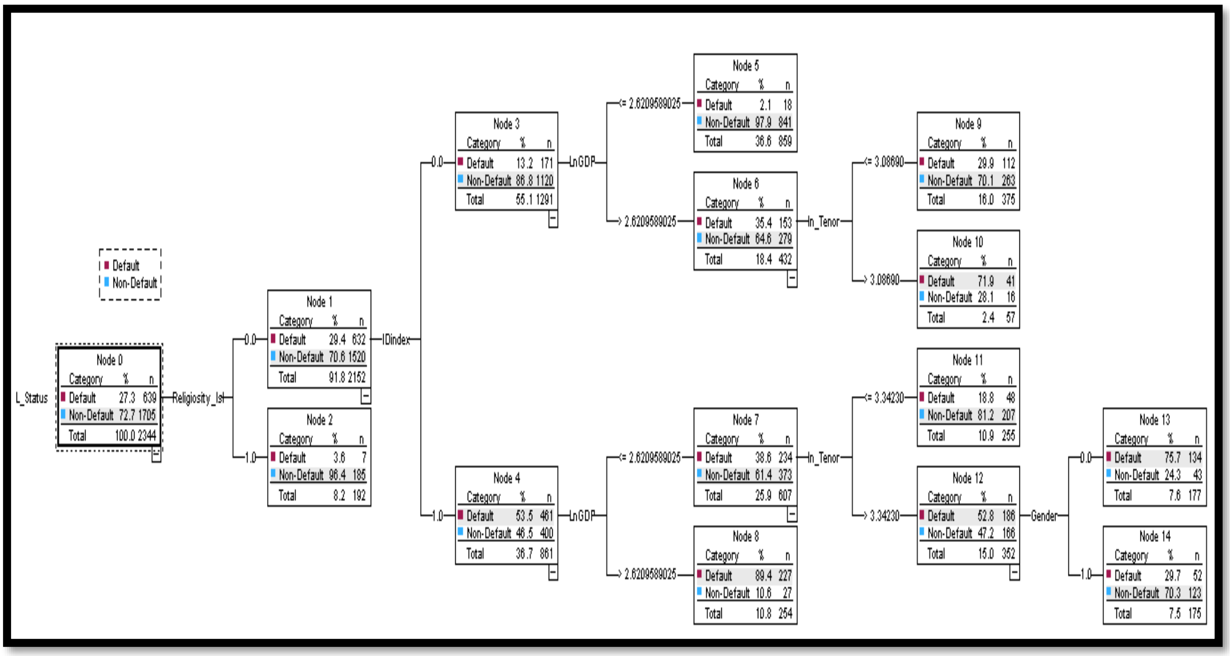

Figure 61. Classification and regression tree model result for Religiosity (Islam belief) on Loan Risk- (Takoradi branch).

