Group C08

FRIENDS OR FOES? CASE OF ARISING FINANCIAL TECHNOLOGY IN FINANCIAL INDUSTRY

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A final year project submitted in partial fulfillment of the requirement for the degree of

BACHELOR OF BUSINESS ADMINISTRATION (HONS) BANKING AND FINANCE

UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF BUSINESS AND FINANCE
DEPARTMENT OF FINANCE

SEPTEMBER 2020

DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the research project.

(4) The word count of this research report is 19,669 words.

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ACKNOWLEDGEMENT

We would like to appreciate Universiti Tunku Abdul Rahman (UTAR) for the opportunity to us to partake in this final year project. Throughout this research project, we had acquired various useful skills and abilities which can be an advantage for us in the future, including leadership skills, communication skills, teamwork enhancement and time management as well. Besides that, we would like to give thanks to whom have helped and guided us along the way in completing this research project.

First and foremost, we would like to express our sincere appreciation to our supervisor and coordinator, Mr. Koh Chin Min for the guidance, useful information, advice and constructive criticisms throughout these two semesters so that we able to complete our research project smoothly. Moreover, we also grateful for his willingness to sacrifice precious time for assisting and lead our entire research be able to work within the time frame scheduled.

Secondly, sincere thanks to our examiner, Ms. Chia Mei Si, who provided us the valuable advices and further enhancing our research project quality. Without her advice, we might overlook or fail in amend some error before submission. We appreciate her in offering suggestion for us in order to increase the quality of our research project.

Last but not least, much thanks to each team members offering their precious time in doing this research project and played their respective role in a good manner so that the research project can be completed within the time frame. Furthermore, the contribution, collaboration and determination from each of members allows us to complete this research project effectively and efficiently. We built a strong friendship connection to each other from these two semesters.

DEDICATION

We would like to dedicate this final year project to our supervisor, Mr. Koh Chin Min as he provided us full of advices, guidance and motivation so that our final year project can be completed successfully. We would also like to dedicate this project to our parents and course mates as we are able to fulfill our bachelor's degree by accomplishing this whole research paper with their full support and encouragement.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARDL	Autoregressive Distributed Lag
CUSUM	Cumulative Sum of Recursive Residuals
COINTEQ	Cointegration Equation
ECM	Error Correction Model
FDI	Foreign Direct Investment
FINCEN	Financial Crimes Enforcement Network
FINTECH	Financial Technology
GMM	Generalized Method of Payments
INF	Inflation
IRF	Impulse Response Function
JB	Jarque-Bera
JOBS	Jumpstart Our Business Startups
LBANKSIZE	Natural Logarithm of Bank Size
LGDP	Natural Logarithm of Gross Domestic Products
LFDI	Natural Logarithm of Foreign Direct Investment
LFINTECH	Natural Logarithm of Financial Technology
LINF	Natural Logarithm of Inflation
LROA	Natural Logarithm of Return of Assets

NGO	Non-Government Organization
NYDFS	New York Department of Financial Services
OCC	Office of Comptroller of the Currency
OLS	Ordinary Least Square
P2P	Peer-to-Peer
SEC	United States Securities and Exchange Commission
SIC	Schwarz Information Criterion
USA	United Stated of America
USD	United States Dollar
US	United States
RAROA	Risk-Adjusted Return on Asset
RGDP	Real Gross Domestic Products
ROA	Return on Assets
ROE	Return on Equity
VAR	Vector Autoregressive
VD	Variance Decomposition
VECM	Vector Error Correction Model
VEC	Vector Error Correction

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PREFACE

This research project is submitted as a partial fulfillment of the requirement for the graduate student of Bachelor of Business Administration (Hons) Banking and Finance in Universiti Tunku Abdul Rahman (UTAR). The title for this research paper entitles “Friends or Foes? Case of Arising Financial Technology in Financial Industry” with the supervision by Mr. Koh Chin Min. The final year project is completed solely by the authors based on others researches and resources quoted as in references.

This primary focus of this research is to investigate and provide in-depth understanding on how financial technology (FinTech) influence bank performance in the United States (US). The independent variables used in this research are FinTech, represent Peer-to-Peer (P2P) lending, along with other variables such as Bank Size, Foreign Direct Investment (FDI), Gross Domestic Product (GDP) as well as Inflation while Return on Asset (ROA) used as the dependent variable for measuring bank performance.

We sincerely hope that our research is helpful for us or others to understand more on how financial technology influence the bank performance in the same time bring a substantial contribution to the society.

ABSTRACT

The objective of this research is to investigate and provide in-depth understanding on how the financial technology (FinTech) influencing the financial industry in the United States of America (USA). Furthermore, this research examines how the internal factor, which is Bank Size as well as macroeconomic factors comprises of Foreign Direct Investment (FDI), Gross Domestic Product (GDP) and Inflation brings impact to the dependent variable used in this research, Return on Assets (ROA). In addition, the relationship between exogeneous and endogenous variables are observed. Moreover, quarterly time series data from year 2012 was applied in this study by consisted total of 32 observations. To mark the results, E-View was used and several tests such as Bound Test, Cointegration test, Vector Error Correction Model (VECM) and others related test method were applied in this research. From the outcome generated, it shows that FinTech, Bank Size, FDI and GDP have significant relationship to ROA except for Inflation. However, all the variables do not have significant relationship to ROA when it comes to short run relationship. Nevertheless, limitation and recommendation had discussed in Chapter 5 to provide some useful hints for future researcher who are interested in relevant topic.

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

Last decade marks with strong global growth in digital innovation, especially in the innovation of 4G technology and the current innovation and implementation of 5G technology has promote the strong growth in financial technology (FinTech). The term "FinTech" shows up in the 20th century when the internet and electronic commerce (e-commerce) started to flourish and marks the shift from analogue to digital which led by the traditional financial institutions, and those financial services provided by the financial institutions are getting more digitalized through payment apps, mobile wallet or known as "e-wallet", Peer-to-Peer (P2P) lending platforms, which allows the public to enter into alternative investment opportunities and online lending & borrowing platforms (Rega, 2017).

Traditional financial institutions in the United States started to adapt and participate in this financial technology (FinTech) in these recent years and this sector considered new for them and those traditional financial institutions only have certain knowledge on this field. Therefore, there is a high chance the traditional financial institutions might not willing to accept the risk to invest or even participate until they gain some hand-on experience or acquire experts in these field. Hence, the FinTech firm's performance can outperform from those traditional financial institutions as some of the them still offer and operate old-fashioned, costly and time-consuming banking and financial activities to the publics. Thus, it is an opportunity for FinTech firms to take over some key functions that are currently offered by the financial institutions with more efficiency, less time consuming and less costly in function meanwhile, increase satisfaction among public beside provide alternative banking and financing services to them.

Furthermore, when global financial or economic crisis took place back in 2007-2008, the commercial banks in the United States seems in a situation that not willing to loan money to the general publics in order to keep their bank risks at the minimum level. Since then, borrowers started to turn their choices of financing services with Peer-to-Peer (P2P) platforms. Americans who were able to take loan financing from the commercial banks start to realise that P2P lenders give better deals than the commercial banks, even the investors have chosen P2P lending as their preferred investment choice as the platforms were not as volatile as stock market, thus bring lesser risks to the investors (Barry, 2019). The mind set still continuing hereafter where the borrowers able to access credit with more competitive rates than commercial banks to finance themselves while investors also willing to provide them with the funds, seeking to get higher return on their investments.

This research aims to study whether the financial technology (FinTech) will affect financial industry in United States (US). Following studies includes background of study, problem statement, research questions as well as objective of study and significant of study which will be further discussed and identified.

1.1 Background of Study

Under this section, the overview of financial industry and financial technology (FinTech) will be discussed, followed by Peer-to-Peer lending (P2P) versus bank loans, trends of P2P lending, and past studies regarding to the relationship between FinTech and bank performance.

1.1.1 Overview of Financial Industry

Money and financial service have been in the world around us for centuries. Money serve as an exchange medium, store of value and unit of account.

Financial industry act as an institution that provide financial services that involved money and aimed to increase the monetary value as the time goes by. The function of financial industry is depending on the nature of business generated by different type of services. The main role of the financial service industry is to provide value of exchange; act as a financial intermediary between the surplus and deficit unit; risk transfer by allocating certain risk and provide liquidity of asset. A financial service can be said is not the financial good itself. For example, a mortgage financing plan to purchase a house or a car insurance policy is best defined as the process of obtaining the financial goods (Asmundson, 2011). The financial service industry also includes the insurance and related services, banking sector, foreign exchange service and other financial services for example debt resolution and high frequency trading. All over the world, the financial company have put their effort to become global leading financial company. J. P. Morgan Chase And Co is the top financial company located at United Stated which provide different kinds of financial service and give a huge impact in the financial industry (Inferisx, 2019).

1.1.2 Overview of Financial Technology (FinTech)

In year 1918, there was an arisen of globalization to bring financial sector to another journey by start-up FinTech 1.0 and focused on financial infrastructure. In that year, United States Federal Reserve bank had developed Fedwire in order to implement the first electronic fund transfer system in the world and created an awareness by enhancing the standard of financial technology in year 1920. FinTech 2.0 is related to financial institution where transform the feature of Fintech into digital and created first handheld calculator and the first Automated Teller Machine (ATM) installed by Barclays Bank in the year 1967. In year 1971, National Association of Securities Dealers Automated Quotations (NASDAQ) established United States first digital stock exchange in the world and created a chance for companies to raise their capital through public market. In year 1995, Wells Fargo was the first bank that produces the online cheque account located in New York. Turn to year 2008, FinTech had forced to change to FinTech 3.0 as a turning point faced by financial industry. The development of Fintech 3.0 was a fundamental force to change the bank from traditional to become technology advanced. Not only that, financial crisis is a key factor that cause the global financial system on the brink of systemic collapse ("Evolution of Fintech," n.d.). Today, Web 2.0 has eased the people or organizations to create online markets and community (Emekter, Tu, Jirasakuldech, & Lu, 2015). There are a lot of financing methods generated by FinTech due to the Web 2.0 advancement e.g. crowdfunding, Peer-to-Peer lending as well as electronic payment.

Crowdfunding is one of the online platforms to let the borrowers raise their capital through an effort made by large pools of individuals. According to Mollick (2013), crowdfunding refers to the contribution given by each of the individual who aim for profit and invest their capital together to become a huge amount of funds at online platform without financial intermediaries. Crowdfunding also defined as new internet-based method to raise capital in which individuals can put their involvements for projects on related website such as LendingClub. Crowdfunding, in other mean, is aiming for gathering small amount of fund rather than single large sum from a funding agency (Wheat, Wang, Byrnes, & Ranganathan, 2013).

In contrast of crowdfunding, Peer-to-Peer (P2P) lending is meant by where both the borrower and lender able to make a loan transaction through online platform under the condition where they do not know each other. (Emekter, Tu, Jirasakuldech, & Lu, 2015). According to Gao and Feng (2014), P2P network is serving for small and micro credit business after emerge of Web 2.0 and these networks normally assists small and medium-sized enterprises or businesses (SMEs) along with investors who have insufficient funds in needs.

Electronic payment, known as online payment system is related to the transaction for goods and services through online sources without using cash (Konior, 2016). This payment is designed for the advantage of consumer in term of their accessibility and lower the transaction cost (Teoh, Chong, Lin, & Chua, 2013). Each of the method played an important role in a financial industry which interdependent with financial service company and banking industry. In case arising of smartphone, E-wallet and mobile payment emerged over the world, financial technology (FinTech) become more popular in mind of people from time by time. FinTech had successfully created an endless possibility to financial sector whereby making the new journey of financial service industry.

1.1.3 Peer-to-Peer (P2P) Lending versus Bank Loans

This research will focus on the Peer-to-Peer (P2P) lending to represent the financial technology (FinTech) because P2P lending is a loan service platform through online and the data used in this research is the total loan amount in quarter. The researchers are able to investigate the total loan amount of P2P lending compare with the loan issued by bank whether the emerge of P2P lending has impact towards the bank performance positively or negatively. P2P lending allows people to lend their money to borrower through online platform without intermediary. To overcome the large scale of lending between investor and borrower, Lending Club and Prosper, the leading company of P2P lending in United Stated assisted thousands of borrowers and lenders connecting each other. These two companies help the lenders and borrowers in the aspect of trustee issue, investment strategic and loan repayment. The type of loan that P2P lending provided is similar to bank loan but P2P lending is more focus on personal loan perspective. For example, P2P lending give the borrowers to cover their existing loans such as debt consolidation and credit card balances. P2P lending platform offers liquidity of money to the borrower and in the same time, offer a fair rate as compared to the bank.

Peer-to-Peer (P2P) lending and bank lending can be differentiated in terms of time consuming. P2P lending allows to apply the loans thought online portal while the traditional bank is compulsory for the borrower to physically present at the financial institution. Bank is being forced to increase the cost of borrowing and require a lot of money to maintain the operations and expenses incurred which generated by the physical asset such as building (Majesty Alliance, 2017). This has enhanced the competitive advantages between P2P lending and bank lending in term of their cost of borrowing and probably create a negative impact to the bank. Furthermore, P2P lending's goal is in contrast with the bank. Financial technology (FinTech) focus on two customer segments which are the non-bankable small and medium-sized enterprises or businesses (SMEs) with conditions of younger customer history along with little collateral; and bankable SMEs with existing bank loans but looking for additional loan. The objective of P2P lending in selecting these two segments is because they focus on the SMEs cash flow unlike the bank focus on the SMEs' asset to determine the ability to make the repayment of the loan (Tung, n.d.). Thus, the bank could reduce the default risk or non-performing loan but might lose their potential customers due to the restriction on the ability of repayment. This resulting in lower down the bank performance when customer switch themselves to P2P lending as another option of the bank lending (Tang, 2019).

1.1.4 Trends of Peer-to-Peer (P2P) Lending

The Peer-to-Peer (P2P) lending industry flourished back in the year 2005, providing a substitution of financing plan as opposed to the traditional lending institutions to those borrowers who are in need, particularly when the presence of credit crisis made the credit market became unreachable. Throughout the presence of credit freeze, the conventional lenders usually will reject those borrowers with high credit risks and these borrowers switch their preference to P2P lenders to apply for their desired financing plans (Magee, 2011). In United States, P2P lending is more focusing on the credit of the consumer whereby the amount of consumer market place lending is around ten times larger than the sum of market place lending for small business (Wardrop et al., 2016). The United States market has developed further away from the initial idea of directly connecting individual lenders and borrowers, becoming an instrument for selling loans to institutional investors (Milne & Parboteeah, 2016).

Prosper founded United States first Peer-to-Peer (P2P) lending marketplace back in year 2005. Ever since Prosper has founded, it has facilitated more than $16 billion of loans to more than 1 million of people. Prosper provide a platform for the people to invest in each other that brought them rewards both in financially and socially. Meanwhile, borrowers can apply online for a fixed-rate, fixed-term loan between $2,000 and $40,000 (Prosper Funding LLC, n.d.). Not only that, LendingClub, the second largest P2P platforms helped Americans achieve their life goals. Since 2007, they have been bringing the borrowers and investors together, help to transform the way people access for credit (Lending Club, n.d.).

According to SAP Analytics Cloud (n.d.), as shown in Figure 1.1, LendingClub had achieved a significant increase in the number of loans issued which is from $603 in 2007 to $443,579 in 2017. However, their growth rate seems to have plateaued over the years.

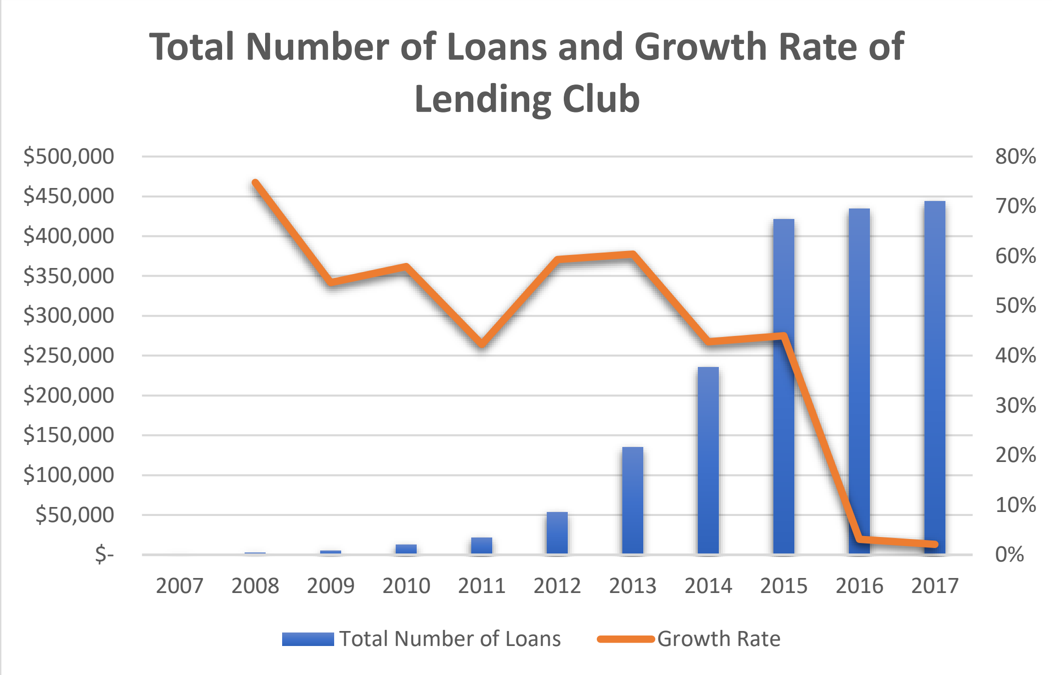


Figure 1.1: Total Number of Loans and Growth Rate of Lending Club

Source: SAP Analytics Cloud

1.1.5 Past Research

In the study of Phan, Narayan, Rahman, and Hutabarat (2019), they had developed a hypothesis that the growth of financial technology (FinTech) influence the bank performance negatively. They applied the consumer theory and disruptive innovation theory to explain the consequence of FinTech companies towards bank. The bank-level data from Indonesia was used to test their hypothesis. The first key finding is that FinTech reduces Net Interest Margin (NIM), Return on Equities (ROE), Return on Assets (ROA), and yield on earning assets (YEA) of their sample mean values. Second, FinTech predicts bank performance. They found that FinTech forecasts NIM, ROE, ROA, and YEA of their sample means negatively with each new FinTech company that introduced into the market. Third, they investigated the bank characteristics such as market value (MV) and firm age (FA) able to affect the way FinTech influences bank performance. They concluded their study by examining whether FinTech affects bank performance differently for state-owned banks against private banks. The result shown that FinTech has a larger and bigger effect on state-owned banks. Specifically, the result presented that high in value, more matured, and state-owned banks are negatively impacted by FinTech at a higher rate compared to lower valued, younger, and private banks. The main conclusion of their study showed that FinTech companies can provide cheaper and more efficient services and it will substitute traditional banks eventually. How FinTech can affect bank performance is this study's main contribution whereby there is no studies on this subject at present. Thus, this study represents the first empirical study exploring the hypothesis that FinTech negatively influences bank performance.

Furthermore, Temelkov (2018) studied whether the financial technology (FinTech) firms are opportunity or threat for banks. The researcher pointed out that there is an increasing disruption level in the financial markets over the years. This disruption represents the digital revolution toward the financial institution services. The results from this digitalization of financial institution services mostly influence the banking sector due to the new form of entrants. FinTech firms are taking over the customers gradually from the banks as they are operating with lesser costs. Because of these, the researcher stated that these new FinTech firms are the biggest or major threat for banks. But they could also be the biggest opportunity toward the banks simultaneously. It is depending on the banks' future plans whether the FinTech firms will be a threat or opportunity for banks. Therefore, the researcher recommended that the banks could continue to perform their traditional banking and finance business activities while neglect this threat or be proactive and initiate some arrangements of collaboration with FinTech firms in order to adapt this environment.

In addition, Risk and opportunities of financial technology (FinTech) in the banks had been identified along with the recent trends in banking by

Romānova and Kudinska (2017). The has increased rivalry from non-bank financial institution which encountered by the competition by the banks beyond the financial services as FinTech started to develop as a vital part of banking. As a result, the traditional banking institution have started to lose part of their market share in the overall financial institution's market share. Thus, FinTech development pose an additional challenge for banks. However, it can support the banks growth when this challenge is transformed into opportunity. Therefore, banks can be said is crucial to cooperate among FinTech firms particularly in the business fields where FinTech firms offer complimentary services that also provided by the banks. The researcher recommended the banking institution to allocate more budget in latest technologies to become participants that is more sophisticated and more innovative because banks cannot simply ignore or underestimate the inner potential of FinTech. Thus, the researcher concluded that FinTech firms and traditional banks can be competitors and partners at the same time, but mutual cooperation can be very important for banks as it can benefits to both parties mutually. Banking institution are able to utilize the FinTech companies' comparative advantages with highly standardized, cheaper financial services and providing financial services and products at a lower risk if the banks have a tighter cooperation with FinTech providers.

Moreover, Siek and Sutanto (2019) had studied an analysis regarding the impact of financial technology (FinTech) on banking industry. The researchers revealed that the modern disruptive innovations as the Fintech quick development on creation of payment gateway and Peer-to-Peer (P2P) lending and payment gateway are affecting the traditional financial services. Some issues might be arisen during digital disruption which will affect the business models of bank because of the changing customer trends with an added impact to the conventional firms. This past research utilized the quantitative approaches such as statistical hypothesis testing and convenient random sampling in analysing the Indonesia FinTech firms' effects on its conventional banking institutions. The results indicated that the FinTech payment had disrupted the banks since the introduction of FinTech companies mainly because of the superior value propositions provided by FinTech companies. This is because when the FinTech companies have the digital strategies when implementing customer centric mindset and developing the products or services based on the customer's requirement which able to achieve high customer satisfaction.

Not only that, Thakor (2019) had further explained that the financial technology (FinTech) impacted negatively on bank performance. This past research emphasizes on the interaction between the FinTech and banking industry. The researchers pointed out that the financial technology such as Peer-to-Peer (P2P) lending will not replace traditional bank in the future. However, it will take away some market share from banks when the banks are capital-constrained for those borrowers who do not have enough collateral on applying the loan.

1.2 Problem Statement

Since the advent of FinTech, short for financial technology, the financial services industry has been turned on its head. From coffee purchasing, managing finances, building business until further study even, FinTech is all around us in century. Amongst various uses of FinTech, Peer-to-Peer (P2P) Lending platform, obviously brings heavy impact towards economy. By reaching to era of financial globalization and leading to a whole new financial revolution start up meanwhile, it directly affecting the financial industry performance somehow in a negative way, as P2P Lending comprises numerous of lenders contributing to one fundraise, make it increasingly popular as alternative sources of funding. Peer-to-Peer (P2P) Lending first emerged in year 2005 in United States (U.S.) with lending and borrowing concentrated, also named as marketplace lending platforms. It acts as a different model where offered an alternative to traditional banking and payment systems. For instance, they cater to the underserved with services like consumer lending, student loans, real estate loans and small-business lending. When these primarily online providers create a marketplace for lenders and borrowers, lenders can also expect a higher rate in this system. Thereafter, it creates new opportunity for both investors and individual, but at the same time disrupt bank performance directly by emerging this platform in the market. Instead of traditional bank, it is now possible to go straight to investors for support of a project or company.

According to Statista (n.d.) in United States (U.S.), transaction value in Peer-to-Peer (P2P) lending segment amounts to US$24,766.7m in 2020, and the number of P2P users amount to 1,620 thousand in the same year. From a global comparison perspective, it is shown that U.S. is in the top 3 highest transaction value (US$24,767m) as at 2020.

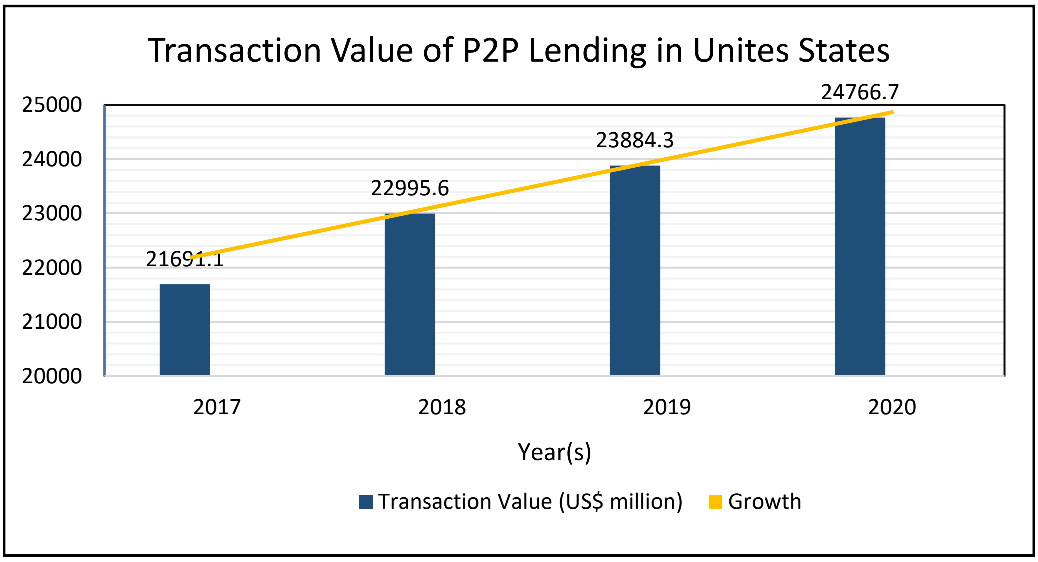


Figure 1.2: Transaction Value of Peer-to-Peer (P2P) Lending in United States

Source: Statista

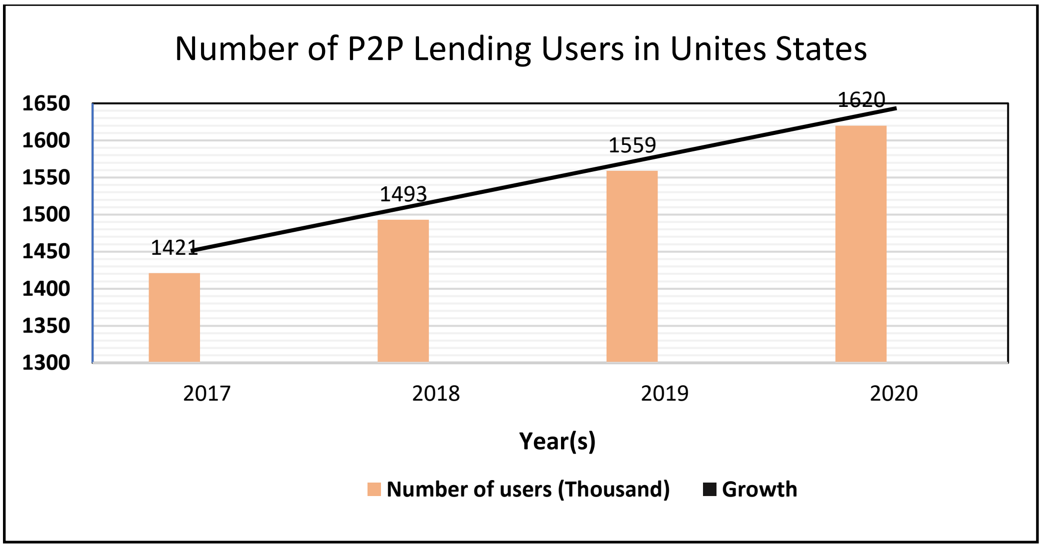


Figure 1.3: Number of Peer-to-Peer (P2P) Lending Users in United States

Source: Statista

Despite the increasing number on people who adopt or replace the traditional baking system with the use of technology as fundamental for managing their finance purpose, it negatively affected financial industry mainly on bank performance. Preferable of using FinTech sources, especially for business motive, the traditional banking system would be abandoned by them from time to time as it acquires long process of credit risk and default risk confirmation. Either for borrower to proceed for a loan, or a lender to earn the interest, it helps them to reach their benefit for own to the top. The returns in P2P lending usually fixed rate in way of split between investors and the platform. For example, if borrower paying 7% interest per annum, 4% of it will goes to investors and the remaining 3% for the borrowing platform. From individual perspectives, the easy the way to loan a lump sum to the reason of emergency or further study, while for business perspective, either stats-up a new form of business or to solve the problem of liquidity, P2P platform indeed brought a new way for them. Generally, it provides better plan than traditional banking system which the interest acquire will be fully receive by bank itself. For instance, in year 2014, LendingClub announced a total amount of $250 million in borrower's interest charges had saved (Barry, 2019). P2P is expected to continue growing. Goldman Sachs predicts that when this happens, bank profits could be reduced by as much as $11 billion (7%). This helps explain reason for the 146-year-old investment bank's 2016 launch into the P2P space, called Marcus by Golman Sachs.

It typically a siren calls to Peer-to-Peer (P2P) Lending platform borrower and lenders when such an advertisement, "why putting money in account when it could actually be languishing with a 7 percent of interest in elsewhere?" emerged in market. However, for the next seconds, should client of P2P lending platforms worry be being lured into the products without adequate warning for the hidden risk? LendingClub, the top P2P lending platforms in United States (U.S.) provided with 6.95%–35.89% annual percentage rate (APR), and no prepayment penalties for personal loan segments ("LendingClub," n.d.). It is much higher than other investment and bank platforms. This explain why P2P lending platforms growth rapidly in recent and futures. Just like every coin has two sides, in order to chase a higher return, investors in P2P Lending are bearing the risk of losing large chunks of their capital. In other words, borrowers may cause losses to investors due to arrears and poor initial credit decisions. Furthermore, investments that contributed are not covered by the Financial Services Compensation Scheme (FSCS). In meaning that, client could not reclaim any money should the provider experience of financial distress.

Nevertheless, investors may involve potential information asymmetry as investors unable to identify the identity of the borrower in P2P lending platforms. The platforms will conduct all necessary due diligence and investors use this information to decide whether the opportunity suits their investment profile. Lack of information for both lenders and borrowers could be the most crucial part that may increase the risk for their portfolio plan because investors may not be able to obtain accurate and complete personal information to understand their background, which further increases the risk of loan defaults faced by investors (Chen, Dong, Liu, & Sriboonchitta, 2019). Borrowers with a high risk of loan defaults are likely to obtain funds successfully when investors fail to properly identify the borrowers' default risk. Such a situation will cause investors to lose their income protection and at the same time, reputable borrowers may withdraw from P2P lending platform.

It also evolved into the occurrence of adverse selection. Meanwhile, Hu, Liu, He, and Ma (2019) believe that it leads to the stagnation or even retrogress of the platform because it is difficult for the platform to embrace new investors and borrowers, and it will even suffer from the abandonment of current users.

1.3 Research Objective

This section will present the objectives proposed for this research including general and specific objective as follows:

1.3.1 General Objective

Generally, this research aims to investigate and provide in-depth understanding on how financial technology (FinTech) influencing the financial industry.

1.3.2 Specific Objective

i) To examine the effect of Peer-to-Peer Lending (P2P) platform on bank performance.
ii) To examine the impact of internal factor on bank performance.
iii) To examine the relationship between macroeconomic factors and bank performance.

1.4 Research Question

Concerned with the objectives of this research, this research will raise the following research questions:

i) How Peer-to-Peer Lending (P2P) platform bring impacts to banks?

ii) Will internal factor have impact on bank performance?

iii) Do macroeconomic factors influence bank performance?

1.5 Significance of Study

This research intends to examine whether financial technology (FinTech) will influence financial industry in a positive or negative way. According to past researches, there is lack of researches discussing the impact of FinTech on bank performance. For this research, the selected dependent variable used to explore the research includes return on asset (ROA). Peer-to-Peer (P2P) lending, bank size, inflation (INF), gross domestic product (GDP), and foreign direct investment (FDI) are the chosen independent variable for this study purpose. These variables can be determined from this research in result of the kind of relationship they are, and also to be used in obtain accurate results.

The researchers and academicians could get benefit from this research when providing the data evidence and generating the test results regarding financial technology industry. The research's findings also lead future researchers and academicians to more detailed information and further knowledge on how financial technology disrupts bank performance, and at the same time it allows them to reduce uncertainty about whether financial technology is positively or negatively affecting financial industry when choosing a similar research.

Furthermore, this research is significant to investors and it may help them to develop a deep understanding about investment decisions. Since the research is about the impact between financial technology and bank performance, so it means that investors will look at which industry is performing well and proactively choose to invest funds in that industry. When investors can make investment decision based on this research's findings, they may be able to reduce risk and uncertainty in investing.

Other than that, this research could also bring contribution to the government and policy makers in helping to gain valuable information on the impact of financial technology on financial industry (i.e. bank performance). With valuable information and the result of this investigation, it will be more convenient for government and policy makers since they can use it as reference when making decisions about investing or pioneering new policies.

1.6 Conclusion

Throughout this chapter, the paper had further discussed financial technology (FinTech) on the background of study in which the overview of Financial Industry, revolution of FinTech, Peer-to-Peer (P2P) lending Versus bank loans follow by its trend and the past researcher's findings based on their studies after the introduction of FinTech into financial industry. Moreover, problem statement brings the concerning issue along with the details of the research objective, specific objective with research questions which include impact of internal and macroeconomic factor towards the bank performance in United States (U.S.). In a nutshell, the significant of study focus on whether the introduce of FinTech will either illustrates positive or negative effect toward the bank performance and if the future researcher can gain benefit from this research study. The next chapter, literature review will observe previous researchers that have provided some evidences on the relationship between internal, macroeconomic factors and bank performance.

CHAPTER 2: LITERATURE REVIEW

2.1 Theoretical Review

Theoretical models indicate financial technology (FinTech), internal factors, bank size influence on banking performance as well as macroeconomic indicators, comprise of foreign direct investment (FDI), inflation (INF), and gross domestic product (GDP). This section indicates the overview of theoretical regarding the connection of banking performance, FinTech, internal variables, and external variables.

2.1.1 Technology Acceptance Theory (TAT)

Technology Acceptance Theory (TAT) can be used to explain the usage of Financial Technology (Fintech). This theory first introduced by Davis, Bagozzi, and Warshaw (1989). This model suggests that when a new technology is presented to the users, they will make their decision on how and whether they will use it based on number of factors. Under their introducing, the factors are divided into Perceived usefulness (PU) and Perceived ease-of-use (PEOU), which brings a significant impact on the adoption of new technology. PU implies that how the consumer believes that using a new technology will help them save a lot of effort, and thus increase the work efficiency whereas PEOU can be defined as the degree of effort involved in using the new technology and therefore embrace the new technology in their life (Hu, Ding, Chen, & Yang, 2019). If the individual think that the new technology is hard to use and the user interface (UI) is complicated, they might have a negative attitude towards it. A research from Kiilu (2016) use TAT to test the effect of fintech firms' performance to listed banks in Kenya. He explains that bank not only have to come out with innovative technologies for banking but the technologies has to be accepted and adopted by the bank customers.

2.1.2 Stewardship Theory

Donaldson and Davis introduced Stewardship theory in 1989 and eventually replaced the norm of agency theory. According to stewardship theory, it explained that executive managers are the kind of people who tend to complete their jobs well and become good corporate asset managers rather than the ones who always do their best to protect and increase their own interests in economic activities. Likewise, this theory also noted that managers are considered to be trustworthy and therefore will not abuse company resources before improving management performance, which can easily achieve management goals of company (Davis, Schoorman, & Donaldson, 1997).

As described above, the link between bank performance and bank size are able explained by stewardship theory. Though sometimes there are situations where the manager's behaviour and decisions are biased towards personal interests, but the consequences must be borne by himself when he engages in other behaviours that harm others. Then imagine the situation from another part, if the bank is considered large in scale, which present the bank has stricter rules and regulations than other small banks. Hence, it is said that the rules and regulations must followed in each of the department of bank and banks tend to be more efficient in using resources to generate profits. Gul, Irshad, and Zaman (2011) found to have large economies of scale and the larger bank size, the larger capital and equity. This situation may reduce the risk and may have positive impacts on bank profitability.

2.1.3 Endogenous Optimum Currency Area Theory

Endogenous Optimum Currency Area Theory applied to explain relations among the Foreign Direct Investment (FDI) with bank performance (Adigwe, Okaro, Emejulu, & Ananwude, 2018). To relate, the trade barrier increase will lead to the increase in FDI inflow in the host economy. It is also known as Capital Market Theory of FDI. This theory equipped with the assumption that if there is a trade barrier within two countries, the best solution is that taking bold step, entering and focusing in that country, followed by setting up the plants and machineries for the production purpose to make the products and services ready for sale. For example, in Nigeria, the banking sector considered the most regulated sector due to banking operations and resultant effect in the financial industries. FDI in banking industries toward oversee investor is constrained to 10% of total capital in the financial institution. The foreign ownership's limitation at banking sector cause the foreign investors suffered in difficulties. However, if foreign investor obtains the ownership less than 10%, they considered unable to fulfil the Endogenous Optimum Currency Area Theory that expected the trade barrier will increase inflow of FDI in the host country. The strict law and regulation contribute to a reliable, sound and secured financial industries which accomplished to mobilize the funds for development purpose.

2.1.4 Inflation Theory

Revell introduced Inflation Theory in 1979 and he pointed that inflation influence bank's profitability through its effect on overhead costs, salaries and operating costs. If increases in inflation rate, salaries and operating costs will move in line, and therefore bank's profitability will decrease to the effect. However, the profitability will have a positive impact if the inflation rate is fully anticipated by the bank's management as it enables bank to adjust interest rates appropriately to increase revenues faster than costs (Trujillo-Ponce, 2013). According to Cameron (1972), inflation will reduce the value of money and increase potential risk, resulting small value in investment. This argument is correlated to the fact that inflation is a tax on money and revenue in the private sector of the economy and due to such tax, hence resulting little or no value in investment. This school of thought described the effect of inflation on profitability position of firms as being distorting on the firms' performance and valuations of its capital. The theory concludes that inflation exerts a negative influence on investment decision and hence lead to the decrease of bank performance.

2.1.5 Business Cycle Theory

Some of the researchers claimed that gross domestic product (GDP) had strong connection to the bank performance (Saksonova & Koleda, 2016; Narusevicius, 2018). They stated that the economic will achieve at the pro-cyclical stage and the bank can loan more to the borrowers because of the risk concerned is decreased. Not only that, the borrowers or deficit units tend to apply loan from bank for expanding business purpose. Increase in the demand of loan allows banks to set wide range of interest rate margin whereby generate a higher revenue and lower the cost of financing.

According to Rumler and Waschiczek (2012), they apply the Business Cycle Theory to determine whether business cycle will significantly affect the bank profitability. GDP growth was used as a measurement of macroeconomic development whereby it can indicate the demand of bank services and credit risks. They expected GDP growth will positively affect the bank profitability which supported by the theory of business cycle. The result proved that significant positive relationship among growth of GDP and bank profitability. Another result shown increase in GDP will initiate the borrowing and investing activities in the economic environment and lead to a higher net income generated by bank. This result also in line with pro-cyclical feature which related to the bank profitability (Narusevicius, 2018). Thus, GDP is proved by business cycle theory and assumed a positive relationship to the bank performance.

2.2 Literature Review

Economic literature indicate that the indicators permit computing bank performance in term of profitability (ROA). Volatility of the indicators compared to the bank buffers will allow the enhancement of bank's profitability risk. Theoretical models illustrate an interaction between banking performance, financial technology (FinTech), internal factors and macroeconomic indicators, such as Peer-to-Peer (P2P) lending, bank size, foreign direct investment (FDI), inflation (INF), and gross domestic product (GDP). This part provides the overall links between endogenous and exogeneous variables.

2.2.1 Financial Technology (Fintech)

FinTech will be one of the main concern variables in this paper. The paragraph below will discuss whether FinTech will positively or negatively affect the bank performance based on research conducted by past researcher.

2.2.1.1 Positive Relationship between Financial Technology and Bank Performance

An empirical study from Misati, Kamau, Kipyegon, and Wandaka (2015) argued that the fintech are complementary to commercial banking business. Their research finding shows that although there is an increasing trend on the consumer get their financing from non-bank credit only institutions, its market share on the entire loan market only contributes to less than 1%. Their results further show that non-bank credit only institutions get their funds for lending from local commercial banks, offshore banks as well as their own funds. Thus, contributes to the growth of local bank performance. Serge, Rugemintwari, and Sauviat (2019) also shows that the bank adoption and involvement in mobile money will bring positive impact to their bank performance.

2.2.1.2 Negative Relationship between Financial Technology and Bank Performance

Numerous researchers pointed that there is an inverse relationship between Financial Technology (Fintech) and bank's performance (Phan, Narayan, Rahman, & Hutabarat, 2018; Li, Spigt, & Swinkels, 2017; Romānova & Kudinska, 2017; Jünger & Mietzner, 2019; Kolesova & Girzheva, 2018). For instance, a research from Phan et al. (2018) that study the effect of Fintech towards the bank performance in Indonesia, has found that Fintech negatively impact the bank in Indonesia in terms of performance, in which the Indonesia bank's Net Interest Margin (NIM), Return on Equity (ROE), Return on Asset (ROA) as well as Yield on Earning Assets (YEA) in means value. They also use Fintech to forecast bank performance and found that Fintech negatively forecasts Indonesia bank NIM, ROE, ROA and YEA in sample means. In the meantime, they realized that Fintech affect more towards large and matured banks rather than small and younger banks in terms of the bank Market Value (MV) and Firm Age (FA). Hence, development of Fintech can affect the bank performance in a negative way as Fintech can purchase the products and services which are information-based offered by banks from different financial service providers (Romānova & Kudinska, 2017).

Apart from that, as Financial Technology (FinTech) providers or companies operates through internet based platform, it means that they do not rely on geographically concentrated area and their potential customers are diversified throughout the world, FinTech providers or companies offer standardized services or products that has low or without additional costs that can be provided throughout the world and are not limited to only one country or region (Romānova & Kudinska, 2017; Li et al., 2017). New FinTech entrants will try to utilize the usage of innovations and offer less expensive services to meet the expectation of the customers and existing financial institutions or traditional banks will lose their market share or profits eventually (Kolesova & Girzheva, 2018). Therefore, new FinTech entrants able to attract the small enterprises that are risky to finance themselves that would be normally rejected by the traditional banks (Dunkley, 2015). FinTech providers or companies simply match the savers and borrowers directly rather than converting their short-term liabilities into long-term assets like mortgages that the traditional retail banks would normally do, and the borrower default risk is fully bear by the lender (The Economist, 2015; Li et al., 2017) as the FinTech companies or providers just providing the lending platform (Romānova & Kudinska, 2017).

Furthermore, Kolesova and Girzheva (2018) studies the effect of financial technologies (FinTech) on banking sector in Russia. FinTech such as Peer-to-Peer (P2P) lending can negatively affect the banking sector because no intermediaries such as banks or credit institutions, interfere or participate themselves in the process of issuing loan except that individuals itself (Kolesova & Girzheva, 2018; Vives, 2017). Individuals can obtain financing or loan that is way easier and hassle-free through FinTech, which has an upper hand compared to traditional banks. A research from Jünger and Mietzner (2018) shows that customers or individuals are less price-sensitive when they are engaged with the FinTech credit providers as the interest rate in P2P lending platform are somehow lower than that traditional banks. The rapid development of FinTech leads them to enter into financial services market freely with minimum barriers that can exist separately from the banks, providing a narrower segment of financial services with a reasonable price (Kolesova & Girzheva, 2018; Dapp, Slomka, & Hoffmann, 2018). To cope with this kind of competition, bank have to modify their business models according to the latest market trends, which becomes harder for them as the time goes by.

Another study from Lenz (2016) that conducts research on Peer-to-Peer Lending (P2P) in Europe Countries depicts that investor and borrower are attracted to P2P lending as the P2P lending platforms does not bear the credit risk on their own balance sheets and hence, P2P platform fees will be lower than those traditional banks' interest rate as the amount of equity capital used to finance the P2P platform is not dependent on the platform's loan volume. It also suggests that the investors and borrowers can gain advantage from here as the margin that the bank earned can be shared by platform. Hence, the borrowers can get their financing at a lower cost while the investors can receive a return as a compensation for them for taking the risk.

2.2.2 Bank Size

Bank size is a variable worth exploring and act as determinants on bank performance. Despite banks significant in financial system therefore, it is strictly supervised and regulated.

2.2.2.1 Positive Relationship between Bank Size and Bank Performance

Most previous studies mentioned bank size shown a positive effect to bank performance (Alper & Anbar, 2011; Gul, et al., 2011; Khrawish, 2011; Rao & Lakew, 2012; Rahman, Kamid, & Khan, 2015; Djalilow & Piesse, 2016). Alper and Anbar (2011) investigated that the impact of bank-specific and macroeconomic variables on profitability of banks in Turkey using data of 10 banks' financial statement over the period from year 2002 to 2010. With respect to bank-specific variables, they chose to use fixed effect model to estimate and these results showed that larger banks will present positive and significant impacts on profitability while remaining bank-specific variables include capital adequacy, liquidity, net interest margin (NIM) and deposits show no significant relations to profitability.