Estimated Risk= 0.138, Accuracy= 86.20%, Standard Error =0.007, R^2 =0.525

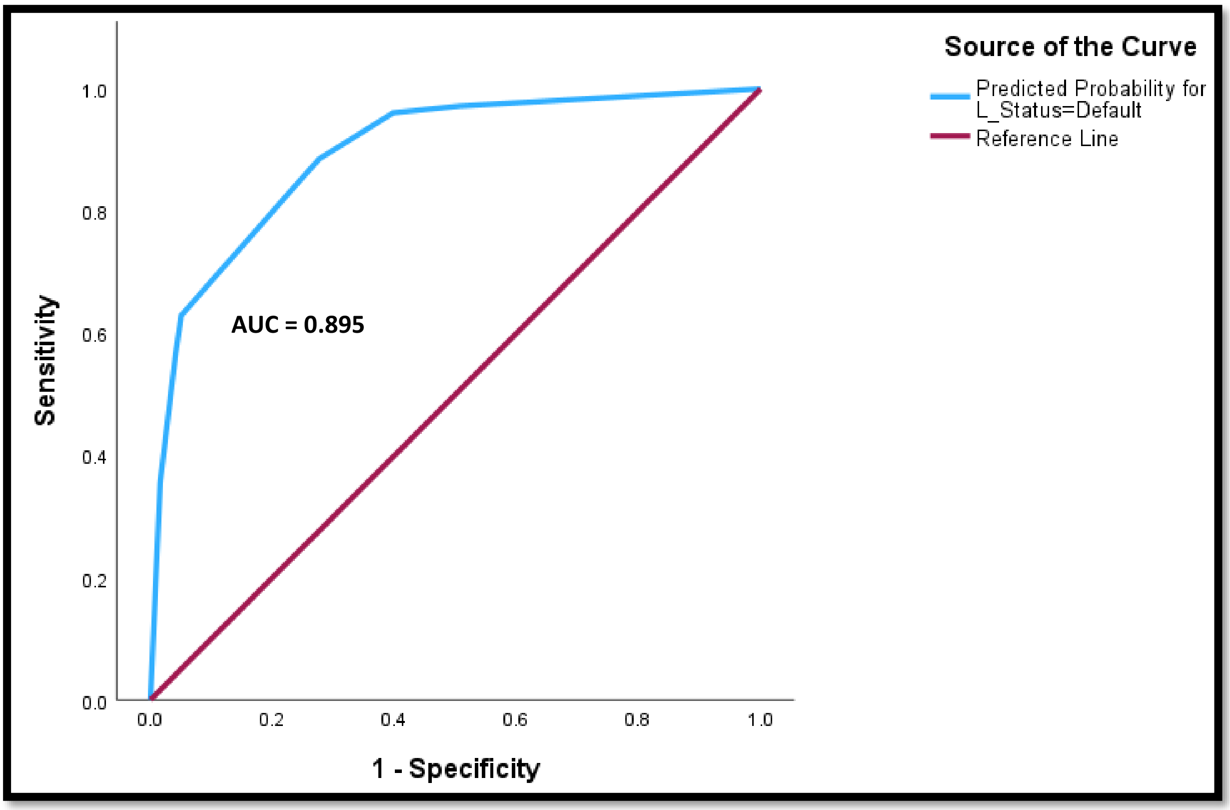

Figure 62. ROC-AUC Graph for Religiosity (Islamic belief) on Loan Risk using Classification and regression tree and Logit Models (Takoradi branch).

APPENDIX B-SUPPLEMENTARY TABLES

Table 61. Collinearity Statistics for variables

Independent Variables	Tolerance	VIF
Borrower Age	0.9850	1.0150
Gender (Female)	0.9090	1.1000
Income Category (Formal Salary)	0.9950	1.0050
Employer (Public sector)	0.9810	1.0200
Profession (Professional)	0.9710	1.0300
Loan Amount	0.8630	1.1590
Loan Tenor	0.7360	1.3580
Borrower Identity Document (More than 1)	0.8260	1.2110
Borrower Affordability (35%)	0.9810	1.0200
Mobile phone account ownership (=2)	0.9600	1.0410
Bank account ownership (Yes)	0.9860	1.0150
Fintech (Mobile Money Account Ownership)	0.9480	1.0550
Interest Rate	0.7630	1.3100
GDP	0.8880	1.1260

Table 62. Coefficient of Logit regression controlling for branch effect

Dependent Variable: Log (Default/Non-Default)

INDEPENDENT VARIABLES	Likelihood Ratio Chi-Square =1810.897, df=14, sign. =0.000		Likelihood Ratio Chi-Square =1672.619, df=14, sign. =0.000		Likelihood Ratio Chi-Square =1225.965, df=14, sign. =0.000	
	Accra-sample regressions		Kumasi-sample regressions		Takoradi-sample regressions	
	COEFF.	STAND. ERROR	COEFF.	STAND. ERROR	COEFF.	STAND. ERROR
Religiosity [Christian belief]	-0.1110	0.1162	-0.103	0.1341	-0.7340***	0.1908
Control Variables						
Borrowers Age	0.6970***	0.2064	0.5010*	0.2229	0.8550**	0.3092
Gender (Female)	-0.8240***	0.0913	-0.6430***	0.1031	-0.6380***	0.135
Mobile phone account ownership (=2)	-0.4980***	0.1303	-0.5380***	0.1477	-0.4840***	0.1894
Borrower Identity Document (More than 1)	2.3820***	0.1157	2.3980***	0.1400	2.8560***	0.1837
Professionals	-0.4780***	0.1361	-0.7720***	0.1407	-0.5710***	0.1993
Employer (Public sector)	-2.1970***	0.1983	-1.9460***	0.2117	-1.7980***	0.2508
Income Category (Formal Salary)	-0.7360***	0.2203	-0.4960*	0.2336	-0.3940	0.3036
Borrower Affordability (35%)	2.8670**	0.5266	4.5630***	0.7959	3.7180***	0.9214
Loan Amount	0.2810***	0.0557	0.2720***	0.0590	0.2870***	0.082
Loan Tenor	0.6750***	0.0698	0.3280***	0.0743	0.8700***	0.1064
Interest Rate	-1.3980***	0.2315	-0.0480	0.2612	-0.6680**	0.2823
Bank account ownership (Yes)	-1.1730***	0.1887	-0.5630*	0.3181	-0.3900**	0.2024
GDP	9.2700***	0.5055	12.9430***	0.5804	13.2140***	0.7623
Intercept	-26.1140***	2.0039	-38.9930***	2.2736	-41.0800***	2.9307
a= Model classification accuracy	a= 85.50, R^2 =0.639		a= 87.40, R^2 = 0.625		a= 84.90, R^2 = 0.601	
Asterisks: ****Indicates a coefficient significantly different from zero at the ***1%, ** at 5%; and *at the 10% level						

Table 63. Coefficient of Logit regression (Religiosity-Islam belief) controlling for branch effect.

(**Default is the explained variable)**

Explanatory Variables	Accra branch-sample regressions		Kumasi branch-sample regressions		Takoradi branch-sample regressions	
	COEFF.	STAND. ERROR	COEFF.	STAND. ERROR	COEFF.	STAND. ERROR
Religiosity [Islamic belief]	-2.4430***	0.3286	-2.3960***	0.4251	-2.3480***	0.4573
Control Variables						
Borrowers Age	0.6030***	0.2096	0.4240*	0.225	0.7720***	0.3129
Gender (Female)	-1.0290***	0.0935	-0.7950***	0.1041	-0.8420***	0.1373
Mobile phone account ownership (=2)	-0.4610***	0.1322	-0.4880***	0.1497	-0.3850**	0.1906
Borrower Identity Document (More than 1)	2.2230***	0.1183	2.3000***	0.1418	2.7000***	0.1837
Professionals	-0.4530***	0.1376	-0.7410***	0.1408	-0.4850**	0.1987
Employer (Public sector)	-2.2300***	0.1996	-1.9390***	0.2108	-1.7820***	0.2509
Income Category (Formal Salary)	-0.6440***	0.2214	-0.4540**	0.235	-0.3610	0.3081
Borrower Affordability (35%)	2.7140***	0.5265	4.3950***	0.7889	3.5950***	0.8994
Loan Amount	0.2720***	0.0564	0.2620***	0.0589	0.2480***	0.0821
Loan Tenor	0.7080***	0.0710	0.3570***	0.0748	0.9020***	0.1069
Interest Rate	-1.2090***	0.2324	0.0310	0.2597	-0.5700**	0.283
Bank Account ownership (Yes)	-1.1270***	0.1939	-0.4710	0.3215	-0.3790*	0.2049
GDP	8.8510***	0.5045	12.5100***	0.5789	12.8940***	0.7594
Intercept	-25.1830***	2.0006	-37.7880***	2.2633	-39.9810***	2.9078
a= Model classification accuracy	a= 85.70, R^2 = 0.771		a= 87.30, R^2 = 0.603		a= 85.60, R^2 = 0.60	
Likelihood Ratio Chi-Square	1907.3090****	df=14	1735.0210****	df=14	1252.025****	df=14

Asterisks: ****Indicates a coefficient significantly different from zero at the <1%,***1%, ** at 5%; and *at the 10% level

Table 64. Coefficient of Probit regression: Religiosity and Gender on Loan Risk.