Gul et al. (2011) explained further by using the study of Pakistan commercial banks from year 2005 to 2009 and developed that hypothesis for analyzing bank profitability. The finding of study indicated that return on asset (ROA) was successfully explained by bank size, which is larger bank size, larger capital and equity. They also pointed out that the measurement of ROA is according to bank size, for instance, startup banks have small scale as well as the capital and equity. Furthermore, Khrawish (2011) attempted to identify the determinants of commercial profitability of bank in Jordan during the period range 2000 to 2010 and explore the connection of bank size and return on asset (ROA). The method of Multiple Linear Regression (MLR) was used in this research to measure a number of internal and external factors. The study indicated that bank size was positive and significant on ROA in Jordan. ROA refer the ability of company to generate revenue from assets. In other words, larger bank size will lead the company more efficient in using its resources to generate the income.

Rao and Lakew (2012) empirically indicated impact of internal and external factor to performance of Ethiopian banks. By using fixed effects model, the internal factors are statistically significant and the study found that the internal factors used in exploring the key factors that influences bank performance are capital adequacy, diversification and bank size. In addition, there also have positively affect the bank performance in Ethiopia. He explained large commercial banks benefit from economies of scale or scope and use market power via strong brand image, which enables them to obtain more profits. Rahman et al. (2015) took several financial reforms to investigate the determinants of bank profitability in Bangladesh through an unbalanced panel data over time period 2006 to 2013. Empirical evidence from their study considered bank size as important determinants of bank profitability in their research, which means the relationship among bank size and bank performance exists due to the existence of economies of scale.

Djalilov and Piesse (2016) study the effects of bank profitability in Central and Eastern Europe countries using generalized method of payments (GMM) techniques over the period 2000 to 2012. It concludes the impact of internal variable on bank profitability is relatable to bank size. He also pointed out large and medium banks are more profitable than small scale banks since it will tend to enjoy economies of scale and reduce risk through diversified products and loans, which can increase their profitability by improving operational efficiency.

2.2.2.2 Negative Relationship between Bank Size and Bank Performance

Some researchers justified that between bank size and bank performance have a negative relationship (Akhtar, Ali, & Sadakat, 2011; Obayumi, 2013; Tam, Trang, & Hanh, 2017). Akhtar et al. (2011) attempted to examine relationship of bank-specific factors for performance of Islamic banks. The study collected sample of Islamic banks in Pakistan since 2006 until 2009. Using both of statistical multivariate regression models, the outcome expressed bank size is negative relation in both model I and model II. They also stated that the occurrence of this situation happened was affected by return on asset (ROA) and most Islamic banks have faced losses in recent years.

Moreover, Obayumi (2013) observed that the variables of bank capital, bank size, interest income, expenses management and economic condition that affected bank performance over the time period 2006 to 2012. By using fixed effects regression model, he found that the significant relation of the above variables which explained by the bureaucratic procedures have negatively influenced the performance. Tam et al. (2017) studied impact of performance of Vietnamese commercial banks via panel data over the time period 2007 to 2013. The study examine bank size is inversely affect profitability of banks, which means it will face the reduction of profits if banks desire to expand the bank size. The existence of this situation was negatively affected by bureaucratic procedures and the banks size are becoming extremely large. For instance, mergers and acquisitions of banks in Vietnam have reduced numbers of banks, which will lead to lower bank earnings (SBV, 2013).

2.2.2.3 Insignificance Relationship between Bank Size and Bank Performance

Though most literature presented there exits of positive or negative relation among bank size and bank performance, yet there has a research obtained bank size insignificant to bank performance. According to Heffernan and Fu (2010), the Chinese banks were studied by using the sample of 75 banks over the period 1999 to 2006. It pointed out bank size was not the factor of influential on bank performance however, the type of bank has correlation between bank performance. Likewise, the bank performance normally measured by Economic Value Added (EVA) and Net Interest Margin (NIM). By using EVA method, the finding of study indicated efficiency and loan loss reserves as a significant positive determinant of bank performance, whereas foreign equity investment has not been affected or performance has declined significantly. There is an issue that rural commercials have a positive average EVA, and its performance was significantly better than the big four, joint stocks and city commercial banks, which might due to operating near a local monopoly. Hence, bank size is unnecessary in illustrating bank performance.

2.2.3 Foreign Direct Investment (FDI)

Following paragraphs will discuss the literature reviews drawn from previous studies about the positive and negative relationship among foreign direct investment (FDI) and bank performance, followed by insignificant relationship indicated by researchers.

2.2.3.1 Positive Relationship between Foreign Direct Investment and Bank Performance

There are many earlier researchers had investigated that foreign direct investment (FDI) and bank performance are positive in relationship (Tajgardoon, Noormohamadi, & Behname, 2012; Sheeba, Patil, & Srinivas, 2016; Konara, Tan, & Johnes, 2017; Adigwe, Okaro, Emejulu, & Ananwude, 2018; Musah, Gakpetor, Kyei, & Akomeah, 2018; Kariuki & Sang, 2018). Tajgardoon, Noormohamadi, and Behname (2012) examined the causality relationship between FDI and Islamic banking. The result shown that the FDI will reinforce Islamic banking. The researchers emphasised on the smart banking existed in a host country has lower risk and dynamic economy. Hence, it is very suitable for FDI under this environment. FDI brings their funds into the host country's economy due to there is a relationship between the multinational firms and international finance markets. Hence, FDI will spend their funds for investment purpose and reinforce the banking system in the host country. Furthermore, Sheeba, Patil, and Srinivas (2016) had further explained by pointing out the fact that the profitability and productivity of South Indian Bank is related to the FDI inflow into the bank. This paper examined the importance and role of FDI on bank's operational efficiency in the basis of profitability and productivity. The result indicated that FDI in South Indian Bank brought positive impact on bank's overall performance whereby FDI increased resulting in the bank's profitability and productivity increased.

Moreover, Konara, Tan, and Johnes (2017) determined impact of foreign direct investment (FDI) to internal and external measure of efficiencies in the banking sector. The internal measure of efficiencies used include the managerial efficiency, technical efficiency and cost efficiency while the revenue efficiency used as the external measure. The findings suggested that the foreign banks have positive and significant impact on the managerial efficiency, technical efficiency and scale efficiency in banking sector while the revenue and cost efficiency have no clear impact from the foreign banks. Hence, a higher capitalization contributed to the improvement of revenue and cost efficiency, but the risk will be higher in more concentrated banking sector. In addition, this result can be supported by Adigwe, Okaro, Emejulu, and Ananwude (2018) who revealed the existence of positive significant relationship among FDI and banking sector's total deposit. They mentioned that FDI boosts and increase the deposits of Nigeria's banking sector where Adeniyi, Omisakin, Egwaikhide, and Oyinlola (2012) also obtained identical findings in Ghana.

Besides, Musah, Gakpetor, Kyei, and Akomeah (2018) identified that influence of foreign direct investment (FDI) to commercial bank performance in Ghana. Their findings supported the view that FDI inflow consist of positive significant impact to commercial bank's profitability which measured by return on assets. The outcome is same with opinions of previous research as mentioned above. The banking sector able to obtain benefits hugely from FDI inflow by improving their bottom line. This is because the FDI inflows able to expand business climate which can lead to a more credit creation and higher profitability to the bank. Not only that, Kariuki and Sang (2018) had further discussed the FDI and bank performance in Kenya. Their results indicated the foreign equity capital has a positive and significant effect to the commercial banks' return on equity in Kenya. This finding also consistent with the study of Saddimbah (2014) and Salazar, Soto, and Mosqueda (2012) that the equity capital will result in the higher value for equity holders which can lead to a better bank performance.

2.2.3.2 Negative Relationship between Foreign Direct Investment and Bank Performance

On the other hand, some researchers indicated foreign direct investment (FDI) shown a negative relationship to bank performance (Sun & Li, 2012; Amos, 2016). Sun and Li (2012) had proposed a study related to impact of FDI in manufacturing sector to China's domestic banking performance. The researchers had ascertained that the competition from FDI had generated negative impacts on domestic firms in short run period. From researchers' result, the coefficient of standard deviation of FDI in manufacturing sector is negative significantly. This means that variation in FDI inflow in manufacturing sector will not bring any benefits toward the domestic bank performance. If the high variation in FDI will reflect risk increased in the manufacturing sector. Hence, FDI will affect the domestic banks performance negatively. Moreover, this result can be supported by Amos (2016) that proves the effect of FDI on bank performance in Ghana. The results revealed that the FDI was negative significantly impact on financial institutions' profitability in Ghana. According to their research, an increase by 100% in FDI is associated with about 13% reduction in the return on asset for the financial institutions in Ghana.

2.2.3.3 Insignificant Relationship between Foreign Direct Investment and Bank Performance

However, few studies determined the insignificant relationship among foreign direct investment (FDI) and bank performance (Korna, Ajekwe, & Idyu, 2013; Tsaurai, 2014). According to Korna, Ajekwe, and Idyu (2013), FDI is insignificant positive impact on the capital base while insignificant negative impact on liquidity position and total assets of Nigerian banking industries. According to their result, change in liquidity of banking sector do not necessarily based on the change of FDI. In other words, the growth of banking industries is not mainly influenced by the increase in the flow of foreign capital. Reason given by the researchers is that for Nigerian banking sector, they mainly depend on alternative sources of capital rather than foreign capital to their sustainability and growth. In addition, Tsaurai (2014) had further explained that there is no direct causality relationship among banking sector development and FDI inflows. Their study confirmed the indirect relationship among banking sector development and FDI inflows in long run perspectives. As a conclusion, there exists of other factors that will impact the bank performance instead of FDI.

2.2.4 Inflation (INF)

The results of the economist were mixed for the relations of inflation to bank performance however, most of the researcher showed a significant, negatively view for the impact mentioned.

2.2.4.1 Negative Relationship between Inflation and Bank Performance

There are number of studies figured out that there is significant, negative relationship between inflation and bank performance (Scott & Ovuefeyen, 2014; Bettencourt, 2010; Khrawish, 2011; Namazi & Salehi, 2010; Umar, Maijamai'a, & Adamu, 2014; Duraj & Moci, 2015). Scott and Ovuefeyen (2014) pointed that inflation adversely affected commercial banks' profitability in the heat of the global financial crisis (2007-2010) in Nigeria. This further explain with Bettencourt (2010) that high and uncertain inflation rate is found to be detrimental in a stable financial sector performance. In addition, lower inflation level serves as a prerequisite condition for attaining a stable and deep financial sector. They concluded that the effect is more significant and vulnerable to market-based than bank-based financial system.

Furthermore, Khrawish (2011) who focus on determinants of commercial banks performance in Jordanian investigated that relationship between commercial banks which measure by ROA and inflation rate from year 2000 to 2010 by using 72 countries as approach is significant and negative. This supported by Namazi and Salehi (2010) in which study of the role of inflation in financial repression in Iran found a direct correlation between inflation and decrease of absorbed deposit and loan given capacities of banks. This means that any increase of inflation rate will lead to a corresponding decrease in banking system performance. When the rate of inflation becomes stronger, the banking system cannot absorb the shock even though banks able to withstand the effects of inflation at its initial stages. Umar, Maijamai'a, and Adamu (2014) observed that inflation has an adverse effect on banking sector performance and its spill over effect is detrimental to the overall economy. They further explain inflation acts as a drag on performance as banks are usually compelled to shift their resources from more productive activities simply to focus on profit and losses from currency inflation.

Moreover, Duraj and Moci (2015) illustrated that inflation appears to be significant and related negatively to the bank profitability. The inflation of operational costs increased more than the effect of interest rates in Albanian financial sector resulting lower profitability for the banks. They found that the profitability of Albanian banks is not only influenced by factors related to their management decisions which are classified as internal factors, but also to changes in the external macroeconomic environment (i.e. inflation) which resulted as significantly related to profitability of the banks.

2.2.4.2 Positive Relationship between Inflation and Bank Performance

Some researchers having divergent opinion from negative relationship argued that inflation, in other side is significant, positively relationship with bank performance (Trujillo-Ponce, 2013; Tan & Floros, 2012; Angeloni & Faina, 2013; Nasambu, 2014). Trujillo-Ponce (2013) pointed that the bank can adjust interest rates appropriately to increase revenues faster than costs, which should have a positive impact on profitability if the inflation rate is fully anticipated by the bank's management. This is because it may raise salaries and operating costs when there is an increases of inflation rate and therefore, decrease bank's profitability in advance.

Tan and Floros (2012) examine there is a positive relationship between bank profitability, cost efficiency, banking sector development, stock market development and inflation in China. This implies that during the period of study (2003-2009), inflation is anticipated which gives banks the opportunity to adjust the interest rates accordingly, resulting in revenues that increase faster than costs, with a positive impact on profitability. This is supported by Angeloni and Faina (2013) state that "monetary expansion and positive productivity shock increases bank leverage and risk". Nsambu (2014) figured that inflation has a positive significant impact on return on equity for domestic commercial banks in Uganda. The results observed that bank income increased more than bank costs. This implies that either domestic commercial banks management predicted correctly the trend of inflation and adjusted interest rates accordingly to earn more profits or bank customers never accurate estimate the inflation.

2.2.4.3 Insignificance Relationship between Inflation and Bank Performance

Other than significant relationship either negatively or positively, minor of researcher found also there is no relationship between inflation and bank performance. Saad and El-Moussawi (2012) which study the determinants of net interest margins of commercial bank reveal that the inflation in Lebanon does not influence commercial banks' profitability. They mentioned that net interest margin not really determined by the inflation, and therefore a clear explanation is hard to proposed on the possible changes in inflation caused by banking net margin since the coefficient of the variable inflation has the expected sign but the relationship is not statistically significant. In addition, they added that this could be explained by the fact that inflation was largely under control during the study period (2000-2010). The net interest margin seems to be not much explained by the inflation rate and operating costs.

2.2.5 Gross Domestic Product (GDP)

The following paragraphs will discuss the literature reviews drawn from previous studies about the positive and negative relationship between gross domestic product (GDP) and bank performance, followed by the insignificant relationship between GDP and bank performance.

2.2.5.1 Positive Relationship between Gross Domestic Product and Bank Performance

Many earlier researchers had investigated that gross domestic product (GDP) on bank performance are positive in relationship (Gul, Irshad, & Zaman, 2011; Zeitun, 2012; Klein, 2013; Hong & Razak, 2015). Gul, Irshad, and Zaman (2011) studied the relations between bank-specific and macro-economic characteristics on the bank profitability. Their research indicated the bank profitability really determined by internal and external factors, and thus GDP on bank's return on assets (ROA) are positive in relationship. It also represented that large scaled banks can enjoy a higher profitability than small scaled banks when it comes to economies of scale in transactions. Moreover, this can be supported by Zeitun (2012) that the result shown the GDP along with banking institution profitability is positively correlated. Their finding of study clearly specified that Islamic and conventional banks performance are determined by GDP.

Not only that, Klein (2013) investigated that both macroeconomic and bank-level factors can affect the non-performing loan (NPL). The findings suggested that gross domestic product (GDP) growth results in lower NPL. This is because the GDP growth with a higher rate will translate into higher revenue, in which able to improve the debt servicing capacity of the borrowers. In other words, during the time where the economy is slowing down, this will increase the difficulties for the borrowers to pay back their debt as the unemployment rate will rise and resulted in the increased level of NPL. Hong and Razak (2015) had further explained that GDP is positive significant relate on return on average asset (ROAA), liquidity ratio and equity to total liquidity (EQL). The findings supported the view that the increase in lending rates have a positive impact on bank profitability is relatable to GDP growth.

2.2.5.2 Negative Relationship between Gross Domestic Product and Bank Performance

However, some researchers found that negative relationship among gross domestic product (GDP) and performance of bank (Tan & Floros, 2012; Combey & Togbenou, 2017). Tan and Floros (2012) investigated GDP growth shown a negative impact to bank profitability. The result from the study were supported partially by the view that the high growth of growth will cause business environment improved. Hence, lower the bank entry barriers is examined. The lower the bank profitability in China was affected by the high GDP growth as the profitability of banking sector in China is mainly influenced by the level of non-performing loan. Furthermore, Combey and Togbenou (2017) had further explained by pointing out the fact that real GDP growth comprise negative significant impact on return on assets (ROA) and return on equity (ROE) of bank in the long-run while in short-run, the result shown that banks' ROA and ROE are insignificance on macroeconomics variables where bank capital to assets ratio and bank size are positively affecting bank's ROA while the bank capital to assets ratio is negatively affecting bank's ROE.

2.2.5.3 Insignificant Relationship between Gross Domestic Product and Bank Performance

However, there are a few studies found gross domestic product (GDP) shown insignificant relationship to bank performance (Alper & Anbar, 2011; Kanwal & Nadeem, 2013). According to Alper and Anbar (2011), they determined that growth of real GDP and inflation rate have insignificant relationship with profitability of bank. Their results revealed only real interest rate positive on bank's profitability, measured by return on equity (ROE). This indicated when real interest rates increase, the ROE of bank move in line with it. Not only that, Kanwal and Nadeem (2013) had further discussed real GDP is insignificant and positive on return on assets (ROA). In overall, the researchers ascertained the selected macroeconomic factors where bank profitability is not really determined by real interest rate, real GDP and inflation. Therefore, if banks want to optimize the risk-adjusted returns, banks need to concentrate on other external factors such as exports, imports, tax rates, exchange rate, and income level or construct policies to enhance internal factors of bank.

2.3 Proposed Theoretical and Conceptual Framework

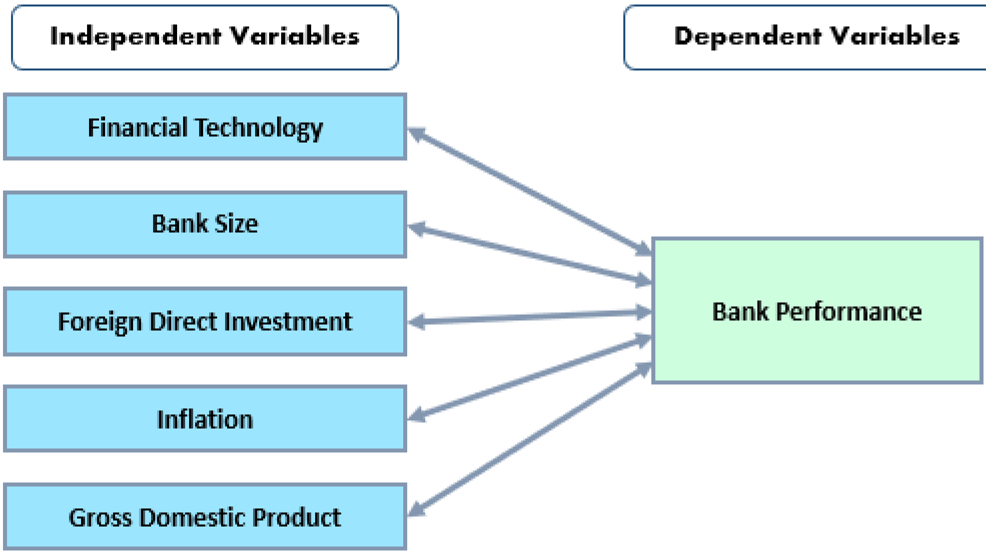


Figure 2.1: Relationship between bank performance and its independent variables

According to Technology Acceptance Theory, Stewardship Theory, Endogenous Optimum Currency Area Theory, Inflation Theory and Business Cycle Theory, the conceptual framework is constructed as shown in Figure 2.1. This paper tends to investigate and provide in-depth understanding on how financial technology (FinTech) influencing the financial industry in term of bank performance. The main variable in this research is financial technology which supported by the theory of Technology Acceptance. This theory stated that new technology in term of the perceived of usefulness (PU) and Perceived ease-of-use (PEOU) will attract new customers while directly impact the position in the banking performance since the relationship of banking industries and financial technology company are substitution.

By referring to past studies, bank size, foreign direct investment (FDI), inflation and gross domestic product (GDP) are linked to bank performance at certain extent. Thus, a comprehensive model is constructed in this paper by adding these four independent variables as control variables. Bank size is categorized as internal factor where supported by Stewardship Theory which stated that large economic scales (bank size) will need more capital and efficiency to generate the profit of the bank. Hence, the relationship of bank size and bank performance exist in this model. GDP, inflation and FDI are considered as external factor which need to be included in this model. Each of the external factors had been supported by different theory while all the factors are interrelated to the bank performance. GDP is supported by the business cycle theory where emphasized that the pro-cyclical stage and the bank can loan more to the borrowers because of the risk concerned is decreased. It also resulting an increase of bank performance since majority of the return are generated by loan charge and interest. Besides, Inflation Theory had pointed out that inflation will lead to increase the overhead cost of the bank and decrease the bank performance. FDI is supported by the theory of Endogenous Optimum Currency Area where mentioned that the trade barrier lead to the FDI come in to set up their business instead of operating their business between countries boundaries. So, increase in FDI will lead to the bank have more capital and ability to increase their profit since the foreign investor are participate in the economy of home country. Thus, this research has combined all the important variable in a logically ways and supported by the relevant theory to make a completeness model.

2.4 Conclusion

The results observed by past researchers has illustrated the relationship between the endogenous as well as exogenous variables from different perspectives and concepts. Throughout the literature studies, most of previous researchers proposed that some variables have significant and relatively positive impact on bank performance such as bank size, the internal factors; macroeconomics factors, gross domestic product (GDP) and foreign direct investment (FDI). For financial technology (FinTech) and inflation observed a significant but negatively influence performance of bank. Based on the literature studies done above, there are lack of researches study regarding the effects of Peer-to-Peer (P2P) Lending to bank performance. Thus, this gap will be filled by the results obtained and further clarified in this chapter.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter examines the designed study method and investigate the relationship among exogenous and endogenous variables. Vector Error Correction Model (VECM) analysis is conducted for anticipating value of exogenous variable, return on assets together with endogenous variables. This analysis based on quarterly data ranging from year 2012 to 2019. Moreover, source of data, research framework as well as hypothesis testing is explained.

3.1 Research Design

Research design basically aims to assimilate the dissimilar mechanisms in the paper with a logical and coherent way in reaching well address research problem. Method of quantitative research design is embraced to examine relationship among variables by using numbers and statistics for the motive of evaluating and explaining its finding. Here, the advantage of quantitative data is where it able to be explained via statistical analysis which the statistics are according to principles of mathematics (Carr, 1994; Denscombe, 2010). According to Antonius (2003), it was also applicable for hypothesis testing due to the use of statistical analysis. Furthermore, descriptive research is constructed for further explaining between relationship of dependent variable and macroeconomic variables. The use of descriptive data allows researchers to get the useful information with reference to proceed for hypothesis testing. Nevertheless, one of the sub-categories under quantitative research, which is experimental approach will be endorse in this study for better examination. Experimental approach considered cause and effect relationship between or among variables by manipulating independent variables to observe its effect on the dependent variable.