(Default is the explained variable)

Independent Variable	**Likelihood Ratio Chi-Square =4513.925, df=13, sign. =0.000**	
	COEFF.	**STAND. ERROR**
Religiosity_(Female)	-0.2930***	0.0570
Control Variables		
Borrowers Age	0.3340***	0.0746
Mobile phone account ownership (=2)	-0.2670***	0.0462
Borrower Identity Document (More than 1)	1.3600***	0.0396
Profession (Professionals)	-0.3130***	0.0499
Employer (Public sector)	-1.0530***	0.0594
Income Category (Formal Salary)	-0.3470***	0.0780
Borrower Affordability (35%)	1.9860***	0.1902
Loan Amount	0.1490***	0.0201
Loan Tenor	0.2850***	0.0241
Interest Rate	-0.2590**	0.0841
Bank Account ownership (Yes)	-0.5320***	0.0695
GDP	6.6530***	0.1618
Intercept	-19.7720***	0.6452
a= Model classification accuracy	a=84.80%, R2 = 0.6400	
Asterisks: ***Indicates a coefficient significantly different from zero at the <1%,**1%, and *at the*at 5% level		

Table 65. Panel regression result-Religious Connectedness (Christian belief) and Gender on Loan Risk-Accra Branch

Independent Variable	Coefficient	Std. Err.	z	P>z	[95% conf.	
Religious connectedness (Females)	-0.0624	0.0290	2.1500	0.0320	-0.1192	-0.0055
Control Variables						
Borrower Age	-5.2386	3.1654	1.6500	0.0980	-11.4426	0.9655
Loan Amount	-0.0415	0.0326	1.2700	0.2030	-0.1055	0.0224
Loan Tenor	0.0400	0.0385	1.0400	0.3000	-0.0356	0.1155
GDP growth	0.9305	0.3078	3.0200	0.0020	0.3273	1.5336
Interest Rate	-0.0433	0.0373	1.1600	0.2460	-0.1163	0.0298
Income Category (Formal Salary)	0.0457	0.0450	1.0200	0.3100	-0.0425	0.1338
Employer (Public sector)	-0.0083	0.0324	0.2600	0.7980	-0.0719	0.0552
Profession (Professionals)	-0.1296	0.0355	3.6500	0.0000	-0.1992	-0.0600
Borrower Identity Document (More than 1)	0.0085	0.0214	0.4000	0.6910	-0.0334	0.0505
Borrower Affordability (35%)	0.3924	0.1526	2.5700	0.0100	0.0934	0.6914
Mobile phone account ownership (=2)	0.0287	0.0203	1.4100	0.1580	-0.0111	0.0686
Bank Account ownership (Yes)	-0.0232	0.0401	0.5800	0.5630	-0.1018	0.0554
Intercept	-2.6524	0.8347	3.1800	0.0010	-4.2883	-1.0164
sigma_u	0.0000	rho	0.0000			
sigma_e	0.2201	R-squared:				
Wald chi2(16)	107.7100	Within	0.1197			
Prob > chi2	0.0000	Between	0.1846			
Number of obs	626	Overall	0.1503			

Table 66. Panel regression result-Religious Connectedness (Christian belief) and Gender on Loan Risk-Kumasi Branch