3.2 Data Description

According to Trochim (2020) and Kenton (2019), the main purpose of descriptive statistics is allowing the people to know the main characteristics for data in a research as it delivers brief conclusions with its unit of measurement of the data taken. In simple words, descriptive statistics used for describing the characteristics of data that have collected to generate short conclusions for the measurement and sample of data. Data in this research is collected from secondary source, hence it need to be presented in the way that is meaningful, otherwise a raw data would be very difficult to visualize what the data wants to show and the data will become meaningless, especially if there is a lot of data (Lund Research Ltd, 2018).

3.3 Data Collection

In order to analyse and achieve objectives, time series data used since year 2012 Q1 until year 2019 Q4. Data is collected from several sources such as Ycharts, Federal Reserve Economic Data (FRED), FRED is a database centre under the provision of Research division of Federal Reserve Bank of St. Louis, as well as from LendingClub, one of the largest Peer-to-Peer (P2P) lending platform in United States. Table 3.1 shown variables selected, unit measurements, descriptions and source of the data.

Table 3.1:

Summary of Variables, Unit Measurement, Descriptions and Sources of Data

Variables	**Unit of Measurements**	**Descriptions**	**Sources**
Return on Asset (ROA)	Percentage (%)	ROA is measured from 2012 Q1 to 2019 Q4	Bank Reg Data
Fintech (Peer to Peer Lending)	United States Dollar (USD)	Peer to Peer total loan issuance measured from 2012 Q1 to 2019 Q4	LendingClub
Bank Size	United States Dollar (USD)	Total assets for commercial banks in US measured from 2012 Q1 to 2019 Q4	FRED
Foreign Direct Investment (FDI)	United States Dollar (USD)	FDI measured from 2012 Q1 to 2019 Q4	FRED
Inflation rate	Percentage (%)	Inflation rate measured from 2012 Q1 to 2019 Q4	Y Charts
Real Gross Domestic Product (RGDP)	United States Dollar (USD)	GDP measured from 2012 Q1 to 2019 Q4	FRED

Table 3.1 shown the return on asset (ROA) used to examine US's bank performance in this paper. ROA shows how much profit can be earned by the bank with total assets invested. ROA can also be utilized for identifying operating efficiency of business. Based on Mcclure (2020), ROA is better than ROE when measuring bank performance because ROA takes into account both company debt and equity, which

can help the company to see how well these financing forms are being utilized whereas ROE does not tell this information, since it only measures the net income of the business against its owner's equity. Moreover, ROE has limitation as it does not take the risks into account since banks return can be increased by taking more risk in the short-run (Klaassen & Eeghen, 2015). Hence, this paper use ROA to determine the bank performance as ROA contains more information compared to ROE.

3.4 Research Framework

The functional form of bank performance model is construed as below:

$$\begin{aligned}&Bank\ Performance = \\ &f(Financial\ Technology, Bank\ Size, Foreign\ Direct\ Investment, \\ &Inflation, Gross\ Domestic\ Product)\end{aligned} \tag{1}$$

The Equation (1) shown there are five independent variables including financial technology, bank size, foreign direct investment, inflation and gross domestic product which might impacts on bank performance.

3.4.1 Empirical Framework Model

To quantify the relationship in Equation (1), this paper applies the regression analysis as below:

$$LROA_t = \beta_0 + \beta_1 LFINTECH_t + \beta_2 LBS_t + \beta_3 LFDI_t + \beta_4 LINF_t + \beta_5 LRGDP_t + \varepsilon_t \quad (2)$$

where,

ROA_t = Return on Asset (%)

$FINTECH_t$ = Financial Technology - Peer to Peer Lending (USD)

BS_t = Bank Size (USD)

FDI_t = Foreign Direct Investment (USD)

INF_t = Inflation Rate (%)

$RGDP_t$ = Real Gross Domestic Product (USD)

ε_t = Error Term

β_0 = Intercept Coefficient

β_n = Slope Coefficient (n=1,2,3,4,5)

3.5 Research Methodology

In this section, the flow chart of methodology will be discussed and followed by the tests and analysis of regression that will be conduct in this paper. Furthermore, some of the diagnostic checking methods will be proposed.

3.5.1 Flow Chart of Methodology

This section discusses flow of methodology that will be conduct in this paper.

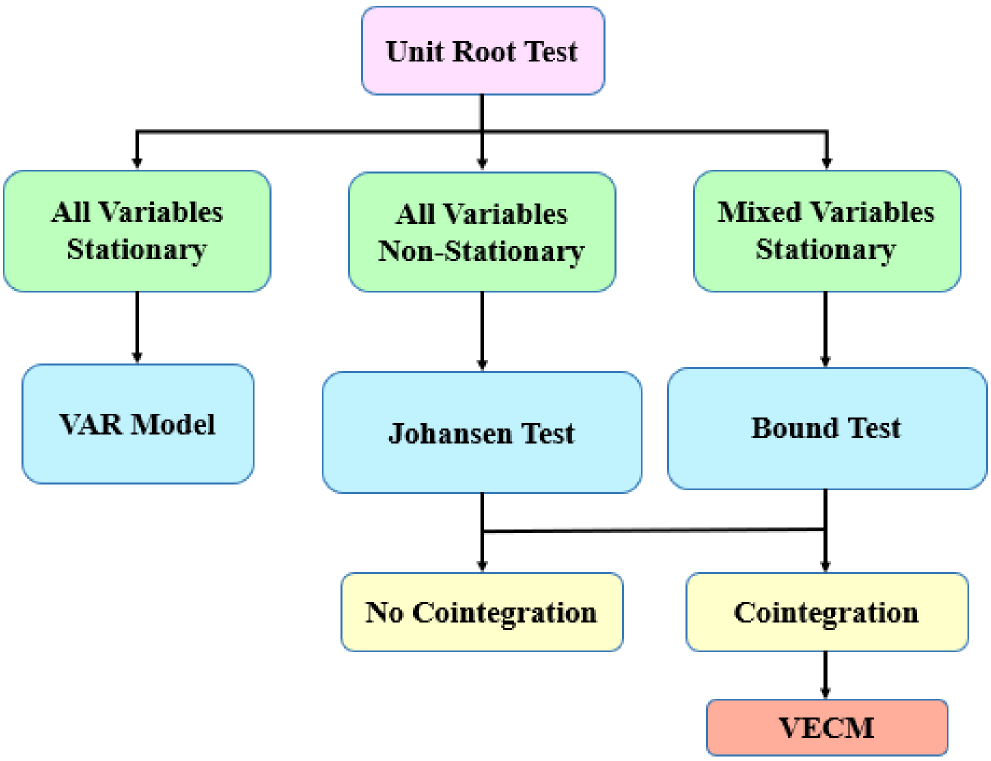


Figure 3.1: Flow Chart of Methodology

Source: Shrestha & Bhatta (2018)

Based on Figure 3.1, this research will run the test of unit root to identify the variables are stationary or non-stationary. This test is necessary to certify that the data collected is fulfilled the requirements of Vector Autoregressive (VAR) model and Ordinary Least Square (OLS) model to avoid spurious regression. If all the variables are stationary, the researcher can continue to run the Vector Autoregressive (VAR) model or Ordinary Least Square (OLS) model. However, if all the variables are non-stationary, the researcher could continue with the Johansen cointegration test to identify long-run relationship exists or not and estimate strength of the relationship between variables. On the other hand, if there are variables stationary at different order, the researcher could continue with the Bound cointegration test. Lastly, if the result shown is no cointegration, the researcher could proceed the analysis by using VAR model while the Vector Error Correction Model (VECM) is used when cointegration exist.

3.5.2 Unit Root Test

Test of unit root is important for differentiating between two important cases which a process with deterministic trend or stochastic trend. Davidson, Meenagh, Minford, and Wickens (2010) stated that majority of macroeconomic data are non-stationary because some parts of the data movement in each quarter is random. Thus, this paper will run the unit root test by applying Augmented Dickey-Fuller (ADF) test for determining the time series data for the variables are stationary or non-stationary in the model.

3.5.2.1 Augmented Dicker-Fuller (ADF) Test

ADF test is an augmented version of Dickey-Fuller test but ADF test can estimate more complicated time series model and eliminate autocorrelation problems (Wai & Ismail, 2014). The hypothesis testing is:

H_0: The series is non-stationary

H_1: The series is stationary

Coefficient equal to zero meaning that model has unit root. To estimate the coefficients' significance, test statistic is calculated. If test statistic larger than critical value, the null hypothesis (H_0) can be rejected. Otherwise, do not reject H_0. If time series data is non-stationary, researchers able to practise the transformation method through difference-stationary process to transfer the data become stationary.

3.5.3 Vector Autoregressive (VAR) Model

VAR model is to indicate the linear interdependencies among the data of multiple time series. This model needs to fulfil two basic requirements which must consist at least two time variables and make sure the variables are influence each other to ensure VAR model is accurate and efficient (Prabhakaran, 2019). VAR model allow the reverse causality between the endogenous and exogenous variables using its own past value for the prediction (Shrestha & Bhatta, 2018). VAR model is used when all the variables are stationary.

3.5.4 Lag Length Selection

Lütkepohl (1993) had stated that overfitted with high order lag length being selected rather than true lag length will cause the increase in the mean square forecast errors of the VAR model while underfitting the lag length will generate autocorrelation problems. Since the lag length is unknown, thus, there are several lag length selection criteria to estimate the number of lags. Schwarz Information Criterion (SIC) and Akaike Information Criterion (AIC) are selected in estimation and will be used in this research. Therefore, minimum value of SIC and AIC will be selected to obtain the optimal lag length.

3.5.5 Cointegration Test

Stock and Watson (2007) stated that more time series which share the identical stochastic trend able to change together over the period. By using this test, the correlation problems can be reduced, and it has better function where its linear combination can be inquired to its most stationary level. In this research, this test used to determine whether the non-stationary variables are co-integrated or not co-integrated. According to Johansen and Juselius (1990), the cointegration test developed maximum likelihood estimation procedure based on reduced rank regression method.

If result shown that co-integrating vector exists, the model will proceed to Vector Error Correction Model (VECM) to determine the long-run relationship between bank performance with the selected independent variables. However, if co-integrating vector does not exist, the model can continue with the Vector Autoregressive (VAR) model for determining the short-run relationship.

On the other side, if the variables are found that stationary at different order, the researchers need to conduct the Bound cointegration test instead of Johansen cointegration test. Bound test is used to examine the relationship between variables in levels whether purely I (0), purely I (1) or mutually integrated (Pesaran, Shin, & Smith, 2001). For the Bound test, if F-statistic calculated is larger than critical value for upper bound, it can be concluded that there is cointegration which means there is a long-run relationship. Null hypothesis is being rejected and can estimate the long-run model using error correction model (ECM).

3.5.6 Vector Error Correction Model (VECM)

In this research, cointegration test used to determine the presence of cointegration which indicates the presence of long-term equilibrium relationship between the variables. Vector Error Correction Model (VECM) used for estimation if result shown cointegration relationship exists. However, if no cointegration relationship exists, VAR model will be used for the estimation. For VECM, it can generate cointegrating vectors accurately and efficiently since it contributes the perfect information maximum likelihood model. Moreover, VECM able to provide the long-run and short-run relationship between the variables through significant error correction term. Not only that, VECM able to overcome the spurious regression problems in the first difference when the models are co-integrated (Gujarati & Porter, 2009).

3.5.7 Granger Causality Test

The Granger Causality test examines correlation between two variables in time series. This test conducted to identify dynamic direction and the existence of causality between the stationary variables in a model. Through this test, detection of unidirectional causality or bi-directional causality will be identified accurately and efficiently. The hypothesis statement is shown as below:

$$H_0 = \text{ Granger cause relationship between dependent variable and independent variables is not exists.}$$

$$H_1 = \text{ Granger cause relationship between the dependent variable and independent variables is exists.}$$

Reject H_0 if test statistic value higher than critical value. Otherwise, do not reject H_0.

3.5.8 Impulse Response Function (IRF)

IRF determines interaction between variables in a model that involved a few of other variables by studying the response of the variable provide an impulse towards another variable (Rossi, n.d.). An additional new information to any of the variable in the model will carry a shock to the variable itself and others variable. Normally, this function is conducted after the Granger Causality test due to result get from the Granger Causality only obtain direction of causal relationship. However, the IRF focuses on the complete information of the relationship which determine the relationship sign and long-run or short-run effect within the certain period after a shock. In Impulse Response Function, if the lag order is over-fitting, the result shown will be less accurate for the estimation whereas if the lag order is under-fitting, the misleading estimation and conclusion will be happened.

3.5.9 Variance Decomposition (VD)

VD is essential tool to identify important of each shock in explaining variation for each of the variables in a model (Sims, 2011). Through Variance Decomposition, the researcher able to identify the amount of the shock for each variable which have the impact on the forecast error of the dependent variables. Furthermore, this method also allows the researchers to determine the ways of macroeconomic and financial variable affect each other individually in the Vector Autoregressive (VAR) model. By using VD, movement of dependent variables will be displayed because of its own impact and the other variables are affected at the same time (Brooks, 2008).

3.5.10 Diagnostic Checking

Diagnostic checking had become the standard tool to distinguish the model before forecasting the data. In detecting the presence of econometric problems on the model like heteroscedasticity, autocorrelation, perform the normality assumption on error term and apply CUSUM test. Following techniques shall be adopted.

3.5.10.1 Heteroscedasticity Test

Heteroscedasticity means that the variance of independent variable is an unfit through the range of values that forecast the variable (Gujarati & Porter, 2009). This problem arises in estimating parameters due to neglect of reasonable independent variable, when there is missing value, outlier as well as abnormal distribution of exogenous and endogenous variables. Heteroscedasticity test carried out for detecting problem of heteroscedasticity with time series data. The way of performing a hypothesis testing for heteroscedasticity problem as following:

H_0: There is no heteroscedasticity problem.

H_1: There is heteroscedasticity problem.

According to results obtained from the regression model, decision rule will be used to determine the existence of heteroscedasticity problem. Reject null hypothesis (H_0) if p-value less than significance level. Otherwise, do not reject the null hypothesis.

3.5.10.2 Serial Correlation LM Test

Autocorrelation refers to correlation among values of same variables at different points in period (Box & Jenkins, 1976). Therefore, it is more likely to occur in regression model with time series data. Some of the reasons resulting autocorrelation problems in a model, for instance, excluded important endogenous variables, wrong functional form and data manipulation. Durbin-Watson test provides inconclusive results where without considering higher orders of series correlation as well as the lagged dependent variable is not applicable in Durbin's h test (Gujarati & Porter, 2009). Accordingly, to detect the existence of autocorrelation problem, Serial Correlation LM test will conduct in model instead of Durbin-Watson or Durbin's h test. Hypothesis testing is stated as follow:

H_0: There is no autocorrelation problem.

H_1: There is autocorrelation problem.

According to results are obtained by conducting regression model, decision rule will be used to determine the existence of autocorrelation problem, in such, reject null hypothesis if p-value is smaller than significance level. Otherwise, do not reject the null hypothesis.

3.5.10.3 Normality Test

Normality test examines whether data set can be performed normally distributed. Gujarati and Porter (2009) stated that model is correct if error term is modelled for the normal distribution and otherwise. The normality assumption provided several methods for determining normality such like graphical method of histogram and normality plot as well as Jarque-Bera (JB) Test in statistical method is applied. In contrast, the JB test of normality has the characteristics of testing many sample data, in such, perform JB test for the normality of error term more accurately. Bai and Ng (2005) stated that benchmark for skewness is 0 whereas the benchmark for kurtosis is 3. JB test can be computed using the formula: $JB = n\left[\frac{skewness^2}{6} + \frac{(kurtosis-3)^2}{24}\right]$. Hypothesis testing is shown as below:

H_0: The error term is normally distributed.

H_1: The error term is not normally distributed.

According to results obtained from regression model, decision rule will be applied to identify the normality assumption on error term. Reject null hypothesis (H_0) if p-value less than significance level. Otherwise, do not reject the null hypothesis.

3.5.10.4 CUSUM Test

The Cumulative Sum of Recursive Residuals (CUSUM) test is a kind of sequential analysis that can be performed in order to explore the sequential changes of variables data and detect the stability of series (Harish & Mallikarjunappa, n.d.). There are several problems that can lead to the occurrence of unstable parameters such as insufficient short-term dynamic modelling and changes in long-term relationship. Yet, the results generated by CUSUM test can be interpreted as statistical data within the 5% significance level or outside the 5% significance level and hence, it can be determined whether estimated coefficients value is structurally stable or not in the systematic movements obtained after applying this test. Hypothesis testing as shown at below:

H_0: There is no parameters are unstable in the model.

H_1: The parameters are not stable in the model.

According to the results are obtained by running the regression model, decision rule will be applied to identify the existence of series stability of this model, in such, reject null hypothesis (H_0) if the statistic shows a blue line crosses the red line. Otherwise, do not reject the null hypothesis.

3.6 Conclusion

Throughout Chapter 3, the data's source had stated with thoroughly explained associated with the tests chosen to study the relationship among exogenous and endogenous variables. In addition, the purpose and specification of each test has been pointed and hypotheses created for each test along with the crucial decision rule. Nevertheless, the hypotheses will be introduced and test with specific methods and procedures in next chapter.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

Examining and testing between relationship of return on asset, bank size, foreign direct investment, inflation and gross domestic product is mainly focused in this chapter by using the methodology employed in Chapter 3 is being discussed. The following section will be targeted on descriptive statistics and inferential analysis by interpreting and explaining the empirical results obtained from EViews 11.0. Furthermore, the empirical tests will be demonstrated in the inferential analysis, namely Unit Root Test, Vector Autoregressive (VAR) Model, Lag length selection, Autoregressive Distributed Lag (ARDL), Bound Test, Vector Error Correction (VEC) Model, Granger Causality test, Impulse Response Function, Variance Decomposition and diagnostic checking. All results will be presented in table or figure format which can give priority to the most important aspects.

4.1 Descriptive Analysis

Table 4.1:

Summary of Descriptive Statistic

	ROA (%)	**BANK SIZE (USD Billion)**	**FDI (USD Billion)**	**FINTECH (USD Billion)**	**GDP (USD Billion)**	**INF (%)**
Mean	1.1185	14.9205	299.4015	20.6651	18621.96	1.6131

Median	1.0503	14.8849	280.8100	17.3571	18387.55	1.6850
Maximum	1.3800	17.3407	955.5800	56.7985	21726.78	2.9300
Minimum	0.9691	12.6315	-293.9680	0.5699	16019.76	-0.0700
Standard Deviation	0.1347	1.4122	208.4196	18.0275	1742.86	0.7463

Table 4.1 illustrates the descriptive statistic of the variables that applied in this research which are ROA, BANKSIZE, FDI, FINTECH, GDP and INF in United State from year 2012 Q1 to year 2019 Q4. The mean for ROA, BANKSIZE, FDI, FINTECH, GDP and INF recorded as 1.12%, USD 14.92 billion, USD 299.40 billion, USD 20.67 billion, USD 18621.96 billion and 1.61% respectively based on Table 4.1. The average change in GDP is higher than other variables. Besides, the median for ROA, BANKSIZE, FDI, FINTECH, GDP and INF are amounted to 1.05%, USD 14.88 billion, USD 280.81 billion, USD 17.36 billion, USD 18387.55 billion and 1.69% respectively. According to Table 4.1, FINTECH achieved USD 56.80 billion at maximum value and USD 0.57 billion at minimum value. In addition, the highest standard deviation goes to GDP followed by FDI, FINTECH, BANKSIZE, INF and ROA which recorded at USD 1742.86 billion, USD 208.42 billion, USD 18.03 billion, USD 1.41 billion, 0.75% and 0.13%. This indicates that high variation in gross domestic product might influence the volatility of the bank performance.

4. 2 Inferential Analysis

The stationary level of the variable will be identified in this section by conducting the unit root test followed by lag length selection, cointegration test, Granger causality test and diagnostics tests.

4.2.1 Unit Root Test

Table 4.2:

Results of Unit-Root Test

Variable	Augmented Dickey-Fuller (ADF) Test			
	Without Trend		With Trend	
	Level	First Difference	Level	First Difference
LROA	0.5599	0.0000***	0.4053	0.0000***
LFINTECH	0.0003***	0.9300	0.0231**	0.3290
LBANKSIZE	0.2360	0.0005***	0.1249	0.0588*
LFDI	0.0007***	0.0000***	0.0036***	0.0000***
LINF	0.1342	0.0084***	0.3020	0.0310**
LGDP	0.9913	0.0003***	0.3620	0.0017***

*Note: *, ** and *** indicate that reject the null hypothesis at significance level of 10%, 5%, 1% respectively.*

Stationary level of variables used in this research is identified by conducting Augmented Dickey-Fuller (ADF) unit root test. The results of ADF unit root test for the six variables is shown in Table 4.2 which are LROA, LFINTECH, LBANKSIZE, LFDI, LINF and LGDP at level form and first difference for both with and without trend of the natural log values. Referring to Table 4.2, at level form for both with and without trend, LROA, LBANKSIZE, LINF and LGDP shown non-stationary since cannot reject null hypothesis (non-stationary) which greater than 10% significance level. However, at level form without trend, LFINTECH and LFDI shown stationary at the 1% significance level. For level form with trend, LFINTECH is stationary at significance level of 5% whereas LFDI is stationary at 1%significance level.

At first difference where there is no trend, LROA, LBANKSIZE, LFDI, LINF and LGDP shown stationary at 1% significance level. For first difference with trend, LROA, LFDI and LGDP is stationary at significance level of 1%. Furthermore, LBANKSIZE is stationary at 10% significance level, yet LINF is stationary at significance level of 5%. However, LFINTECH shown non-stationary at first difference for both with and without trend.

In conclusion, LROA, LBANKSIZE, LFDI, LINF and LGDP are stationary at first difference for both with and without trend, only LFINTECH shown stationary at level form. Thus, it proved that LFINTECH is stationary at the order of I (0) and relatively the other variables are stationary at order of I (1). It also showed that the series are integrated of different orders which means there are a combination of level form and first difference stationarity. Therefore, cointegration test is needed for the purpose of establishing a long run relationship. The Bounds test Pesaran, Shin, and Smith (2001) suggested is the advisable cointegration test in this case as the Johansen cointegration test is invalid. If the result of Bound test shows that the model presence of cointegration, Vector Error Correction Model (VECM) need to be used for the regression analysis.

4.2.2 Lag Length Selection

Table 4.3:

Result of Lag Length Selection

Lag	AIC	SIC
0	-7.334715	-7.051826
1	-20.55744	**-18.57721***
2	-21.59116	-17.91361
3	-23.90263*	-18.52774

*Note: AIC stands for Akaike Information Criterion while SIC means Schwarz Information Criterion. * indicates that the lowest AIC value and SIC value.*

Table 4.3 illustrates the result of lag length selection is in accordance with Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). In this research, Lag 1 chosen is optimum lag length as it has the lowest SIC value which is -18.57721.

4.2.3 Cointegration Test

Table 4.4:

Result of Bound Test

Test Statistic	Value	Significant	I (0)	I (1)
F-statistic	3.307888	**10%**	**2.08**	**3.00**
		5%	2.39	3.38
		1%	3.06	4.15

Table 4.4 indicates the result of Bound test. The relationship between the variables in levels regardless of the underlying regressors whether are purely I (0), purely I (1) or mutually integrated is tested through the Bounds test (Pesaran, Shin, & Smith, 2001). Based on Table 4.4 concluded that there is cointegration since the F-statistic is greater than the critical value for the upper bound, I (1) at 10% significance level. It shown that there is a long run relationship as the null hypothesis (no cointegration) is rejected. Hence, Vector Error Correction Model (VECM) can be used in this paper for predicting long run model.

4.2.4 Vector Error Correction Model (VECM)

Table 4.5:

Long Run Relationship Between LROA and Its Determinants

Variables	Coefficient	Standard Error	T-statistic
C	72.1122		
LROA	1.0000		
LFINTECH	0.1394	0.0334	4.1782***
LBANKSIZE	7.0963	1.2652	5.6088***
LFDI	-0.1024	0.0174	-5.8907***
LINF	-0.0226	0.0148	-1.5207
LGDP	-9.2719	0.8337	-11.1210***

*Note: *, ** and *** indicate that reject the null hypothesis at significance level of 10%, 5% and 1% respectively. Critical value of 10%, 5% and 1% is ± 1.714, ± 2.069 and ± 2.500 respectively.*

Table 4.6:

Short Run Relationship Between LROA and Its Determinants

Variables	Coefficient	Standard Error	T-statistic
C	0.0257	0.0579	0.4445
LROA	-0.2408	0.2214	-1.0878
LFINTECH	-0.2871	0.2499	-1.1490
LBANKSIZE	1.3867	2.0850	0.6651
LFDI	-0.0096	0.0169	-0.5680
LINF	-0.0285	0.0311	-0.9163
LGDP	1.3986	3.1526	0.4436
CointEq	-0.1410	0.1957	-0.7202

*Note: *, ** and *** indicate that reject the null hypothesis at significance level of 10%, 5%, 1% respectively. Critical value of 10%, 5% and 1% is ± 1.717, ± 2.074 and ± 2.508 respectively.*

VECM provides the long run and short run relationship between the variables through the significant error correction term**.** A summary of long run and short run relationship between dependent variable (LROA) and all the independent variables (LFINTECH, LBANKSIZE, LFDI, LINF and LGDP) is shown in Table 4.5 and Table 4.6. It can be seen from the results that in long run, all the endogenous variables have significant effects on LROA except for LINF. However, the estimation result shown that all the independent variables statically insignificant in short run. The cointegration equation (CointEq) represents the previous year's deviation from long run equilibrium is corrected at a speed of -0.14%.

Based on Table 4.5, this study had proved that the LFINTECH shown a positive and significance relationship to return on asset in long run at 5% significance level. Misati, Kamau, Kipyegon, and Wandaka (2015) argued that the relationship between financial technology (FinTech) and commercial bank are complementary instead of substitution. The trend of funding the money from non-bank institution shows a positive sign but only occupied 1% on the entire loan market share. Their results further shown that non-bank credit institutions get their funds for lending from local commercial banks. Thus, FinTech will help the commercial bank directly to increase the loan amount. This research is consistent with the Serge, Rugemintwari, and Sauviat (2019). Hence, when there is 1% increase in Peer-to-Peer lending, on average, the return on asset would increase by 0.14%, holding other variables constant.

Furthermore, bank size shown a positive and statically significant impact to the return on asset in a long run relationship. This result is similar with the Alper and Anbar (2011); Gul, et al. (2011); Khrawish (2011); Rao and Lakew (2012); Rahman, Kamid, and Khan (2015); Djalilow and Piesse (2016). According to the Djalilow and Piesse (2016), the researchers using generalized method of payments (GMM) techniques over the time period 2000 to 2012. Their results further shown that the changes in internal variable have an impact on bank profitability is relatable to the bank size. He also pointed out that large and medium banks are more profitable than small banks in situations where large banks tend to enjoy economies of scale and reduce risk through diversified products and loans, which can increase their profitability by improving operational efficiency. Thus, increase 1% on bank size, on average, return on asset will increase to 7.10% ceteris paribus.

Moreover, the estimation result shown that foreign direct investment (FDI) on return on asset (ROA) are negative and significant in relationship. Thus, increase of 1% on foreign direct investment, on average, return on asset will decrease 0.10%, ceteris paribus. The result indicated that is similar with Amos (2016) examined that an increase of 100% in FDI is associated with about 13% reduction in the return on asset for the financial institutions in Ghana.

Other than that, the results indicated that the inflation shown negative but insignificant impact to the return on asset. This result is similar with Saad and El-Moussawi (2012) stated that net interest margin not really determined by the inflation, and therefore a clear explanation is hard to proposed on the possible changes in inflation caused by banking net margin. Furthermore, the fact of inflation was largely under control during the study period from 2000 to 2010 can used to explain this. The net interest margin seems to be not much explained by the rate of inflation and operating costs.

Besides, real gross domestic product (GDP) shown a negative significant relationship to the return on asset. Based on the result, 1% increase on real gross domestic product, on average, return on asset will decrease 9.27%, ceteris paribus. This result is supported by some researchers namely Tan and Floros (2012); Combey and Togbenou (2017). According to the Combey and Togbenou (2017), they pointed out the fact that banks' return on assets (ROA) and return on equity (ROE) are negatively affected by real GDP growth in the long run. In short run, the result shown that banks' ROA and ROE are insignificant impact on macroeconomics variables where the bank capital to assets ratio and bank size are positively affecting the bank's ROA while the bank capital to assets ratio is negatively affecting the bank's ROE. Hence, the short run insignificant result also consistent with the Combey and Togbenou (2017).

4.2.5 Granger Causality Test

Table 4.7:

Result of Granger Causality between LROA with other variables

Variable	P-value
D(LFINTECH)	0.2506
D(LBANKSIZE)	0.5060
D(LFDI)	0.5700
D(LINF)	0.3595
D(LGDP)	0.6573

*Note: *, ** and *** indicate that reject the null hypothesis at significance level of 10%, 5%, 1% respectively.*

A null hypothesis of granger causality test dependent variables will not granger caused by independent variables. It also can determine the directional of the causality between variables.

From the Table 4.7, LFINTECH does not granger cause LROA as the probability value (0.2506) is higher at significance level of 10%, 5% and 1% are not rejected. This result is consistent with Li, Spigt, and Swinkels (2017) stated that Fintech funding volume is not statically significance and lack of evidence to conclude that Fintech can cause to increase the retail bank's performance. Hence, the result might be fragile due to the insignificance between the variables.

Besides, the null hypothesis (LBANKSIZE does not granger cause on LROA) at significance level of 10%, 5% and 1% are not rejected as the probability value (0.5060) which higher than the significance level. This outcome has been proposed by Ali and Puah (2018) and Heffernan and Fu (2010) which specify that bank size is does not granger cause to risk-adjusted return on asset (RAROA) and the impact between bank size and bank performance is negligible.

Furthermore, the result also indicates that LFDI does not granger cause to LROA as the probability value (0.5700) is higher at significance level of 10% and it is consistent with the study of Korna, Ajekwe, and Idyu (2013) and Tsaurai (2014). According to Korna, Ajekwe, and Idyu (2013), banking sector is depending on other sector rather than foreign capital to generate profit. Besides, Tsaurai (2014) further explained that banking sector development and FDI net inflows have unidirectional causal effect.

Moreover, the estimation result shown that LINF is no causal relationship to LROA as the probability value (0.3595) is higher at significance level of 10%. This result is similar with the Saad and El-Moussawi (2012) mentioned that the profitability of commercial banks will not be influenced by Lebanon's inflation and the net interest margin seem to be not much explained by the rate of inflation and operating costs.

Last but not least, the result indicates that the LGDP does not granger cause the LROA as the probability value (0.6573) is higher at significance level of 10% are not rejected. The result is similar with Kanwal and Nadeem (2013) found that the return on assets are insignificance to real gross domestic product.

Table 4.8:

Result of Granger Causality between LFINTECH with other variables

Variable	P-value
D(LROA)	0.0259**
D(LBANKSIZE)	0.3365
D(LFDI)	0.0957*
D(LINF)	0.4606
D(LGDP)	0.2767

*Note: *, ** and *** indicate that reject the null hypothesis at significance level of 10%, 5%, 1% respectively.*

Based on Table 4.8, the result shown the LROA and LFDI does granger cause LFINTECH at significance level of 5% and 10%. However, the LBANKSIZE, LINF and LGDP does not granger cause to the LFINTECH.

The reason of LROA has a causal relationship to LFINTECH is because of peer-to-peer lending and bank loan are substitution relationship. Bank loan are secured by the collateral while Peer-to-Peer lending are unsecured and more flexible. The financial institution will ensure all the loan are secured to protect their return on asset while the consumer who unable to fulfil this requirement will more preference Peer-to-Peer lending instead of bank loan.

Besides, the result shown that LFDI has granger cause the LFINTECH. The reason might because the foreign direct investment (FDI) inflow will increase the capital of financial technology industries to allow them create more opportunities and financial services to investors. According to the Variyar and Bhakta (2016), FDI is allowed by reserve bank to regulated financial services company up to 100% through automatic route as a result benefits to the Fintech companies to expand the financial services.

Table 4.9:

Result of Granger Causality between LBANKSIZE with other variables

Variable	**P-value**
D(LROA)	0.7865
D(LFINTECH)	0.3178
D(LFDI)	0.7318
D(LINF)	0.0221**
D(LGDP)	0.2434

*Note: *, ** and *** indicate that reject the null hypothesis at significance level of 10%, 5%, 1% respectively.*

Table 4.9 shown that the variables (LROA, LFINTECH, LFDI and LGDP) does not granger cause LBANKSIZE at significance level of 10%, 5% and 1%. However, the result indicates the LINF has causality relationship to the LBANKSIZE at 5% significance level.

The inflation has causality relationship with bank size might because of the high inflation could affect the bank profitability and indirectly cause bank size decrease since the bank size is subject to bank asset. According to Marimba (2018), inflation shown negative but significant correlation to bank profitability that give insight to the low profit generate by the commercial bank. It also affects the asset of commercial bank by reason of decrease of the overall profit.

Table 4.10:

Result of Granger Causality between LFDI with other variables

Variable	**P-value**
D(LROA)	0.0000***
D(LFINTECH)	0.0090***
D(LBANKSIZE)	0.1929
D(LINF)	0.7468
D(LGDP)	0.1665

*Note: *, ** and *** indicate that reject the null hypothesis at significance level of 10%, 5%, 1% respectively.*

From Table 4.10, LBANKSIZE, LINF and LGDP shown does not granger cause the LFDI as the null hypothesis at significance level of 10%, 5% and 1% are not rejected. Conversely, LROA and LFINTECH have causality relationship to the LFDI at a 1% significance level.

According to the Kirikkaleli (2013), the researcher stated that change in return on asset in local bank will change the foreign bank penetration. The change of the bank asset will connect to the unexpected change happened in the local market. However, foreign bank will change faster than local bank due to the foreign bank will respond more sensitive when change in the local market.

The result shown that LFINTECH will cause the foreign direct investment probably because of the foreign investors have confidence in the financial technology. Kirton (2016) stated that United Kingdom’s financial technology offerings were highlighted as a key reason for the heightened investment.

Table 4.11:

Result of Granger Causality between LINF with other variables

Variable	P-value
D(LROA)	0.6092
D(LFINTECH)	0.4017
D(LBANKSIZE)	0.2180
D(LFDI)	0.3448
D(LGDP)	0.4227

*Note: *, ** and *** indicate that reject the null hypothesis at significance level of 10%, 5%, 1% respectively.*

Based on Table 4.11, the variables (LROA, LFINTECH, LBANKSIZE, LFDI and LGDP) shown does not granger cause LINF at a significance level of 10%, 5% and 1%.

Table 4.12:

Result of Granger Causality between LGDP with other variables

Variable	P-value
D(LROA)	0.8710
D(LFINTECH)	0.9984
D(LBANKSIZE)	0.0953*
D(LFDI)	0.7535
D(LINF)	0.2057

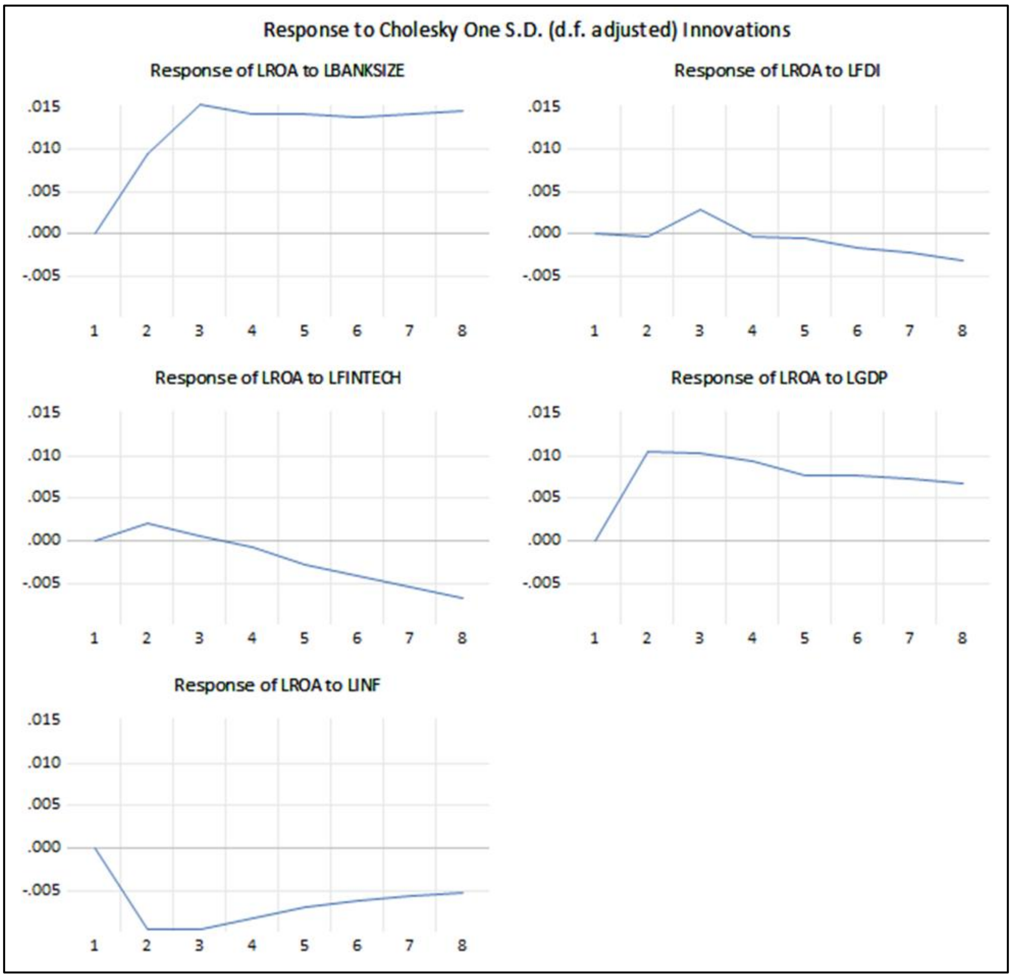
*Note: *, ** and *** indicate that reject the null hypothesis at significance level of 10%, 5%, 1% respectively.*

Table 4.12 shown that the variables (LROA, LFINTECH, LFDI and LINF) does not granger cause LGDP but only LBANKSIZE has a causality relationship with LGDP. The result of LBANKSIZE granger cause LGDP is consistent with the Liang and Reichert (2006) stated that financial sector development has a causality with economic growth.

4.2.6 Impulse Response Function

Figure 4.1:

Result of Impulse Response for LROA



Impulse responses function aimed to further explain the interaction between financial technology (FinTech) and other independent variables. Figure 4.1 illustrates the response of LROA to other variables (LBANKSIZE, LFDI, LFINTECH, LGDP and LINF) because of one unit of the variable's shocks.

Figure 4.1, the response for LROA shown a strong response as one unit of LBANKSIZE and LGDP shocks. There is an increasing trend at early stage but steady at the middle and end period. Respond of LROA due to shock on LFINTECH despites a positive trend at the early period but decline at the middle and end period until negative trend. Response of LROA due to shock of LFDI shown a positive trend and weak responses at early period after that decrease to the negative trend at end period. Response of LROA due to shock of the LINF shown a negative trend at all period and constantly increase until the end of the period.

Figure 4.2:

Result of Impulse Response for LFINTECH

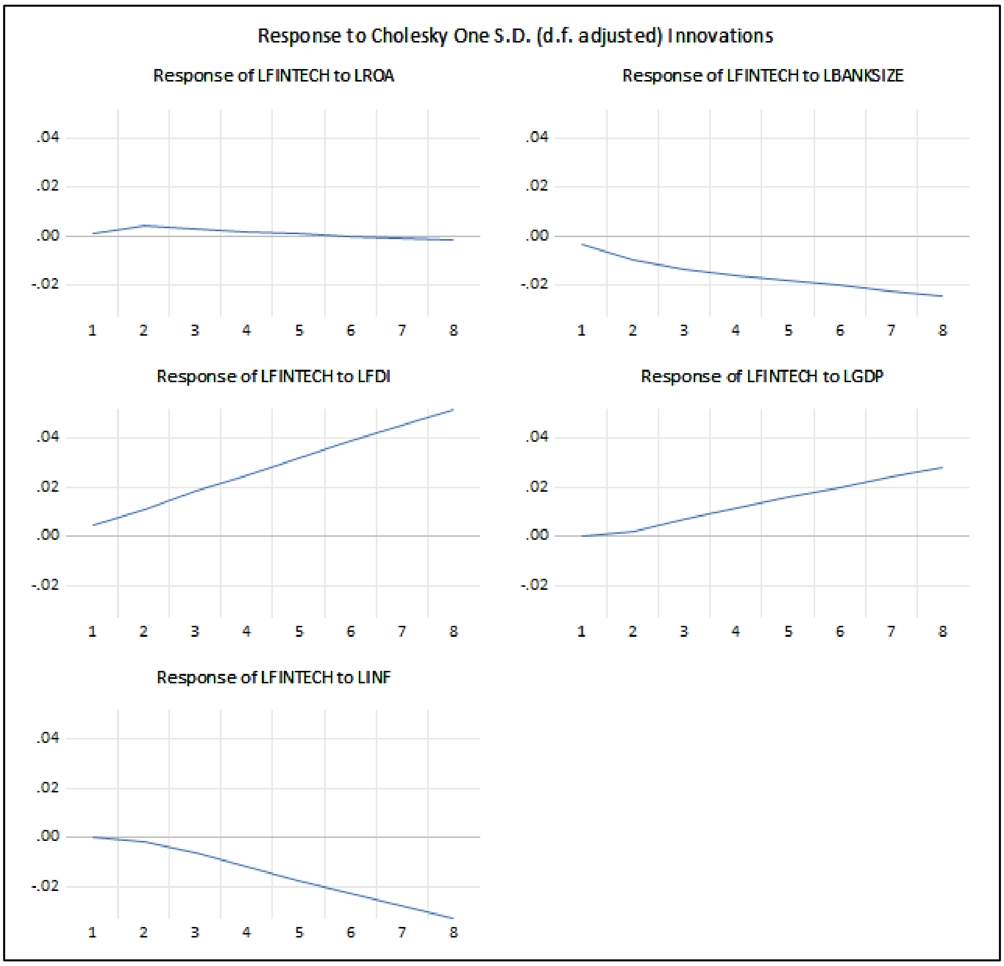


Figure 4.2 indicates the response of LFINTECH to other variables (LROA, LBANKSIZE, LFDI, LGDP and LINF) because of one unit of the variable's shocks. The results of the response for LFINTECH is shown in Figure 4.2 which are weak response as one unit of LROA shocks and the whole period shown a steady movement close to the zero. However, response of LFINTECH to LFDI and LGDP show a strong response which demonstrated by a sign of rising from the early period to the final period. Response for LFINTECH to LBANKSIZE and LINF indicated that the relationship is negative as constantly decrease from first period until the period of eighth.

4.2.7 Variance Decomposition

Table 4.13:

Result of Variance Decomposition of LROA

Period	S.E.	LROA	LBANKSIZE	LFDI	LFINTECH	LGDP	LINF
1	0.068508	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.082260	95.62366	1.317350	0.001218	0.058778	1.634784	1.364207
3	0.094599	91.75986	3.596018	0.095530	0.048248	2.432664	2.067680
4	0.104060	89.87957	4.830410	0.080108	0.044736	2.833372	2.331803
5	0.113856	89.11822	5.584507	0.068973	0.098440	2.822274	2.307583
6	0.122402	88.51763	6.124975	0.076274	0.196022	2.837558	2.247543
7	0.130590	88.01807	6.578857	0.093923	0.346940	2.801238	2.160966
8	0.138333	87.53731	6.973989	0.131794	0.550695	2.740117	2.066094

Table 4.13 indicates the variance decomposition analysis which pointed out the variation of each endogenous variables' component shocks to the variance decomposition. The variance decomposition of LROA shows that the LBANKSIZE is the vitally well explained the innovation to LROA in contrast with other independent variables. Alternatively, one unit of standard deviation innovation in bank size the shocks to the return on asset is between 0% and 6.97%. Simultaneously, LGDP, LINF and LFINTECH are found to contribute marginally minor or little effects to the LROA as

compared to the LBANKSIZE which the shocks to LROA are ranging from 0% to 2.74%, 2.07% and 0.55% respectively.