Independent Variable	Coefficient	Std. Err.	z	P>z	[95% conf.	
Religious connectedness (Females)	-0.1288	0.0308	4.1800	0.0000	-0.1892	-0.0684
Control Variables						
Borrower Age	-0.9203	2.8596	0.3200	0.7480	-6.5250	4.6844
Loan Amount	-0.0125	0.0328	0.3800	0.7040	-0.0768	0.0519
Loan Tenor	-0.0440	0.0320	1.3700	0.1690	-0.1067	0.0187
GDP	0.4598	0.2772	1.6600	0.0970	-0.0836	1.0031
Interest Rate	0.0806	0.0365	2.2100	0.0270	0.0090	0.1521
Income Category (Formal Salary)	-0.0455	0.0410	1.1100	0.2660	-0.1259	0.0348
Employer (Public sector)	-0.0479	0.0311	1.5400	0.1240	-0.1090	0.0131
Profession (Professionals)	-0.1111	0.0422	2.6400	0.0080	-0.1937	-0.0285
Borrower Identity Document (More than 1)	0.0034	0.0247	0.1400	0.8920	-0.0450	0.0518
Borrower Affordability (35%)	na	na	na	na	na	na
Mobile phone account ownership (=2)	0.0006	0.0196	0.0300	0.9770	-0.0379	0.0391
Bank Account ownership (Yes)	0.0940	0.0843	1.1100	0.2650	-0.0713	0.2592
Intercept	-1.2686	0.7569	1.6800	0.0940	-2.7520	0.2149
sigma_u	0.0000	rho	0.0000			
sigma_e	0.2099	R-squared:				
Wald chi2(16)	102.3100	Within	0.1041			
Prob > chi2	0.0000	Between	0.1998			
Number of obs	598	Overall	0.1495			

Table 67. Panel regression result- Religious Connectedness (Christian belief) and Gender on Loan Risk-Takoradi Branch

Independent Variable	Coefficient	Std. Err.	z	P>z	[95% conf.	
Religious connectedness (Females)	-0.0869	0.0408	2.1300	0.0330	-0.1669	-0.0069
Control Variables						
Borrower Age	0.1765	3.9924	0.0400	0.9650	-7.6485	8.0015
Loan Amount	0.0449	0.0412	1.0900	0.2750	-0.0358	0.1256
Loan Tenor	-0.0840	0.0562	1.4900	0.1350	-0.1941	0.0262
GDP	0.2390	0.3792	0.6300	0.5290	-0.5043	0.9822
Interest Rate	0.0455	0.0496	0.9200	0.3590	-0.0517	0.1427
Income Category (Formal Salary)	-0.0105	0.0520	0.2000	0.8400	-0.1125	0.0915
Employer (Public sector)	-0.0509	0.0384	1.3300	0.1850	-0.1261	0.0243
Profession (Professionals)	-0.1040	0.0646	1.6100	0.1070	-0.2306	0.0226
Borrower Identity Document (More than 1)	-0.0066	0.0289	0.2300	0.8180	-0.0633	0.0500
Borrower Affordability (35%)	na	na	na	na	na	na
Mobile phone account ownership (=2)	0.0083	0.0283	0.2900	0.7680	-0.0472	0.0639
Bank Account ownership (Yes)	-0.0795	0.0679	1.1700	0.2420	-0.2126	0.0536
Intercept	-0.7125	1.0383	0.6900	0.4930	-2.7475	1.3225
sigma_u	0.0000	rho	0.0000			
sigma_e	0.1930	R-squared:				
Wald chi2(16)	47.1100	Within	0.0993			
Prob > chi2	0.0000	Between	0.2144			
Number of obs	274	Overall	0.1544			

Table 68. Panel regression result for Religious Connectedness (Islam belief) and Gender on Loan Risk-Accra Branch