Table 4.14:

Result of Variance Decomposition of LFINTECH

Period	S.E.	LROA	LBANKSIZE	LFDI	LFINTECH	LGDP	LINF
1	0.013494	0.611710	5.537291	10.91175	82.93925	0.000000	0.000000
2	0.031599	1.742404	10.07279	13.95618	73.60440	0.347704	0.276520
3	0.054770	0.814217	9.549665	15.73294	70.78126	1.722795	1.399124
4	0.081901	0.392324	8.080714	16.46283	69.39476	2.857291	2.812080
5	0.112093	0.215115	6.857248	16.90856	68.46699	3.558369	3.993723
6	0.144966	0.128620	6.004170	17.23798	67.73819	4.037238	4.853803
7	0.180280	0.085759	5.415296	17.46833	67.14285	4.399600	5.488162
8	0.217789	0.065272	4.987147	17.62571	66.65345	4.682669	5.985759

Table 4.14 stated the variance decomposition analysis which focus on the variation of each independent variables' component shocks to the variance decomposition. The variance decomposition of LFINTECH indicated that the LFDI is the critically explained the innovation to LFINTECH as compared to other variables such as LROA, LBANKSIZE, LGDP and LINF. The LROA have a weak relationship and only contribute about 0.07% to explain the innovation of LFINTECH. LBANKSIZE (4.99%), LGDP (4.68%) and LINF (5.98%) are the moderately contribute the shocks to LFINTECH as compared to LFDI.

4.2.8 Diagnostic Checking

After conducting Vector Error Correction Model (VECM), it could continue with diagnostic checking to detect the presence of econometric problems on VEC model like heteroscedasticity, autocorrelation, test the normality of error term and apply CUSUM Test.

4.2.8.1 VEC Residual Heteroscedasticity Test

Table 4.15:

Result of VEC Residual Heteroscedasticity Test

Chi-Square	319.2193	**Prob.**	0.1502*

*Note: * denote that significant at 10% significance level*

The result of VEC Residual Heteroscedasticity Test is shown in Table 4.15 which states the probability value (0.1502) is greater at significance level of 10%, in such, it provides that the null hypothesis of heteroscedasticity is correct to be accepted and hence, it shows that the model is free from the problem of heteroscedasticity and simultaneously, the equal variance of the error term is exist in this VEC model.

4.2.8.2 VEC Residual Serial Correlation LM Test

Table 4.16:

Result of VEC Residual Serial Correlation LM Test

Rao F-stat	0.865553	**Prob.**	0.6724*

*Note: * denote that significant at 10% significance level*

The result of VEC Residual Serial Correlation LM Test is shown in Table 4.16 which states the probability value (0.6724) is greater at significance level of 10%, at such, it provides that the null hypothesis of autocorrelation is correct to be accepted and hence, it shows that VEC model does not exist in terms of autocorrelation problem.

4.2.8.3 VEC Residual Normality Test

Table 4.17:

Result for VEC Residual Normality Test

Jarque-Bera	31.18525	**Prob.**	0.0018*

*Note: * denote that significant at 10% significance level*

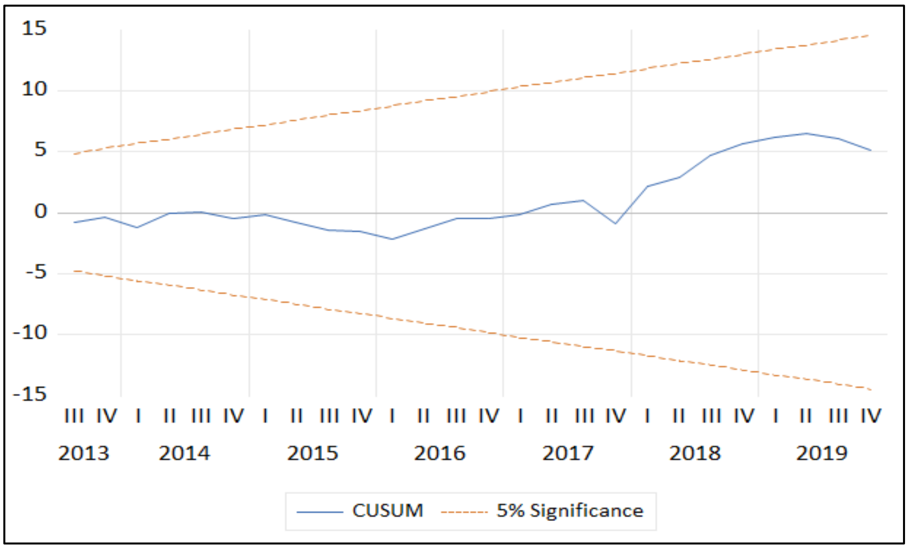
The result of VEC Residual Normality Test is shown in Table 4.17 which illustrates the probability value (0.0018) is lesser at significance level of 10% is rejected as the null hypothesis of error term is normally distributed and hence, it shows that VEC model is failed to fulfil the normality assumption on the error term.

Though the error term obtained in Normality test is not normally distributed, this model has been tested by VEC Residual Heteroscedasticity Test and it provided that this model does not exist in terms of heteroscedasticity problem, and therefore as long as there is no such heteroscedasticity, the failure of VEC model to fulfil the normality assumption on the error term is acceptable in this case (Omoniyi & Olawale, 2015).

4.2.8.4 CUSUM Test

Figure 4.3:

Result of CUSUM Test



The result of Cumulative Sum of Recursive Residuals (CUSUM) Test is shown in Figure 4.3 which finds there are no parameters are unstable respective toward statistic plotted at significance level of 5% is correct to be accepted as the blue line is existing within red line and hence, it concludes that the error variance of this model is stable and no structure break.

4.3 Conclusion

In this chapter, there are several empirical tests are examined and tested between relationship of dependent variable and independent variables and used the collected data of each variable from the resources mentioned in Chapter 3 to generate empirical results by using EViews 11.0. All related empirical results are explained in table or figure format, which allows readers or researchers to understand the results more clearly and simply. Further discussion about major findings, research implication, limitations of this research study and recommendation that will be commented in next chapter.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

Chapter 5 capsules discussion in both experimental and explanatory variables from major finding and research implications. As if that is not enough, limitation of this research study will also cover with the augment of recommendation for future improvement and clarification.

5.1 Major Finding

In short-run perspectives, Vector Error Correction Model (VECM) indicated that causality from ROA to FinTech is negative and insignificance relationship, proved by 1.74% weakly endogenous impact which means ROA does not really impact the FinTech itself, refer weak influence in predicting FinTech in short-run variance period of two. Li, Spigt, and Swinkels (2017) explained that even a successful FinTech firms may have weakened the banks' dominant position by improving the efficiency of traditional services meanwhile, banks have taken actions to cope with it, either by acquiring FinTech start-ups or setting up their own FinTech affiliates. Thereafter, it is said that the complementary and substitute may offset in this case. Besides that, ROA also encounter a direct causality to foreign direct investment (FDI) with negative significant relationship while FDI do not undergo causality impact to ROA. This contrasts with most of the economist proof with FDI and ROA should have positive relationship but move in line with Tsaurai (2014), who had further explained that there is no direct causality relationship between banking sector development and FDI net inflows. The study pointed out there are other factors that will influence the bank performance instead of FDI. Furthermore, FDI have a positive causality relationship to FinTech while FinTech result a negative causality relationship to FDI. Both variables are insignificant related. Other variables like inflation (INF) and gross domestic products (GDP) does not meet any causality relation from and to all variables in short-run period. From long run perspectives, FinTech and bank size is said have positive and significant relationship to the ROA, which affirm movement of bank performance will be same as movement of FinTech and bank size. The outcome from FinTech is distinct with expected and most researchers from the prediction of inversely relationship to ROA. FDI and GDP are negative and significant relate to ROA while INF found with negative but insignificant relationship to ROA.

5.2 Research Implication

This empirical study brought a brand-new sight to both investor and borrower in the concept perspectives. Majority of capital provider tends to practise Peer-to-Peer (P2P) Lending due to its favourable return rate but ignore the potential aside influence. Similar to P2P Lending user, bank's lending client might lack of knowledge to P2P Lending. Thus, looking at the consequence of this study, the intention of P2P Lending is introduced to readers, in which provides a more welfare lending platform to both investors and borrower while also encounter risk that conventional lending might not occur.

5.2.1 Managerial Implication

Since there are no laws or regulations in the United States (U.S.) that restrict Financial Technology (FinTech) to engage in the market, any form of FinTech company that conduct their business in U.S. are not subjected to a regulation framework by federal or state regulator that is particularly specified to FinTech. However, certain FinTech company that involves in consumer lending, money transmission as well as virtual currency licenses might be required to fulfil the requirements if they wish to get the operating license. Therefore, it is subjected to law and regulations in both federal and state levels. In order to reduce the cybercrime, fraud or any undesirable events that may occur in the FinTech marketplace, constant supervision in the field of FinTech is required from time to time. The presence of government agencies is a must so that the law and regulations can be regulated by the government from time to time. For instance, New York Department of Financial Services (NYDFS), which enforced virtual currency licensing regulation in 2015 that gives permission to certain businesses that involves in virtual currency commission in New York. Other agencies like Financial Crimes Enforcement Network (FinCEN), US Securities and Exchange Commission (SEC) and etc., are currently implement new laws and regulations for any new FinTech grow in the U.S.

From the view of banking and finance industry, since Peer-to-Peer (P2P) Lending would not inversely impact to the bank performance, banks could evolve with FinTech, short for financial technology to enhance more worldwide users and creates opportunity in the market. The amount of growing in P2P platform mostly cause by the attractive rate in return to the investors, and the convenient to obtain fund by borrower or entrepreneurs. Therefore, despite the preference by investors my differentiated into banks and P2P Lending types, the development of banks with FinTech would let investors and entrepreneur have multiple sources of fund which indirectly encourage more entrepreneur in region. The economy will be advantageous by this enhancement as it creates more opportunity in the market associated a positive effect to one another. Moreover, capital provider will benefit by designing a portfolio to invest in difference sources to avoid default risk and asymmetric claim. Entrepreneur also able to maintain the need for a new start up business as there are multiple sources of finance, even one of it failed.

Apart from that, financial analyst from banks or other financial firm may take the implication of FinTech to bank performance into account in order to improve the growth of investor with new marketing strategy. For instance, analyst may differentiate source of finance users into two major part, ones comfortable with banks' lending and ones with P2P Lending. The analyst may suggest both banks' lending and P2P Lending to each opposite side of investor types, by promoting the benefit of each well to investors rather than just stand for a certain type of lending. Hence, either conventional lending or P2P Lending would have a balance and complement growth and the most significant is that, deliver deeper understanding to lenders and borrower.

5.2.2 Policy Implication

Besides that, the government of the United States (U.S.) can implement policies or rules to ensure the stability of its country commercial banks despite of the growing number of FinTech. One of the policies is that the US government enact an act or ordinance to ensure that the size of the FinTech firms or companies does not exceed the size of its country commercial banks in order to protect the stability of bank and its interests. To execute, US government has introduced Jumpstart Our Business Startups Act or JOBS Act back on April 2012. In this act, Peer-to-Peer (P2P) firms are required to incorporated in the US and must not raise more than USD 1.07 million in its platforms during a 12-month period (Nonaka, DeCresce, Hooper, & Konko, 2019). As if that is not enough, US national banks primary federal bank regulator, the Office of the Comptroller of the Currency (OCC) also established to keep the healthy competition between US national banks and FinTech companies (Sahni, 2020). Moreover, in order to keep the banks are always in a state that is stable and healthy, US government should also monitor their country financial stability in real time, such example are the Board of Governors of the Federal Reserve System, which has its Division of Financial Stability to monitor their financial markets, institutions as well as structures and conducts research on financial stability issues.

5.3 Limitation of Study

Examine the effect of Peer-to-Peer (P2P) Lending platform, for impact of internal factor as well as the relationship among macroeconomics factors on bank performance represents the aim of this research however, some of the limitations occurred when doing this research. First and foremost, process of data collection. Since United States of America (USA) consists of different states where considered a large and advanced economy, their information of data, the economic indicator is scattered into various type of websites including those owned by the government and non-government organization (NGO). Besides that, despite most of the economic indicator in USA published in yearly or annually form, it resulted more time is acquired to collect and clarify the data needed and somehow cause the limit of data in this research study.

Furthermore, the discussion on Peer-to-Peer (P2P) Lending still considered as a new research topic where comprise only limited amount of journal published in the past few years act as one of the limitations found, especially when focus solely on the United States of America (USA). To cope with this limitation, certain appropriate

FinTech journal or article publication was acquired from other country as reference for this research to compensate the insufficient information of USA. As if this is not enough, the main concern in this research paper is said to emphasize on FinTech (Peer-to-peer Lending) with connection of internal and factors of macroeconomic likes Bank Size, Foreign Direct Investment (FDI), Inflation and Real Gross Domestic Product (RGDP). However, there are other important qualitative and quantitative factors that may bring impact to Return on Assets (ROA) which does not take into account in this research. For instance, economic policies, the spending behaviour of Americans and so forth; unemployment rate, interest rate and etc. for qualitative and quantitative factors respectively.

5.4 Recommendations

Future researcher is recommended to increase the sample size as it is quite important. High figure of sample size tends to generate more reliable and better accuracy results. Gujarati (2009) cited that researcher should use minimum 50 or higher sample size when conducting research since higher sample size can reduce the chance or probability of obtaining results that are false negative. A low sample size tends to cause the model to get econometric problem of autocorrelation, heteroscedasticity as well as multicollinearity and etc., which may cause the result from the research become unreliable at the end. Furthermore, it is suggesting that the future researcher could study other FinTech related products and services such as cryptocurrency and blockchain, Robo-Advising or even Stock-Trading Applications, in order to determine whether it or other relevant factors that bring effect to them will affect the performance of the finance industry especially banking sector in both short run and long run perspectives.

5.5 Conclusion

In a nutshell, the purpose for this research mainly to identify whether Peer-to-Peer (P2P) Lending, represent as FinTech along with other internal and macroeconomic variables can influence the bank profitability in USA in terms of Return of Asset (ROA). A number of 32 sample size has been taken range from year 2012 to year 2019 in form of quarterly data to conduct this research paper. Endogenous variable consists of FinTech itself, referring P2P Lending, bank size, Foreign Direct Investment (FDI), Inflation rate and Real Gross Domestic Product (RGDP). Additionally, implication of study which along with limitation met while carried out this empirical with recommendation for the future researchers had presented throughout this research chapter.

REFERENCES

Adeniyi, O., Omisakin, O., Egwaikhide, F. O., & Oyinlola, A. (2012). Foreign direct investment, economic growth and financial sector development in small open developing economies. *Economic Analysis and Policy, 42*(1), 105-127.

Adigwe, P. K., Okaro, C. S., Emejulu, I. J., & Ananwude, A. C. (2018). Banking sector operations and foreign direct investment in Nigeria: A causality analysis. *Asian Themes in Social Sciences Research, 1*(2), 60-75.

Akhtar, M. F., Ali, K., & Sadaqat, S. (2011). Factors influencing the profitability of Islamic Banks of Pakistan. *International Research Journal of Finance and Economics, 66*, 126-132.

Alper, D., & Anbar, A. (2011). Bank specific and macroeconomic determinants of commercial bank profitability: Empirical evidence from Turkey. *Business and Economics Research Journal, 2*(2), 139-152.

Ali, M., & Puah, C. H. (2018). Does bank size and funding risk effect banks' stability? A lesson from Pakistan. *Global Business Review, 19*(5).

Amos, A. J. (2016). *The impact of foreign direct investment on banking sector performance in Ghana* (Master's thesis, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana). Retrieved from http://dspace.knust.edu.gh/bitstream/123456789/8495/1/AMOS%20ASANTE%20JNR.pdf

Angeloni, I., & Faina, E. (2013). Capital regulation and monetary policy with fragile banks. *Journal of Monetary Economics, 60*, 311-324.

Antonius, R. (2003). *Interpreting Quantitative Data with SPSS*. India: Sage Publications India Pvt Ltd.

Asmundson, I. (2011). What are financial services? *International Monetary Fund.* Retrieved from https://www.imf.org/external/pubs/ft/fandd/2011/03/basics.htm

Barry, E. (2019, October 16). *A history of peer-to-peer lending in the US*. Retrieved from https://www.finder.com/p2p-lending-usa

Bai, J., & Ng, S. (2005). Tests for skewness, kurtosis, and normality for time series data. *Journal of Business & Economic Statistics, 23*(1), 49-60.

Bettencourt, M. (2010). Inflation and financial development: Evidence from Brazil. *Economic Modelling*, *28*, 91- 99.

Box, G. E. P., & Jenkins, G. (1976). *Time Series Analysis: Forecasting and Control, Holden-Day*.

Brooks, C. (2008). *Introductory Econometric for Finance. (2nd.ed.)*. Cambridge University Press.

Cameron, R. (1972). *Banking lending and economic development: Some lessons of history*. New York: Oxford University Press.

Carr, J. R. (1994). Book review. *Mathematical Geology*, *26*(4), 519-522. Davidson, J., Meenagh, D., Minford, P., & Wickens, M. (2010). *Why crises happen-nonstationary macroeconomics.* CEPR Discussion Paper No. DP8157.

Chen, C. W. S., Dong, M. C., Liu, N., & Sriboonchitta, S. (2019). Inferences of default risk and borrower characteristics on P2P lending. *The North American Journal of Economics and Finance*, *50*(101013), 1–14. doi: 10.1016/j.najef.2019.101013

Combey, A., & Togbenou, A. (2017). The bank sector performance and macroeconomics environment: Empirical evidence in Togo. *International Journal of Economics and Finance*, *9*(2), 180-188.

Dapp, T., Slomka, L., AG, D. B., & Hoffmann, R. (2014). Fintech–The digital (r) evolution in the financial sector. *Deutsche Bank Research", Frankfurt am Main*, 11.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982-1003.

Davis, J. H., Schoorman, F. D., & Donaldson, L. (1997). Toward a stewardship theory of management. *Acad. Manage*, *22*, 20-47.

Denscombe, M. (2010). *The Good Research Guide: for small-scale social research.* McGraw Hill.

Djalilov, K., & Piesse, J. (2016). Determinants of bank profitability in transition countries: What matters most? *Res. Int. Bus. Finance*, *38*, 69-82.

Dunkley, E. (2015). *Lending services revolution piles pressure on banks as fintech sector grows*. Retrieved from https://www.ft.com/content/653d64b2-77ce-11e5-a95a-27d368e1ddf7#axzz41waAnOyv

Duraj, B., & Moci, E. (2015). Factors influencing the bank profitability: Empirical evidence from Albania. *Asian Economic and Financial Review, 5*(3), 483-494. https://doi.org/10.18488/journal.aefr/2015.5.3/102.3.483.494

Emekter, R., Tu, Y., Jirasakuldech, B., & Lu, M. (2015). Evaluating credit risk and loan performance in online peer-to-peer (P2P) lending. *Applied Economics, 47*(1), 54-70.

Evolution of Fintech. (n.d.). Retrieved from https://www.e-zigurat.com/innovation-school/blog/evolution-of-fintech/

Gao, R. Q., & Feng, J. W. (2014). An overview study on P2P lending. *International Business and Management, 8*(2), 14-18.

Gujarati, D. N. (2009). *Basic Econometrics* (5th ed). USA: McGraw-Hill.

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). Boston, MA: McGraw-Hill.

Gul, S., Irshad, F., & Zaman, K. (2011). Factors affecting bank profitability in Pakistan. *Romanian Economic Journal, 14*(39), 61-89.

Harish, S. N., & Mallikarjunappa, T. (n.d.). *An examination of the beta stability in the Indian capital market*.

Heffernan, S. A., & Fu, X. (2010). Determinants of financial performance in Chinese banking. *Applied Financial Economics*, *20*, 1585-1600.

Hong, S. C., & Razak, S. H. A. (2015). The impact of nominal GDP and inflation on the financial performance of Islamic banks in Malaysia. *Journal of Islamic Economics, Banking and Finance*, *11*(1), 157-180.

Hu, R., Liu, M., He, P., & Ma, Y. (2019). Can investors on P2P lending platforms identify default risk? *International Journal of Electronic Commerce*, *23*(1), 63–84. doi: 10.1080/10864415.2018.1512279

Hu, Z., Ding, S., Li, S., Chen, L., & Yang, S. (2019). Adoption intention of FinTech services for bank users: An empirical examination with an extended Technology Acceptance Model. *Symmetry*, *11*(3), 340.

Inferisx. (2019, July 22). Top 10 finance companies in the world. *Topyaps*. Retrieved from topyaps.com/top-10-finance-companies-in-the-world/

Jim, F. (2020, April 12). *Multicollinearity in Regression Analysis: Problems, Detection, and Solutions*. Retrieved from https://www.datasciencecentral.com/profiles/blogs/multicollinearity-in-regression-analysis-problems-detection-and

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration-With applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, *52*(2), 169-210.

Jünger, M., & Mietzner, M. (2019). Banking goes digital: The adoption of FinTech services by German households. *Finance Research Letters.*

Kanwal, S., & Nadeem, M. (2013). The impact of macroeconomic variables on the profitability of listed commercial banks in Pakistan. *European Journal of Business and Social Sciences*, *2*(9), 186-201.

Kariuki, A. K., & Sang, P. (2018). Foreign direct investment and bank performance in Kenya. *IOSR Journal of Business and Management*, *20*(7), 10-20.

Kenton, W. (2019). *Descriptive Statistics*. Retrieved from https://www.investopedia.com/terms/d/descriptive_statistics.asp

Khrawish, H. A. (2011). Determinants of Commercial Banks performance: Evidence from Jordan. *International Research Journal of Finance and Economics*, *81*, 148-159.

Kiilu, N. (2016) *Effect of Fintech firms on financial performance of the banking sector in Kenya*. University of Nairobi.

Kirikkaleli, D. (2013). Foreign direct investment in the banking sector: Empirical evidence from Turkey. Stirling Management School.

Klaassen, P., & Eeghen, I. (2015). Analyzing Bank Performance: Linking ROE, ROA and RAROC. *SSRN Electronic Journal*, *3*(2). doi: 10.2139/ssrn.2389443

Klein, N. (2013). *Non-performing loans in CESEE: Determinants and macroeconomic performance* (Working Paper No. 13/72). Retrieved from https://pdfs.semanticscholar.org/f48a/a7dc7a51fe8b00f3944f2c165cb7cb66ba3c.pdf

Kolesova, I. V., & Girzheva, Y. S. (2018). Impact of financial technologies on the banking sector. *KnE Social Sciences*, 215-220.

Konara, P., Tan, Y., & Johnes, J. (2017). FDI and heterogeneity in bank efficiency: Evidence from Emerging Markets. *SSRN Electronic Journal*.

Konior, S. W. (2016, August 29). *What is an e-payment system?* Retrieved from https://www.business2community.com/ecommerce/e-payment-system-01641721

Korna, J. M., Ajekwe, T., & Idyu, I. A. (2013). The impact of foreign direct investment on the Nigerian banking sector. *IOSR Journal of Business and Management*, *7*(4), 77-92.

Ky, S., Rugemintwari, C., & Sauviat, A. (2019). Is fintech good for bank performance? The case of mobile money in the East African Community. *The Case of Mobile Money in the East African Community*.

LendingClub. (n.d.). *Helping Americans meet their life goals*. Retrieved from https://www.lendingclub.com/company/about-us

LendingClub. (n.d.). *Personal loan rates and fees*. Retrieved from https://www.lendingclub.com/loans/personal-loans/rates-fees

Lending Works. (n.d.). *Peer-to-peer lending: Advantages and disadvantages for loan customers*. Retrieved from https://www.lendingworks.co.uk/finance-guides/p2p-lending/peer-to-peer-lending-advantages-disadvantages-borrowers

Lenz, R. (2016). Peer-to-peer lending: opportunities and risks. *European Journal of Risk Regulation*, 7(4), 688-700.

Li, Y., Spigt, R., & Swinkels, L. (2017). The impact of FinTech start-ups on incumbent retail banks' share prices. *Financial Innovation*, *3*(1). doi: 10.1186/s40854-017-0076-7

Liang, H. Y., & Reichert, A. (2006). The relationship between economic growth and banking sector development. *Banks & bank systems*, *1(*2), 19-35.

Lund Research Statistics (2018). *Descriptive and Inferential Statistics*. Retrieved from https://statistics.laerd.com/statistical-guides/descriptive-inferential-statistics.php

Lütkepohl, H. (1993). *Introduction to Multiple Time Series Analysis. Second Edition*. Berlin: Springer-Verlag, Chapter 4.

Magee, J. R. (2011). Peer-to-peer lending in the United States: Surviving after Dodd-Frank. *North Carolina Banking Institute*, *15*(1), 139-174.

Majesty Alliance. (2017). *P2P investment vs traditional banking*. Retrieved from https://www.majestyalliance.com/news/2017/7/3/p2p-investment-vs-traditional-banking

Marimba, K. (2018). *Effect of inflation rate on profitability of commercial banks in Kenya*. University of Nairobi.

Mcclure, B. (2020). *How ROA and ROE Give a Clear Picture of Corporate Health*. Retrieved from https://www.investopedia.com/investing/roa-and-roe-give-clear-picture-corporate-health/

Milne, A., & Parboteeah, P. (2016). The business models and economics of peer-to-peer lending. *European Credit Research Institute, 17*.

Misati, R. N., Kamau, A., Kipyegon, L., & Wandaka, L. (2015) Is the evolution of Fintech/Digital financial services complementary to bank performance in Kenya?

Mollick, E. (2013). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing, 29*(2014), 1-16.

Musah, A., Gakpetor, E. D., Kyei, S. N. K., & Akomeah, E. (2018). Foreign direct investment (FDI), economic growth and bank performance in Ghana. *International Journal of Finance and Accounting, 7*(4), 97-107.

Namazi, M., & Salehi, M. (2010). The role of inflation in financial repression: Evidence from Iran. *World Applied Science Journal, 11,* 653-661.

Narusevicius, L. (2018). Bank profitability and macroeconomy: Evidence from Lithuania. *Technological and Economic Development of Economy, 24*(2), 383-405.

Nonaka, M., DeCresce, C., Hooper, R., & Konko, J. (2019). Retrieved from https://uk.practicallaw.thomsonreuters.com/w-017-4511

Nsambu, K. F. (2014). Factors affecting performance of commercial banks in Uganda: A case for domestic commercial banks. *Proceedings of 25th international Business Research Conference 13-14 Jan, 2014*.

Obamuyi, T. M. (2013). Determinants of banks' profitability in a developing economy: Evidence from Nigeria. *Organizations and Markets in Emerging Economies, 4*(2), 97-111.

Omoniyi, L. G., & Olawale, A. N. (2015). An application of ARDL bounds testing procedure to the estimation of level relationship between exchange rate, crude oil price and inflation rate in Nigeria. *International Journal of Statistics and Applications, 5*(2), 81-90.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289-326.

Phan, D. H. B., Narayan, P. K., Rahman, R. E., & Hutabarat, A. R. (2019). Do financial technology firms influence bank performance? *Pacific-Basin Finance Journal*, 101210. doi: 10.1016/j.pacfin.2019.101210

Prabhakaran, S. (2019). Vector Autoregression (VAR) – Comprehensive guide with examples in Python. *Machine Learning Plus*. Retrieved from https://www.machinelearningplus.com/time-series/vector-autoregression-examples-python/

Prosper Funding LLC. (n.d.). *Our Story*. Retrieved from https://www.prosper.com/about

Rahman, M. M., Hamid, M. K., & Khan, M. A. M. (2015). Determinants of bank profitability: Empirical evidence from Bangladesh. *International Journal of Business and Management*, *10*(8). doi: 10.5539/ijbm.v10n8p135

Rao, K. R. M., & Lakew, T. B. (2012). Determinants of profitability of commercial banks in a developing country: Evidence from Ethiopia. *International Journal of Accounting and Financial Management Research*, *2*(3), 1-20.

Revell, J. (1979). *Inflation and Financial Institutions*. Financial Times Limited.

Romānova, I., & Kudinska, M. (2017). Banking and Fintech: A challenge or opportunity? *Contemporary Studies in Economic and Financial Analysis, 98*, 21-35.

Rossi, E. (n.d.). *Impulse Response Functions*. University di Pavia. Retrieved from http://economia.unipv.it/pagp/pagine_personali/erossi/dottorato_svar.pdf

Rumler, F., & Waschiczek, W. (2012). Have changes in the financial structure affected bank profitability? Evidence for Austria. *The European Journal of Finance*, *22*(10), 803-824.

Saad, W., & El-Moussawi, C. (2012). The determinants of net interest margins of commercial banks in Lebanon. *Journal of Money, Investment and Banking, 23*, 118-132.

Saddimbah, G. (2014). Effect of foreign direct investments (FDI) inflow in Kenya on economic growth (GDP), exports and balance of payment (BOP). *United States International University Africa*. Retrieved from http://erepo.usiu.ac.ke/handle/11732/203

Sahni, R. (2020). Fintech 2020 | Laws and Regulations | USA | ICLG. Retrieved from https://iclg.com/practice-areas/fintech-laws-and-regulations

Saksonova, S., & Koleda, O. (2016). Evaluating the interrelationship between actions of Latvian. *Procedia Engineering, 178*, 123-130.

Salazar, L. A., Soto, C. R., & Mosqueda, E. R. (2012). The impact of financing decisions and strategy on small business competitiveness. *Global Journal of Business Research, 6*(2), 93-103.

SAP Analytics Cloud. (n.d.). *A look at Lending Club's peer-to-peer lending platform.* Retrieved from https://www.sapanalytics.cloud/resources-lending-club/

Statista. (n.d.). *Marketplace Lending-Consumer*. Retrieved from https://www.statista.com/outlook/338/109/marketplace-lending-consumer-/united-states

SBV (State Bank of Viet Nam). (2014). *Annual Statistics [Online]*. Retrieved from http://www.sbv.gov.vn/portal/faces/en/enm/enpages_home/statistic/balanceofpayment_adf.ctrl-state=14s0la308y4&afrLoop=4812941933026600

Scott, A. O., & Ovuefeyen, E. J. (2014). Effects of economic openness and inflation on commercial banks' profitability: Panel data evidence from Nigeria, Post-Banking Sector Consolidation (2005-2012). *European Journal of Business and Management, 6*(30).

Sheeba, D. L., Patil, B. S., & Srinivas, K. T. (2016). Impact of FDI on the operational efficiency of South Indian Bank. *International Journal of Engineering and Management Research, 6*(3), 734-741.

Shrestha, M. B., & Bhatta, G. R. (2018). Selecting appropriate methodological framework for time series data analysis. *The Journal of Finance and Data Science*, 1-19.

Shukur, G., & Mantalos, P. (2004). Size and power of the RESET test as applied to systems of equations: A Bootstrap approach. *Journal of Modern Applied Statistical Methods, 3*(2), 370-385.

Siek, M., & Sutanto, A. (2019). Impact analysis of fintech on banking industry. *International Conference on Information Management and Technology*, 356-361.

Sims, E. (2011). *Graduate Macro Theory II: Notes on Time Series.* University of Notre Dame.

Sun, S., & Li, S. (2012). Manufacturing sector FDI and performance of domestic banks. *Regional Development and Economic Growth in China, 7*, 141-156.

Stock, J., & Watson, M. (2007). *Introduction to econometrics*. *2nd ed.* Boston, MA Pearson Education, Inc.

Tajgardoon, G., Noormohamadi, K., & Behname, M. (2012). Foreign direct investment and Islamic banking: A Granger causality test. *Economics and Finance Review, 2*(5), 8-13.

Tam, L. T., Trang, P. X., & Hanh, L. N. (2017). Determinants of bank profitability: The case of commercial banks listed on the Vietnam's stock exchange. *Journal of Business Sciences*, *1*(2), 1-12.

Tang, H. (2019). Peer-to-peer lenders versus banks: Substitutes or complements? *The Review of Financial Studies, 32(*5), 1900-1938.

Tan, Y., & Floros, C. (2012). Bank profitability and inflation: The case of China. *Journal of Economics Studies, 39*, 675-696.

Tan, Y., & Floros, C. (2012). Bank profitability and GDP growth in China: A note. *Journal of Chinese Economic and Business Studies, 10*(3), 267-273.

Temelkov, Z. (2018). FinTech firms opportunity or threat for banks? *International Journal of Information, Business and Management, 10*(1), 137-143.

Teoh, W. M., Chong, S. C., Lin, B., & Chua, J. W. (2013). Factors affecting consumers' perception of electronic payment: An empirical analysis. *Internet Research, 23*(4), 465-485.

Thakor, A. V. (2019). Fintech and banking: What do we know? *Journal of Financial Intermediation.*

The FinTech revolution. Retrieved from http://www.economist.com/news/leaders/21650546-wave-startups-changing-financefor-better-FinTech-revolution.

Trochim, W. (2020). *Descriptive Statistics.* Retrieved from https://socialresearchmethods.net/kb/descriptive-statistics/

Trujillo-Ponce, A. (2013). What determines the profitability of banks? Evidence from Spain. *Accounting and Finance, 53*(2), 561-586. https://doi.org/10.1111/j.1467-629x.2011.00466.x

Tsaurai, K. (2014). Banking sector development and foreign direct investment: A case of Botswana. *Risk Governance and Control: Financial Markets and Institutions, 4*(3), 44-50.

Tung, Y, H. (n.d.). *Financing your business – P2P lenders or bank loans?* Retrieved from https://www.dbs.com.sg/sme/businessclass/articles/finance-and-operations/p2p-lending-or-bank-loan

Umar, M., Maijamai'a, D., & Adamu, M. (2014). Conceptual exposition of the effect of inflation on bank performance. *Journal of World Economic Research, 3*(5), 55-59.

Variyar, M., & Bhakta, P. (2016). *New FDI norms may open vaults for fintech companies.* Retrieved from https://economictimes.indiatimes.com/news/economy/policy/new-fdi-norms-may-open-vaults-for-fintech companies/articleshow/55023955.cms?from=mdr

Vives, X. (2017). The impact of FinTech on banking. *European Economy*, (2), 97-105.

Wai, P. S., & Ismail, M. T. (2014). Measuring nonlinear behaviour in time series data. *International Conference on Quantitative Sciences and Its Applications*, AIP Conf. Proc. 1635, 837-842.

Wardrop, R., Rosenberg, R., Zhang, B., Ziegler, T., Squire, R., Burton, J., . . . Garvey, K. (2016). *Breaking New Ground: The Americas Alternative Finance Benchmarking Report.* Retrieved from https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/publications/breaking-new-ground/#.Xl0dCqgzbIU

Wheat, R. E., Wang, Y., Byrnes, J. E., & Ranganathan, J. (2013). Raising money for scientific research through crowdfunding. *Trends in Ecology and Evolution*, *28*(2), 71-72.

Zeitun, R. (2012). Determinants of Islamic and conventional banks performance in GCC countries using panel data analysis. *Global Economy and Finance Journal*, *5*(1), 53-72.

APPENDICES

Appendix 1: Descriptive Statistics

	ROA	BANKSIZE	FDI	FINTECH	GDP	INF
Mean	1.118483	14.92052	299.4015	20.66513	18621.96	1.613125
Median	1.050346	14.88491	280.8100	17.35707	18387.55	1.685000
Maximum	1.380017	17.34066	955.5800	56.79845	21726.78	2.930000
Minimum	0.969130	12.63150	-293.9680	0.569891	16019.76	-0.070000
Std. Dev.	0.134729	1.412216	208.4196	18.02748	1742.857	0.746283
Skewness	0.978972	-0.002748	0.410913	0.516402	0.221711	-0.654278
Kurtosis	2.305704	1.805527	6.097311	1.958887	1.896911	3.114486
Jarque-Bera	5.754117	1.902393	13.69165	2.867469	1.884571	2.300568
Probability	0.056300	0.386279	0.001064	0.238417	0.389736	0.316547
Sum	35.79145	477.4565	9580.849	661.2843	595902.7	51.62000
Sum Sq. Dev.	0.562707	61.82495	1346601.	10074.69	94164116	17.26509
Observations	32	32	32	32	32	32

Appendix 2: Unit Root Test

Bank Size

Null Hypothesis: LBANKSIZE has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.128342	0.2360
Test critical values:	1% level	-3.737853	
	5% level	-2.991878	
	10% level	-2.635542	

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

Null Hypothesis: LBANKSIZE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.097968	0.1249
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

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

Null Hypothesis: D(LBANKSIZE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.861478	0.0005
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

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

Null Hypothesis: D(LBANKSIZE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 6 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.528183	0.0588
Test critical values:	1% level	-4.394309	
	5% level	-3.612199	
	10% level	-3.243079	

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

Foreign Direct Investment

Null Hypothesis: LFDI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.716942	0.0007
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

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

Null Hypothesis: LFDI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.713024	0.0036
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

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

Null Hypothesis: D(LFDI) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.348124	0.0000
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

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

Null Hypothesis: D(LFDI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.226588	0.0000
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

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

Financial Technology

Null Hypothesis: LFINTECH has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.013672	0.0003
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

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

Null Hypothesis: LFINTECH has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.928768	0.0231
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

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

Null Hypothesis: D(LFINTECH) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.185803	0.9300
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

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

Null Hypothesis: D(LFINTECH) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.492930	0.3290
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

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

Gross Domestic Product

Null Hypothesis: LGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.748601	0.9913
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

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

Null Hypothesis: LGDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.420180	0.3620
Test critical values:	1% level	-4.323979	
	5% level	-3.580622	
	10% level	-3.225334	

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

Null Hypothesis: D(LGDP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.022141	0.0003
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

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

Null Hypothesis: D(LGDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.034203	0.0017
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

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

Inflation

Null Hypothesis: LINF has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.462963	0.1342
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

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

Null Hypothesis: LINF has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.554248	0.3020
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

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

Null Hypothesis: D(LINF) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.753695	0.0084
Test critical values:	1% level	-3.679322	
	5% level	-2.967767	
	10% level	-2.622989	

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

Null Hypothesis: D(LINF) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.802749	0.0310
Test critical values:	1% level	-4.309824	
	5% level	-3.574244	
	10% level	-3.221728	

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

Return on Asset

Null Hypothesis: LROA has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.419609	0.5599
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

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

Null Hypothesis: LROA has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.332551	0.4053
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

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

Null Hypothesis: D(LROA) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.081398	0.0000
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

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

Null Hypothesis: D(LROA) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.981874	0.0000
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

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

Appendix 3: Vector Autoregression (VAR) Model

Vector Autoregression Estimates
Date: 07/11/20 Time: 22:46
Sample (adjusted): 2012Q2 2019Q4
Included observations: 31 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	LROA	LBANKSIZE	LFDI	LFINTECH	LGDP	LINF
LROA(-1)	0.269633	-0.024484	-2.679642	0.133521	0.008540	0.327352
	(0.21976)	(0.02093)	(2.77899)	(0.07043)	(0.01621)	(1.66993)
	[1.22694]	[-1.16987]	[-0.96425]	[1.89586]	[0.52669]	[0.19603]
LBANKSIZE(-1)	0.276363	0.457599	-22.69914	-0.979354	0.161164	4.064561
	(1.60641)	(0.15299)	(20.3141)	(0.51482)	(0.11852)	(12.2070)
	[0.17204]	[2.99106]	[-1.11741]	[-1.90234]	[1.35977]	[0.33297]
LFDI(-1)	-0.012146	0.002833	-0.020474	0.000326	-7.09E-05	-0.138579
	(0.01727)	(0.00165)	(0.21843)	(0.00554)	(0.00127)	(0.13126)
	[-0.70316]	[1.72246]	[-0.09373]	[0.05897]	[-0.05561]	[-1.05580]
LFINTECH(-1)	-0.098454	0.010101	0.787372	0.998993	-0.000105	0.084827
	(0.04869)	(0.00464)	(0.61571)	(0.01560)	(0.00359)	(0.36999)
	[-2.02206]	[2.17839]	[1.27880]	[64.0222]	[-0.02910]	[0.22927]
LGDP(-1)	1.879183	0.414170	12.47142	0.107101	0.834627	-4.788729
	(1.52719)	(0.14544)	(19.3122)	(0.48943)	(0.11268)	(11.6049)
	[1.23049]	[2.84763]	[0.64578]	[0.21883]	[7.40720]	[-0.41265]
LINF(-1)	-0.000791	0.004650	-0.006680	-0.015861	0.001722	0.763752
	(0.01849)	(0.00176)	(0.23385)	(0.00593)	(0.00136)	(0.14052)
	[-0.04277]	[2.64011]	[-0.02857]	[-2.67633]	[1.26210]	[5.43514]
C	-18.82599	-2.635344	-57.21045	1.726064	1.199440	36.70120
	(11.4570)	(1.09113)	(144.881)	(3.67169)	(0.84531)	(87.0609)
	[-1.64318]	[-2.41525]	[-0.39488]	[0.47010]	[1.41893]	[0.42156]
R-squared	0.794485	0.997073	0.209432	0.999843	0.998195	0.706364
Adj. R-squared	0.743107	0.996341	0.011790	0.999804	0.997744	0.632955
Sum sq. resids	0.081985	0.000744	13.11036	0.008420	0.000446	4.734107
S.E. equation	0.058447	0.005566	0.739097	0.018731	0.004312	0.444133
F-statistic	15.46332	1362.632	1.059654	25459.25	2211.870	9.622308
Log likelihood	48.00855	120.9018	-30.64803	83.28503	128.8147	-14.85959
Akaike AIC	-2.645713	-7.348500	2.428905	-4.921615	-7.859014	1.410296
Schwarz SC	-2.321909	-7.024696	2.752709	-4.597812	-7.535210	1.734100
Mean dependent	0.108371	2.703594	5.590848	2.460095	9.832598	0.293174
S.D. dependent	0.115315	0.092025	0.743493	1.336683	0.090781	0.733084

Determinant resid covariance (dof adj.)	3.21E-17
Determinant resid covariance	6.91E-18
Log likelihood	348.5452
Akaike information criterion	-19.77711
Schwarz criterion	-17.83429
Number of coefficients	42

Appendix 4: Lag Length Selection

VAR Lag Order Selection Criteria
Endogenous variables: LROA LBANKSIZE LFDI LFINTECH LGDP LINF
Exogenous variables: C
Date: 07/11/20 Time: 22:47
Sample: 2012Q1 2019Q4
Included observations: 29

Lag	LogL	LR	FPE	AIC	SC	HQ
0	112.3534	NA	2.63e-11	-7.334715	-7.051826	-7.246118
1	340.0828	345.5206	5.04e-17	-20.55744	-18.57721*	-19.93726
2	391.0718	56.26374*	2.55e-17	-21.59116	-17.91361	-20.43940
3	460.5881	47.94223	7.90e-18*	-23.90263*	-18.52774	-22.21928*

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix 5: Autoregressive-Distributed Lag (ARDL)

Dependent Variable: LROA
Method: ARDL
Date: 07/11/20 Time: 22:48
Sample (adjusted): 2012Q2 2019Q4
Included observations: 31 after adjustments
Maximum dependent lags: 1 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (1 lag, automatic): LBANKSIZE LFDI LFINTECH LGDP LINF
Fixed regressors: C
Number of models evalulated: 32
Selected Model: ARDL(1, 0, 0, 0, 0, 0)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LROA(-1)	0.134806	0.184523	0.730565	0.4721
LBANKSIZE	-2.792555	1.406789	-1.985056	0.0587
LFDI	-0.000396	0.015557	-0.025429	0.9799
LFINTECH	-0.056279	0.042516	-1.323692	0.1981
LGDP	4.390206	1.326810	3.308843	0.0029
LINF	0.009894	0.016586	0.596502	0.5564
C	-35.38459	9.883896	-3.580024	0.0015

R-squared	0.831071	Mean dependent var	0.108371
Adjusted R-squared	0.788839	S.D. dependent var	0.115315
S.E. of regression	0.052990	Akaike info criterion	-2.841754
Sum squared resid	0.067390	Schwarz criterion	-2.517950
Log likelihood	51.04718	Hannan-Quinn criter.	-2.736202
F-statistic	19.67863	Durbin-Watson stat	1.974409
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Appendix 6: Bound Test

ARDL Long Run Form and Bounds Test
Dependent Variable: D(LROA)
Selected Model: ARDL(1, 0, 0, 0, 0, 0)
Case 2: Restricted Constant and No Trend
Date: 07/11/20 Time: 22:49
Sample: 2012Q1 2019Q4
Included observations: 31

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-35.38459	9.883896	-3.580024	0.0015
LROA(-1)*	-0.865194	0.184523	-4.688823	0.0001
LBANKSIZE**	-2.792555	1.406789	-1.985056	0.0587
LFDI**	-0.000396	0.015557	-0.025429	0.9799
LFINTECH**	-0.056279	0.042516	-1.323692	0.1981
LGDP**	4.390206	1.326810	3.308843	0.0029
LINF**	0.009894	0.016586	0.596502	0.5564

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LBANKSIZE	-3.227663	1.495195	-2.158690	0.0411
LFDI	-0.000457	0.017985	-0.025423	0.9799
LFINTECH	-0.065047	0.046812	-1.389549	0.1774
LGDP	5.074244	1.125481	4.508509	0.0001
LINF	0.011435	0.019177	0.596321	0.5565
C	-40.89786	7.677241	-5.327156	0.0000