Independent Variable	Coefficient	Std. Err.	z	P>z	[95% conf.	
Religious connectedness (Male)	-0.0391	0.0207	-1.8900	0.0590	-0.0798	0.0016
Control Variables						
Borrower Age	-5.2386	3.1682	-1.6500	0.0980	-11.4480	0.9709
Loan Amount	-0.0415	0.0326	-1.2700	0.2030	-0.1055	0.0224
Loan Tenor	0.0400	0.0386	1.0400	0.3000	-0.0356	0.1156
GDP	0.9305	0.3080	3.0200	0.0030	0.3268	1.5342
Interest Rate	-0.0597	0.0363	-1.6400	0.1000	-0.1309	0.0115
Income Category (Formal Salary)	0.0325	0.0441	0.7400	0.4610	-0.0539	0.1188
Employer (Public sector)	-0.0075	0.0324	-0.2300	0.8170	-0.0711	0.0561
Profession (Professionals)	-0.1244	0.0356	-3.4900	0.0000	-0.1941	-0.0546
Borrower Identity Document (More than 1)	0.0258	0.0190	1.3600	0.1740	-0.0114	0.0630
Borrower Affordability (35%)	0.4250	0.1517	2.8000	0.0050	0.1276	0.7223
Mobile phone account ownership (=2)	0.0226	0.0202	1.1200	0.2640	-0.0170	0.0622
Bank Account ownership (Yes)	-0.0355	0.0398	-0.8900	0.3730	-0.1136	0.0426
Intercept	-2.6492	0.8355	-3.1700	0.0020	-4.2867	-1.0118
sigma_u	0.0000	rho	0.0000			
sigma_e	0.2201	R-squared:				
Wald chi2(16)	106.4600	Within	0.1197			
Prob > chi2	0.0000	Between	0.1814			
Number of obs	626	Overall	0.1488			

Table 69. Panel regression result for Religious Connectedness (Islam belief) and Gender on Loan Risk-Kumasi Branch

Independent Variable	Coefficient	Std. Err.	z	P>z	[95% conf.	
Religious connectedness (Male)	-0.0068	0.0208	-0.3300	0.7430	-0.0476	0.0340
Control Variables						
Borrower Age	-0.9203	2.9019	-0.3200	0.7510	-6.6079	4.7673
Loan Amount	-0.0125	0.0333	-0.3700	0.7080	-0.0778	0.0529
Loan Tenor	-0.0440	0.0325	-1.3500	0.1760	-0.1076	0.0197
GDP	0.4598	0.2813	1.6300	0.1020	-0.0917	1.0112
Interest Rate	0.0402	0.0360	1.1200	0.2640	-0.0304	0.1108
Income Category (Formal Salary)	-0.0826	0.0407	-2.0300	0.0430	-0.1624	-0.0027
Employer (Public sector)	-0.0581	0.0316	-1.8400	0.0660	-0.1201	0.0038
Profession (Professionals)	-0.1086	0.0428	-2.5400	0.0110	-0.1924	-0.0247
Borrower Identity Document (More than 1)	0.0664	0.0199	3.3400	0.0010	0.0274	0.1054
Borrower Affordability (35%)	na	na	Na	Na	Na	Na
Mobile phone account ownership (=2)	-0.0049	0.0201	-0.2400	0.8080	-0.0444	0.0346
Bank Account ownership (Yes)	0.0693	0.0854	0.8100	0.4170	-0.0981	0.2367
Intercept	-1.3103	0.7680	-1.7100	0.0880	-2.8155	0.1950
sigma_u	0.0000	rho	0.0000			
sigma_e	0.2099	R-squared:				
Wald chi2(16)	82.5200	Within	0.1041			
Prob > chi2	0.0000	Between	0.1464			
Number of obs	598	Overall	0.1242			

Table 70. Panel regression result for (Islam belief) and Gender on Loan Risk-Takoradi Branch