EC = LROA - (-3.2277*LBANKSIZE -0.0005*LFDI -0.0650*LFINTECH + 5.0742 *LGDP + 0.0114*LINF - 40.8979)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	3.307888	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15
Actual Sample Size	31		Finite Sample: n=35	
		10%	2.331	3.417
		5%	2.804	4.013
		1%	3.9	5.419
			Finite Sample: n=30	
		10%	2.407	3.517
		5%	2.91	4.193
		1%	4.134	5.761

Appendix 7: Vector Error Correction Model (VECM)

Vector Error Correction Estimates
Date: 07/11/20 Time: 22:51
Sample (adjusted): 2012Q3 2019Q4
Included observations: 30 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
LROA(-1)	1.000000
LBANKSIZE(-1)	7.096316 (1.26521) [5.60882]
LFDI(-1)	-0.102438 (0.01739) [-5.89068]
LFINTECH(-1)	0.139417 (0.03337) [4.17816]
LGDP(-1)	-9.271940 (0.83373) [-11.1210]
LINF(-1)	-0.022573 (0.01484) [-1.52072]
C	72.11219

Error Correction:	D(LROA)	D(LBANKSIZE)	D(LFDI)	D(LFINTECH)	D(LGDP)	D(LINF)
CointEq1	-0.140950 (0.19571) [-0.72018]	-0.032690 (0.01674) [-1.95241]	5.475617 (1.99138) [2.74966]	-0.101336 (0.03855) [-2.62876]	0.014060 (0.01271) [1.10605]	-0.892463 (1.22023) [-0.73139]

D(LROA(-1))	-0.240795	-0.005130	-9.519174	0.097144	0.002334	0.705631
	(0.22137)	(0.01894)	(2.25238)	(0.04360)	(0.01438)	(1.38016)
	[-1.08777]	[-0.27090]	[-4.22627]	[2.22799]	[0.16234]	[0.51127]
D(LBANKSIZE(-1))	1.386673	0.026886	-27.62513	-0.394742	0.225913	-16.01306
	(2.08504)	(0.17837)	(21.2151)	(0.41068)	(0.13542)	(12.9997)
	[0.66506]	[0.15073]	[-1.30214]	[-0.96119]	[1.66821]	[-1.23180]
D(LFDI(-1))	-0.009613	-0.000496	-0.159547	-0.005554	0.000345	-0.099690
	(0.01692)	(0.00145)	(0.17221)	(0.00333)	(0.00110)	(0.10552)
	[-0.56800]	[-0.34275]	[-0.92648]	[-1.66606]	[0.31398]	[-0.94474]
D(LFINTECH(-1))	-0.287118	-0.021357	6.641474	0.897227	-3.17E-05	-1.306650
	(0.24990)	(0.02138)	(2.54268)	(0.04922)	(0.01623)	(1.55804)
	[-1.14895]	[-0.99900]	[2.61199]	[18.2285]	[-0.00195]	[-0.83865]
D(LGDP(-1))	1.398583	-0.314601	44.38513	-0.458191	0.007008	-15.75935
	(3.15263)	(0.26971)	(32.0778)	(0.62096)	(0.20476)	(19.6559)
	[0.44362]	[-1.16645]	[1.38367]	[-0.73787]	[0.03423]	[-0.80176]
D(LINF(-1))	-0.028531	0.006096	0.102280	-0.006671	-0.002559	0.335487
	(0.03114)	(0.00266)	(0.31683)	(0.00613)	(0.00202)	(0.19414)
	[-0.91625]	[2.28834]	[0.32282]	[-1.08775]	[-1.26545]	[1.72804]
C	0.025722	0.016524	-1.102436	0.017747	0.007443	0.527087
	(0.05787)	(0.00495)	(0.58885)	(0.01140)	(0.00376)	(0.36082)
	[0.44446]	[3.33749]	[-1.87219]	[1.55688]	[1.98005]	[1.46081]
R-squared	0.206876	0.367671	0.623622	0.977075	0.232079	0.261415
Adj. R-squared	-0.045482	0.166476	0.503866	0.969780	-0.012259	0.026410
Sum sq. resids	0.103252	0.000756	10.68962	0.004006	0.000436	4.013629
S.E. equation	0.068508	0.005861	0.697059	0.013494	0.004450	0.427127
F-statistic	0.819773	1.827434	5.207421	133.9492	0.949827	1.112382
Log likelihood	42.50852	116.2683	-27.08930	91.25029	124.5329	-12.39563
Akaike AIC	-2.300568	-7.217885	2.339286	-5.550020	-7.768863	1.359709
Schwarz SC	-1.926915	-6.844232	2.712939	-5.176367	-7.395210	1.733361
Mean dependent	0.008527	0.010301	-0.029499	0.146196	0.009883	0.010724
S.D. dependent	0.067001	0.006419	0.989624	0.077622	0.004422	0.432882

Determinant resid covariance (dof adj.)	1.16E-17
Determinant resid covariance	1.80E-18
Log likelihood	357.4959
Akaike information criterion	-20.23306
Schwarz criterion	-17.71090
Number of coefficients	54

Appendix 8: Granger Causality

VEC Granger Causality/Block Exogeneity Wald Tests
Date: 07/11/20 Time: 22:52
Sample: 2012Q1 2019Q4
Included observations: 30

Dependent variable: D(LROA)

Excluded	Chi-sq	df	Prob.
D(LBANKSIZE)	0.442302	1	0.5060
D(LFDI)	0.322629	1	0.5700
D(LFINTECH)	1.320078	1	0.2506
D(LGDP)	0.196802	1	0.6573
D(LINF)	0.839505	1	0.3595
All	3.454308	5	0.6303

Dependent variable: D(LBANKSIZE)

Excluded	Chi-sq	df	Prob.
D(LROA)	0.073384	1	0.7865
D(LFDI)	0.117481	1	0.7318
D(LFINTECH)	0.998003	1	0.3178
D(LGDP)	1.360617	1	0.2434
D(LINF)	5.236500	1	0.0221
All	8.906964	5	0.1128

Dependent variable: D(LFDI)

Excluded	Chi-sq	df	Prob.
D(LROA)	17.86137	1	0.0000
D(LBANKSIZE)	1.695574	1	0.1929
D(LFINTECH)	6.822510	1	0.0090
D(LGDP)	1.914542	1	0.1665
D(LINF)	0.104211	1	0.7468
All	21.14384	5	0.0008

Dependent variable: D(LFINTECH)

Excluded	Chi-sq	df	Prob.
D(LROA)	4.963933	1	0.0259
D(LBANKSIZE)	0.923884	1	0.3365
D(LFDI)	2.775766	1	0.0957
D(LGDP)	0.544459	1	0.4606
D(LINF)	1.183207	1	0.2767
All	10.27305	5	0.0679

Dependent variable: D(LGDP)

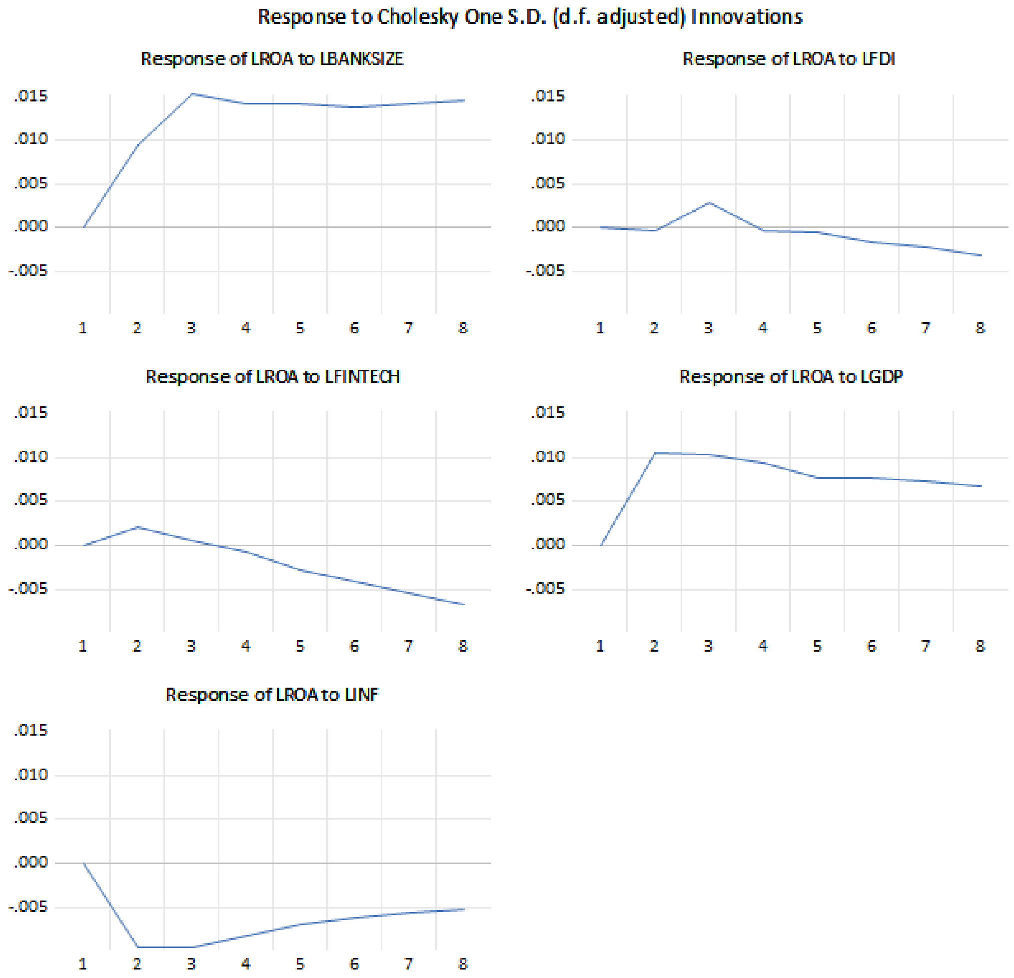
Excluded	Chi-sq	df	Prob.
D(LROA)	0.026354	1	0.8710
D(LBANKSIZE)	2.782939	1	0.0953
D(LFDI)	0.098583	1	0.7535
D(LFINTECH)	3.81E-06	1	0.9984
D(LINF)	1.601375	1	0.2057
All	5.127548	5	0.4005

Dependent variable: D(LINF)

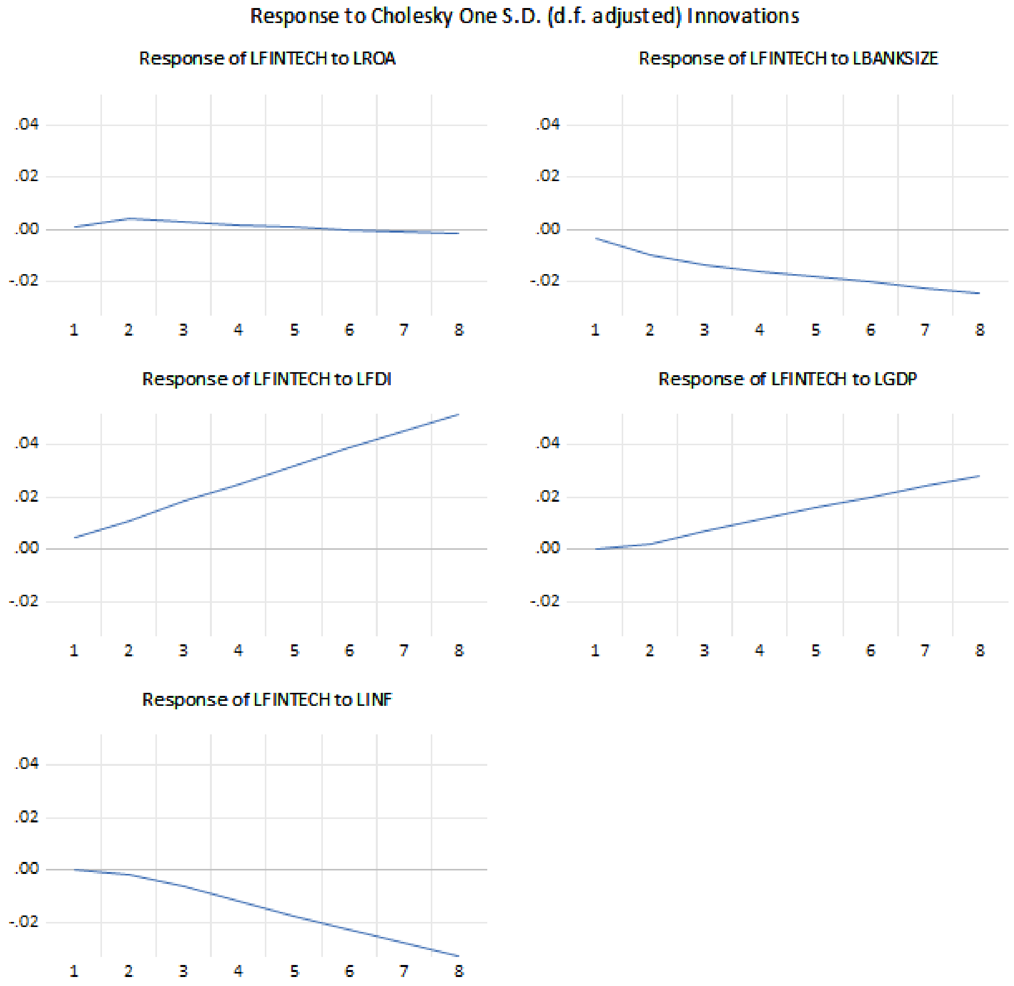
Excluded	Chi-sq	df	Prob.
D(LROA)	0.261395	1	0.6092
D(LBANKSIZE)	1.517337	1	0.2180
D(LFDI)	0.892535	1	0.3448
D(LFINTECH)	0.703330	1	0.4017
D(LGDP)	0.642824	1	0.4227
All	3.448131	5	0.6313

Appendix 9: Impulse Response

Impulse Response of ROA



Impulse Response of FinTech



Appendix 10: Variance Decomposition

Variance Decomposition of LROA:

Period	S.E.	LROA	LBANKSIZE	LFDI	LFINTECH	LGDP	LINF
1	0.068508	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.082260	95.62366	1.317350	0.001218	0.058778	1.634784	1.364207
3	0.094599	91.75986	3.596018	0.095530	0.048248	2.432664	2.067680
4	0.104060	89.87957	4.830410	0.080108	0.044736	2.833372	2.331803
5	0.113856	89.11822	5.584507	0.068973	0.098440	2.822274	2.307583
6	0.122402	88.51763	6.124975	0.076274	0.196022	2.837558	2.247543
7	0.130590	88.01807	6.578857	0.093923	0.346940	2.801238	2.160966
8	0.138333	87.53731	6.973989	0.131794	0.550695	2.740117	2.066094

Variance Decomposition of LBANKSIZE:

Period	S.E.	LROA	LBANKSIZE	LFDI	LFINTECH	LGDP	LINF
1	0.005861	13.56168	86.43832	0.000000	0.000000	0.000000	0.000000
2	0.008953	26.80933	63.65960	0.646194	0.231124	0.284148	8.369602
3	0.011167	35.53272	47.44256	0.509268	0.184170	0.234749	16.09654
4	0.012586	37.71865	41.42207	0.432200	0.148463	0.231533	20.04708
5	0.013788	38.94508	38.54554	0.400982	0.123841	0.220336	21.76422
6	0.014932	39.97355	36.62377	0.413076	0.109300	0.202467	22.67784
7	0.016016	40.93465	35.03376	0.433720	0.107152	0.183966	23.30674
8	0.017017	41.67119	33.78649	0.461431	0.117078	0.168707	23.79510

Variance Decomposition of LFDI:

Period	S.E.	LROA	LBANKSIZE	LFDI	LFINTECH	LGDP	LINF
1	0.697059	0.801508	26.30161	72.89689	0.000000	0.000000	0.000000
2	0.811527	16.03011	22.22431	60.74284	0.934489	0.058344	0.009916
3	0.946347	18.05413	20.24063	56.65929	0.694279	4.331795	0.019882
4	1.015626	15.67518	19.57180	58.78433	0.827053	5.099430	0.042204
5	1.093623	13.59915	18.66645	61.21215	1.130844	5.343628	0.047781
6	1.162063	12.04960	17.92646	62.88757	1.683981	5.405921	0.046466
7	1.235013	10.76701	17.21717	64.24309	2.281258	5.432489	0.058979
8	1.306308	9.649299	16.49606	65.42752	3.025322	5.319325	0.082476

Variance Decomposition of LFINTECH:

Period	S.E.	LROA	LBANKSIZE	LFDI	LFINTECH	LGDP	LINF
1	0.013494	0.611710	5.537291	10.91175	82.93925	0.000000	0.000000
2	0.031599	1.742404	10.07279	13.95618	73.60440	0.347704	0.276520
3	0.054770	0.814217	9.549665	15.73294	70.78126	1.722795	1.399124
4	0.081901	0.392324	8.080714	16.46283	69.39476	2.857291	2.812080
5	0.112093	0.215115	6.857248	16.90856	68.46699	3.558369	3.993723
6	0.144966	0.128620	6.004170	17.23798	67.73819	4.037238	4.853803
7	0.180280	0.085759	5.415296	17.46833	67.14285	4.399600	5.488162
8	0.217789	0.065272	4.987147	17.62571	66.65345	4.682669	5.985759

Variance Decomposition of LGDP:

Period	S.E.	LROA	LBANKSIZE	LFDI	LFINTECH	LGDP	LINF
1	0.004450	5.507950	1.864062	17.74040	20.38035	54.50724	0.000000
2	0.006628	5.918364	12.35584	16.33352	16.74129	45.94493	2.706053
3	0.008111	5.387515	18.69968	15.23923	14.82229	43.13794	2.713342
4	0.009239	4.528656	20.77604	15.57145	13.87322	42.96039	2.290244
5	0.010213	4.224513	21.70082	16.24495	13.06906	42.78502	1.975644
6	0.011105	4.098567	22.44673	16.96327	12.27449	42.45710	1.759851
7	0.011930	4.021362	23.18464	17.61276	11.50561	42.08563	1.589992
8	0.012696	3.941928	23.83418	18.27339	10.78268	41.72364	1.444175

Variance Decomposition of LINF:

Period	S.E.	LROA	LBANKSIZE	LFDI	LFINTECH	LGDP	LINF
1	0.427127	2.082888	7.642321	9.170376	0.092686	2.266821	78.74491
2	0.764532	2.727277	16.26133	7.960018	0.460902	2.844602	69.74587
3	1.012554	3.174761	19.73082	7.494770	0.564980	2.500330	66.53434
4	1.197174	3.293861	20.93833	7.756901	0.648416	2.274295	65.08820
5	1.352769	3.527089	21.06527	8.035874	0.798029	2.235640	64.33809
6	1.495204	3.615230	20.92955	8.288221	0.988849	2.250511	63.92764
7	1.629558	3.649985	20.73006	8.509237	1.202886	2.281078	63.62675
8	1.756991	3.666097	20.49862	8.734668	1.432994	2.319367	63.34826

Cholesky Ordering: LROA LBANKSIZE LFDI LFINTECH LGDP LINF

Appendix 11: VEC Residual Serial Correlation LM Test

VEC Residual Serial Correlation LM Tests
Date: 07/12/20 Time: 00:13
Sample: 2012Q1 2019Q4
Included observations: 30

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	32.42335	36	0.6395	0.865553	(36, 51.1)	0.6724

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	32.42335	36	0.6395	0.865553	(36, 51.1)	0.6724

*Edgeworth expansion corrected likelihood ratio statistic.

Appendix 12: VEC Residual Normality Test

VEC Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 07/12/20 Time: 00:14
Sample: 2012Q1 2019Q4
Included observations: 30

Component	Skewness	Chi-sq	df	Prob.*
1	1.034946	5.355569	1	0.0207
2	-0.333382	0.555719	1	0.4560
3	0.476070	1.133215	1	0.2871
4	-0.759717	2.885851	1	0.0894
5	0.372921	0.695351	1	0.4044
6	-0.399420	0.797683	1	0.3718
Joint		11.42339	6	0.0761

Component	Kurtosis	Chi-sq	df	Prob.
1	6.361058	14.12088	1	0.0002
2	2.545544	0.258163	1	0.6114
3	2.430687	0.405147	1	0.5244
4	4.926490	4.639207	1	0.0312
5	2.808466	0.045857	1	0.8304
6	2.516180	0.292603	1	0.5886
Joint		19.76186	6	0.0031

Component	Jarque-Bera	df	Prob.
1	19.47645	2	0.0001
2	0.813882	2	0.6657
3	1.538362	2	0.4634
4	7.525058	2	0.0232
5	0.741207	2	0.6903
6	1.090285	2	0.5798
Joint	31.18525	12	0.0018

*Approximate p-values do not account for coefficient estimation

Appendix 13: VEC Residual Heteroscedasticity Test

VEC Residual Heteroskedasticity Tests (Levels and Squares)
Date: 07/12/20 Time: 00:17
Sample: 2012Q1 2019Q4
Included observations: 30

Joint test:

Chi-sq	df	Prob.
319.1293	294	0.1502

Individual components:

Dependent	R-squared	F(14,15)	Prob.	Chi-sq(14)	Prob.
res1*res1	0.693842	2.428164	0.0497	20.81526	0.1065
res2*res2	0.472088	0.958132	0.5294	14.16265	0.4377
res3*res3	0.889581	8.631879	0.0001	26.68743	0.0211
res4*res4	0.758976	3.373897	0.0128	22.76929	0.0641
res5*res5	0.598686	1.598374	0.1890	17.96059	0.2086
res6*res6	0.535877	1.237071	0.3431	16.07630	0.3087
res2*res1	0.580344	1.481685	0.2294	17.41033	0.2350
res3*res1	0.592624	1.558643	0.2019	17.77871	0.2170
res3*res2	0.544360	1.280050	0.3199	16.33079	0.2936
res4*res1	0.511022	1.119731	0.4138	15.33067	0.3559
res4*res2	0.744109	3.115617	0.0182	22.32326	0.0722
res4*res3	0.748510	3.188890	0.0165	22.45529	0.0697
res5*res1	0.551598	1.318011	0.3006	16.54795	0.2811
res5*res2	0.308318	0.477591	0.9124	9.249546	0.8147
res5*res3	0.460909	0.916045	0.5627	13.82728	0.4627
res5*res4	0.645867	1.954065	0.1052	19.37600	0.1511
res6*res1	0.247593	0.352573	0.9708	7.427801	0.9170
res6*res2	0.338666	0.548674	0.8654	10.15998	0.7504
res6*res3	0.663634	2.113877	0.0813	19.90902	0.1330
res6*res4	0.382647	0.664093	0.7749	11.47942	0.6480
res6*res5	0.584971	1.510150	0.2188	17.54914	0.2281

Appendix 14: CUSUM Test