Independent Variable	Coefficient	Std. Err.	z	P>z	[95% conf.	
Religious connectedness (Males)	-0.0589	0.0290	-2.0300	0.0420	-0.1158	-0.0020
Control Variables						
Borrower Age	0.1765	3.9956	0.0400	0.9650	-7.6547	8.0077
Loan Amount	0.0449	0.0412	1.0900	0.2760	-0.0359	0.1257
Loan Tenor	-0.0840	0.0562	-1.4900	0.1350	-0.1942	0.0263
GDP growth	0.2390	0.3795	0.6300	0.5290	-0.5049	0.9828
Interest Rate	0.0195	0.0488	0.4000	0.6900	-0.0761	0.1150
Income Category (Formal Salary)	-0.0356	0.0494	-0.7200	0.4710	-0.1324	0.0612
Employer (Public sector)	-0.0562	0.0383	-1.4700	0.1430	-0.1314	0.0189
Profession (Professionals)	-0.1006	0.0645	-1.5600	0.1190	-0.2271	0.0259
Borrower Identity Document (More than 1)	0.0253	0.0254	1.0000	0.3180	-0.0244	0.0750
Borrower Affordability (35%)	na	na	na	na	na	na
Mobile phone account ownership (=2)	-0.0066	0.0280	-0.2300	0.8140	-0.0614	0.0483
Bank Account ownership (Yes)	-0.0746	0.0681	-1.0900	0.2740	-0.2081	0.0590
Intercept	-0.7011	1.0393	-0.6700	0.5000	-2.7381	1.3359
sigma_u	0.0000	rho	0.0000			
sigma_e	0.1930	R-squared:				
Wald chi2(16)	46.6300	Within	0.0993			
Prob > chi2	0.0000	Between	0.2116			
Number of obs	598	Overall	0.1531			

Table 71. First Probit regression result for Fintech on Lon risk-Heckman test result 1.

Independent Variable	Coefficient	Std. Err.	z	P>z	[99.5% conf. interval]	
Fintech	-1.1811	0.0367	-32.1700	0.0000	-1.2841	-1.0780
Control Variables						
Borrower Age	0.3401	0.0814	4.1800	0.0000	0.1116	0.5687
Gender	-0.4178	0.0367	-11.3700	0.0000	-0.5209	-0.3146
Income Category (Formal Salary)	-0.2472	0.0846	-2.9200	0.0030	-0.4847	-0.0098
Employer (Public sector)	-1.0379	0.0643	-16.1300	0.0000	-1.2185	-0.8573
Profession (Professionals)	-0.3204	0.0533	-6.0100	0.0000	-0.4699	-0.1708
Loan Amount	0.1490	0.0217	6.8600	0.0000	0.0880	0.2100
Loan Tenor	0.2981	0.0264	11.3000	0.0000	0.2241	0.3722
Borrower Identity Document (More than 1)	1.2943	0.0435	29.7400	0.0000	1.1721	1.4164
Borrower Affordability (35%)	1.7281	0.2045	8.4500	0.0000	1.1540	2.3021
Mobile phone account ownership (=2)	-0.1882	0.0501	-3.7600	0.0000	-0.3287	-0.0477
Bank Account ownership (Yes)	-0.4678	0.0765	-6.1200	0.0000	-0.6826	-0.2531
Interest Rate	-0.3170	0.0866	-3.6600	0.0000	-0.5602	-0.0738
GDP	6.7484	0.1919	35.1700	0.0000	6.2098	7.2870
Intercept	-19.4680	0.7668	-25.3900	0.0000	-21.6204	-17.3156

Log likelihood = -3243.8509	Number of obs.	=	12,045
	LR chi2(14)	=	5807
	Prob > chi2	=	0
	Pseudo R2	=	0.4723

Table 72. Second Probit regression result for Fintech on Lon risk-Heckman test result 2.

Independent Variable	Coefficient	Std. Err.	z	P>z	[99.5% conf. interval]	
Fintech	-1.0437	0.1389	-7.5100	0.0000	-1.4337	-0.6537
Control Variables						
Borrower Age	0.3025	0.0893	3.3900	0.0010	0.0519	0.5532
Gender	-0.3697	0.0595	-6.2100	0	-0.5368	-0.2027
Income Category (Formal Salary)	-0.2212	0.0882	-2.5100	0.012	-0.4688	0.0264
Employer (Public sector)	-0.914	0.137	-6.6700	0.0000	-1.2985	-0.5295
Profession (Professionals)	-0.2819	0.0652	-4.3200	0.0000	-0.465	-0.0988
Loan Amount	0.131	0.028	4.6900	0.0000	0.0525	0.2095
Loan Tenor	0.2667	0.0404	6.6000	0.0000	0.1532	0.3801
Borrower Affordability (35%)	1.1440	0.1527	7.4900	0.0000	0.7153	1.5727
Borrower Affordability (35%)	1.5631	0.2586	6.0400	0.0000	0.8372	2.2889
Mobile phone account ownership (=2)	-0.1652	0.0549	-3.0100	0.0030	-0.3194	-0.0110
Bank Account ownership (Yes)	-0.4158	0.0917	-4.5300	0.0000	-0.6734	-0.1583
Interest Rate	-0.2760	0.0955	-2.8900	0.0040	-0.544	-0.0080
GDP	5.9911	0.7617	7.8700	0.0000	3.8529	8.1293
lambda	**-0.1662**	**0.1627**	**-1.0200**	**0.3070**	**-0.6228**	**0.2903**
Intercept	-17.1534	2.3801	-7.2100	0.0000	-23.8344	-10.4724

Log likelihood = -3243.8509	Number of obs	=	12,045
	LR chi2(15)	=	5808
	Prob > chi2	=	0
	Pseudo R2	=	0.4724

Table 73. Hausman test result

Variables	Coefficients (b)	(B)	(b-B)	sqrt(diag(V_bV_B))
	fixed	random	Difference	Std. err.
Loan Tenor	-0.0576	-0.0646	0.0070	0.0253
GDP growth	20.2230	20.3893	-0.1663	0.0723

b = Consistent under H0 and Ha.
B = Inconsistent under Ha, efficient under H0.

chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 6.50

Probability > chi2 = 0.0387

Table 74. Results for Breusch-Pagan Lagrange multiplier (LM) test

	Var	SD = sqrt(Var)
Loan status	0.9067	0.9522
e	0.0459	0.2141
u	0	0

Test: Var(u) = 0

chibar2(01) = 0.00

Prob > chibar2 = 1.0000

Table 75. Result for Heteroskedacity test

H0: sigma(i)^2 = sigma^2 for all i	
chi2 (749) =	0.0000
Prob>chi2 =	1.0000

Table 76. Fixed-Effect panel regression result for time-variant variables.

Variable	Coefficient	Std. Err.	t-static	P>t	[95% conf.	
Borrower Age	na	na	na	na	na	na
Loan Amount	na	na	na	na	na	na
Loan Tenor	-0.0576	0.0362	-1.5900	0.1120	-0.1287	0.0135
GDP	20.2230	0.1442	140.2100	0.0000	19.9398	20.5062
Intercept	-2.6519	0.0243	-109.1300	0.0000	-2.6996	-2.6042
sigma_u	0.1504	rho	0 .3305			
sigma_e	0.2141	R-squared:				
F(2,748)	10934.3300	Within	0.9670			
Prob > F	0.0000	Between	0.8961			
Number of obs	1498	Overall	0.9499			

Table 77. Between-Effect panel regression result for time-variant variables.

Variable	Coefficient	Std. Err.	t-static	P>t	[95% conf.	
Borrower Age	-2.0310	1.9414	-1.0500	0.2960	-5.8422	1.7802
Loan Amount	0.0598	0.0299	2.0000	0.0460	0.0011	0.1185
Loan Tenor	-0.0605	0.0372	-1.6300	0.1040	-0.1335	0.0126
GDP	21.0322	0.2718	77.3900	0.0000	20.4987	21.5657
Intercept	-2.7785	0.0517	-53.7600	0.0000	-2.8799	-2.6770
F(4,744)	1617.2900	R-squared:				
Prob > F	0.0000	Within	0.9670			
sd(u_i + avg(e_i.)) = .1490142		Between	0.8969			
Number of obs	1498	Overall	0.9502			

Table 78. Augmented Dickey-Fuller test result at level

Variables	**ADF test [t-values [Z(t)]**	***P*-Values**
Voltm	-3.3550	0.0126
Valtm	-2.3270	0.1633
Valps	-3.4920	0.0219
Volps	-3.4720	0.0087
Cash	-2.1290	0.2328